# An Empirical Examination of Industry Returns for Evidence of Cyclical Performance

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**Abstract**

This dissertation provides three empirical studies of industry performance related to different financial market cycles. Popular belief holds that industries provide systematic cyclical performance. Such systematic performance would present a challenge to basic assumptions of market efficiency. The three industry cycles investigated are sentiment cycles, political cycles, and business cycles.

The first study investigates the interaction between three popular investor-sentiment measures and industry performance. Investor sentiment has a widespread and systematic effect on industry performance. Similar to prior market studies, investor sentiment predicts short-term industry mispricing. Predictable long-term industry reversals are weaker. Moreover, the effect of investor sentiment is widespread, with limited evidence of cross-sectional industry differences. Unlike prior market studies, there is no evidence of a relationship between investor sentiment and industry characteristics that serve as a proxy for valuation uncertainty. Lastly, an industry rotation strategy based on investor sentiment generates marginal outperformance, which turnover and transaction costs would consume. Results generally show that investor sentiment has a market-wide effect, questioning its usefulness in timing industry investments.

The second study examines industry returns for presidential election cycles. Risk-adjusted industry returns provide no evidence of political cycles previously documented in the U.S. stock market. In spite of the existence of market-wide effects, realized industry returns exhibit neither systematic nor persistent outperformance related to a president's political affiliation or the year of a president's term. Expected industry performance is equally unaffected by political cycles, exhibiting no systematic response to presidential elections and indicating that the market does not systematically price a president's political affiliation in industry returns. The study's results question the popular belief that certain industries systematically perform better under Democrats or Republicans and provide evidence that political cycles are solely a market-wide phenomenon best explained at a macroeconomic level.

The third study investigates industry returns for systematic business-cycle performance. Popular guidance holds that sectors/industries provide systematic performance and that business-cycle rotation strategies generate excess market performance. The study tests these two fundamental assumptions of popular rotation strategies. Initially, the study assumes investors can perfectly anticipate business cycles and implement conventional sector rotation. However, there is no evidence of systematic sector performance where popular belief anticipates it will occur. At best, conventional sector rotation generates 2.3 percent annual excess returns. This performance quickly diminishes after an allowance for transaction costs and incorrectly timing business cycles. An examination of all sectors across all business-cycle stages produces evidence of in-sample systematic sector performance, but an out-of-sample alternative rotation strategy fails to generate excess performance. Overall, the study documents unsystematic sector performance across business cycles, questioning the popularity of sector rotation as a viable investment strategy.

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# Chapter 1 Introduction

## 1.1 Introduction

The efficient market hypothesis is the basis of modern financial theory. In a seminal study, Fama (1970, pg. 383) states, "A market in which prices always 'fully reflect' available information is called 'efficient'." Stock prices should follow a random walk, without predictable patterns, due to the unpredictable arrival of price-relevant information. Fama (1970) describes weak, semi-strong and strong form market efficiency. Weak form efficiency requires that there are no predictable patterns in historical stock prices. Semi-strong form efficiency requires that prices immediately reflect all publicly available information affecting fundamental values. Additionally, strong form efficiency requires that prices reflect all publicly and privately available information. The empirical evidence, generally, supports weak and semi-strong form efficiency, but not strong form efficiency. The efficient market hypothesis allows for the possibility that individual investors may overreact or underreact to stock information. However, market prices should quickly adjust to reflect rational expectations and fundamental values. In efficient markets, there should be no opportunity for investors to formulate trading strategies that generate systematic outperformance (Malkiel (2003)). Nonetheless, empirical evidence of market cycles and the popularity of trading strategies based on predictable market cycles appear to contradict the efficient market hypothesis.

Behavioral finance theory provides an alternative to the efficient market hypothesis, describing mechanisms that allow for price divergence from fundamental values and predictable patterns in stock returns. An important survey by Shiller (2003, pg. 83) describes behavioral finance as "vital research [that] stands in sharp contradiction to much of efficient markets theory." His survey reviews a litany of market anomalies unexplained by rational expectations. Shiller (2003) argues that irrational investor exuberance leads to speculative cycles and, ultimately, asset pricing bubbles. Shiller (2003) also observes that speculative pricing, unrelated to fundamentals, commonly occurs in certain investment "styles." Take industry styles, for example. In a key paper, Barberis and Shleifer (2003) formalize a model where investor cognitive limitations lead to style investing and temporary mispricing. Teo and Woo (2004), among others, provide empirical evidence of excess style performance unrelated to fundamentals and rational expectations. A number of important studies, such as Hong, Torous, and Valkanov (2007) and Santa-Clara and Valkanov (2003), document predictable cycles in asset returns unexplained by fundamental values that are in violation of market efficiency. The behavioral finance literature thus suggests predictable industry cycles and profitable investment strategies, contrary to market efficiency.

Popular investor belief holds that predictable market cycles allow for profitable investment strategies. Common cyclical investment strategies relate to seasonal cycles, political election cycles, or business cycles. Kamstra, Kramer, and Levi (2003), for instance, document a seasonal affective disorder (SAD) in stocks, which translates into seasonal stock market patterns driven by investor sentiment. The financial press also widely reports on investor-sentiment cycles as predictors of market performance. A number of studies, for instance Santa-Clara and Valkanov (2003) and Snowberg, Wolfers, and Zitzewitz (2007), confirm political cycles in market index returns. Business cycles also provide the basis for different investment strategies. Siegel (2002) describes a profitable investment strategy that rotates between equities and cash at business cycle turning points. Sector rotation is another widely followed investment strategy, which rotates sector and industry investments with business-cycle stages. Other stock market cycles relate to the month of the year; Federal Reserve Bank monetary policy; sporting events; and credit expansion and contraction. This dissertation examines industry performance for evidence of sentiment cycles, political cycles, and business cycles.

The empirical studies that comprise this dissertation investigate industry cycles and investor sentiment, contributing to the asset pricing, market efficiency, and investment strategy literatures. The first study explores the interaction between investor-sentiment cycles and industry performance. The second study examines industry returns for evidence of political cycles. The third study analyzes industry performance over business cycles. That study also investigates whether a popular investment strategy, known as sector rotation, generates excess returns. Any evidence of systematic industry cycles is inconsistent with the basic tenets of market efficiency. Nonetheless, investors popularly believe that trading on different industry cycles systematically generates excess returns. The popularity of industry investing is evident from the capital flows it attracts. A rigorous examination of cyclical industry performance contributes to the literature from both theoretical and practical perspectives, providing new insights into stock market cycles and industry investing.

Prior to discussing the research questions addressed by the empirical studies, the next section reviews background literature.

## 1.2 General Literature Overview

This section provides an extended discussion of key literature related to the dissertation. Section 1.2.1 discusses influential literature on style investing theories, which support the idea of industry style cycles and viable industry rotation strategies. Sections 1.2.2 to 1.2.4 briefly discuss key literature on stock-market cycles. The concluding section discusses literature on industry-style investing.

### 1.2.1 Behavioral finance and style investing

This dissertation examines the relationship between industry performance and investor sentiment, presidential election cycles and business cycles. Recurring cycles such as these should have no effect on expected industry returns. A basic tenet of the efficient market hypothesis states that asset prices follow a random walk, without predictable patterns. Nonetheless, popular belief suggests that predictable cycles lead to profitable trading strategies. Behavioral finance provides an alternative theory on style investing, which results in predictable cycles and mispricing.

In a seminal paper, Barberis and Shleifer (2003) formulate a behavioral model of style investing. The model maintains that investors make investment decisions on styles rather than stock fundamentals. Barberis and Shleifer (2003) base their model on a simple premise: humans naturally categorize to simplify otherwise complex analysis. The theory also argues that individual traders invest in styles due to their limitations in processing information on individual stocks. Barberis and Shleifer (2003) further suggest that institutional investors benefit from style categorization, which allows performance evaluation and adherence to fiduciary guidelines. Some common investment styles are, for example, small-cap stocks, large-cap stocks, value stocks, growth stocks, and industry groups. The Barberis and Shleifer (2003) style model makes two basic assumptions. The first is that investors base allocation decisions on past style performance, rotating into good-performing styles and rotating out of bad-performing styles. The second assumption is that style investing affects prices. Barberis and Shleifer (2003) theorize that style investing results in the correlated returns of stocks that share a style classification, independent of fundamental stock values. The style model holds that style values deviate from fundamental value as their popularity ebbs and flows, resulting in short-term mispricing and long-term reversals.

A study by Peng and Xiong (2006) extends the Barberis and Shleifer (2003) style-investing model specifically to industry styles. Peng and Xiong (2006) also base their model on limited investor attention, which leads to category learning. Attention deficits cause investors to focus their attention on market- and industry-level information rather than firm-level information. The Peng and Xiong (2006) model additionally states that investor overconfidence in their ability to process industry information results in overreaction to news and biased price valuations. The model predicts that a combination of investor category learning and overconfidence ultimately results in industry return correlations in excess of fundamental values. Moreover, Peng and Xiong (2006) predict that differences in industry return correlations relate to the informational content of industry-constituent stocks. Industries with less informative prices exhibit greater return correlations and related mispricing. Conversely, the model predicts that investors allocate more attention to firm-specific information for concentrated industries where stock prices are more informative. As such, the stocks in those industries are less subject to predictable investor overreaction. Peng and Xiong (2006, pg. 566) conclude that the attention-allocation decisions of investors ultimately result in predictable cycles in industry returns.

The next three sections briefly discuss sentiment cycles, political cycles, and business cycles, investigated by the three empirical studies comprising this dissertation.

### 1.2.2 Sentiment cycles

At times, investor sentiment seemingly drives stock market values. Baker and Wurgler (2006) summarize well-known stock market cycles, such as the 1980s biotechnology and 1990s Internet bubbles, that coincide with cycles of investor sentiment. High investor sentiment typifies periods of speculative market values and low investor sentiment typifies the opposite. In either instance, market values can appear inconsistent with market efficiency and rational expectations. A growing literature, nevertheless, discusses how investor sentiment affects asset values and provides empirical evidence that investor sentiment predicts prices that deviate from fundamental values.

An empirical study by Brown and Cliff (2005) explores the ability of investor sentiment to predict market-pricing errors. Brown and Cliff (2005) find that excessively positive (negative) investor sentiment initially drives market prices above (below) fundamental value. Investor sentiment predicts market reversals at one- to three-year horizons, which are economically significant. However, Brown and Cliff (2005) question the practicality of trading on investor-sentiment strategies, given the potential for protracted periods of market mispricing. Nonetheless, Brown and Cliff (2005) confirm that investor sentiment predictably affects asset prices, in contravention of market efficiency.

Baker and Wurgler (2006) investigate the interaction between investor sentiment and stocks grouped by common characteristics. The central finding of Baker and Wurgler (2006) is that cross-sectional differences in the effect of investor sentiment on stock values relate to speculative demand and limits on arbitrage. Baker and Wurgler (2006) provide evidence that difficult-to-value stocks are especially subject to speculative investor sentiment. Difficult-to-value stocks share certain characteristics, described by profitability, return momentum, overall risk, dividend policy, asset tangibility, growth opportunities, and financial distress. Baker and Wurgler (2006) argue that it is also difficult to arbitrage away mispricing with stocks sharing those same attributes. Baker and Wurgler (2006) provide evidence that investor sentiment leads to predictable patterns of mispricing and subsequent price reversals, which traditional rational-expectations arguments fail to explain.

### 1.2.3 Political cycles

Political stock market cycles center on the four-year term of office for a U.S. president. Investors popularly believe that presidential politics affect the performance of financial markets. The Stock Trader's Almanac, published by Yale Hirsch, originally popularized the "Presidential Election Cycle" trading strategy. Conventional wisdom maintains that rotating investments based on the outcomes of presidential elections generates market outperformance. In particular, investors believe that whether a president is a Democrat or a Republican determines the performance of particular industries. Based on the efficient market hypothesis, presidential politics should have no predictable effect on stock prices.

Extant literature documents political stock market cycles related to a president's political affiliation and the year of a presidential term of office. The premise of presidential election cycles is that politicians formulate policies that benefit groups with shared ideologies.[1] The market perceives the Republican Party as favoring business and the Democratic Party as favoring labor (Hibbs (1977)). However, empirical research, such as Herbst and Slinkman (1984) and Santa-Clara and Valkanov (2003), finds that the stock market actually performs best under Democrats. Quadrennial cycles depend on the year of a presidential term of office.[2] The basis of quadrennial cycles is the belief that politicians manipulate the economy in the second half of their term for reelection benefit. A seminal study by Nordhaus (1975) provides a theoretical model of quadrennial election cycles. Nordhaus (1975) theorizes that politicians manipulate the economy to gain re-election. The Nordhaus (1975) model stipulates a cyclical trade-off between inflation and employment, where the economy oscillates between austerity and excess over an incumbent president's term.

### 1.2.4 Business cycles

The National Bureau of Economic Research (NBER) defines business cycles by phases of economic expansion and economic contraction. Investors widely believe that business cycles drive asset returns. A popular investment strategy believed to generate excess returns, known as sector rotation, invests in particular sectors or industries across different stages of the business cycles. Systematic strategy performance timing industry investments with the business cycle is inconsistent with market efficiency. Nonetheless, a nascent literature documents predictable industry performance and exploitable investment strategies.

[1] The literature also refers to presidential election cycles as partisan election cycles.
[2] The literature also refers to quadrennial cycles as opportunistic cycles

Recent research provides some evidence that the trading patterns of investors in industry portfolios do track business cycles. Beber, Brandt, and Kavajecz (2010) investigate the active order flows of institutional investors using Trades and Quotes (TAQ) data from 1993 to 2005. Their study maps each stock in the Center for Research on Stock Prices (CRSP) database to one of 10 Global Industry Classification Standard (GICS) sectors. Beber, Brandt, and Kavajecz (2010) define active order flows as the difference between total sector order flows and sector order flows relative to their total market capitalization. Beber, Brandt, and Kavajecz (2010) speculate that institutional investors base their trades on macroeconomic news. The primary finding of Beber, Brandt, and Kavajecz (2010) is that the active trade flows of institutional investors predict macroeconomic conditions. Moreover, Beber, Brandt, and Kavajecz (2010) observe that the portfolio rebalancing of institutional investors emulates a conventional sector rotation strategy. As such, institutional investors appear to base their expectations for sector performance on business-cycle fluctuations. Further, Beber, Brandt, and Kavajecz (2010) conclude that translating the active order rebalancing of institutional investors into a sector rotation strategy results in excess performance.

The concluding section discusses the importance of industry-level research.

### 1.2.5 Industry-level research

Additional insight into industry returns is important from both academic and practical perspectives. An influential study by Moskowitz and Grinblatt (1999, pg. 1251) recognizes "an important role for industries in understanding financial markets." Moskowitz and Grinblatt (1999) investigate the contribution of industries to individual stock momentum strategies over the period 1963 to 1995. Their study finds that industry performance largely explains previously documented momentum profits. Moreover, Moskowitz and Grinblatt (1999) speculate that investor herding in "hot" industries creates speculative price pressure and excess returns. Similarly, Jame and Tong (2009) attribute the poor performance of individual investors documented by Barber, Odean, and Zhu (2009), among others, to industry herding. Jame and Tong (2009) examine investor trade imbalances, using the Trade and Quote (TAQ) database, over the sample period 1983 to 2000. Their results show industry selection accounts for 60 percent of the portfolio performance of individual investors. Studies such as Moskowitz and

Grinblatt (1999) and Jame and Tong (2009) confirm the Barberis and Shleifer (2003) style model, which predicts short-term style momentum and long-term reversals.

Insight into industry performance has important practical implications. Industry mutual and exchange-traded funds are important growth segments for equities markets.[3] Cavaglia, Brightman, and Aked (2000) and Baca, Garbe, and Weiss (2000) show that industry investing provides greater diversification than country investing. More recently, Phylaktis and Xia (2006) report on the increasing importance of industry diversification since 1999. Studies also document the value of industry investing for portfolio returns. Kacperczyk, Sialm, and Zheng (2005) investigate the performance of mutual fund managers, using data from 1984 to 1999. Their study documents that targeted industry investments generate fund outperformance. Rapach, Strauss, Tu, and Zhou (2010), with data from 1946 to 2008, provide evidence that common economic variables predict widespread industry performance. Their study reports different levels of industry predictability, which could allow profitable industry rotation. Nonetheless, Rapach, Strauss, Tu, and Zhou (2010) note the lack of empirical research on industry investment performance, a gap this dissertation bridges.

## 1.3 Contribution to the Literature

This section reviews the research questions addressed by this dissertation's three empirical studies and contributions to the literature. The main contribution is a systematic investigation of industry returns for evidence of cyclical performance previously documented in the general market and the basis of popular investment strategies. The three cycles investigated are investor-sentiment cycles, political cycles, and business cycles.

### 1.3.1 Investor sentiment and industry returns

The first study, "Investor Sentiment and Industry Returns," examines the interaction between investor-sentiment measures and industry performance. The financial media widely report on different measures of investor sentiment as predictors of market values. Yet market efficiency states that market values reflect rational expectations,

[3] Investment Company Institute (2010)

leaving no role for investor sentiment in asset pricing. Baker and Wurgler (2006) provide anecdotal evidence that implies otherwise. Baker and Wurgler (2006) show a correlation between stock market cycles and investor sentiment. The performance of particular industries appears especially affected by investor sentiment. A nascent empirical literature documents evidence of market mispricing related to investor sentiment. Given the implication for market efficiency, understanding how investor sentiment affects industry returns provides a worthwhile research topic, from theoretical and practical perspectives. Firstly, cross-sectional differences in the effect of sentiment on industry performance can potentially explain the market-wide effect of investor sentiment. Secondly, industry groups denote important investment styles susceptible to speculative investor sentiment. As such, understanding the effect of investor sentiment on industry performance also has practical implications for industry investment strategies.

While several empirical studies document investor sentiment predictability of market returns, none document industry return predictability. Fisher and Statman (2000), Brown and Cliff (2005), and Baker and Wurgler (2006) provide evidence that investors' sentiment causes short-term mispricing, followed by predictable long-term price reversal to fundamentals. The literature, such as Kumar (2009) and Barber, Odean, and Zhu (2009), further documents that mispricing results from the collective trades of uninformed investors, who base decisions on sentiment rather than fundamental values. A related study by Kumar (2009) reports that individual investors shift preferences between style extremes, such as growth and value stocks, which leads to mispricing. Another related study by Jame and Tong (2009) documents that speculative pricing results when investors herd together in industry styles. Baker and Wurgler (2006) report a correlation between speculative investor sentiment and stock characteristics that make objective valuations difficult. Similar to Baker and Wurgler (2006), the first study also examines the relationship between sentiment and common industry characteristics that potentially attract investor speculation. While empirical studies document sentiment-driven mispricing, the literature largely ignores the effect of investor sentiment on industry performance.

The first study's main contribution is a rigorous examination of how investor sentiment affects industry performance. Such an examination is important from different perspectives. Firstly, prior research documents that investor sentiment predicts market returns. Return predictability violates market efficiency, which states that asset values reflect fundamentals and rational expectations. However, prior research by Moskowitz and Grinblatt (1999) documents a link between efficient market violations and industry returns. A thorough investigation of the interaction between investor sentiment and industry returns could thus explain the market-wide effect of investor sentiment. Secondly, the first study contributes to the literature that predicts investor sentiment leads to mispricing in investment styles, such as industry categories. Lastly, popular belief holds that investor sentiment determines industry values. Industry investing is also a growing segment of the equities market. Thus, examining the value of investor sentiment in industry rotation strategies has important practical implications.

The first study provides evidence that investor sentiment predicts industry returns. An industry rotation strategy that times investor sentiment, however, generates only marginal outperformance. The study investigates the predictability of industry returns using three sentiment measures: the American Association of Independent Investors survey, the Investors Intelligence survey and the Baker and Wurgler (2006) sentiment index. The sample period runs from 1967 to 2007, which corresponds with the availability of investor sentiment data. Confirming prior market studies, the results show short-term mispricing and long-term reversals, especially in equal-weighted market indices. Investor sentiment predicts a similar pattern of industry returns, almost universally. Negative predictability of long-term industry reversals is, for the full sample, much weaker than in previous market studies. Notably, long-term industry reversals are greater during bear markets. An interpretation is that industry mispricing takes longer to correct in bull markets, due to short-sale restrictions. There is no evidence that industry characteristics, which serve as a proxy for valuation difficulty, attract speculative mispricing. Lastly, rotating industries with investor sentiment generates 3 to 6 percent outperformance, before high turnover costs. The results document that investor sentiment has a market-wide rather than industry-specific effect on return predictability, questioning the practical application of investor-sentiment rotation strategies.

### 1.3.2 Political cycles in U.S. industry returns

The second study, "Political Cycles in U.S. Industry Returns," investigates industry returns for evidence of presidential election cycles. The literature documents political stock market cycles related to a president's political party (presidential cycle) and the year of a presidential term (quadrennial cycle). Popular belief also suggests a link between industry performance and political outcomes. An investigation of industry political cycles is important for two different reasons. Firstly, political cycles in the general market violate market efficiency, which industry analysis potentially explains. Secondly, investigating political cycles in industry returns is interesting from a practical perspective, given popular belief that presidential election outcomes determine industry performance.

The second study extends the empirical research of Santa-Clara and Valkanov (2003). The Santa-Clara and Valkanov (2003) study confirms market outperformance during Democratic presidencies relative to Republican ones. The difference in excess market performance between Democratic and Republican presidencies ranges from 9 percent to 16 percent for value-weighted and equal-weighted indices. Santa-Clara and Valkanov (2003) also examine the performance differential for size-deciles formed on all U.S. listed equities. They find that Democratic outperformance increases monotonically from 7 percent to 22 percent from the largest to the smallest firms. Santa-Clara and Valkanov (2003) determine that the Democratic return premium systematically surprises investors each election. Santa-Clara and Valkanov examine explanations of the Democratic premium within a rational-expectations framework. However, counter to a risk-based explanation, market volatility is less during Democratic presidencies. Santa-Clara and Valkanov (2003) show that presidential cycles are not a proxy for business cycles, concluding that presidential election cycles represent an unresolved financial market puzzle.

The main contribution of the second study is an investigation of industry returns for evidence of presidential election cycles, as a possible explanation for the political stock market cycles that the literature documents. A few dominant industries, especially sensitive to political outcomes, could explain political cycles attributed to the general market. Popular belief holds, for instance, that the defense and pharmaceutical industries perform best when a Republican is president. Additionally, Santa-Clara and Valkanov (2003) establish that political stock market cycles comprise unexpected and expected elements. As a result, the second study provides a thorough examination of industry performance over time and in response to election outcomes, in order to understand the dynamics of political stock market cycles.

The second study documents an absence of systematic political cycles in industry returns. The study examines market returns over 21 presidential election cycles from 1926 to 2006. Market and industry performance is systematically higher under Democratic presidents and during the last two years of any four-year presidential term. However, with a Fama and French three-factor risk correction, industry returns show no evidence of systematic performance related to presidential election cycles. Additionally, there is only scant evidence of abnormal industry performance in response to the 2004 presidential election. By implication, it appears that investors do not take election outcomes as a reliable signal of expected industry performance. Generally, presidential election cycles appear restricted to the general market. The results suggest a macroeconomic explanation of the presidential election puzzle, questioning the popular belief that politics drives industry performance.

### 1.3.3 Sector rotation across business cycles

The third study, "Sector Rotation over Business Cycles," investigates a popular investment strategy that rotates sector allocations with business cycles. Sector rotation strategies play a key role in equity fund management (Fabozzi (2007)). Capital inflows into sector and industry funds emphasize the popularity of sector rotation with investors. Profitable sector rotation presumes an ability to predict business-cycle stages and select sectors that perform well during these stages. Despite the significant capital that sector rotation attracts, these basic presumptions run counter to the efficient market hypothesis. Sector returns should follow a random walk rather than exhibit systematic patterns that correspond with business cycles. The popularity of sector rotation is interesting from two perspectives. Evidence of systematic sector performance across business cycles would present a new financial market anomaly. Alternatively, a lack of systematic sector performance would question the popular belief that timing sector investments with business cycles generates excess market performance.

Despite the popularity of sector rotation, the literature has not directly tested sector performance and strategy performance over business cycles. There are a number of related studies. Levis and Liodakis (1999) and Ahmed, Lockwood, and Nanda (2002) report significant strategy outperformance using business-cycle variables to rotate stocks based on accounting characteristics. DeStefano (2004) examines general stock market performance over four NBER-delineated business-cycle stages. DeStefano documents strong evidence of market performance related to business cycle patterns. In a closely related study, Conover, Jensen, Johnson, and Mercer (2008) rotate cyclical stocks and non-cyclical stocks over stages of monetary expansion and contraction, generating systematic strategy outperformance. Investors, however, typically divide business cycles into more discrete stages. They also more commonly think in terms of the performance of industry styles over business cycles (Bodie, Kane, and Marcus (2009) and Lofthouse (2001)). The third study tests industry performance over multiple business-cycle stages, to align the results with conventional sector rotation practice.

The main contribution of the third study is its original and rigorous examination of the basic assumptions of sector rotation. Those assumptions are systematic sector performance that allows the implementation of profitable investment strategies. The difficulty testing sector rotation is correctly timing business cycle stages. The third study takes a new approach to overcome that obstacle, assuming that investors can correctly pick business cycle stages to time their sector investments. The study initially assumes a rotation strategy that follows popular guidance on sector performance. Allowing for possible variants of sector rotation, the third study further tests the performance of all industries across all business cycle stages.

The third study documents unsystematic industry performance across business cycles and questions the practicality of popular sector rotation strategies. The base-case sample covers 10 complete NBER business cycles from 1948 to 2007. Three stages of expansion and two of recession delineate each NBER business cycle. Industries do not generate systematic performance, where popular belief anticipates it or, more generally, anywhere along the business cycle. A popular sector rotation strategy that times industry investments with business cycle stages generates marginal outperformance, even before transaction costs. A battery of robustness tests, which use different industry classifications, samples periods, business cycle measures and risk adjustments, confirm the base-case results. The results generally confirm that no variant of sector rotation generates outperformance. While this finding confirms market efficiency, it questions the validity of sector rotation.

### 1.4 Organization of Dissertation

The remaining chapters of the dissertation are as follows: Chapter 2 examines investor sentiment predictability of industry returns and the practical usefulness of investor-sentiment measures in industry rotation strategies. Chapter 3 explores the relationship between U.S. presidential cycles and industry performance. Chapter 4 investigates industry performance across business cycles and evaluates the profitability of a popular rotation strategy. Lastly, Chapter 5 concludes with a summary of the dissertation's main contributions and outlines a follow-up agenda for future research.

# Chapter 2 Investor Sentiment and Industry Returns

## 2.1 Introduction

Traditional financial theory does not allow a role for investor sentiment in asset pricing. Its principal tenet, the efficient market hypothesis, maintains that rational investors price assets solely on discounted future cash flows. Moreover, traditional theory further posits that stock prices will immediately reflect fundamental news. If temporary stock mispricing occurs, market efficiency suggests that arbitrageurs quickly restore stock prices to fair value.[4] Yet casual observation suggests that irrational investor behavior periodically drives prices from fundamentals over protracted periods. NASDAQ stock valuations in the 1990s illustrate one well-documented example. Other examples of stock market cycles further suggest that stock prices periodically reflect investor sentiment and that prices revert to fair value only with a delay.[5]

An evolving body of literature, coupled with practitioner interest in the topic, provides evidence that investor sentiment, in some part, affects stock valuations. Brown and Cliff (2005), for instance, document a statistically and economically significant relationship between investor sentiment and the market, where index values initially overshoot and then revert, with a delay, to fundamental value. Baker and Wurgler (2006) argue that mispricing is prevalent in stocks that are difficult to objectively value. For instance, stocks in an emerging industry, which characteristically have uncertain future earnings, are especially subject to speculative investor valuations. Additionally, the financial media (such as *Barron's*, *Wall Street Journal*, *Forbes*, and *CNBC*) regularly report on different market sentiment measures.[6] John Hancock Financial, a leader in financial products, recently released the latest measure of investor sentiment.[7] Practitioner interest in market sentiment measures reflects conventional market wisdom that investor sentiment affects stock values. Indeed, Tetlock (2007) confirms that financial media reporting affects investor sentiment and, ultimately, market values.

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[4] This study adopts the standard definition of mispricing as price deviations that contradict rational values implied by market efficiency. A necessary condition for determining mispricing is the assumption of a pricing model, such as the Capital Asset Pricing Model.
[5] Baker and Wurgler (2006) discuss episodes where sentiment anecdotally appears to drive market values.
[6] See, for example, the *Barron's* weekly summary of various investor sentiment readings available at http://online.barrons.com/public/page/9_0210-investorsentimentreadings.html
[7] http://finance.yahoo.com/news/John-Hancock-Inaugurates-prnews-3389825386.html

Thus, combined academic and practitioner interest in investor sentiment motivates a better understanding of the role it plays in asset pricing.

This study examines the interaction between investor sentiment and industry returns. The study addresses three specific research questions: Does investor sentiment systematically predict industry returns? Does investor sentiment systematically affect the performance of industries that share certain characteristics? Lastly, does investor sentiment provide a practical signal for profitable industry rotation? These questions, from both financial theory and practical perspectives, remain largely unanswered. One complicating factor in studying the effect of sentiment on industry returns is the choice of an appropriate measure of investor sentiment. Baker and Wurgler (2006) comment, “There are no uncontroversial or universally accepted measures of investor sentiment.” Consequently, the analysis investigates industry return predictability using three different investor sentiment measures.[8] Comparing different measures provides the study with added rigor and insight into the effect of investor sentiment on industry performance.

The effect of investor sentiment on industry values is interesting from theoretical and practical perspectives. Fisher and Statman (2000), Brown and Cliff (2005) and Baker and Wurgler (2006) establish a positive correlation between investor sentiment and contemporaneous market mispricing, followed by predictable market reversals. Return predictability counters market efficiency theory. However, Barberis and Shleifer (2003) describe a behavioral style-investing theory. The theory posits that investors base their investments on styles (such as market capitalization or industry affiliation) rather than rational expectations. Empirical research, such as Baker and Wurgler (2006), already confirms the effect of sentiment on stocks that share common styles. Further, Kumar and Lee (2006), Edelen, Marcus, and Tehranian (2010) and Froot and Teo (2008) document investor herding in styles, which leads to mispricing. Small investors, moreover, are particularly prone to trade on sentiment. An analysis of the industry-level effect of sentiment helps better to understand its market-wide effect previously documented in the literature. Additionally, industries represent one of the important

[8] This study fully discusses the three different investor sentiment measures in a subsequent section.

style categories described by the Barberis and Shleifer (2003) model. The popularity of industry investing also makes an examination of industry return predictability interesting from a practical perspective. Yet, empirical research gives scant attention to the effect of investor sentiment on industry performance.

The study's main result is that investor sentiment has a market-wide effect rather than an industry-specific effect. Additionally, the results document only marginal strategy returns timing industry investments with investor sentiment. To begin, the results confirm previous research that investor sentiment predicts market mispricing, followed by reversals. Results similarly confirm a stronger effect of investor sentiment in equal-weighted indices. The results document the same pattern of investor sentiment predictability in industry returns. At a one-week horizon, investor sentiment positively predicts systematic performance, irrespective of the industry. Predictability turns largely negative over longer 8- to 52-week horizons. However, long-term predictability generally lacks statistical significance. Observing different periods of sentiment, industry reversal predictability is greater during bear markets than during bull markets. Contrasting prior firm-level studies, industry-wide characteristics, which act as a proxy for valuation uncertainty, do not systematically attract speculative mispricing. To that extent, markets appear more efficient at industry level. Lastly, the study evaluates the practical application of an industry rotation strategy that times investor sentiment. Results document statistically significant performance of 3 to 6 percent, which varies across time horizon, sentiment measure, and risk correction. While such a return may appear large enough for some, a sentiment rotation strategy would incur high turnover and transactions costs.

Analysis of industry return predictability is subject to a battery of alternative robustness tests. One test examines whether the effect of sentiment on industry performance varies across sub-periods, dividing the full sample into equal 1987–1997 and 1997–2007 sub-periods. The most notable difference is with BW sentiment, which overall has greater predictive power in the second period. Contrary to prior studies, American Association of Independent Investors (AAII) sentiment predictability does improve slightly in the later period. However, overall, the results remain largely comparable between the two sub-periods. Next, another test examines industry returns corrected for well-known sources of systematic risk. After a four-factor risk correction, short-term positive predictability decreases slightly, while negative long-term predictability noticeably increases. Thus, risk corrections do partially explain return predictability for some industries, while not for others. Lastly, a final test examines alternative industry classifications. The results are comparable for Fama and French (1993), Kacperczyk, Sialm, and Zheng (2005), and Global Industry Classification Standard (GICS) industry and sector classifications. Generally, the overall results on industry return predictability continue to hold regardless of the period, industry classification, or risk correction.

This study contributes to the literature in two important respects. First, it documents limited cross-sectional differences in the effect of investor sentiment on predictable industry performance. Investor sentiment almost universally affects the performance of all industries at short horizons up to four weeks. Thus, the effect of investor sentiment broadly extends from the market to industries. However, unlike market studies, systematic long-term predictability is almost absent. An interpretation of the results here is that industry prices revert quickly to fundamental values. Additionally, industry values appear to correct sooner in bear markets. The implication is that arbitrage traders are able to correct mispricing sooner in bear markets than in bull markets, where short sales restrictions lead to delayed price corrections. Moreover, while the literature documents mispricing related to firm characteristics causing valuation difficulties, the results show no equivalent relationship with similar industry characteristics.

Secondly, the study adds to a growing body of literature that investigates the practical importance of industry-level investment strategies. Moskowitz and Grinblatt (1999) provide evidence, for example, that industry return co-movement largely explains momentum trading profits. Moskowitz and Grinblatt (1999) argue that "investors simply herd toward (away from) hot (cold) industries, causing price pressures that create [return] persistence." The results provide limited evidence that investors can profitably use investor sentiment to form a simple industry timing strategy. Effectively, the market rationally prices industry values, to the extent that strategy outperformance would quickly dissipate with reasonable transaction fees. The results thus do not support the Barberis and Shleifer (2003) model's predictions of profitable style rotation trading strategies. Nonetheless, the study adds to others, such as Cavaglia, Brightman, and

Aked (2000), Baca, Garbe, and Weiss (2000), and Phylaktis and Xia (2006), that explore the practical validity of industry-level investing.

## 2.2 Literature Review and Hypotheses Development

Industry prices periodically appear to reflect investor sentiment rather than fundamentals, in contradiction of market efficiency. Indeed, investor "irrational exuberance," as described by Alan Greenspan, former chair of the U.S. Federal Reserve, can drive industry values, such as the 1990s technology bubble.[9] Measures of investor sentiment, perhaps coincidentally, correspond with industry return co-movement, such as electronics in the 60s, gaming in the 70s, biotechnology in the 80s, Internet in the 90s, and recently housing.[10] Financial theory provides two possible explanations of industry return co-movement. First, market efficiency suggests that return co-movement reflects changes in common industry fundamentals. Second, behavioral finance suggests that irrational investor sentiment creates speculative price pressure, which can cause mispricing in industry prices. Behavioral finance further predicts that systematic patterns of industry momentum and reversals result when investors base their trades on sentiment, rather than on underlying fundamental values.

Behavioral finance theory provides a mechanism that allows for price divergence from fundamental value. The Hong and Stein (1999) gradual information diffusion theory describes boundedly rational markets, populated by noise traders and momentum traders. Noise traders process price-relevant information slowly, which can lead to mispricing. Momentum traders construct simple trading models to exploit such mispricing, resulting in predictable short-term momentum and long-term price reversals. Similarly, the Barberis and Shleifer (2003) theory of style investing describes mispricing that results from investors' inability to process firm-specific news. The style model posits that investors analyze investments grouped by styles, such as industries, rather than individual stock fundamentals. Additionally, the model holds that investors extrapolate future style performance from past performance and chase popular styles. This results in predictable return patterns and style mispricing. Peng and Xiong (2006)

[9] http://www.federalreserve.gov/boarddocs/speeches/1996/19961205.htm
[10] Baker and Wurgler (2006) summarize well-known episodes of industry stock co-movement.

extend the Barberis and Shleifer (2003) model. Specifically, Peng and Xiong (2006) articulate a style model in which traders focus on industry-level fundamentals rather than firm-level fundamentals. These theoretical models suggest the possibility that investor sentiment could predict industry returns, providing the basis for profitable rotation strategies.

Empirical research provides evidence that investor sentiment results in market return predictability. For instance, Brown and Cliff (2005), Baker and Wurgler (2006), and Barber, Odean, and Zhu (2009) document a positive correlation between investor sentiment and market mispricing. Brown and Cliff (2005) evaluate investor sentiment predictability using Bakshi and Chen (2005) market mispricing and Investors Intelligence sentiment data from 1963 to 2000. The Bakshi and Chen (2005) study calculates market pricing errors as deviations from a discounted cash-flow model for the 30 Dow Jones Industrial Average stocks. Brown and Cliff (2005) theorize that excessive investor sentiment results in market overvaluation, which reverts to fundamental value with a delay. The Brown and Cliff (2005) study observes statistically significantly 7 percent price reversal in the first year following above-average investor sentiment. Baker and Wurgler (2006) provide evidence that stocks sharing certain characteristics that make objective valuations difficult are the most prone to speculative pricing. Stocks characterized by small market capitalization, high growth potential, or cash flow volatility are particularly susceptible to investor mispricing. Moreover, the stocks most susceptible to speculative pricing are also the most difficult and costly to arbitrage. Barber, Odean, and Zhu (2009) analyze the trade imbalances of individual investors, those most likely to trade on sentiment. They find that the correlated trades of individual investors cause prices to overshoot, which leads to predictable one-year reversals. Generally, empirical market research establishes that investor sentiment leads to short-term mispricing followed by long-term price reversals.

Research shows that individual and institutional investors herding in style categories, such as industries, leads to mispricing. The inclination to categorize stocks by style results from a human tendency to simplify complex analysis.[11] Peng and Xiong (2006)

[11] See, for instance, Feldman (2003).

argue that individual investors, due to attention limitations, are prone to style herding. Moreover, Peng and Xiong (2006) show that the style herding of individual investors results in return co-movement, unrelated to fundamental values.

Predictable cycles in asset returns require that investor mispricing has market impact. In a key study, Kumar and Lee (2006) investigate the effect of individual investor trading on stock market prices. Kumar and Lee (2006) analyse a buy-sell trade imbalance based on 1.85 million trades of 60,000 individual investors. The main conclusion of Kumar and Lee (2006) is that the collective trades of individual investors cause prices to deviate from fundamental value. Kumar and Lee (2006) observe that the trades of individual investors are highly correlated. Their study provides additional evidence that investors concurrently move in and out of similar groups of stocks. Kumar and Lee (2006) show that investor sentiment largely explains stock return co-movement, which is unrelated to systematic risk factors. Kumar and Lee (2006) also observe that individual investors prefer certain style categories (such as small-cap, value, and low-priced stocks). Moreover, the styles preferred by individual investors are more subject to shifts in investor sentiment and predictable mispricing. Meanwhile, a study by Kumar (2009) shows that shifts in individual investor preferences also simultaneously affect the values of style opposites. For instance, when investors grow bullish about defensive industries, they concurrently grow bearish about cyclical industries. Empirical evidence also documents that individual investors concentrate on certain industries, such as technology, pharmaceuticals, retail, and telecom.

Empirical research further shows that institutional investor style herding leads to market impact and return predictability. For instance, Froot and Teo (2008) find that institutional investor order flows positively predict short-term style performance, using data from 1995 to 2003. Froot and Teo (2008) observe that institutional investors rotate between style extremes, for instance cyclical and non-cyclical industries. Choi and Sias (2009) also document that the trades of institutional investors are highly correlated in certain industries, using trade data on institutional ownership from 1983 to 2005. Choi and Sias (2009) observe highly correlated trades into and out of the same industries, which collectively affect industry values. Moreover, Choi and Sias (2009) observe that institutional investors trade on past performance. Choi and Sias (2009) speculate that institutional investors herd together in popular industries to preserve their reputation.

For instance, managers would chase popular industries, such as technologies in the 1990s, to avoid the appearance of missing an investment opportunity. Equally, Jame and Tong (2009) also show that institutional investor order flows affect industry values. Jame and Tong (2009) find that institutional herding in popular industries accounts for 60 percent of long-term portfolio underperformance. Lastly, Beber, Brandt, and Kavajecz (2010) document cyclical patterns in the correlated industry trades of institutional investors. Beber, Brandt, and Kavajecz (2010) argue that the cyclical trading patterns correspond with business cycle stages. However, trading patterns correlated with investor-sentiment cycles could provide an alternative explanation.

Industries represent the best-understood and most widely followed style categories, for institutional and individual investors. Constituent industry firms share common fundamentals (such as product market, competition, regulations, and capital budgets). Industries, thus, present easily defined targets for investor herding. In contrast, other style categories, namely size and value, share less easily understood statistical commonality. Institutional investors are more likely to focus on fundamental rather than statistical categorization. Kacperczyk, Sialm, and Zheng (2005), for instance, show that mutual fund managers concentrate their investments in just a few industries. Popular media reporting on industries suggests the importance of industry styles to individual investors. *The Wall Street Journal*, *Barron's*, and *Business Week*, for instance, provide regular commentary on the outlook for industry performance. Conversely, size and valuation styles receive scant mention in the financial press. The extensive availability of sector and industry financial products further suggests the popularity of those style categories with investors.

A better understanding of industry performance is important from both academic and practical perspectives. Academic research indicates a link between industry performance and violations of market efficiency. Moskowitz and Grinblatt (1999), for instance, argue that industry momentum explains momentum profits. Indeed, Barberis and Shleifer (2003) predict that investor sentiment underlies momentum style returns, such as industry momentum. Hong, Torous, and Valkanov (2007) and Hou (2007) provide evidence of investor bias in processing industry news, which leads to cross-industry return predictability. Other studies, such as Peng and Xiong (2006), show that informational inefficiency causes mispricing in small-cap industries. Research also supports the practical importance of industry-level investing. Cavaglia, Brightman, and Aked (2000), Baca, Garbe, and Weiss (2000), and more recently Phylaktis and Xia (2006) document that industry investing realizes greater diversification benefit than country investing. Moreover, the widespread availability of industry funds makes the implementation of industry investment strategies feasible from a practical perspective. Nonetheless, Rapach, Strauss, Tu, and Zhou (2010) comment on the lack of empirical research on industry investment strategies, a gap this study attempts to bridge.

In sum, theoretical and empirical research supports a role for investor sentiment in asset price determination. Research shows that mispricing results from investors who base their trades on styles, such as industries, rather than underlying fundamentals. However, despite the academic and practical importance of better understanding industry performance, the literature has given the topic only limited attention.

The above discussion leads to a formal statement of this study's null and alternative hypotheses.

**$H_0$**: Industry return performance and cycles of investor sentiment are unrelated.
**$H_1$**: Investor sentiment systematically predicts industry returns.
**$H_2$**: Investors sentiment affects the returns of industries that share common characteristics.
**$H_3$**: Timing industry investments with investor sentiment facilitates profitable rotation strategies.

In answering the research questions, this study contributes to the literature with a thorough examination of investor sentiment predictability of industry returns and the practicality of a simple strategy that times industry investments with investor sentiment.

### 2.3 Investor Sentiment Measures and Market Return Data

Of the many available investor sentiment measures, none is without its critics. To counter the criticism that the results are sample specific, the analysis investigates three different investor sentiment measures. Generally, the literature categorizes investor sentiment measures as direct or indirect measures, (Brown and Cliff (2004)). Investor surveys provide *direct* measures of investor sentiment. Historical financial data provides indirect measures of investor sentiment. The analysis uses two direct measures and one indirect measure of investor sentiment.[12]

### 2.3.1 Sentiment measures

The American Association of Independent Investors (AAII) survey is one of the direct investor sentiment measures. The AAII survey measures the sentiment of small investors. The literature commonly describes small investors as noise traders, who are prone to trade on sentiment rather than fundamental analysis.[13] Studies by Kumar and Lee (2006) and Schmeling (2009), among others, also provide empirical evidence that small investors herd in particular stock categories, such as small-cap stocks. Moreover, such market studies show that the collective trades of small traders cause predictable mispricing. The AAII conducts a weekly survey of its members on their view of future market direction. Specifically, the survey asks members whether they have a bullish, neutral, or bearish stock market outlook for the next six months.[14] Prior to January 2000, the AAII mailed its survey to a random selection of 200 members. Since then, the AAII has conducted an online survey, which is available to all registered members. The AAII publishes its survey results every Thursday. Historical data is available online from 24/07/1987 at no cost. The AAII data comes from the association's website.[15]

The Investors Intelligence (II) survey is the other direct investor sentiment measure. Brown and Cliff (2004) argue that the II survey proxies the sentiment of professional investors, as newsletter writers are mostly retired institutional traders. The financial media, such as *The Wall Street Journal*, widely report II survey results. The II survey reflects the sentiment of financial newsletter writers. Editors at Investor Intelligence categorize the sentiment of newsletter writers from a selection of approximately 150 newsletters as bullish, bearish or correction. The categorization of newsletter sentiment is a subjective process. However, Investors Intelligence editorial staffing has been consistent, with the same two editors since the survey's inception in 1963.[16] The newsletters included in the survey do change over time, with continual additions and

[12] Qiu and Welch (2005) provide a good discussion of differences in investor sentiment measures.
[13] See, for example, Black (1986) and Barber, Odean, and Zhu (2009).
[14] http://www.aaii.com/sentimentsurvey
[15] http://www.aaii.com/files/surveys/sentiment.xls
[16] http://www.investorsintelligence.com/x/us_advisors_sentiment.html

deletions. Newsletters enter the survey only after they have been in print for a period of months. Fisher and Statman (2000) conclude that the II survey provides a measure of investor sentiment distinct from the AAII survey. Investors Intelligence releases its survey results each Thursday. Historical data is available by subscription from 01/04/1963. The II survey data comes directly from Investor Intelligence.

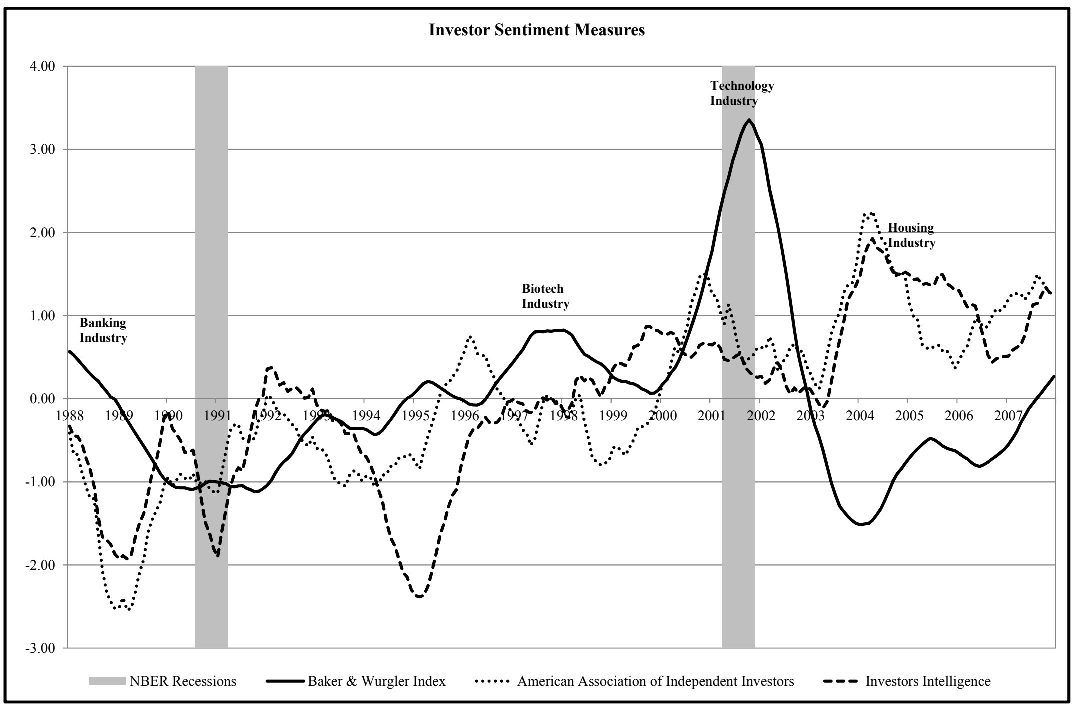
The analysis uses a bull-bear spread for both the AAII and II surveys, calculated as the difference between the reported measure of bullish and bearish sentiment. The AAII and II surveys report bullish sentiment, bearish sentiment and neutral/correction sentiment as a percentage of the total survey results. An example illustrates the bull-bear calculation. For instance, on 24 July 1987, the AAII survey results show bull, bear, and neutral investor sentiment at 36, 14, and 50 percent. The bull-bear spread for that period is therefore 22 percent, calculated as 36 minus 14 percent. Alternatively, one could calculate a bull/bear ratio. However, the financial media widely report on bull-bear spreads. For instance, *The Wall Street Journal* and *Barron's* report weekly bull-bear spreads for both the AAII and II surveys. Other studies, such as Fisher and Statman (2000) and Brown and Cliff (2005), similarly use the bull-bear spread, also citing its popularity with practitioners. As such, the analysis adopts the bull-bear spread as the preferable measure. Results are, however, robust to the use of either bull-bear spreads or bull/bear ratios.

The Baker and Wurgler (2006) index is the indirect investor sentiment measure. Baker and Wurgler (2006) argue that no investor sentiment measure is universally accepted. As such, Baker and Wurgler (2006) construct their sentiment index as the first principal component of six common investor sentiment proxies described in the literature. The six proxies are closed end fund discounts; NYSE share turnover; the number of initial public offerings (IPO); first day average IPO returns; the percentage of equity in capital budgets; and the return premium between dividend-paying and dividend-non-paying firms. Baker and Wurgler (2006) interpret the first principal component of these six variables as the common link to investor sentiment. The Baker and Wurgler (2006) index is available at a monthly frequency from July 1965 to December 2007. To match AAII and II survey frequencies, the study constructs a weekly index (BW) from the Baker and Wurgler (2006) monthly index. Each week during a month assumes the month-end value of the Baker and Wurgler (2006) index.

As such, the analysis assumes that the month-end sentiment prevails throughout the month. The Baker and Wurgler (2006) sentiment index comes from Jeffrey Wurgler's website.[17]

Baker and Wurgler (2006) construct a level sentiment index and a change index. The change index consists of the first principal component of changes in each individual proxy. The level-index series contains an explosive unit root, which consequently invalidates the economic and statistical inferences of predictive regressions.[18] The analysis uses the Baker and Wurgler (2006) change index, which has no unit root and thus allows reliable estimations.

**Figure 2.1 Investor sentiment cycles**




Notes: illustrates investor sentiment cycles for the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker & Wurgler sentiment measures. The shaded areas indicate NBER defined periods of economic recession. The figure also indicates peaks in industry valuation cycles.

Figure 2.1 provides a graphical comparison of the AAII, II, and BW investor sentiment measures. To facilitate comparison, the figure uses a six-month moving

[17] http://pages.stern.nyu.edu/~jwurgler/

[18] See, for example, Campbell and Yogo (2006).

average of normalized sentiment measures. Shaded areas denote National Bureau of Economic Research (NBER) periods of economic recession. All three measures indicate periodic sentiment spikes. The BW sentiment index particularly spikes during the technology industry boom, reflecting the inclusion of IPO returns and IPO issuance as components of that index. While different, the AAII and II sentiment measures do visually move closely together, particularly subsequent to the 2001 recession. The sentiment of small investors, measured by AAII, if anything, lags behind the sentiment of newsletter writers, measured by II. A logical interpretation is that small investors react with a delay to financial newsletter writers.

**Table 2.1 Descriptive statistics for investor sentiment and market indices**

| | Observations | | | Sample Period from 24/07/1987 to 28/12/2007 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Bull | Bear | Total | Mean | Median | Stdev | $\rho_{t-1}$ | $\rho_{i,AAII}$ | $\rho_{i,II}$ | $\rho_{i,BW}$ |
| **Sentiment Measures:** | | | | | | | | | | |
| AAII sentiment | 739 | 328 | 1067 | 0.10 | 0.11 | 0.18 | 0.663 | 1.000 | 0.517 | 0.170 |
| II sentiment | 866 | 201 | 1067 | 0.12 | 0.14 | 0.16 | 0.955 | 0.517 | 1.000 | 0.172 |
| BW sentiment | 560 | 507 | 1067 | -0.01 | 0.05 | 1.02 | 0.799 | 0.170 | 0.172 | 1.000 |
| **Market Indices:** | | | | | | | | | | |
| CRSP value-weighted index | | | 1067 | 0.10 | 0.19 | 0.15 | -0.035 | 0.046 | 0.032 | 0.045 |
| CRSP equal-weighted index | | | 1067 | 0.23 | 0.31 | 0.14 | 0.252 | 0.194 | 0.139 | 0.096 |
| S&P 500 value-weighted index | | | 1067 | 0.09 | 0.15 | 0.15 | -0.077 | 0.027 | 0.017 | 0.041 |
| S&P 500 equal-weighted index | | | 1067 | 0.10 | 0.18 | 0.15 | -0.010 | 0.081 | 0.055 | 0.039 |
| Small stock equal-weighted index | | | 1067 | 0.11 | 0.18 | 0.16 | 0.130 | 0.213 | 0.167 | 0.104 |
| Growth stock equal-weighted index | | | 1067 | 0.07 | 0.17 | 0.21 | 0.076 | 0.065 | 0.044 | 0.050 |

Notes: Table 2.1 reports descriptive statistics for investor sentiment measures and market index returns. Column 4 reports observations for the total sample from 24/07/1987 to 28/12/2007. Columns 2 and 3 report observations for periods of bullish and bearish investor sentiment. A positive (negative) bull-bear spread defines bull (bear) markets, for each investor sentiment measure. The investor sentiment measures come from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). The small-stock index is an equally weighted index of the bottom capitalization decile of all stock in the CRSP database. The growth-stock index is an equally weighted index of the bottom book-to-market (BE/ME) ratio decile of all stocks in the CRSP database. The table reports annualized means, medians, and standard deviations. Table also reports first-order autocorrelations ($\rho_{t-1}$) and cross-correlations ($\rho_{i,j}$) for each sentiment measure.

Table 2.1 confirms that the AAII and II measures have a relatively high .52 correlation coefficient. In contrast, the BW indirect sentiment measure has a low correlation of approximately .17 with both survey measures. The Investors Intelligence bull-bear spread has the highest mean (.12) and autocorrelation (0.95). Clarke and Statman (1998) argue that the sentiment of newsletter writers reflects their expectation that short-term market trends will continue, as the high autocorrelation would indicate. The volatility of AAII is slightly higher than II at 18 and 16 percent. Indro (2010) suggests that the higher AAII volatility results from greater sentiment diversity between small investors and newsletter writers. In overall comparison, each measure appears to provide sufficiently different aspects of investor sentiment.

### 2.3.2 Market data

Market index data comes from multiple sources. All Centre for Research in Security Prices (CRSP) stock market data comes from the Kenneth French website.[19] The CRSP market data comprises all NYSE, AMEX, and NASDAQ listed stocks. The Standard & Poor's 500 index data comes from Global Financial Data and Data Stream.[20] The small stock index represents the bottom NYSE breakpoint capitalization decile of all stocks in the CRSP database. The growth stock index represents the bottom NYSE breakpoint book-to-market ratio (BE/ME) decile of all stocks in the CRSP database. Prior research, by Baker and Wurgler (2006) and Kumar and Lee (2006), concludes that investor sentiment particularly affects the valuation of small-cap stocks. As such, the analysis examines both value- and equal-weighted indices. The one-month Treasury bill, from Ibbotson Associates and downloaded from the Kenneth French website, serves as a proxy for the risk free rate. The common period of data availability for the AAII, II, and BW sentiment measures determines the sample period from 24/07/1987 to 28/12/2007. Table 2.1 reports market index descriptive statistics and correlations with each investor sentiment measures, with annualized means, medians, and standard deviations.

Table 2.1 provides at least two important preliminary observations. First, all sentiment measures have higher correlations with the equal-weighted indices than the value-weighted indices. The S&P 500 value index has the lowest investor sentiment correlation, along with return and standard deviation. The S&P 500 index represents the 500 largest capitalized U.S. stocks; as such, low sentiment correlations are no surprise. Additionally, the literature documents a greater effect of investor sentiment in small-cap stocks. Individual investors, described in the literature as inclined to invest on sentiment, also prefer to invest in small-cap stocks. Therefore, the expectation is to observe larger correlations between small-cap stocks and individual investor sentiment, as is the case. The largest correlations are between AAII sentiment and the equal-

[19] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[20] https://www.globalfinancialdata.com/platform/Welcome.aspx

weighted small-cap index (0.21) and the CRSP equal-weighted index (0.19). The CRSP equal-weighted index has, on average, the highest correlation across all three measures and the highest return. The growth stock equal-weighted index has the lowest sentiment correlation among the equal-weighted indices.

Secondly, the AAII investor sentiment measure has the highest market correlations, while the Baker and Wurgler (2006) index has the smallest correlations. Again, this confirms prior literature that shows sentiment has the most prevalent effect on the investment decisions of individual investors. Another important distinction is that the AAII and II direct survey measures reflect contemporaneous investor sentiment. In contrast, the Baker and Wurgler (2006) index is, by construction, backward looking, originating from historical data. Generally, Table 2.1 shows greater correlations between direct investor sentiment measures and equal-weighted indices.

### 2.4 Markets and Sentiment

This section verifies that investor sentiment predicts market returns, as prior empirical research documents. Fisher and Statman (2000), for instance, investigate the ability of AAII and II investor sentiment surveys to predict S&P 500 returns. Fisher and Statman (2000) find that the AAII investor sentiment surveys negatively forecast market returns from 1985 to 1998. Similarly, Brown and Cliff (2005) document that the II bull-bear spread predicts long-term market-pricing errors. Moreover, their study shows that II predictability is distinct from previously described predictor variables. Siegel (2002) also describes a profitable trading strategy that uses the Investors Intelligence survey to forecast market direction. Indro (2010) investigates the relationship between investor trade flows and the AAII and II sentiment surveys. The Indro (2010) study documents a significant relationship between investor sentiment and fund flows, which in turn leads to market mispricing.

International studies provide further evidence that investor sentiment predicts market returns. Wurgler, Baker, and Yuan (2009), for example, show that national investor sentiment measures negatively predict market index returns in six countries. Similarly, Schmeling (2009) shows that national measures of investor sentiment negatively predict stock market returns in 18 countries. Schmeling (2009) observes a greater effect of investor sentiment in culturally “tight-knit” countries, which he attributes to greater investor herding tendencies. Taken together, the empirical evidence provides convincing evidence that investor sentiment predicts market returns.

**Table 2.2 Investor sentiment predictability of index returns**

| | | Sample period 24/07/1987 - 28/12/2007 | | | | |
|---|---|---|---|---|---|---|
| **Sentiment** | **Market Indices** | **Lag 01** | **Lag 08** | **Lag 13** | **Lag 26** | **Lag 52** |
| **AAII** | CRSP value-weighted index | **0.009** | 0.001 | 0.001 | 0.000 | -0.002 |
| | CRSP equal-weighted index | **0.024** | 0.002 | -0.001 | -0.001 | -0.004 |
| | S&P 500 value-weighted index | 0.006 | 0.000 | 0.002 | 0.000 | -0.001 |
| | S&P 500 equal-weighted index | **0.012** | 0.001 | 0.001 | -0.002 | 0.000 |
| | Small stock equal-weighted index | **0.027** | **0.006** | -0.002 | -0.002 | -0.004 |
| | Growth stock equal-weighted index | **0.013** | -0.002 | -0.006 | 0.000 | **-0.008** |
| **II** | CRSP value-weighted index | 0.004 | **-0.010** | **-0.008** | -0.002 | -0.006 |
| | CRSP equal-weighted index | **0.018** | **-0.009** | **-0.009** | -0.002 | **-0.007** |
| | S&P 500 value-weighted index | 0.002 | **-0.009** | **-0.007** | -0.003 | -0.006 |
| | S&P 500 equal-weighted index | 0.008 | -0.006 | -0.005 | -0.002 | -0.002 |
| | Small stock equal-weighted index | **0.024** | -0.006 | **-0.008** | 0.002 | -0.005 |
| | Growth stock equal-weighted index | 0.008 | **-0.013** | **-0.011** | 0.000 | **-0.011** |
| **BW** | CRSP value-weighted index | 0.001 | -0.001 | 0.000 | 0.001 | **-0.001** |
| | CRSP equal-weighted index | **0.002** | **-0.002** | 0.000 | 0.001 | **-0.002** |
| | S&P 500 value-weighted index | **0.001** | -0.001 | 0.000 | 0.001 | -0.001 |
| | S&P 500 equal-weighted index | **0.001** | -0.001 | 0.000 | 0.000 | **-0.001** |
| | Small stock equal-weighted index | 0.001 | -0.001 | 0.000 | 0.001 | **-0.002** |
| | Growth stock equal-weighted index | 0.001 | -0.001 | 0.001 | 0.001 | **-0.003** |

Notes: Table 2.2 reports the $a_1$ regression coefficients from Equation 2.1. Equation 2.1 estimates investor sentiment predictability of excess market returns at the indicated *k*-week lags over the sample period 24/07/1987 to 28/12/2007. The analysis uses the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW) sentiment measures. The small-stock index is an equally weighted index of the bottom capitalization decile of all stocks in the CRSP database. The growth-stock index is an equally weighted index of the bottom book-to-market ratio (BE/ME) decile of all stocks in the CRSP database. Bold indicates 10 percent or greater statistical significance estimated with White (1980) standard errors.

$$R_{i,t} = a_0 + a_1 Sent_{s,t-k} + e_{i,t} \quad \text{(Eq. 2.1)}$$

Table 2.2 reports the $a_1$ coefficients from Equation 2.1. The equation runs a regression of excess market returns ($R_i$) on a constant and each investor sentiment measure ($Sent_i$) for different *k*-week lags. The $a_1$ coefficients measure investor sentiment predictability of excess market returns. Based on prior studies, the expectation is to observe positive short-term $a_1$ coefficients and negative long-term $a_1$ coefficients. Bold indicates 10 percent or greater statistical significance estimated with White (1980) standard errors.

The results reported in Table 2.2 confirm investor sentiment predictability of market returns. Studies, such as Brown and Cliff (2005), similarly document positive short-term and negative long-term market return predictability.[21] The interpretation is that investor enthusiasm causes prices initially to overshoot, before a delayed price reversion to fundamental value. All statistically significant $a_1$ coefficients, at a one-week lag, have the expected positive sign. The $a_1$ coefficients are more significant and larger for the equal-weighted indices. The results confirm Baker and Wurgler (2006), among others, who document that investor sentiment has a more pronounced effect on small-cap stocks. The statistically significant $a_1$ coefficients at 8- to 52-week lags, with one exception, also have the expected negative sign. Here again, at long-term horizons, investor sentiment has greater predictability of equal-weighted returns. Interestingly, there is no statistically significant predictability at a lag of 26 weeks. Predictability is greatest at a lag of 52 weeks, mostly for the Baker and Wurgler (2006) index. Generally, however, the Investors Intelligence survey provides the greatest long-term return predictability and the AAII survey the least.

## 2.5 Industries and Sentiment

The analysis in this section documents investor sentiment predictability of industry returns. The previous findings verify that investor sentiment reliably predicts the market, particularly for equal-weighted indices. An analysis of industry returns, in part, may help to understand better the drivers of investor sentiment predictability observed at market level. For instance, certain industries, especially exposed to investor sentiment, potentially underlie market sentiment. The Barberis and Shleifer (2003) and Peng and Xiong (2006) models envisage that investor herding in particular styles, such as industries, leads to predictable mispricing and reversals. Baker and Wurgler (2006) also provide anecdotal evidence that industry valuation cycles drive market cycles. For instance, the dramatic increase in Internet stock values elevated the entire stock market during the late 1990s. Moskowitz and Grinblatt (1999) also provide empirical evidence that hot and cold industries underlie market momentum. The following analysis examines industry returns for statistically significant investor sentiment predictability.

[21] See for instance Baker and Wurgler (2006), Brown and Cliff (2005), and Lemmon and Portniaguina (2006).

Additional analysis then evaluates the economic significance of industry return predictability. Lastly, this section then investigates whether investor sentiment affects industry returns differently during periods of bullish and bearish sentiment.

### 2.5.1 Description of industry data

The main analysis investigates the effect of investor sentiment on industry returns using the Fama and French 49 industry portfolios.[22] The Fama and French industry classification maps all NYSE, AMEX, and NASDAQ stocks to one of 49 industry portfolios, using the Standard Industrial Classification (SIC).[23] Prior investor sentiment studies, notably Kumar (2009) and Choi and Sias (2009), similarly use the Fama and French 49 industry classification. The analysis focuses on the Fama and French equal-weighted industry returns. Baker and Wurgler (2006) argue that, "large firms will be less affected by sentiment, and hence value weighting will obscure the more relevant patterns." The earlier analysis also confirms investor sentiment has a greater effect on equal-weighted indices. Unfortunately, the Fama and French industry portfolios are only available at daily and monthly frequencies. Analysis using daily data is inappropriate as it is noisy and, most importantly, because daily data does not match the weekly frequency of AAII and II investor sentiment data. Fortunately, a resolution to those issues simply requires constructing weekly returns by compounding daily returns over each weekly period. The resultant weekly industry return series have 1224 observations that start on 24/07/1987 and end on 28/12/2007.

Table 2.3 provides descriptive statistics for the Fama and French 49 industries. The table reports annualized industry returns and standard deviations. The second column reports the average number of industry constituent firms. The number of industry firms is important for two reasons. First, idiosyncratic risk may dominate the returns of industry portfolios with a small number of firms. For instance, the tobacco, soft drink, and coal industries contain fewer than 10 firms each. As such, the observed effect of sentiment on those industries may reflect fundamental news affecting firm values. Additionally, the number of firms indicates the level of industry competition. Hoberg &

[22] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[23] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for more information.

Phillips (2010) theorize that firms in highly competitive industries are more prone to cash flow uncertainty than non-competitive industries. The table also reports a single-index market beta to measure industry exposure to market risk. Size is the average market capitalization in millions of U.S. dollars for industry constituent firms. The table also reports average industry book-to-market equity (BE/ME) valuations as a growth proxy. Small stocks and growth stocks are especially subject to investor sentiment (Baker and Wurgler (2006)). The final three columns report industry return correlations with the AAII, II, and BW investor sentiment measures. The bottom row reports average statistics across all industries.

Investor sentiment correlations with industry returns vary widely. Similar to the market, average industry correlations with the AAII sentiment measure (0.14) are the highest and BW sentiment measure (0.07) the lowest. Generally, it appears that returns for competitive industries – those with a large number of firms – have higher investor sentiment correlations than non-competitive industries. For instance, the business services industry, with 280 firms, has the highest AAII sentiment correlation (0.19). In contrast, the tobacco industry, with five firms, has the lowest AAII sentiment correlation (0.06). Additionally, industries characterized by many small-cap firms, such as business services (0.19), wholesale (0.19), and lab equipment (0.18), have the highest AAII sentiment correlations. Conversely, industries characterized by a few large-cap firms have the lowest sentiment correlations. For instance, the tobacco industry has only 5 highly capitalized firms and the smallest AAII sentiment correlation (0.03). No obvious pattern appears between sentiment correlations and industry standard deviations, betas, and valuation ratios.

**Table 2.3 Industry descriptive statistics**

| Industry | Firms | Mean | Stdev | $Beta_{Mkt}$ | Size | B/M | $\rho_{i,AAII}$ | $\rho_{i,II}$ | $\rho_{i,BW}$ |
|---|---|---|---|---|---|---|---|---|---|
| Agric | 16 | 0.221 | 0.246 | 0.76 | 1,255 | 0.37 | 0.12 | 0.11 | 0.04 |
| Food | 85 | 0.197 | 0.137 | 0.59 | 2,508 | 0.37 | 0.13 | 0.12 | 0.06 |
| Soda | 8 | 0.159 | 0.240 | 0.65 | 1,914 | 0.65 | 0.10 | 0.05 | 0.05 |
| Beer | 15 | 0.190 | 0.166 | 0.51 | 12,677 | 0.19 | 0.11 | 0.09 | 0.04 |
| Smoke | 5 | 0.203 | 0.297 | 0.63 | 17,376 | 0.40 | 0.06 | 0.03 | -0.03 |
| Toys | 45 | 0.212 | 0.222 | 0.83 | 448 | 0.39 | 0.17 | 0.12 | 0.11 |
| Fun | 81 | 0.229 | 0.229 | 0.97 | 1,423 | 0.54 | 0.18 | 0.13 | 0.10 |
| Books | 49 | 0.143 | 0.211 | 0.89 | 1,641 | 0.44 | 0.15 | 0.10 | 0.11 |
| Hshld | 89 | 0.190 | 0.195 | 0.86 | 2,947 | 0.30 | 0.16 | 0.16 | 0.09 |
| Clths | 73 | 0.204 | 0.215 | 0.90 | 709 | 0.41 | 0.15 | 0.17 | 0.11 |
| Hlth | 103 | 0.278 | 0.203 | 0.82 | 678 | 0.42 | 0.16 | 0.10 | 0.07 |
| MedEq | 173 | 0.292 | 0.201 | 0.84 | 860 | 0.27 | 0.18 | 0.11 | 0.10 |
| Drugs | 261 | 0.268 | 0.264 | 1.07 | 2,675 | 0.21 | 0.16 | 0.10 | 0.08 |
| Chems | 86 | 0.195 | 0.208 | 0.95 | 2,253 | 0.45 | 0.15 | 0.10 | 0.06 |
| Rubbr | 49 | 0.234 | 0.208 | 0.78 | 468 | 0.45 | 0.18 | 0.11 | 0.08 |
| Txtls | 30 | 0.113 | 0.237 | 0.86 | 584 | 0.74 | 0.13 | 0.11 | 0.09 |
| BldMt | 92 | 0.248 | 0.222 | 0.80 | 937 | 0.49 | 0.15 | 0.08 | 0.07 |
| Cnstr | 63 | 0.210 | 0.274 | 1.10 | 789 | 0.57 | 0.14 | 0.17 | 0.07 |
| Steel | 68 | 0.168 | 0.267 | 1.17 | 1,146 | 0.72 | 0.15 | 0.13 | 0.08 |
| FabPr | 22 | 0.186 | 0.257 | 0.96 | 195 | 0.64 | 0.13 | 0.07 | 0.07 |
| Mach | 174 | 0.230 | 0.218 | 1.04 | 1,245 | 0.45 | 0.16 | 0.12 | 0.08 |
| ElcEq | 79 | 0.282 | 0.213 | 0.94 | 1,637 | 0.36 | 0.19 | 0.07 | 0.13 |
| Autos | 66 | 0.160 | 0.254 | 1.10 | 1,745 | 1.02 | 0.16 | 0.13 | 0.10 |
| Aero | 23 | 0.235 | 0.221 | 0.87 | 5,328 | 0.48 | 0.17 | 0.15 | 0.09 |
| Ships | 10 | 0.126 | 0.274 | 0.91 | 1,573 | 0.53 | 0.14 | 0.13 | 0.04 |
| Guns | 10 | 0.213 | 0.240 | 0.64 | 2,587 | 0.50 | 0.14 | 0.09 | 0.00 |
| Gold | 22 | 0.320 | 0.428 | 0.45 | 1,291 | 0.35 | 0.04 | 0.07 | -0.03 |
| Mines | 18 | 0.261 | 0.280 | 0.93 | 1,397 | 0.51 | 0.11 | 0.09 | 0.05 |
| Coal | 7 | 0.133 | 0.405 | 1.22 | 1,650 | 0.78 | 0.09 | 0.08 | -0.06 |
| Oil | 182 | 0.280 | 0.266 | 0.96 | 3,686 | 0.55 | 0.15 | 0.08 | -0.01 |
| Util | 153 | 0.124 | 0.135 | 0.53 | 2,756 | 0.94 | 0.10 | 0.06 | 0.00 |
| Telcm | 129 | 0.188 | 0.253 | 1.12 | 4,473 | 0.62 | 0.13 | 0.07 | 0.13 |
| PerSv | 58 | 0.237 | 0.206 | 0.86 | 633 | 0.43 | 0.16 | 0.12 | 0.10 |
| BusSv | 280 | 0.264 | 0.192 | 0.91 | 707 | 0.33 | 0.19 | 0.12 | 0.13 |
| Hardw | 158 | 0.258 | 0.275 | 1.18 | 3,201 | 0.36 | 0.14 | 0.06 | 0.13 |
| Softw | 337 | 0.290 | 0.261 | 1.12 | 1,575 | 0.20 | 0.15 | 0.07 | 0.14 |
| Chips | 292 | 0.283 | 0.274 | 1.21 | 1,525 | 0.37 | 0.15 | 0.08 | 0.12 |
| LabEq | 116 | 0.343 | 0.226 | 1.02 | 603 | 0.40 | 0.18 | 0.07 | 0.12 |
| Paper | 65 | 0.142 | 0.214 | 0.95 | 2,256 | 0.51 | 0.12 | 0.10 | 0.05 |
| Boxes | 14 | 0.151 | 0.234 | 0.93 | 1,402 | 0.49 | 0.11 | 0.05 | 0.06 |
| Trans | 110 | 0.193 | 0.209 | 0.95 | 1,477 | 0.75 | 0.15 | 0.12 | 0.08 |
| Whlsl | 203 | 0.246 | 0.187 | 0.87 | 668 | 0.47 | 0.19 | 0.15 | 0.12 |
| Rtail | 264 | 0.201 | 0.216 | 1.01 | 2,405 | 0.34 | 0.13 | 0.13 | 0.08 |
| Meals | 99 | 0.239 | 0.192 | 0.81 | 1,059 | 0.35 | 0.16 | 0.16 | 0.09 |
| Banks | 552 | 0.215 | 0.150 | 0.62 | 1,516 | 0.59 | 0.14 | 0.10 | 0.04 |
| Insur | 190 | 0.199 | 0.176 | 0.81 | 2,872 | 0.67 | 0.12 | 0.11 | 0.04 |
| RlEst | 36 | 0.218 | 0.223 | 0.77 | 399 | 0.62 | 0.15 | 0.14 | 0.10 |
| Fin | 320 | 0.256 | 0.176 | 0.82 | 1,677 | 0.54 | 0.14 | 0.11 | 0.10 |
| Other | 73 | 0.235 | 0.191 | 0.76 | 4,372 | 0.37 | 0.20 | 0.13 | 0.11 |
| Average | | 0.218 | 0.230 | 0.88 | 2,269 | 0.49 | 0.14 | 0.10 | 0.07 |

Notes: Table 2.3 reports industry descriptive statistics for the weekly Fama and French 49 equal-weight industry portfolio returns from 24/07/1987 to 28/12/2007. The descriptive statistics include the average number of industry firms, annualized means, annualized standard deviations, single-index market betas, average industry firm market capitalization (millions USD), and average industry book-to-market valuation ratios. The last three columns report cross-correlations ($\rho_{i,s}$) between industry returns and the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW) investor sentiment measures. The bottom row reports averages for all industries.

### 2.5.2 Basic industry regressions

The analysis now examines whether investor sentiment systematically predicts industry returns. Additionally, the analysis further investigates cross-sectional differences in the effect of investor sentiment on industry performance. Equation 2.2 runs a regression of excess industry returns ($R_i$) on a constant, the sentiment measures ($Sent_s$) for the indicated k-week lag, and the market risk premium ($R_m$). The variable of interest in Equation 2.2 is the $a_1$ regression coefficient. The interpretation of the $a_1$ coefficient is industry outperformance predicted by investor sentiment. Effectively, the $a_0$ and $a_1$ coefficients together represent a traditional Jensen's alpha. Bold indicates statistical significance of 10 percent or greater estimated with White (1980) standard errors. The bottom two rows of Table 2.4 report the number of significantly positive or negative $a_1$ regression coefficients.

$$R_{i,t} = a_0 + a_1 Sent_{s,t-k} + b_0 R_{m,t} + e_t \qquad \text{(Eq. 2.2)}$$

Table 2.4 reports the $a_1$ regression coefficient from Equation 2.2. At a casual glance, Table 2.4 reveals investor sentiment systematically predicts returns for a high percentage of industries. Nonetheless, the economic magnitude of investor sentiment, as measured by the size of the $a_1$ coefficients, varies considerably. Based on market studies, the expectation is that initial investor overreaction causes short-term positive predictability. Significant and negative return predictability at longer horizons would indicate industry price reversion to fundamental value. The $a_1$ coefficients on all sentiment measures have the correct positive sign at a one-week lag, with one exception. The $a_1$ coefficients on AAII sentiment are, on average, the largest of all sentiment measures. The AAII sentiment measures are all statistically significant, with the exception of precious metals (gold). In contrast, the BW index has significant coefficients at a one-week lag for only about 60 percent of all industries.

Investor sentiment predictability provides mixed results at longer horizons. At an eight-week lag, there is a ratio of 2:3 positive to negative $a_1$ coefficients. Predictability drops substantially at 13- to 52-week horizons, along with the magnitude of $a_1$ coefficients. Most statistically significant $a_1$ coefficients have the expected negative sign at 13-week and 52-week horizons. As with the market, investor sentiment has the least significant predictability at a 26-week lag. Generally, the BW index provides the least predictability and the AAII measure the greatest, at all horizons.

**Table 2.4 Investor sentiment predictability of industry returns**

| | 1 week | | | 8 week | | | 13 week | | | 26 week | | | 52 week | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Agric | **0.019** | **0.019** | 0.000 | **0.012** | 0.007 | 0.000 | 0.000 | 0.002 | -0.001 | **0.008** | 0.004 | 0.001 | 0.003 | 0.000 | 0.001 |
| Food | **0.010** | **0.011** | 0.001 | 0.002 | -0.002 | **-0.001** | 0.000 | -0.003 | 0.000 | 0.001 | 0.002 | 0.000 | **-0.003** | -0.002 | 0.000 |
| Soda | **0.013** | 0.009 | 0.001 | **0.009** | 0.001 | **-0.002** | 0.006 | 0.003 | 0.000 | -0.001 | 0.002 | 0.000 | 0.001 | 0.000 | 0.001 |
| Beer | **0.011** | **0.011** | 0.000 | 0.001 | -0.001 | 0.000 | 0.002 | 0.004 | **-0.001** | 0.003 | **0.008** | 0.000 | 0.001 | 0.002 | -0.001 |
| Smoke | **0.011** | 0.005 | -0.002 | -0.006 | -0.012 | -0.001 | 0.000 | -0.008 | 0.000 | 0.004 | -0.004 | -0.002 | 0.004 | 0.000 | 0.000 |
| Toys | **0.021** | **0.019** | **0.002** | 0.003 | -0.005 | -0.001 | -0.003 | -0.004 | 0.000 | 0.000 | -0.002 | 0.000 | **-0.008** | **-0.008** | **-0.002** |
| Fun | **0.022** | **0.019** | **0.002** | 0.003 | -0.002 | -0.001 | 0.002 | -0.004 | -0.001 | 0.002 | 0.000 | 0.000 | 0.001 | 0.002 | **-0.001** |
| Books | **0.015** | **0.012** | **0.002** | 0.001 | **-0.005** | **-0.001** | -0.002 | **-0.005** | 0.000 | **0.004** | 0.003 | 0.000 | -0.002 | 0.000 | **-0.001** |
| Hshld | **0.019** | **0.019** | **0.001** | 0.003 | -0.001 | -0.001 | -0.003 | -0.002 | -0.001 | -0.004 | -0.001 | 0.000 | -0.002 | -0.001 | 0.000 |
| Clths | **0.020** | **0.024** | **0.002** | 0.000 | 0.001 | **-0.002** | -0.003 | -0.004 | -0.001 | -0.002 | 0.000 | 0.000 | 0.001 | 0.000 | -0.001 |
| Hlth | **0.016** | **0.015** | 0.001 | 0.002 | **-0.009** | -0.001 | -0.003 | **-0.010** | -0.001 | -0.001 | -0.001 | 0.000 | **-0.007** | **-0.008** | 0.000 |
| MedEq | **0.020** | **0.015** | **0.002** | 0.002 | -0.006 | 0.000 | **-0.006** | **-0.009** | **-0.001** | -0.001 | -0.002 | 0.000 | **-0.009** | **-0.010** | -0.001 |
| Drugs | **0.024** | **0.018** | 0.002 | 0.002 | -0.003 | 0.000 | **-0.010** | -0.003 | -0.001 | -0.001 | 0.003 | 0.001 | **-0.015** | **-0.016** | -0.002 |
| Chems | **0.013** | **0.012** | 0.001 | 0.002 | 0.000 | -0.001 | 0.003 | 0.002 | 0.000 | -0.002 | 0.002 | 0.000 | -0.003 | 0.003 | 0.000 |
| Rubbr | **0.020** | **0.016** | **0.001** | 0.000 | -0.003 | **-0.001** | -0.002 | -0.003 | 0.000 | -0.003 | -0.001 | 0.000 | -0.003 | 0.000 | -0.001 |
| Txtls | **0.018** | **0.016** | **0.002** | 0.001 | -0.004 | -0.001 | 0.001 | -0.007 | -0.001 | **-0.007** | -0.005 | 0.000 | -0.005 | 0.000 | -0.001 |
| BldMt | **0.018** | **0.013** | **0.001** | 0.004 | 0.002 | -0.001 | 0.003 | 0.000 | 0.000 | -0.002 | 0.000 | 0.000 | -0.001 | -0.001 | 0.000 |
| Cnstr | **0.024** | **0.027** | 0.001 | 0.002 | -0.001 | 0.000 | -0.003 | -0.001 | **-0.001** | -0.002 | -0.002 | 0.000 | -0.006 | -0.005 | -0.001 |
| Steel | **0.019** | **0.020** | **0.001** | **0.007** | 0.005 | -0.001 | 0.000 | 0.005 | -0.001 | -0.003 | **0.008** | **0.002** | -0.003 | **0.008** | 0.000 |
| FabPr | **0.017** | **0.010** | 0.001 | 0.002 | -0.004 | -0.001 | -0.005 | **-0.007** | 0.000 | 0.000 | 0.005 | 0.001 | -0.006 | 0.001 | 0.000 |
| Mach | **0.016** | **0.016** | **0.001** | **0.004** | -0.001 | 0.000 | -0.004 | **-0.005** | 0.000 | -0.002 | 0.002 | 0.000 | **-0.004** | 0.001 | 0.000 |
| ElcEq | **0.021** | **0.010** | **0.003** | 0.002 | **-0.007** | 0.001 | -0.002 | **-0.007** | 0.001 | -0.003 | **-0.006** | 0.001 | **-0.006** | -0.005 | 0.000 |
| Autos | **0.020** | **0.018** | **0.002** | 0.001 | -0.004 | **-0.001** | 0.000 | -0.003 | -0.001 | -0.001 | 0.001 | 0.000 | -0.004 | -0.001 | 0.000 |
| Aero | **0.021** | **0.023** | **0.002** | **0.006** | 0.005 | 0.000 | **0.012** | 0.005 | 0.000 | 0.003 | 0.004 | 0.001 | -0.004 | 0.003 | 0.000 |
| Ships | **0.025** | **0.025** | 0.001 | 0.007 | 0.005 | -0.001 | 0.000 | 0.008 | -0.001 | -0.008 | 0.003 | -0.001 | -0.005 | -0.002 | 0.000 |
| Guns | **0.021** | **0.018** | 0.000 | 0.007 | 0.006 | -0.001 | 0.006 | 0.007 | -0.001 | -0.001 | 0.003 | -0.001 | -0.003 | 0.001 | 0.000 |
| Gold | 0.010 | **0.025** | -0.002 | **0.015** | **0.020** | 0.001 | 0.006 | 0.008 | -0.002 | -0.014 | 0.000 | **0.004** | -0.003 | -0.007 | 0.004 |
| Mines | **0.015** | **0.018** | 0.001 | **0.010** | **0.012** | -0.001 | 0.001 | 0.009 | 0.000 | -0.004 | -0.001 | 0.001 | **-0.009** | 0.003 | 0.001 |
| Coal | **0.015** | **0.021** | **-0.003** | **0.015** | **0.014** | 0.000 | **0.015** | **0.021** | -0.001 | 0.011 | 0.010 | **0.003** | -0.001 | 0.005 | 0.002 |
| Oil | **0.015** | **0.013** | -0.001 | **0.016** | **0.011** | 0.001 | **0.009** | **0.010** | 0.001 | -0.001 | -0.001 | **0.002** | -0.002 | 0.001 | 0.000 |
| Util | **0.005** | **0.005** | 0.000 | 0.002 | 0.003 | 0.000 | 0.003 | **0.005** | 0.000 | 0.002 | 0.002 | -0.001 | 0.000 | **0.004** | 0.000 |
| Whlsl | **0.015** | **0.012** | **0.003** | **-0.007** | **-0.008** | -0.001 | **-0.009** | **-0.012** | 0.001 | 0.000 | 0.000 | 0.002 | -0.004 | 0.000 | 0.000 |
| PerSv | **0.019** | **0.017** | **0.002** | -0.003 | -0.003 | **-0.001** | **-0.008** | -0.006 | **-0.001** | -0.001 | 0.003 | 0.000 | **-0.006** | -0.004 | 0.000 |
| BusSv | **0.020** | **0.015** | **0.002** | 0.000 | **-0.005** | -0.001 | -0.004 | **-0.008** | 0.000 | 0.000 | -0.001 | 0.001 | -0.004 | -0.004 | -0.001 |
| Hardw | **0.021** | **0.011** | **0.004** | -0.007 | **-0.010** | 0.000 | **-0.014** | **-0.013** | 0.000 | -0.002 | -0.002 | 0.001 | **-0.007** | -0.007 | -0.001 |
| Softw | **0.021** | **0.012** | **0.004** | -0.006 | **-0.010** | 0.000 | **-0.016** | **-0.012** | -0.001 | 0.001 | 0.001 | 0.001 | -0.007 | -0.006 | **-0.002** |
| Chips | **0.022** | **0.014** | **0.003** | -0.001 | -0.001 | 0.000 | **-0.009** | -0.007 | 0.001 | -0.002 | 0.000 | 0.002 | -0.006 | -0.003 | 0.000 |
| LabEq | **0.023** | **0.009** | **0.003** | 0.003 | **-0.007** | 0.000 | -0.005 | **-0.013** | 0.001 | 0.000 | -0.005 | **0.001** | **-0.009** | **-0.008** | 0.000 |
| Paper | **0.012** | **0.011** | 0.000 | 0.002 | -0.001 | 0.000 | 0.000 | -0.003 | 0.000 | -0.001 | -0.001 | 0.000 | -0.001 | 0.001 | 0.000 |
| Boxes | **0.014** | 0.007 | 0.001 | **-0.009** | **-0.011** | **-0.002** | -0.002 | **-0.008** | -0.001 | -0.001 | -0.007 | -0.001 | -0.001 | -0.004 | -0.001 |
| Trans | **0.017** | **0.016** | **0.001** | **0.005** | 0.000 | **-0.001** | 0.002 | -0.003 | -0.001 | -0.003 | 0.001 | 0.001 | -0.002 | 0.003 | 0.000 |
| Whlsl | **0.020** | **0.018** | **0.002** | **0.004** | 0.000 | -0.001 | -0.002 | -0.002 | -0.001 | 0.000 | 0.004 | 0.000 | -0.002 | 0.000 | 0.000 |
| Rtail | **0.016** | **0.018** | **0.001** | -0.001 | -0.003 | **-0.002** | -0.003 | -0.003 | **-0.002** | -0.001 | -0.001 | 0.000 | -0.001 | 0.000 | -0.001 |
| Meals | **0.019** | **0.020** | **0.001** | 0.002 | 0.000 | -0.001 | 0.000 | -0.004 | **-0.001** | -0.001 | -0.001 | 0.000 | -0.002 | -0.002 | **-0.001** |
| Banks | **0.009** | **0.009** | 0.000 | 0.000 | **-0.004** | **-0.001** | -0.003 | **-0.004** | **-0.001** | -0.002 | -0.003 | 0.000 | **-0.005** | **-0.006** | 0.000 |
| Insur | **0.010** | **0.010** | 0.000 | 0.002 | -0.001 | -0.001 | -0.003 | -0.003 | **-0.001** | -0.001 | -0.002 | -0.001 | -0.001 | -0.003 | -0.001 |
| RlEst | **0.020** | **0.019** | **0.002** | 0.002 | -0.003 | **-0.002** | -0.003 | -0.002 | 0.000 | -0.002 | 0.002 | 0.000 | -0.005 | -0.002 | 0.000 |
| Fin | **0.012** | **0.011** | **0.001** | -0.002 | -0.001 | 0.000 | **-0.005** | -0.004 | **-0.001** | **-0.005** | -0.003 | **0.001** | **-0.005** | -0.001 | 0.000 |
| Other | **0.021** | **0.019** | **0.002** | 0.004 | -0.001 | 0.000 | 0.001 | 0.000 | **-0.001** | 0.002 | 0.002 | 0.001 | -0.004 | -0.003 | 0.000 |
| Positive | 48 | 46 | 28 | 11 | 4 | 0 | 3 | 3 | 0 | 2 | 2 | 6 | 0 | 2 | 0 |
| Negative | 0 | 0 | 1 | 2 | 10 | 12 | 8 | 13 | 10 | 2 | 1 | 0 | 13 | 6 | 5 |

Notes: Table 2.4 reports the $a_1$ coefficients estimated with Equation 2.2. The equation runs a regression of excess industry returns on a constant, sentiment measures for the indicated $k$-week lags, and the market-risk premium. Sentiment measures are from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). Bold indicates statistical significance of 10 percent or greater estimated with White (1980) standard errors.

### 2.5.3 Economic significance of investor sentiment predictability

Table 2.5 reports the economic significance of industry return predictability. The industry sentiment betas come from Equation 2.2, reported as the $a_1$ regression coefficients in Table 2.4. The table reports industry returns attributable to a one standard deviation change in investor sentiment. For example, the AAII sentiment has an 18 percent standard deviation Table 2.4 also reports that food has a 0.01 AAII sentiment beta at a one-week lag. Therefore, as Table 2.5 reports, a one standard deviation change in AAII sentiment at a one-week lag predicts 10 percent annual excess return for food. Table 2.5 reports annualized returns attributable to changes in the indicated sentiment measures and *k*-week lags. Bold indicates 10 percent or greater statistical significance estimated with White (1980) standard errors.

The economic impact of sentiment on industries varies across measures, industries, and horizons. Economic significance is greatest for AAII sentiment and at one-week horizons. A one standard deviation change in the AAII survey, on average, results in 19 percent annualized industry returns. Comparably, the II and BW measures are 13 percent and 7 percent. Economic significance is greatest for shipping (0.28) and least for coal (-0.17) for the AAII and BW measures. Investor sentiment seemingly has the smallest economic effect on large-cap industries. Take, for instance, the economic impact of AAII sentiment on utilities (.05), banking (0.09), beer (0.11), and tobacco (0.12). There are notable exceptions, such as the large-cap drug industry (0.26), which question whether industry characteristics, such as capitalization, systematically attract investor sentiment. At longer horizons, the absolute value of economically significant predictability diminishes. For instance, at 52 weeks, the average economic impact of AAII sentiment drops from 19 to 4 percent. In absolute terms, the greatest economic significance at 52 weeks is drugs (-0.14) for AAII sentiment. The average economic significance of II and BW predictability at 52 weeks is negligible, at only negative one percent. Generally, economic significance only partially reverses over a 52-week horizon, although the results largely lack statistical significance.

**Table 2.5 Economic significance of investor sentiment predictability**

| | 1 week | | | 8 week | | | 13 week | | | 26 week | | | 52 week | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Agric | **0.20** | **0.17** | 0.03 | **0.13** | 0.06 | 0.02 | 0.00 | 0.02 | -0.06 | **0.09** | 0.03 | 0.04 | 0.03 | 0.00 | 0.07 |
| Food | **0.10** | **0.09** | 0.03 | 0.02 | -0.02 | **-0.06** | 0.00 | -0.02 | -0.02 | 0.01 | 0.02 | -0.01 | **-0.03** | -0.01 | 0.00 |
| Soda | **0.13** | 0.07 | 0.06 | **0.09** | 0.01 | **-0.09** | 0.06 | 0.03 | 0.00 | -0.01 | 0.02 | 0.02 | 0.01 | 0.00 | 0.06 |
| Beer | **0.11** | **0.09** | 0.02 | 0.01 | 0.00 | -0.03 | 0.01 | 0.03 | **-0.06** | 0.03 | **0.07** | 0.02 | 0.01 | 0.02 | -0.03 |
| Smoke | **0.12** | 0.04 | -0.08 | -0.06 | -0.09 | -0.04 | 0.00 | -0.07 | 0.00 | 0.04 | -0.03 | -0.10 | 0.04 | 0.00 | -0.02 |
| Toys | **0.23** | **0.16** | **0.12** | 0.03 | -0.04 | -0.05 | -0.03 | -0.03 | -0.02 | 0.00 | -0.02 | 0.01 | **-0.08** | **-0.06** | **-0.08** |
| Fun | **0.24** | **0.17** | **0.10** | 0.03 | -0.01 | -0.05 | 0.02 | -0.03 | -0.03 | 0.02 | 0.00 | 0.00 | 0.01 | 0.02 | **-0.08** |
| Books | **0.16** | **0.10** | **0.09** | 0.01 | **-0.04** | **-0.06** | -0.02 | **-0.04** | -0.01 | **0.05** | 0.02 | -0.01 | -0.02 | 0.00 | **-0.06** |
| Hshld | **0.21** | **0.17** | **0.07** | 0.03 | 0.00 | -0.03 | -0.02 | -0.02 | -0.04 | -0.04 | -0.01 | 0.00 | -0.02 | -0.01 | -0.02 |
| Clths | **0.21** | **0.21** | **0.11** | 0.00 | 0.00 | **-0.10** | -0.03 | -0.03 | -0.04 | -0.02 | 0.00 | 0.00 | 0.01 | 0.00 | -0.03 |
| Hlth | **0.17** | **0.13** | 0.06 | 0.02 | **-0.07** | -0.05 | -0.03 | **-0.08** | -0.05 | -0.01 | -0.01 | -0.01 | **-0.07** | **-0.06** | -0.02 |
| MedEq | **0.22** | **0.13** | **0.10** | 0.02 | -0.05 | -0.02 | **-0.06** | **-0.07** | **-0.06** | -0.01 | -0.02 | 0.00 | **-0.08** | **-0.08** | -0.06 |
| Drugs | **0.26** | **0.16** | 0.10 | 0.02 | -0.03 | 0.02 | **-0.09** | -0.03 | -0.03 | -0.01 | 0.02 | 0.04 | **-0.14** | **-0.12** | -0.08 |
| Chems | **0.13** | **0.10** | 0.04 | 0.02 | 0.00 | -0.03 | 0.03 | 0.02 | -0.02 | -0.02 | 0.02 | 0.02 | -0.03 | 0.02 | -0.02 |
| Rubbr | **0.21** | **0.14** | **0.07** | 0.00 | -0.02 | **-0.06** | -0.02 | -0.02 | -0.01 | -0.03 | -0.01 | -0.01 | -0.03 | 0.00 | -0.05 |
| Txtls | **0.19** | **0.14** | **0.11** | 0.01 | -0.03 | -0.07 | 0.01 | -0.05 | -0.05 | **-0.07** | -0.04 | 0.01 | -0.05 | 0.00 | -0.04 |
| BldMt | **0.19** | **0.11** | **0.08** | 0.04 | 0.02 | -0.03 | 0.03 | 0.00 | 0.00 | -0.02 | 0.00 | 0.01 | -0.01 | -0.01 | 0.01 |
| Cnstr | **0.26** | **0.24** | 0.06 | 0.02 | -0.01 | 0.00 | -0.03 | -0.01 | **-0.06** | -0.02 | -0.02 | -0.02 | -0.06 | -0.04 | -0.04 |
| Steel | **0.20** | **0.17** | **0.08** | **0.07** | 0.04 | -0.05 | 0.00 | 0.04 | -0.03 | -0.03 | **0.07** | **0.08** | -0.03 | **0.07** | 0.02 |
| FabPr | **0.18** | **0.08** | 0.07 | 0.02 | -0.04 | -0.06 | -0.05 | **-0.06** | -0.02 | 0.00 | 0.05 | 0.07 | -0.06 | 0.01 | 0.03 |
| Mach | **0.18** | **0.13** | **0.06** | **0.04** | 0.00 | -0.02 | -0.03 | **-0.04** | 0.00 | -0.02 | 0.01 | 0.02 | **-0.04** | 0.01 | 0.00 |
| ElcEq | **0.22** | **0.08** | **0.15** | 0.02 | **-0.06** | 0.04 | -0.02 | **-0.06** | 0.05 | -0.03 | **-0.04** | 0.03 | **-0.06** | -0.04 | 0.02 |
| Autos | **0.22** | **0.15** | **0.09** | 0.01 | -0.03 | **-0.06** | 0.00 | -0.03 | -0.05 | -0.01 | 0.01 | 0.02 | -0.04 | -0.01 | -0.01 |
| Aero | **0.23** | **0.20** | **0.09** | **0.06** | 0.04 | -0.01 | **0.13** | 0.04 | 0.00 | 0.03 | 0.03 | 0.04 | -0.04 | 0.02 | -0.01 |
| Ships | **0.28** | **0.23** | 0.03 | 0.07 | 0.04 | -0.04 | 0.00 | 0.06 | -0.06 | -0.08 | 0.03 | -0.05 | -0.04 | -0.02 | -0.01 |
| Guns | **0.22** | **0.15** | -0.02 | 0.07 | 0.05 | -0.06 | 0.06 | 0.05 | -0.03 | -0.01 | 0.02 | -0.04 | -0.03 | 0.01 | 0.02 |
| Gold | 0.10 | **0.22** | -0.09 | **0.16** | **0.18** | 0.04 | 0.06 | 0.06 | -0.08 | -0.13 | 0.00 | **0.23** | -0.03 | -0.05 | 0.21 |
| Mines | **0.16** | **0.15** | 0.05 | **0.10** | **0.10** | -0.03 | 0.01 | 0.07 | 0.00 | -0.04 | -0.01 | 0.07 | **-0.09** | 0.02 | 0.05 |
| Coal | **0.16** | **0.19** | **-0.17** | **0.15** | **0.12** | -0.02 | **0.16** | **0.19** | -0.04 | 0.11 | 0.08 | **0.17** | -0.01 | 0.04 | 0.11 |
| Oil | **0.16** | **0.11** | -0.04 | **0.17** | **0.09** | 0.05 | **0.09** | **0.08** | 0.07 | -0.01 | -0.01 | **0.09** | -0.02 | 0.01 | -0.01 |
| Util | **0.05** | **0.04** | -0.02 | 0.02 | 0.02 | 0.01 | 0.03 | **0.04** | 0.01 | 0.02 | 0.02 | -0.03 | 0.00 | **0.04** | 0.00 |
| Whlsl | **0.16** | **0.10** | **0.17** | **-0.06** | **-0.07** | -0.04 | **-0.08** | **-0.09** | 0.07 | 0.00 | 0.00 | 0.09 | -0.04 | 0.00 | 0.00 |
| PerSv | **0.20** | **0.15** | **0.10** | -0.03 | -0.02 | **-0.06** | **-0.07** | -0.05 | **-0.06** | -0.01 | 0.03 | 0.02 | **-0.06** | -0.03 | -0.01 |
| BusSv | **0.22** | **0.13** | **0.12** | 0.00 | **-0.04** | -0.03 | -0.04 | **-0.06** | -0.01 | 0.00 | -0.01 | 0.04 | -0.04 | -0.03 | -0.04 |
| Hardw | **0.23** | **0.09** | **0.20** | -0.07 | **-0.08** | 0.02 | **-0.13** | **-0.10** | -0.02 | -0.02 | -0.02 | 0.05 | **-0.07** | -0.06 | -0.06 |
| Softw | **0.23** | **0.11** | **0.21** | -0.06 | **-0.08** | -0.02 | **-0.15** | **-0.09** | -0.03 | 0.01 | 0.01 | 0.03 | -0.07 | -0.04 | **-0.10** |
| Chips | **0.24** | **0.12** | **0.18** | -0.01 | -0.01 | 0.02 | **-0.09** | -0.05 | 0.05 | -0.02 | 0.00 | 0.08 | -0.06 | -0.02 | -0.01 |
| LabEq | **0.25** | **0.07** | **0.15** | 0.03 | **-0.06** | 0.01 | -0.05 | **-0.10** | 0.06 | 0.00 | -0.04 | **0.06** | **-0.08** | **-0.06** | -0.02 |
| Paper | **0.13** | **0.09** | 0.02 | 0.02 | -0.01 | -0.01 | 0.00 | -0.03 | -0.02 | -0.01 | -0.01 | 0.02 | -0.01 | 0.01 | 0.01 |
| Boxes | **0.15** | 0.06 | 0.05 | **-0.08** | **-0.09** | **-0.10** | -0.02 | **-0.06** | -0.03 | -0.01 | -0.05 | -0.04 | -0.01 | -0.03 | -0.05 |
| Trans | **0.19** | **0.13** | **0.06** | **0.05** | 0.00 | **-0.07** | 0.02 | -0.02 | -0.04 | -0.03 | 0.01 | 0.05 | -0.02 | 0.02 | 0.01 |
| Whlsl | **0.21** | **0.16** | **0.11** | **0.04** | 0.00 | -0.04 | -0.02 | -0.01 | -0.03 | 0.00 | 0.04 | 0.01 | -0.02 | 0.00 | -0.02 |
| Rtail | **0.17** | **0.16** | **0.06** | -0.01 | -0.02 | **-0.09** | -0.02 | -0.02 | **-0.08** | -0.01 | -0.01 | -0.01 | -0.01 | 0.00 | -0.03 |
| Meals | **0.21** | **0.17** | **0.07** | 0.02 | 0.00 | -0.04 | 0.00 | -0.03 | **-0.05** | -0.01 | -0.01 | 0.01 | -0.02 | -0.01 | **-0.06** |
| Banks | **0.09** | **0.07** | 0.01 | 0.00 | **-0.03** | **-0.04** | -0.03 | **-0.03** | **-0.04** | -0.02 | -0.02 | -0.02 | **-0.05** | **-0.05** | 0.00 |
| Insur | **0.10** | **0.09** | 0.01 | 0.02 | -0.01 | -0.04 | -0.02 | -0.03 | **-0.04** | -0.01 | -0.01 | -0.03 | -0.01 | -0.02 | -0.03 |
| RlEst | **0.21** | **0.17** | **0.11** | 0.02 | -0.03 | **-0.08** | -0.03 | -0.02 | 0.00 | -0.02 | 0.02 | -0.03 | -0.05 | -0.02 | -0.02 |
| Fin | **0.13** | **0.10** | **0.07** | -0.02 | -0.01 | -0.02 | **-0.05** | -0.03 | **-0.04** | **-0.05** | -0.02 | **0.04** | **-0.05** | -0.01 | -0.01 |
| Other | **0.23** | **0.16** | **0.11** | 0.04 | -0.01 | -0.03 | 0.01 | 0.00 | **-0.07** | 0.02 | 0.01 | 0.03 | -0.04 | -0.03 | 0.00 |
| Positive | 48 | 46 | 28 | 11 | 4 | 0 | 3 | 3 | 0 | 2 | 2 | 6 | 0 | 2 | 0 |
| Negative | 0 | 0 | 1 | 2 | 10 | 12 | 8 | 13 | 10 | 2 | 1 | 0 | 13 | 6 | 5 |

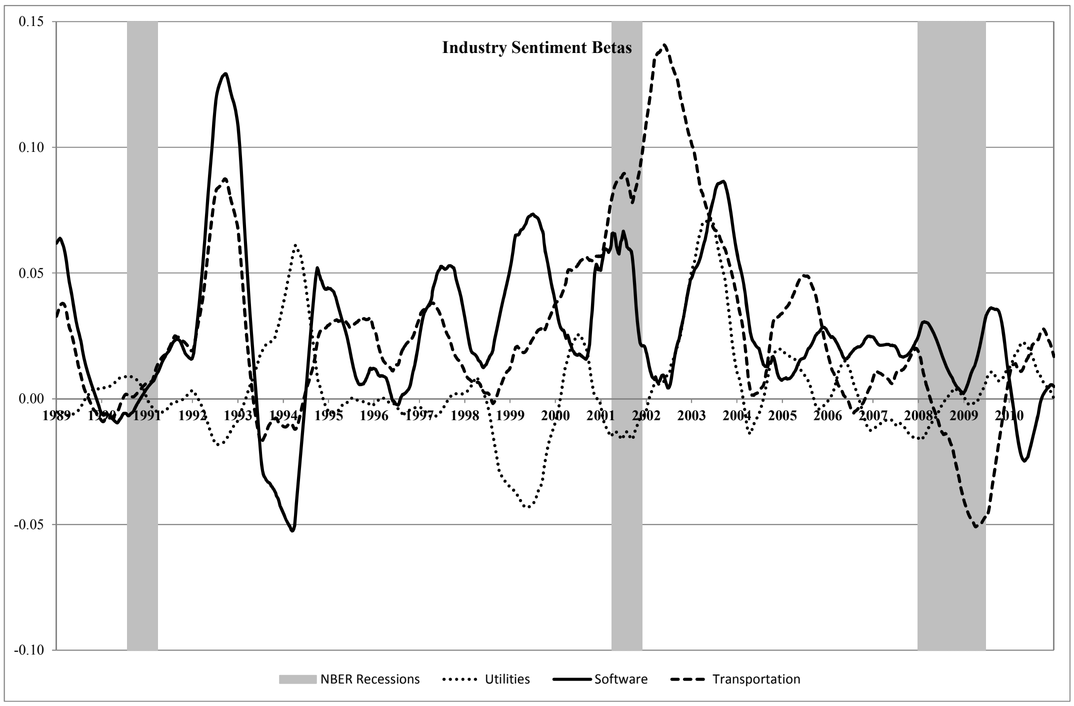
Notes: Table 2.5 reports the economic significance of investor sentiment predictability of excess industry returns at different *k*-week lags. The analysis first uses Equation 2.2 to estimate investor sentiment betas. Next, the analysis calculates annualized excess industry returns attributable to a one standard deviation change in either the American Association of Independent Investors (AAII), Investors Intelligence (II), or Baker & Wurgler (BW) sentiment measures. Bold indicates 10 percent or greater statistical significance estimated with White (1980) standard errors.

### 2.5.4 Bullish and bearish investor sentiment

This section investigates whether there are differences in industry return predictability when investor sentiment is bullish or bearish. Differences may occur due to investor preferences or market frictions. Conventional wisdom holds that certain industries perform best during bull (bear) markets, characterized by high (low) investor sentiment.

For instance, *CNN Money* reports that finance and technology shares are good bets as market sentiment ebbs in the later stage of a bull market.[24] On the other hand, bearish sentiment favors the energy, health-care, and tech industries.[25] Additionally, short-sale limitations restrict the ability of arbitrage investors to correct inflated values when the market is bullish (Gromb and Vayanos (2010)). Conversely, arbitrage investors face no restrictions taking the opposite side of deflated values during bear markets. The expectation is to observe greater investor predictability during periods of bullish sentiment than periods of bearish sentiment.

**Figure 2.2 Time-variant industry sentiment betas**




Notes: Figure 2.2 illustrates time-variant industry sentiment betas estimated using Investors Intelligence sentiment (II) data and 52-week rolling window beta estimations. Shaded areas indicate National Bureau of Economic Research defined periods of economic recession.

Figure 2.2 illustrates industry return sensitivity to investor sentiment over time. Equation 2.2 estimates time-variant $a_1$ coefficients over 52-week rolling windows. The rolling $a_1$ coefficient estimates provide a measure of differences in time-variant industry exposure to investor sentiment. For clarity of illustration, the figure focuses on the

[24] http://money.cnn.com/2011/03/04/markets/bull_market_sector_rotation/index.htm
[25] http://blogs.forbes.com/investor/2011/05/26/investors-favor-energy-health-care-and-tech/

utilities, software, and transportation industries, as representative of defensive, cyclical, and neutral industries. The shaded area in Figure 2.2 indicates National Bureau of Economic Research (NBER) defined recessions. All three industries illustrate different cyclical exposure to investor sentiment. The cyclical software industry clearly has the most variable exposure to investor sentiment and the defensive utilities industry the least. Investor bullish and bearish sentiment, similarly, is pro-cyclical, as Figure 2.1 illustrates. Industry exposure to sentiment thus potentially relates to cyclical bullish and bearish investor sentiments, which Equation 2.3 investigates.

$$R_{i,t} = a_0 + a_2 Sent_{s,t-k} * Bull_{s,t-k} + a_3 Sent_{s,t-k} * Bear_{s,t-k} + b_0 R_{m,t} + e_t \qquad \text{(Eq.2.3)}$$

Table 2.6 and Table 2.7 report industry return predictability for periods of bullish and bearish sentiment estimated with Equation 2.3. The equation runs a regression of excess industry returns ($R_i$) on a constant, investor sentiment ($Sent_s$) delineated by *Bull* and *Bear* dummy variables for the indicated *k*-week lags, and the market risk premium ($R_m$). The analysis defines bullish (bearish) sentiment for the AAII and II measures by a positive (negative) bull-bear spread. Brown and Cliff (2005) similarly delineate bull and bear markets. Positive (negative) BW index values define periods of bullish (bearish) sentiment. The *bull* dummy variables take a value of one during periods of bullish sentiment and zero otherwise. The construction of *bear* dummy variables is similar. Table 2.1 reports the number of bullish and bearish observations in the second and third columns. For instance, the AAII has 739 weeks of bullish sentiment and 328 weeks of bearish sentiment. The BW index, by construction, has roughly equal periods of bullish and bearish sentiment. Table 2.6 reports the $a_2$ regression coefficients from Equation 2.3, interpreted as industry return predictability during bullish periods. Table 2.7 reports the $a_3$ regression coefficients from Equation 2.3, interpreted as industry return predictability during bearish periods.

Table 2.6 and Table 2.7 documents three distinctions between investor sentiment predictability for bull and bear markets. First, statistically significant and positive predictability increases with bullish sentiment at an eight-week lag. AAII sentiment significantly predicts positive returns for 33 industries during bull markets, compared with AAII predictability of 11 industries for the full sample. Economic significance for all measures also increases at an eight-week lag. Conversely, significant predictability diminishes at long horizons. An interpretation is that bullish sentiment, particularly of small investors, causes short-term momentum and reversals. Secondly, positive predictability decreases at short horizons with bearish sentiment. The II survey now predicts positive returns for 22 industries at a one-week horizon and one industry at an eight-week horizon. At long horizons, negative predictability increases, compared with the full sample and bullish sentiment. The BW index now negatively predicts the returns of 31 and 23 industries at 8-week and 52-week lags, comparing with BW index predictability of twelve and five industries at similar horizons over the full sample. The evidence here suggests that investor sentiment results in greater price reversals when sentiment is bearish. Lastly, there is no clear difference in the effect of investor sentiment on cyclical and non-cyclical industries across periods of bullish and bearish sentiment.

**Table 2.6 Investor sentiment predictability during bull markets**

| | 1 week | | | 8 week | | | 13 week | | | 26 week | | | 52 week | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Agric | **0.017** | 0.007 | 0.000 | **0.023** | 0.001 | 0.002 | 0.006 | -0.007 | -0.002 | 0.006 | -0.005 | 0.000 | 0.009 | 0.006 | **0.004** |
| Food | **0.009** | **0.009** | 0.002 | **0.007** | -0.002 | 0.000 | 0.003 | -0.003 | 0.001 | 0.000 | -0.001 | 0.000 | -0.002 | **-0.006** | **0.001** |
| Soda | **0.015** | 0.013 | 0.001 | **0.018** | 0.005 | **-0.003** | 0.012 | 0.012 | 0.000 | -0.005 | -0.002 | 0.000 | -0.007 | **-0.017** | 0.002 |
| Beer | **0.009** | **0.011** | 0.001 | 0.006 | 0.001 | -0.001 | -0.002 | **0.009** | 0.000 | **0.009** | **0.014** | 0.000 | 0.001 | 0.001 | 0.000 |
| Smoke | 0.007 | 0.004 | 0.002 | -0.014 | -0.005 | 0.000 | 0.000 | 0.003 | 0.001 | 0.007 | -0.006 | 0.000 | 0.005 | 0.006 | 0.001 |
| Toys | **0.020** | **0.017** | **0.004** | **0.011** | -0.004 | **0.002** | -0.001 | **-0.015** | 0.001 | 0.006 | -0.009 | 0.000 | 0.003 | -0.006 | 0.001 |
| Fun | **0.019** | **0.016** | 0.003 | 0.006 | -0.001 | 0.002 | 0.006 | -0.008 | 0.000 | 0.003 | -0.003 | 0.000 | 0.007 | -0.005 | 0.000 |
| Books | **0.018** | **0.011** | **0.003** | **0.011** | **-0.009** | 0.001 | 0.001 | **-0.010** | **0.002** | 0.007 | -0.001 | 0.000 | -0.002 | 0.000 | 0.000 |
| Hshld | **0.020** | **0.017** | **0.002** | **0.009** | -0.001 | **0.001** | 0.005 | **-0.011** | 0.000 | 0.001 | -0.005 | 0.000 | 0.006 | -0.003 | 0.001 |
| Clths | **0.015** | **0.022** | **0.003** | 0.008 | 0.002 | 0.000 | 0.004 | -0.006 | -0.001 | 0.005 | -0.001 | 0.000 | 0.007 | -0.002 | 0.001 |
| Hlth | **0.021** | **0.014** | 0.003 | **0.013** | -0.005 | 0.001 | 0.002 | **-0.013** | 0.001 | 0.007 | 0.004 | 0.000 | -0.001 | -0.008 | 0.001 |
| MedEq | **0.026** | **0.015** | 0.003 | **0.011** | -0.003 | 0.002 | 0.001 | **-0.012** | -0.001 | 0.000 | 0.006 | 0.000 | -0.002 | **-0.010** | 0.001 |
| Drugs | **0.031** | **0.016** | 0.003 | 0.009 | -0.006 | 0.004 | -0.004 | **-0.015** | 0.000 | 0.004 | **0.014** | 0.000 | -0.008 | -0.007 | 0.000 |
| Chems | **0.013** | **0.014** | **0.002** | **0.006** | 0.002 | 0.000 | **0.009** | 0.002 | 0.000 | 0.001 | -0.003 | 0.000 | 0.000 | 0.002 | 0.000 |
| Rubbr | **0.015** | **0.016** | 0.002 | 0.007 | -0.002 | 0.001 | 0.005 | -0.009 | -0.001 | 0.006 | -0.005 | 0.000 | 0.000 | 0.003 | 0.000 |
| Txtls | **0.019** | **0.013** | 0.002 | **0.011** | -0.005 | 0.000 | 0.009 | -0.008 | 0.000 | -0.004 | -0.008 | 0.000 | -0.002 | 0.002 | **0.004** |
| BldMt | **0.011** | 0.003 | 0.000 | **0.013** | 0.001 | 0.000 | **0.008** | -0.005 | 0.000 | 0.005 | 0.000 | **0.000** | -0.001 | -0.001 | **0.002** |
| Cnstr | **0.024** | **0.031** | **0.002** | **0.018** | -0.003 | 0.001 | 0.003 | **-0.012** | 0.000 | 0.003 | -0.003 | 0.000 | -0.002 | 0.002 | 0.002 |
| Steel | **0.014** | **0.025** | 0.000 | **0.016** | **0.011** | 0.000 | 0.005 | 0.006 | -0.002 | 0.002 | 0.010 | 0.000 | 0.000 | **0.013** | 0.001 |
| FabPr | **0.018** | 0.009 | 0.001 | 0.007 | -0.002 | 0.001 | 0.000 | **-0.015** | 0.000 | 0.000 | **0.011** | 0.000 | -0.007 | -0.004 | 0.001 |
| Mach | **0.015** | **0.018** | 0.002 | **0.009** | 0.004 | 0.001 | 0.001 | -0.007 | 0.000 | 0.001 | -0.001 | 0.000 | 0.000 | -0.001 | 0.001 |
| ElcEq | **0.022** | 0.007 | **0.004** | **0.009** | -0.007 | **0.003** | 0.000 | **-0.014** | 0.001 | 0.002 | **-0.011** | 0.000 | -0.007 | -0.005 | 0.000 |
| Autos | **0.018** | **0.020** | 0.001 | **0.011** | -0.004 | 0.000 | 0.003 | **-0.010** | 0.000 | 0.004 | -0.003 | 0.000 | -0.001 | -0.004 | 0.001 |
| Aero | **0.018** | **0.025** | 0.002 | 0.009 | 0.006 | 0.000 | **0.017** | 0.002 | 0.001 | 0.004 | 0.005 | 0.000 | -0.009 | 0.001 | 0.001 |
| Ships | **0.015** | **0.022** | 0.001 | **0.019** | -0.001 | 0.002 | 0.011 | 0.010 | 0.000 | 0.004 | 0.012 | 0.000 | -0.005 | -0.002 | 0.001 |
| Guns | **0.030** | **0.024** | 0.001 | **0.015** | 0.013 | 0.000 | **0.018** | 0.004 | -0.001 | 0.006 | 0.004 | 0.000 | 0.007 | -0.004 | 0.001 |
| Gold | -0.015 | 0.025 | -0.001 | 0.014 | 0.016 | 0.004 | 0.007 | 0.000 | **-0.006** | -0.015 | -0.010 | **0.000** | 0.001 | -0.018 | **0.010** |
| Mines | 0.004 | **0.024** | 0.001 | **0.016** | 0.008 | 0.001 | 0.006 | **0.017** | -0.001 | -0.001 | -0.007 | **0.000** | -0.001 | 0.005 | **0.003** |
| Coal | **0.016** | **0.030** | 0.002 | **0.025** | **0.021** | 0.001 | **0.019** | **0.024** | 0.000 | **0.024** | 0.013 | 0.000 | 0.003 | 0.001 | 0.004 |
| Oil | **0.010** | **0.012** | 0.002 | **0.017** | 0.010 | **0.003** | **0.014** | 0.007 | 0.002 | 0.003 | 0.001 | 0.000 | -0.006 | 0.000 | 0.001 |
| Util | 0.005 | 0.005 | 0.001 | 0.004 | 0.002 | 0.000 | 0.004 | 0.004 | 0.001 | 0.005 | 0.004 | 0.000 | -0.003 | **0.011** | 0.000 |
| Whlsl | **0.012** | 0.009 | 0.002 | -0.002 | **-0.010** | 0.001 | -0.006 | **-0.022** | -0.001 | 0.001 | -0.001 | 0.000 | 0.002 | -0.003 | 0.000 |
| PerSv | **0.024** | **0.017** | 0.002 | **0.011** | -0.001 | 0.000 | 0.006 | **-0.012** | **-0.002** | 0.001 | 0.004 | 0.000 | -0.002 | -0.006 | 0.000 |
| BusSv | **0.022** | **0.014** | **0.002** | **0.007** | **-0.008** | **0.002** | 0.000 | **-0.014** | -0.001 | 0.003 | 0.001 | 0.000 | -0.003 | -0.005 | 0.000 |
| Hardw | **0.025** | **0.016** | 0.004 | 0.000 | -0.010 | **0.005** | -0.012 | **-0.018** | -0.001 | 0.001 | 0.004 | 0.000 | -0.003 | -0.011 | 0.000 |
| Softw | **0.026** | **0.013** | 0.003 | 0.001 | **-0.012** | **0.003** | **-0.019** | **-0.022** | -0.003 | 0.001 | 0.002 | 0.000 | -0.003 | -0.009 | 0.000 |
| Chips | **0.022** | **0.016** | 0.003 | 0.007 | 0.001 | **0.005** | -0.009 | **-0.013** | 0.001 | 0.002 | 0.003 | 0.000 | -0.004 | -0.007 | 0.001 |
| LabEq | **0.024** | 0.009 | **0.004** | 0.008 | -0.007 | **0.004** | -0.005 | **-0.018** | 0.001 | -0.001 | -0.004 | 0.000 | -0.006 | **-0.012** | 0.001 |
| Paper | **0.013** | **0.014** | 0.001 | **0.006** | -0.003 | 0.001 | 0.001 | **-0.008** | 0.000 | 0.003 | -0.005 | 0.000 | 0.000 | 0.005 | **0.002** |
| Boxes | **0.013** | **0.012** | **0.003** | 0.000 | -0.009 | -0.002 | 0.001 | **-0.010** | -0.001 | -0.001 | -0.010 | 0.000 | 0.001 | -0.007 | 0.001 |
| Trans | **0.018** | **0.014** | **0.002** | **0.011** | -0.002 | 0.000 | 0.005 | **-0.009** | -0.001 | 0.000 | -0.002 | 0.000 | 0.001 | 0.005 | 0.001 |
| Whlsl | **0.021** | **0.020** | **0.002** | **0.013** | 0.002 | 0.001 | 0.005 | **-0.007** | -0.001 | 0.002 | 0.004 | 0.000 | 0.003 | -0.002 | 0.001 |
| Rtail | **0.014** | **0.014** | 0.002 | **0.007** | -0.003 | 0.000 | 0.003 | -0.004 | **-0.002** | 0.004 | -0.005 | 0.000 | 0.003 | -0.004 | 0.001 |
| Meals | **0.022** | **0.016** | **0.002** | **0.010** | -0.004 | 0.001 | **0.007** | **-0.008** | 0.001 | 0.004 | -0.003 | 0.000 | -0.002 | -0.003 | -0.001 |
| Banks | **0.008** | 0.002 | 0.000 | **0.008** | **-0.011** | 0.000 | 0.005 | **-0.012** | 0.000 | 0.004 | **-0.006** | 0.000 | 0.003 | -0.002 | 0.000 |
| Insur | **0.010** | 0.005 | 0.001 | **0.008** | -0.004 | 0.000 | 0.004 | **-0.006** | 0.000 | 0.002 | -0.002 | 0.000 | 0.000 | 0.000 | -0.001 |
| RlEst | **0.017** | **0.016** | **0.003** | **0.014** | -0.009 | -0.001 | **0.008** | -0.003 | 0.001 | 0.001 | 0.003 | 0.000 | 0.004 | 0.002 | 0.000 |
| Fin | **0.011** | **0.010** | 0.001 | **0.005** | -0.003 | 0.001 | -0.001 | **-0.012** | -0.001 | 0.001 | **-0.009** | 0.000 | -0.002 | -0.001 | -0.001 |
| Other | **0.020** | **0.015** | **0.003** | **0.008** | 0.000 | 0.001 | 0.001 | **-0.010** | 0.000 | 0.007 | 0.001 | 0.000 | 0.000 | 0.000 | 0.002 |
| Positive | 45 | 37 | 15 | 33 | 2 | 9 | 8 | 3 | 1 | 2 | 3 | 1 | 0 | 2 | 7 |
| Negative | 0 | 0 | 0 | 0 | 5 | 1 | 1 | 26 | 3 | 0 | 3 | 2 | 0 | 4 | 0 |

Notes: Table 2.6 reports the $a_2$ slope coefficients from Equation 2.3. The equation runs a regression of excess industry returns on a constant, bull and bear sentiment dummy variables for the indicated *k*-week lags, and the market-risk premium. Sentiment measures are from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). Bold indicates statistical significance of 10 percent or greater estimated with White (1980) standard errors.

**Table 2.7 Investor sentiment predictability during bear markets**

| | 1 week | | | 8 week | | | 13 week | | | 26 week | | | 52 week | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Agric | **0.023** | **0.052** | 0.001 | -0.014 | 0.021 | -0.001 | -0.014 | **0.026** | 0.000 | 0.013 | **0.029** | -0.001 | -0.013 | -0.015 | -0.001 |
| Food | **0.013** | **0.015** | -0.001 | **-0.009** | -0.004 | **-0.002** | -0.007 | -0.001 | **-0.002** | 0.003 | 0.010 | -0.001 | -0.008 | **0.012** | **-0.001** |
| Soda | 0.008 | -0.003 | 0.001 | -0.014 | -0.009 | 0.000 | -0.008 | -0.019 | 0.000 | 0.011 | 0.013 | 0.002 | 0.020 | **0.046** | 0.000 |
| Beer | **0.014** | 0.010 | 0.000 | -0.010 | -0.006 | 0.000 | 0.009 | -0.009 | **-0.002** | -0.009 | -0.009 | 0.000 | 0.002 | 0.005 | -0.001 |
| Smoke | 0.021 | 0.007 | **-0.005** | 0.014 | -0.031 | -0.002 | -0.001 | -0.040 | -0.001 | -0.003 | 0.001 | -0.005 | 0.001 | -0.016 | -0.002 |
| Toys | **0.022** | **0.024** | 0.001 | -0.016 | -0.008 | **-0.004** | -0.006 | **0.025** | -0.001 | -0.013 | 0.014 | 0.001 | **-0.035** | -0.011 | **-0.004** |
| Fun | **0.027** | **0.030** | 0.001 | -0.006 | -0.003 | **-0.003** | -0.009 | 0.008 | -0.001 | 0.000 | 0.006 | 0.000 | -0.013 | **0.020** | **-0.003** |
| Books | 0.008 | **0.015** | 0.000 | **-0.022** | 0.006 | **-0.003** | **-0.011** | 0.008 | **-0.002** | 0.000 | **0.012** | -0.001 | -0.004 | 0.000 | **-0.002** |
| Hshld | **0.017** | **0.025** | 0.001 | -0.013 | 0.002 | **-0.002** | **-0.021** | **0.020** | -0.001 | **-0.017** | 0.011 | 0.000 | **-0.021** | 0.006 | **-0.001** |
| Clths | **0.030** | **0.029** | 0.001 | **-0.020** | -0.004 | **-0.004** | **-0.021** | 0.001 | -0.001 | **-0.020** | 0.003 | 0.000 | **-0.014** | 0.006 | **-0.002** |
| Hlth | 0.003 | 0.017 | 0.000 | **-0.023** | **-0.020** | **-0.003** | **-0.018** | -0.003 | **-0.003** | **-0.019** | -0.017 | -0.001 | **-0.021** | -0.008 | **-0.002** |
| MedEq | 0.006 | 0.015 | 0.001 | **-0.022** | -0.012 | **-0.003** | **-0.025** | 0.000 | -0.001 | -0.006 | **-0.024** | 0.000 | **-0.026** | -0.010 | **-0.003** |
| Drugs | 0.006 | **0.023** | 0.001 | -0.015 | 0.002 | **-0.003** | **-0.026** | **0.028** | -0.001 | -0.011 | **-0.027** | -0.001 | **-0.031** | **-0.038** | **-0.003** |
| Chems | **0.013** | 0.008 | -0.001 | -0.008 | -0.005 | -0.001 | -0.010 | 0.002 | 0.000 | -0.009 | **0.015** | 0.000 | **-0.011** | 0.003 | **-0.001** |
| Rubbr | **0.031** | 0.016 | 0.001 | **-0.017** | -0.006 | **-0.003** | **-0.020** | 0.013 | 0.000 | **-0.023** | 0.007 | 0.000 | -0.010 | -0.008 | -0.002 |
| Txtls | **0.016** | **0.026** | 0.002 | **-0.022** | -0.002 | **-0.003** | -0.018 | -0.005 | -0.001 | -0.014 | 0.005 | -0.001 | -0.015 | -0.006 | **-0.005** |
| BldMt | **0.033** | **0.038** | **0.002** | **-0.018** | 0.004 | -0.001 | -0.011 | 0.011 | 0.000 | **-0.017** | 0.001 | 0.001 | -0.002 | -0.002 | **-0.001** |
| Cnstr | **0.023** | **0.018** | 0.000 | **-0.037** | 0.004 | -0.001 | -0.016 | **0.029** | **-0.002** | -0.014 | 0.001 | 0.000 | -0.017 | **-0.024** | **-0.003** |
| Steel | **0.030** | 0.006 | **0.003** | -0.014 | -0.011 | -0.002 | -0.013 | 0.002 | 0.000 | **-0.017** | 0.005 | **0.003** | -0.012 | -0.004 | -0.001 |
| FabPr | 0.014 | 0.012 | 0.002 | -0.010 | -0.010 | **-0.003** | -0.017 | 0.013 | -0.001 | 0.002 | -0.010 | 0.001 | -0.005 | 0.012 | 0.000 |
| Mach | **0.020** | 0.010 | 0.001 | -0.006 | -0.012 | **-0.002** | **-0.013** | 0.002 | 0.000 | -0.009 | 0.010 | 0.001 | **-0.014** | 0.007 | **-0.001** |
| ElcEq | **0.018** | 0.016 | **0.002** | **-0.014** | -0.008 | -0.001 | -0.007 | 0.012 | 0.001 | **-0.015** | 0.009 | 0.001 | -0.004 | -0.004 | 0.000 |
| Autos | **0.026** | 0.013 | **0.002** | **-0.022** | -0.001 | **-0.002** | -0.006 | 0.013 | **-0.002** | -0.012 | 0.011 | 0.001 | -0.010 | 0.006 | **-0.002** |
| Aero | **0.028** | 0.017 | 0.001 | 0.001 | 0.002 | -0.001 | 0.000 | 0.014 | -0.001 | 0.001 | 0.002 | 0.001 | 0.006 | 0.007 | -0.001 |
| Ships | **0.048** | 0.034 | 0.000 | -0.024 | 0.019 | **-0.003** | -0.028 | 0.002 | -0.002 | **-0.037** | -0.022 | -0.002 | -0.003 | -0.002 | -0.001 |
| Guns | -0.002 | 0.001 | -0.002 | -0.015 | -0.012 | -0.003 | **-0.023** | 0.014 | 0.000 | -0.016 | 0.001 | -0.004 | **-0.027** | 0.015 | 0.000 |
| Gold | **0.068** | 0.024 | -0.002 | 0.016 | 0.031 | -0.002 | 0.004 | 0.027 | 0.002 | -0.011 | 0.025 | 0.000 | -0.011 | 0.021 | -0.003 |
| Mines | **0.043** | 0.000 | 0.000 | -0.005 | 0.021 | -0.002 | -0.011 | -0.013 | 0.001 | -0.012 | 0.015 | -0.001 | **-0.030** | -0.003 | -0.001 |
| Coal | 0.013 | -0.002 | **-0.008** | -0.011 | -0.004 | -0.002 | 0.005 | 0.014 | -0.001 | -0.020 | 0.001 | 0.003 | -0.010 | 0.014 | 0.000 |
| Oil | **0.027** | 0.014 | **-0.003** | 0.013 | 0.012 | -0.001 | -0.003 | 0.017 | 0.000 | -0.011 | -0.006 | 0.002 | 0.008 | 0.004 | -0.001 |
| Util | 0.005 | 0.006 | **-0.002** | -0.001 | 0.006 | 0.000 | 0.002 | 0.006 | -0.001 | -0.007 | -0.003 | -0.001 | 0.006 | **-0.012** | 0.000 |
| Whlsl | **0.021** | **0.019** | **0.004** | **-0.018** | -0.004 | -0.002 | -0.014 | 0.015 | **0.004** | -0.003 | 0.004 | **0.003** | **-0.018** | 0.008 | 0.000 |
| PerSv | 0.007 | 0.017 | **0.002** | **-0.037** | -0.009 | **-0.002** | **-0.042** | 0.010 | -0.001 | -0.006 | 0.003 | 0.000 | **-0.016** | 0.001 | 0.000 |
| BusSv | **0.016** | **0.019** | **0.002** | **-0.015** | 0.000 | **-0.003** | -0.013 | 0.011 | 0.001 | -0.007 | -0.006 | 0.001 | -0.007 | -0.002 | **-0.002** |
| Hardw | 0.011 | -0.003 | **0.003** | **-0.024** | -0.011 | **-0.004** | **-0.018** | -0.001 | 0.000 | -0.010 | -0.019 | 0.002 | **-0.019** | 0.004 | -0.002 |
| Softw | 0.011 | 0.011 | **0.005** | **-0.023** | -0.004 | **-0.003** | -0.008 | 0.014 | 0.002 | 0.001 | -0.003 | 0.001 | **-0.017** | 0.004 | **-0.003** |
| Chips | **0.022** | 0.009 | 0.003 | **-0.019** | -0.009 | **-0.004** | -0.009 | 0.009 | 0.001 | -0.013 | -0.009 | 0.002 | -0.012 | 0.009 | -0.002 |
| LabEq | **0.021** | 0.007 | 0.002 | -0.010 | -0.007 | **-0.003** | -0.006 | 0.002 | 0.001 | 0.004 | -0.007 | 0.002 | -0.013 | 0.002 | **-0.002** |
| Paper | 0.010 | 0.003 | 0.000 | -0.005 | 0.005 | **-0.002** | -0.003 | 0.009 | -0.001 | -0.010 | 0.010 | 0.000 | -0.003 | -0.009 | -0.001 |
| Boxes | 0.015 | -0.006 | -0.001 | **-0.029** | -0.018 | -0.002 | -0.011 | -0.002 | 0.000 | -0.001 | 0.001 | 0.000 | -0.005 | 0.004 | **-0.003** |
| Trans | **0.017** | **0.020** | 0.000 | -0.010 | 0.003 | **-0.002** | -0.003 | 0.013 | -0.001 | -0.008 | 0.007 | 0.001 | -0.009 | -0.003 | -0.001 |
| Whlsl | **0.016** | **0.013** | **0.002** | **-0.017** | -0.005 | **-0.002** | **-0.018** | **0.013** | -0.001 | -0.006 | 0.004 | 0.000 | **-0.015** | 0.004 | **-0.002** |
| Rtail | **0.018** | **0.030** | 0.001 | **-0.020** | -0.003 | **-0.004** | **-0.015** | 0.001 | **-0.002** | -0.012 | 0.007 | -0.001 | -0.012 | 0.012 | **-0.002** |
| Meals | **0.013** | **0.030** | 0.001 | **-0.018** | 0.008 | **-0.002** | **-0.015** | 0.009 | **-0.002** | **-0.013** | 0.005 | 0.000 | -0.004 | 0.003 | **-0.002** |
| Banks | **0.010** | **0.027** | 0.000 | **-0.021** | **0.013** | **-0.001** | **-0.022** | **0.016** | **-0.002** | **-0.016** | 0.006 | -0.001 | **-0.024** | **-0.017** | 0.000 |
| Insur | 0.009 | **0.024** | -0.001 | **-0.014** | 0.006 | **-0.001** | **-0.019** | 0.004 | **-0.002** | -0.008 | 0.000 | -0.001 | -0.004 | -0.008 | -0.001 |
| RlEst | **0.026** | **0.028** | 0.001 | **-0.027** | 0.011 | **-0.002** | **-0.030** | 0.000 | -0.001 | -0.010 | 0.000 | -0.001 | **-0.027** | -0.014 | -0.001 |
| Fin | **0.015** | **0.015** | **0.002** | **-0.020** | 0.004 | **-0.002** | **-0.015** | **0.017** | -0.001 | **-0.019** | **0.012** | 0.001 | **-0.013** | -0.002 | 0.000 |
| Other | **0.023** | **0.028** | 0.001 | -0.005 | -0.004 | **-0.002** | 0.002 | **0.026** | **-0.003** | -0.012 | 0.002 | 0.000 | -0.013 | -0.013 | **-0.002** |
| Positive | 33 | 22 | 11 | 0 | 1 | 0 | 0 | 9 | 1 | 0 | 4 | 2 | 0 | 3 | 0 |
| Negative | 0 | 0 | 4 | 25 | 1 | 31 | 18 | 0 | 11 | 11 | 2 | 0 | 18 | 4 | 23 |

Notes: Table 2.7 reports the $a_3$ slope coefficients from Equation 2.3. The equation runs a regression of excess industry returns on a constant, bull and bear sentiment dummy variables for the indicated *k*-week lags, and the market-risk premium. Sentiment measures are from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). Bold indicates statistical significance of 10 percent or greater estimated with White (1980) standard errors.

## 2.6 Control for Conditional Time-variant Market-risk Premium

The analysis now investigates a rational expectations explanation of sentiment return predictability. The possibility exists that investor sentiment captures time-variant differences in the expected market-risk premium. For instance, rational investors may require less compensation for market risk when sentiment is high and more when sentiment is low. As such, the industry return predictability previously documented may serve as a proxy for a market-risk premium, conditioned by prevailing investor general market sentiment. Baker and Wurgler (2006) similarly control for conditional market betas. After correcting for conditional market risk, if anything, predictability strengthens. Thus, the effect of investor sentiment on industry return predictability appears unrelated to a conditional market-risk premium.

Table 2.8 reports the $a_1$ regression coefficients from Equation 2.4. The $a_1$ coefficients measure the predictability of industry returns after a correction for conditional market risk. Equation 2.4 runs a regression of excess industry returns ($R_i$) on a constant, investor sentiment at different $k$-week lags ($Sent_{t-k}$), the market-risk premium ($R_m$), and an interaction term between the market-risk premium and investor sentiment ($R_m Sent_{t-k}$). The interaction term effectively controls for the market-risk premium conditional on investor sentiment, following the methodology of Baker and Wurgler (2006, pg. 1673). Collectively, the $a_0$ and $a_1$ coefficient represent a decomposed Jensen's alpha, modified with a conditional risk premium. Table 2.8 indicates in bold $a_1$ coefficients that are statistically significant at 10 percent or greater using White (1980) standard errors. The bottom of Table 2.8 reports the total number of statistically significant positive and negative $a_1$ coefficients.

$$R_{i,t} = a_0 + a_1 Sent_{s,t-k} + b_0 R_{m,t} + b_1 R_{m,t} Sent_{s,t-k} + e_t \qquad \text{(Eq.2.4)}$$

**Table 2.8 Interaction between investor sentiment and the market**

| Industry | 1 week AAII | II | BW | 8 week AAII | II | BW | 13 week AAII | II | BW | 26 week AAII | II | BW | 52 week AAII | II | BW |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Agric | **0.021** | **0.021** | 0.001 | **0.010** | 0.000 | 0.001 | -0.002 | -0.005 | -0.001 | 0.005 | 0.000 | 0.001 | -0.001 | -0.008 | 0.000 |
| Food | **0.012** | **0.012** | **0.001** | 0.000 | **-0.008** | **-0.001** | -0.002 | **-0.008** | 0.000 | -0.002 | -0.001 | 0.000 | **-0.006** | **-0.007** | **-0.001** |
| Soda | **0.016** | 0.010 | **0.002** | 0.007 | -0.006 | **-0.002** | 0.004 | -0.003 | 0.000 | -0.004 | -0.002 | 0.000 | -0.002 | -0.008 | 0.000 |
| Beer | **0.013** | **0.013** | 0.001 | 0.000 | **-0.006** | 0.000 | -0.001 | -0.002 | -0.001 | 0.001 | 0.005 | 0.000 | -0.002 | -0.004 | **-0.001** |
| Smoke | **0.014** | 0.007 | -0.001 | -0.008 | **-0.020** | -0.001 | -0.003 | **-0.015** | 0.000 | 0.001 | -0.009 | -0.002 | 0.001 | -0.007 | -0.001 |
| Toys | **0.024** | **0.021** | **0.003** | 0.000 | **-0.014** | -0.001 | -0.006 | **-0.012** | 0.000 | -0.004 | -0.007 | 0.000 | **-0.013** | **-0.018** | **-0.003** |
| Fun | **0.025** | **0.022** | **0.003** | 0.000 | **-0.011** | -0.001 | -0.002 | **-0.013** | 0.000 | -0.003 | -0.006 | 0.000 | -0.003 | **-0.009** | **-0.003** |
| Books | **0.018** | **0.014** | **0.002** | -0.001 | **-0.013** | -0.001 | -0.005 | **-0.013** | 0.000 | 0.001 | -0.002 | 0.000 | **-0.006** | **-0.009** | **-0.002** |
| Hshld | **0.022** | **0.021** | **0.002** | 0.000 | **-0.009** | 0.000 | -0.005 | **-0.010** | 0.000 | **-0.008** | -0.006 | 0.000 | **-0.006** | **-0.010** | **-0.002** |
| Clths | **0.023** | **0.026** | **0.003** | -0.003 | **-0.008** | **-0.002** | -0.006 | **-0.012** | 0.000 | -0.007 | -0.005 | 0.000 | -0.004 | **-0.010** | **-0.002** |
| Hlth | **0.019** | **0.017** | **0.002** | 0.000 | **-0.018** | -0.001 | -0.007 | **-0.019** | 0.000 | -0.006 | -0.007 | 0.000 | **-0.011** | **-0.017** | **-0.002** |
| MedEq | **0.023** | **0.017** | **0.003** | -0.002 | **-0.015** | 0.000 | **-0.010** | **-0.018** | -0.001 | -0.006 | **-0.008** | 0.000 | **-0.013** | **-0.021** | **-0.003** |
| Drugs | **0.028** | **0.020** | **0.003** | -0.003 | **-0.017** | 0.001 | **-0.015** | **-0.016** | 0.000 | -0.008 | -0.005 | 0.001 | **-0.022** | **-0.031** | **-0.004** |
| Chems | **0.016** | **0.014** | **0.001** | -0.001 | **-0.009** | -0.001 | 0.000 | -0.006 | 0.000 | **-0.006** | -0.003 | 0.001 | **-0.007** | **-0.007** | **-0.002** |
| Rubbr | **0.022** | **0.018** | **0.002** | -0.002 | **-0.010** | -0.001 | -0.005 | **-0.010** | 0.000 | -0.006 | -0.006 | 0.000 | **-0.007** | **-0.008** | **-0.002** |
| Txtls | **0.021** | **0.018** | **0.003** | -0.001 | **-0.012** | -0.001 | -0.001 | **-0.015** | 0.000 | **-0.010** | **-0.009** | 0.000 | **-0.009** | **-0.009** | **-0.002** |
| BldMt | **0.020** | **0.014** | **0.002** | 0.003 | -0.005 | -0.001 | 0.001 | -0.007 | 0.000 | -0.006 | -0.005 | 0.000 | -0.005 | **-0.010** | **-0.001** |
| Cnstr | **0.027** | **0.029** | **0.002** | -0.001 | **-0.010** | 0.000 | -0.006 | **-0.010** | 0.000 | -0.007 | -0.008 | 0.000 | **-0.011** | **-0.017** | **-0.002** |
| Steel | **0.023** | **0.022** | **0.002** | 0.004 | -0.005 | -0.001 | -0.004 | -0.005 | 0.000 | **-0.009** | 0.001 | **0.002** | **-0.009** | -0.004 | -0.001 |
| FabPr | **0.020** | **0.012** | **0.002** | -0.001 | **-0.013** | -0.001 | -0.008 | **-0.015** | 0.000 | -0.004 | 0.000 | **0.001** | **-0.010** | -0.009 | -0.001 |
| Mach | **0.020** | **0.018** | **0.002** | 0.001 | **-0.011** | 0.000 | **-0.007** | **-0.015** | 0.001 | **-0.007** | -0.005 | 0.001 | **-0.010** | **-0.011** | **-0.001** |
| ElcEq | **0.024** | **0.011** | **0.004** | -0.002 | **-0.017** | 0.001 | -0.006 | **-0.017** | **0.002** | **-0.009** | **-0.012** | 0.001 | **-0.011** | **-0.017** | -0.001 |
| Autos | **0.024** | **0.020** | **0.002** | -0.001 | **-0.013** | -0.001 | -0.003 | **-0.012** | 0.000 | -0.005 | -0.004 | 0.000 | **-0.008** | **-0.012** | **-0.002** |
| Aero | **0.025** | **0.025** | **0.002** | 0.004 | -0.004 | 0.000 | **0.010** | -0.003 | 0.001 | -0.001 | -0.002 | 0.001 | **-0.009** | -0.007 | **-0.002** |
| Ships | **0.028** | **0.027** | 0.001 | 0.004 | -0.003 | -0.001 | -0.003 | 0.000 | -0.001 | **-0.011** | -0.001 | -0.001 | **-0.008** | -0.011 | -0.001 |
| Guns | **0.022** | **0.019** | 0.000 | 0.004 | 0.000 | -0.001 | 0.003 | 0.001 | 0.000 | -0.004 | -0.001 | -0.001 | -0.005 | -0.005 | -0.001 |
| Gold | 0.010 | **0.025** | -0.002 | 0.014 | **0.019** | 0.001 | 0.006 | 0.006 | -0.001 | -0.015 | -0.002 | **0.004** | -0.003 | -0.008 | 0.003 |
| Mines | **0.018** | **0.019** | 0.002 | 0.007 | 0.004 | 0.000 | -0.002 | 0.001 | 0.000 | -0.009 | -0.006 | 0.001 | **-0.013** | -0.006 | 0.000 |
| Coal | **0.019** | **0.023** | -0.003 | 0.012 | 0.005 | -0.001 | 0.012 | 0.013 | 0.000 | 0.006 | 0.004 | **0.003** | -0.005 | -0.007 | 0.001 |
| Oil | **0.018** | **0.014** | 0.000 | **0.013** | 0.003 | 0.001 | 0.006 | 0.002 | **0.002** | -0.005 | -0.007 | **0.002** | -0.006 | **-0.008** | -0.001 |
| Util | **0.006** | **0.006** | 0.000 | 0.001 | -0.002 | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 | -0.001 | -0.001 | -0.002 | -0.001 | -0.001 |
| Whlsl | **0.019** | **0.014** | **0.004** | **-0.011** | **-0.021** | -0.001 | **-0.013** | **-0.024** | **0.002** | -0.008 | -0.008 | 0.002 | **-0.011** | **-0.016** | -0.002 |
| PerSv | **0.022** | **0.019** | **0.003** | -0.006 | **-0.012** | -0.001 | **-0.011** | **-0.014** | -0.001 | -0.005 | -0.002 | 0.000 | **-0.010** | **-0.014** | **-0.001** |
| BusSv | **0.024** | **0.017** | **0.003** | -0.003 | **-0.015** | 0.000 | **-0.008** | **-0.017** | 0.001 | -0.006 | **-0.007** | 0.001 | **-0.009** | **-0.016** | **-0.002** |
| Hardw | **0.025** | 0.013 | **0.005** | **-0.013** | **-0.025** | 0.001 | **-0.019** | **-0.027** | 0.001 | -0.011 | **-0.011** | 0.001 | **-0.015** | **-0.024** | **-0.003** |
| Softw | **0.026** | **0.015** | **0.005** | **-0.011** | **-0.024** | 0.000 | **-0.022** | **-0.026** | 0.001 | -0.008 | -0.009 | 0.001 | **-0.015** | **-0.023** | **-0.004** |
| Chips | **0.026** | **0.016** | **0.004** | -0.006 | **-0.017** | 0.001 | **-0.015** | **-0.021** | 0.002 | **-0.011** | -0.010 | 0.002 | **-0.014** | **-0.021** | -0.002 |
| LabEq | **0.026** | 0.011 | **0.004** | -0.002 | **-0.019** | 0.000 | **-0.010** | **-0.024** | **0.002** | -0.007 | **-0.012** | 0.001 | **-0.015** | **-0.023** | **-0.002** |
| Paper | **0.015** | **0.013** | 0.001 | 0.000 | **-0.009** | 0.000 | -0.003 | **-0.011** | 0.000 | -0.004 | -0.005 | 0.000 | -0.005 | **-0.008** | **-0.001** |
| Boxes | **0.017** | 0.009 | 0.002 | **-0.012** | **-0.021** | **-0.002** | -0.006 | **-0.017** | 0.000 | -0.006 | **-0.013** | -0.001 | -0.006 | **-0.015** | **-0.002** |
| Trans | **0.021** | **0.018** | **0.002** | 0.002 | **-0.010** | -0.001 | -0.001 | **-0.012** | 0.000 | **-0.008** | -0.005 | 0.001 | **-0.007** | **-0.008** | **-0.001** |
| Whlsl | **0.023** | **0.020** | **0.003** | 0.001 | **-0.009** | -0.001 | -0.005 | **-0.010** | 0.000 | -0.005 | -0.001 | 0.000 | **-0.007** | **-0.011** | **-0.002** |
| Rtail | **0.019** | **0.020** | **0.002** | -0.004 | **-0.013** | **-0.002** | -0.006 | **-0.013** | -0.001 | -0.006 | -0.008 | 0.000 | -0.006 | **-0.011** | **-0.002** |
| Meals | **0.022** | **0.022** | **0.002** | 0.000 | **-0.008** | -0.001 | -0.002 | **-0.011** | 0.000 | -0.005 | -0.005 | 0.000 | **-0.006** | **-0.010** | **-0.002** |
| Banks | **0.011** | **0.010** | 0.001 | -0.002 | **-0.010** | **-0.001** | **-0.005** | **-0.010** | 0.000 | -0.005 | **-0.006** | 0.000 | **-0.008** | **-0.012** | **-0.001** |
| Insur | **0.012** | **0.012** | 0.001 | 0.000 | **-0.009** | -0.001 | -0.005 | **-0.010** | 0.000 | -0.005 | **-0.006** | 0.000 | **-0.005** | **-0.011** | **-0.002** |
| RlEst | **0.022** | **0.020** | **0.002** | 0.001 | **-0.009** | **-0.001** | -0.005 | **-0.008** | 0.000 | -0.005 | -0.001 | 0.000 | **-0.008** | **-0.009** | **-0.001** |
| Fin | **0.015** | **0.013** | **0.002** | -0.005 | **-0.009** | 0.000 | **-0.008** | **-0.011** | 0.000 | **-0.009** | **-0.008** | 0.001 | **-0.009** | **-0.010** | **-0.001** |
| Other | **0.025** | **0.021** | **0.003** | 0.001 | **-0.011** | 0.000 | -0.002 | **-0.009** | -0.001 | -0.003 | -0.004 | 0.001 | **-0.009** | **-0.014** | -0.001 |
| Postive | 48 | 44 | 35 | 2 | 1 | 0 | 1 | 0 | 4 | 0 | 0 | 5 | 0 | 0 | 0 |
| Negative | 0 | 0 | 0 | 4 | 37 | 7 | 12 | 35 | 0 | 10 | 10 | 0 | 34 | 36 | 32 |

Notes: Table 2.8 reports the $a_1$ coefficients from Equation 2.4. The equation runs a regression of excess industry returns on investor sentiment, the market-risk premium, and the interaction between investor sentiment and the market-risk premium for the indicated *k*-week lags. Sentiment measures are from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). Bold indicates 10 percent or greater statistical significance estimated with White (1980) standard errors.

A time-variant risk premium fails to explain investor sentiment predictability. Significant predictability compares with the earlier results at a four-week horizon. Average economic significance does increase modestly. The most noticeable difference is for longer-term predictability and II sentiment. At a 52-week lag, II sentiment negatively predicts the returns for 36 industries, compared with six industries previously. The absolute value of economic significance noticeably increases at longer horizons, for all sentiment measures. For instance, at a 52-week lag, AAII sentiment predicts average industry performance of -0.008, double that previously observed. An increase in the statistical and economic significance of negative predictability provides some evidence of a time-variant risk premium. However, the results reported in Table 2.8 support the view that investor sentiment predictability reflects only a limited component of compensation for conditional market risk. As such, the previous results, showing positive short-term and negative long-term predictability, continue to hold. However, a correction for a time-variant risk premium provides no better understanding of the industries that are most susceptible to speculative mispricing.

### 2.7 Interaction of Industry Characteristics with Investor Sentiment

This section takes several different approaches to investigate whether industries that share certain characteristics attract investor sentiment. The prior results indicate that the effect of investor sentiment is market wide, affecting the performance of most industries without distinction. Prior research also establishes that certain characteristics, which make objective valuations difficult, lead to speculative demand. For instance, Baker and Wurgler (2006) identify capitalization, valuation and dividend payout as stock characteristics that attract investor sentiment mispricing. Baker and Wurgler (2006) argue that valuation difficulties provide a channel for speculative behavior to drive prices from fundamentals, especially during periods of extreme investor sentiment. In a similar way, industries grouped by certain characteristics are potentially more subject to mispricing than are others. For instance, industries with low capital requirements tend to be more competitive, with less ability to control product prices.[26] Consequently, the cash flows of highly competitive industries are relatively uncertain, which potentially leads to speculative mispricing. The analysis considers characteristics that broadly relate to industry competition, structure, growth, momentum, and risk. For thoroughness, the analysis incorporates a number of different empirical approaches, to evaluate the effect of investor sentiment on industry returns.

[26] See for example Hoberg and Phillips (2010).

### 2.7.1 Industry characteristics

The literature, such as Baker and Wurgler (2006) and Kumar and Lee (2006), identifies greater speculative demand for stocks characterized as difficult to value and costly to arbitrage. In a similar spirit, the analysis identifies industry characteristics that potentially attract speculative demand due to valuation difficulties. Specifically, the industry characteristics investigated are return momentum, return volatility, systematic market risk, valuation ratios, sales volatility, capitalization, number of constituent firms, and Herfindahl concentration measures. Industry characteristics data comes from different sources. Monthly data for industry firms, BE/ME ratios, and capitalization come from the Kenneth French website.[27] Quarterly data for industry sales, book equity, and total assets come from Compustat. In order to match the frequency of investor sentiment measures, the analysis assumes that the monthly and quarterly reported data remain constant during the weeks included in each period. The following discussion motivates each industry characteristic.

Industry standard deviations of returns and market betas provide two volatility measures. Barberis and Shleifer (2003), Peng and Xiong (2006), and Kumar (2009) argue that speculative demand in popular investment styles leads to more volatile returns. The analysis uses a 12-week rolling window estimation of industry standard deviations. A market beta estimated with a single-index model provides an additional measure of industry volatility, estimated over 26-week rolling windows. The expected relationship between investor sentiment and both industry standard deviations and market betas is positive.

Momentum provides a measure of speculative industry mispricing. The literature describes momentum as short-term return continuation, unexplained by traditional asset-pricing models. Momentum, generally, remains an unsolved market anomaly, despite extensive literature on the topic.[28] However, Moskowitz and Grinblatt (1999) argue that industry momentum largely explains stock-return momentum. Investor herding in popular industries potentially leads to predictable return momentum driven by investor

[27] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[28] See, for instance, Fama and French (2008).

sentiment.[29] The analysis uses 12-week rolling windows to estimate industry momentum, which has an expected positive relationship with investor sentiment.

The structure of an industry further determines its level of competitiveness. Average firm capitalization and the average number of constituent firms define industry structure. Hoberg and Phillips (2010) argue that industry structures determine cash flow volatility and analyst coverage. Peng and Xiong (2006) also discuss how a lack of analyst coverage in small-cap industries leads to informational inefficiencies. The analysis uses the natural log of industry market capitalization in millions of U.S. dollars. The number of constituent industry firms also proxies for industry competition. Industry competition is greater in industries characterized by a large number of small firms. The analysis uses the natural log of industry firms. The expectation is that investor sentiment has a negative relationship with industry capitalization and a positive relationship with the number of industry firms.

Industry sales volatility and book-to-market valuation ratios (BE/ME) provide measures of industry growth potential.[30] Baker and Wurgler (2006) argue that high-growth firms face greater speculative price pressure, due to valuation uncertainty. Sales volatility characterizes uncertain industry profitability, such as for technology stocks in the dot.com market. Baker and Wurgler (2006) document a positive relationship between investor sentiment and sales volatility. Baker and Wurgler (2006) also provide evidence that investor sentiment has a greater effect on growth firms as characterized by small BE/ME ratios. The expectation is to observe that investor sentiment has a positive relationship with sales volatility and a negative relationship with BE/ME ratios.

The Herfindahl index measures industry concentration, estimated as the sum of the squared market share for each firm in an industry.[31] A lower Herfindahl score indicates greater industry competition. A recent empirical study by Hoberg and Phillips (2010) examines the predictability of industry boom-and-bust cycles related to industry competition. Hoberg and Phillips (2010) theorize that investor valuations fail to

[29] Moskowitz and Grinblatt (1999).
[30] Baker and Wurgler (2006).
[31] See http://en.wikipedia.org/wiki/Herfindahl_index for an in-depth discussion of the construction and interpretation of Herfindahl measures.

incorporate the effect of industry competition on distant cash flows. The study classifies stocks by their three-digit Standard Industrial Classification (SIC) code, with data from 1972 to 2004. Hoberg and Phillips (2010) use the Herfindahl concentration measure to classify an industry as competitive or non-competitive. Hoberg and Phillips (2010) find that investors systematically neglect to assess the impact of competition on future industry performance. Therefore, inflated industry valuations result in predictable and economically significant industry reversals. Hoberg and Phillips (2010) also observe that stocks in competitive industries have upwardly biased analyst earnings estimates and high return co-movement. Hoberg and Phillips (2010) hypothesize that gathering information for competitive industries is costly. Consequently, investors rely on industry-specific rather than firm-specific information for valuations. The results reported in Hoberg and Phillips (2010) are robust to traditional risk corrections, leaving the possibility of a behavioral explanation linked to investor sentiment. Following Hou and Robinson (2006), the analysis uses three Herfindahl index measures, calculated as the sum of squared market share for industry sales, book equity and total assets. The expectation is for a negative relationship between Herfindahl concentration measures and investor sentiment.

### 2.7.2 Non-parametric ranking of industry performance

The examination begins with a simple non-parametric view of the performance of portfolios constructed from industries that share common characteristics.[32] There are ten different portfolios, one for each industry characteristic. The numeric performance rankings for the 10 portfolios formed on industry characteristics therefore range from a low of one to a high of 10. Given there are 10 possible performance ranks, the average ranking is 5.5, which falls between a rank of 5 and a rank of 6. Therefore, a ranking below 5.5 indicates below average performance and a ranking above 5.5 indicates above average performance. To illustrate, industries grouped by HH sales have an average rank of 5 for the full sample. A rank of 5 indicates that the performance of industries grouped by HH sales characteristic is below average, when compared with the performance of all industry characteristic portfolios.

[32] Baker and Wurgler (2006) take a similar approach in their analysis of firm-level characteristics.

Table 2.9 reports the performance ranking for long-short portfolios formed on the decile sorts of the 10 different industry characteristics. The analysis first sorts the Fama and French 49 industries into decile portfolios from highest to lowest values – for each industry characteristic. Next, the analysis constructs long-short portfolios from these top-bottom decile groups for each characteristic. For instance, the momentum portfolio comprises a long (short) position in the five industries with highest (lowest) 12-week momentum. The objective of the long-short portfolios is to better measure differences in performance attributable to a particular shared industry characteristic. Panel A reports the average portfolio ranking across all 10 industry characteristic portfolios. Panel B reports the percentage of time that an industry characteristic portfolio's performance ranks in the top 30 percentile. The table reports results for periods of bullish and bearish sentiment, and for comparison, the full sample.

Table 2.9 reveals similar portfolio rankings across periods of bullish and bearish investor sentiment, for all sentiment measures and industry characteristics. This comes as a surprise. For instance, prior literature, such as Baker and Wurgler (2006), suggests higher returns for more volatile industries when sentiment is high, such as during periods of bullish sentiment. However, the performance of industries portfolios characterized by return risk and market risk is constant across all periods. The momentum portfolio provides a notable exception, with an average ranking above 8 for bull and bear markets. By construction, the momentum portfolios comprise the winning-losing industries based on 12-month returns. This result thus indicates a continuation of past performance. The growth (BE/ME) and Herfindahl portfolios rank consistently below the average rank of 5.5, irrespective of bullish or bearish sentiment. The interpretation is that growth and competitive industries perform consistently above average. Nonetheless, there is no clear distinction for portfolio rankings between bullish and bearish sentiment. Panel B provides a different view. Here, the Herfindahl portfolios are the clear standouts. Average Herfindahl portfolio performance ranks in the top 30 percent approximately 15 percent of the time, independent of investor sentiment. Generally, however, the non-parametric analysis provides no guidance on the effect of investor sentiment on the returns of portfolios formed on common industry characteristics.

**Table 2.9 Performance ranking by industry characteristic**

| | Full | Bull Markets | | | Bear Markets | | |
|---|---|---|---|---|---|---|---|
| **Panel A:** | **Sample** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Stdev | 5.4 | 5.5 | 5.5 | 5.4 | 5.2 | 5.1 | 5.4 |
| Mom | 8.1 | 8.2 | 8.1 | 8.3 | 8.1 | 8.3 | 8.0 |
| Beta | 5.4 | 5.5 | 5.4 | 5.5 | 5.4 | 5.5 | 5.4 |
| Firms | 5.4 | 5.5 | 5.4 | 5.6 | 5.1 | 5.4 | 5.0 |
| Size | 5.3 | 5.2 | 5.3 | 5.3 | 5.6 | 5.2 | 5.3 |
| BE/ME | 4.7 | 4.7 | 4.6 | 4.6 | 4.9 | 5.1 | 4.9 |
| HH sales | 5.1 | 5.0 | 5.1 | 5.1 | 5.1 | 4.8 | 5.1 |
| HH equity | 5.0 | 5.0 | 5.0 | 4.9 | 4.9 | 4.8 | 5.1 |
| HH assets | 5.1 | 5.0 | 5.0 | 5.0 | 5.1 | 5.2 | 5.2 |
| Sales $\sigma$ | 5.4 | 5.4 | 5.4 | 5.3 | 5.4 | 5.3 | 5.4 |

| | Full | Bull Markets | | | Bear Markets | | |
|---|---|---|---|---|---|---|---|
| **Panel B:** | **Sample** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Stdev | 0.33 | 0.33 | 0.33 | 0.33 | 0.32 | 0.30 | 0.33 |
| Mom | 0.72 | 0.71 | 0.71 | 0.74 | 0.73 | 0.77 | 0.69 |
| Beta | 0.38 | 0.37 | 0.38 | 0.38 | 0.38 | 0.35 | 0.36 |
| Firms | 0.35 | 0.36 | 0.35 | 0.39 | 0.34 | 0.38 | 0.31 |
| Size | 0.24 | 0.22 | 0.24 | 0.24 | 0.27 | 0.24 | 0.23 |
| BE/ME | 0.21 | 0.21 | 0.21 | 0.19 | 0.22 | 0.23 | 0.24 |
| HH sales | 0.16 | 0.15 | 0.16 | 0.15 | 0.17 | 0.12 | 0.16 |
| HH equity | 0.16 | 0.16 | 0.17 | 0.15 | 0.16 | 0.14 | 0.17 |
| HH assets | 0.17 | 0.17 | 0.17 | 0.15 | 0.16 | 0.15 | 0.19 |
| Sales $\sigma$ | 0.25 | 0.25 | 0.25 | 0.24 | 0.24 | 0.25 | 0.25 |

Notes: Table 2.9 reports the return rankings for long-short decile portfolios formed on industries grouped by shared characteristics. Rankings range from a low of 1 to a high of 10. By construction, the mean rank is 5.5. The analysis first constructs long-short portfolios from the top decile-bottom decile sorts on industry characteristics. The industry characteristics considered are 12-week return volatility (stdev), 12-week return momentum (Mom), 26-week systematic market risk (Beta), number of firms in an industry (Firms), market capitalization (Size), book-to-market valuation ratios (BE/ME), Herfindahl sales (HH sales), Herfindahl book equity (HH equity), Herfindahl total assets (HH assets), and sales volatility (Sales $\sigma$). The table reports results for the full sample, bull markets and bear markets. Positive (negative) bull-bear sentiment spread defines bull (bear) markets, for each sentiment measure. Panel A reports the relative return performance ranking across all 10 industry characteristics for the indicated periods. Panel B reports the percentage of time that the performance of each long-short characteristic portfolio ranks in the top 30 percent across all characteristic portfolios for the indicated periods.

### 2.7.3 Interaction between investor sentiment and industry characteristics

The analysis now investigates the relationship between industry returns and the interaction between investor sentiment and industry characteristics, estimated with Equation 2.5. Similar in spirit to Baker and Wurgler (2006), the objective of this section is to evaluate whether investor sentiment has systematic effect on the returns of industries that share certain characteristics. As a point of difference, the focus of previous sections has been investor sentiment predictability of industry mispricing and long-term reversals. As such, the analysis now considers the contemporaneous relationship between industry characteristics and investor sentiment. The equation runs a regression of excess industry returns (*$R_i$*) on a constant, investor sentiment (*$Sent_s$*), industry characteristics (*$Char_c$*), an investor sentiment and industry characteristic interaction term (*$Sent_sChar_c$*), and the market-risk premium (*$R_m$*).[33] All data is weekly and described in an earlier section. The variable of interest is the $a_3$ regression coefficient, reported in Table 2.10. The table reports results for each sentiment measure and each industry characteristic. Bold indicates statistical significance of 10 percent or greater, estimated with White (1980) standard errors. The bottom two rows of Table 2.10 report the number of significant positive and negative $a_3$ regression coefficients.

$$R_{i,t} = a_0 + a_1 Sent_{s,t} + a_2 Char_{c,t} + a_3 Sent_{s,t} Char_{c,t} + b_0 R_{m,t} + e_t \qquad \text{(Eq. 2.5)}$$

The results reported in Table 2.10 are inconclusive. Based on the literature, the expectation is for a positive investor interaction with industry standard deviation, momentum, beta, firms, and sales volatility characteristics. The expectation is for negative investor-sentiment interaction terms with size and the three Herfindahl competition measures. For instance, research shows that higher investor sentiment creates higher return volatility, which should result in a positive sentiment and standard deviation interaction term. Indeed, AAII and II sentiment indices have a significantly positive interaction with standard deviation for 23 and 20 industries. Industry firm numbers and capitalization also have the expected negative interaction with BW sentiment for 16 and 29 industries. Otherwise, statistical significance is not much more than expected by random chance, at 10 percent, or has the incorrect sign.

[33] Equation 2.5 includes investor sentiment and industry characteristics as individual terms for correct model specification (Brambor, Clark, and Golder (2006)).

## Table 2.10 Interaction between investor sentiment and industry characteristics

| | Stdev | | | Mom | | | Beta | | | Firms | | | Size | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Agric | -0.174 | 0.684 | -0.109 | **-1.018** | -0.828 | -0.093 | 0.016 | 0.002 | **0.013** | 0.009 | 0.027 | 0.004 | -0.005 | **-0.012** | 0.000 |
| Food | **0.676** | **1.181** | 0.047 | -0.130 | 0.314 | 0.083 | 0.013 | **-0.076** | **0.005** | -0.007 | -0.008 | **0.005** | 0.004 | 0.000 | -0.002 |
| Soda | 0.872 | -0.045 | **0.187** | 1.124 | 1.270 | 0.123 | 0.003 | -0.016 | **0.007** | 0.001 | -0.001 | 0.000 | -0.006 | 0.004 | -0.002 |
| Beer | 0.214 | 0.715 | 0.165 | 0.296 | -0.142 | 0.014 | -0.008 | 0.003 | 0.003 | 0.020 | 0.029 | 0.000 | -0.002 | -0.002 | 0.000 |
| Smoke | 0.036 | -0.558 | -0.012 | -0.121 | -0.994 | -0.250 | **-0.028** | -0.016 | 0.003 | -0.043 | -0.069 | **0.021** | 0.005 | 0.001 | **-0.003** |
| Toys | **1.074** | **1.889** | -0.009 | 0.037 | 0.612 | 0.071 | 0.004 | **-0.050** | 0.001 | **0.022** | **0.048** | -0.002 | -0.002 | **-0.011** | **-0.003** |
| Fun | **0.716** | **1.447** | -0.024 | -0.135 | 0.341 | 0.068 | **0.027** | **-0.038** | -0.001 | 0.006 | 0.023 | 0.001 | -0.002 | -0.003 | **-0.002** |
| Books | **1.213** | **1.626** | 0.000 | 0.043 | 0.381 | 0.098 | 0.026 | -0.032 | -0.006 | **-0.021** | **-0.035** | **0.006** | **0.013** | **0.015** | -0.001 |
| Hshld | **0.984** | **0.995** | 0.012 | -0.262 | 0.272 | 0.088 | **0.035** | -0.020 | 0.004 | **-0.012** | -0.009 | **0.005** | 0.003 | 0.001 | **-0.004** |
| Clths | **0.921** | **1.531** | 0.095 | -0.281 | 0.474 | **0.161** | 0.013 | -0.018 | 0.003 | -0.006 | 0.017 | 0.005 | 0.000 | -0.001 | **-0.004** |
| Hlth | **0.893** | **1.363** | 0.036 | 0.018 | 0.260 | 0.043 | -0.025 | **-0.039** | 0.002 | **-0.022** | **-0.023** | **0.006** | **0.006** | 0.002 | **-0.003** |
| MedEq | 0.140 | 0.423 | **-0.114** | -0.024 | 0.360 | -0.038 | -0.024 | **-0.063** | 0.002 | 0.012 | 0.026 | -0.003 | **0.009** | 0.000 | **-0.003** |
| Drugs | -0.016 | -0.211 | **-0.168** | -0.104 | 0.473 | -0.084 | -0.024 | **-0.060** | 0.002 | **0.036** | -0.017 | **-0.008** | **0.023** | -0.004 | **-0.004** |
| Chems | **0.639** | **1.175** | -0.031 | -0.130 | 0.218 | -0.008 | 0.010 | -0.001 | 0.000 | -0.024 | -0.024 | 0.007 | 0.009 | 0.006 | **-0.004** |
| Rubbr | **0.798** | **1.861** | 0.063 | -0.021 | 0.325 | 0.019 | 0.000 | **-0.067** | 0.003 | -0.013 | 0.004 | **0.005** | 0.000 | **-0.014** | -0.002 |
| Txtls | **1.611** | **2.146** | 0.026 | -0.166 | -0.172 | 0.074 | 0.005 | -0.027 | 0.001 | -0.009 | **-0.018** | 0.001 | 0.001 | -0.001 | 0.000 |
| BldMt | -0.077 | 1.754 | 0.182 | **-0.692** | -0.288 | 0.044 | **0.020** | -0.011 | -0.001 | **-0.030** | -0.031 | **0.006** | -0.001 | -0.002 | **-0.004** |
| Cnstr | **1.073** | 0.637 | -0.024 | -0.316 | 0.508 | 0.075 | 0.015 | -0.006 | 0.000 | -0.015 | -0.017 | **0.009** | 0.005 | 0.006 | **-0.003** |
| Steel | **0.592** | 0.776 | 0.006 | -0.255 | 0.161 | 0.042 | 0.004 | 0.001 | -0.001 | **-0.029** | -0.020 | 0.004 | 0.002 | **0.020** | -0.001 |
| FabPr | 0.288 | 0.807 | -0.049 | -0.233 | 0.407 | 0.010 | -0.009 | **0.031** | 0.000 | 0.003 | -0.016 | 0.000 | -0.016 | -0.004 | 0.003 |
| Mach | **0.660** | **1.148** | -0.058 | -0.232 | 0.020 | 0.029 | 0.011 | 0.015 | -0.003 | -0.018 | -0.029 | **0.010** | 0.001 | **0.010** | **-0.003** |
| ElcEq | 0.490 | **1.020** | **-0.143** | -0.006 | 0.086 | -0.006 | **-0.023** | **-0.067** | **-0.006** | -0.017 | 0.002 | 0.004 | 0.004 | 0.001 | -0.001 |
| Autos | **0.956** | **1.655** | 0.093 | -0.325 | 0.203 | 0.066 | -0.005 | **-0.040** | -0.001 | **-0.049** | **-0.036** | 0.000 | -0.007 | -0.015 | **-0.007** |
| Aero | 0.900 | 1.385 | 0.036 | -0.269 | 0.000 | 0.011 | 0.015 | 0.025 | -0.001 | **-0.048** | **-0.059** | 0.002 | **0.013** | **0.015** | -0.001 |
| Ships | 0.875 | 0.105 | 0.120 | -0.359 | -0.331 | 0.170 | **0.028** | 0.023 | 0.001 | **-0.052** | -0.018 | -0.003 | -0.004 | -0.001 | **-0.003** |
| Guns | 0.123 | -0.241 | -0.213 | -0.059 | 0.256 | 0.052 | 0.003 | -0.008 | **0.009** | **-0.069** | **-0.095** | **0.009** | **0.028** | 0.008 | **-0.003** |
| Gold | -0.050 | 0.509 | **-0.284** | -1.057 | -0.230 | -0.198 | -0.002 | -0.028 | 0.005 | 0.007 | 0.004 | **0.005** | 0.005 | 0.000 | -0.003 |
| Mines | -0.737 | -0.501 | 0.168 | -0.444 | -0.188 | 0.118 | 0.012 | 0.001 | -0.003 | -0.020 | -0.013 | **0.008** | 0.008 | 0.012 | **-0.004** |
| Coal | -0.267 | 0.849 | **-0.241** | 0.077 | 0.087 | 0.010 | -0.001 | 0.015 | 0.001 | 0.006 | 0.000 | 0.004 | -0.001 | 0.010 | -0.001 |
| Oil | -0.032 | 0.784 | -0.110 | -0.355 | 0.256 | **0.119** | 0.008 | 0.009 | -0.003 | **-0.041** | **-0.060** | **0.010** | 0.009 | 0.013 | **-0.004** |
| Util | **1.244** | 0.960 | 0.058 | -0.656 | 0.198 | -0.111 | -0.003 | 0.022 | **0.005** | **-0.018** | -0.018 | -0.001 | 0.004 | 0.003 | 0.000 |
| Telcm | -0.076 | 0.519 | -0.022 | 0.018 | **0.660** | 0.006 | -0.002 | -0.009 | 0.001 | 0.017 | 0.011 | 0.000 | 0.008 | 0.006 | -0.002 |
| PerSv | -0.359 | 0.986 | -0.006 | -0.086 | -0.025 | **0.162** | 0.000 | **-0.035** | 0.002 | -0.018 | 0.009 | **-0.010** | 0.006 | 0.000 | **-0.003** |
| BusSv | **0.745** | **1.077** | -0.042 | -0.233 | 0.060 | 0.037 | 0.018 | -0.017 | -0.001 | **0.049** | **0.077** | -0.005 | 0.004 | 0.000 | **-0.002** |
| Hardw | 0.123 | 0.514 | -0.004 | 0.384 | 0.525 | -0.024 | -0.024 | **-0.030** | 0.002 | -0.017 | 0.010 | 0.001 | **0.011** | 0.005 | -0.001 |
| Softw | 0.232 | 0.320 | -0.013 | 0.308 | 0.582 | -0.003 | -0.010 | **-0.024** | 0.002 | **0.019** | 0.008 | -0.001 | 0.005 | -0.003 | -0.001 |
| Chips | -0.012 | 0.183 | -0.046 | 0.523 | 0.631 | -0.047 | -0.017 | **-0.028** | -0.001 | 0.024 | 0.080 | -0.002 | 0.004 | 0.000 | -0.001 |
| LabEq | 0.304 | 0.494 | **-0.094** | 0.089 | 0.178 | -0.044 | -0.013 | **-0.056** | -0.003 | 0.015 | -0.003 | 0.005 | 0.002 | -0.007 | **-0.003** |
| Paper | **0.729** | 0.640 | -0.059 | -0.247 | 0.339 | 0.046 | 0.005 | **-0.038** | 0.001 | **-0.015** | -0.017 | 0.002 | 0.005 | **0.012** | **-0.002** |
| Boxes | 0.442 | 0.642 | 0.028 | 0.115 | 0.145 | **-0.204** | -0.001 | -0.006 | -0.002 | 0.011 | 0.013 | -0.002 | -0.006 | 0.000 | 0.000 |
| Trans | **0.722** | **1.422** | 0.068 | -0.357 | -0.026 | 0.020 | 0.011 | -0.015 | 0.002 | -0.007 | 0.010 | -0.003 | 0.004 | 0.001 | **-0.003** |
| Whlsl | **0.748** | **1.156** | -0.058 | -0.135 | 0.249 | 0.048 | 0.010 | -0.018 | -0.003 | **-0.017** | -0.010 | **0.005** | **0.006** | 0.004 | **-0.003** |
| Rtail | **0.800** | **1.739** | -0.052 | -0.174 | 0.162 | 0.000 | 0.002 | **-0.031** | -0.003 | -0.020 | **0.032** | -0.002 | 0.001 | -0.001 | **-0.003** |
| Meals | **1.343** | **1.669** | **0.123** | -0.302 | 0.198 | 0.057 | 0.003 | **-0.033** | 0.003 | 0.001 | **0.035** | -0.001 | 0.005 | -0.001 | **-0.004** |
| Banks | 0.272 | **1.045** | 0.079 | 0.086 | 0.615 | 0.108 | -0.006 | **-0.050** | **0.005** | -0.008 | **-0.026** | **-0.007** | **-0.007** | **-0.015** | **-0.003** |
| Insur | **0.529** | 0.552 | -0.035 | -0.203 | 0.019 | 0.095 | 0.000 | **-0.033** | 0.003 | -0.009 | -0.001 | 0.004 | 0.000 | -0.005 | **-0.002** |
| RlEst | 0.615 | 0.718 | **0.143** | -0.158 | 0.051 | 0.074 | -0.013 | -0.029 | -0.002 | 0.001 | **0.021** | **0.007** | -0.001 | 0.002 | **-0.003** |
| Fin | 0.066 | 0.550 | -0.008 | 0.113 | 0.527 | 0.102 | 0.001 | **-0.026** | 0.002 | -0.003 | -0.001 | 0.000 | 0.000 | -0.001 | -0.001 |
| Other | **0.709** | **1.374** | -0.058 | -0.128 | 0.299 | 0.013 | 0.000 | 0.012 | 0.003 | 0.004 | -0.006 | **0.011** | 0.000 | 0.001 | **-0.001** |
| **Positive** | 23 | 20 | 3 | 0 | 1 | 3 | 4 | 1 | 6 | 4 | 5 | 16 | 8 | 5 | 0 |
| **Negative** | 0 | 0 | 6 | 2 | 0 | 1 | 2 | 20 | 1 | 13 | 8 | 3 | 1 | 4 | 29 |

***Continued:***

| Industry | BE/ME | | | HH sales | | | HH equity | | | HH assets | | | Sales σ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AAII | II | BW | AAII | II | BW | AAII | II | BW | AAII | II | BW | AAII | II | BW |
| Agric | 0.014 | 0.026 | -0.003 | 0.031 | 0.074 | **0.044** | 0.023 | **0.108** | -0.005 | -0.020 | 0.068 | -0.010 | -0.002 | -0.021 | -0.003 |
| Food | -0.027 | **-0.108** | 0.007 | **0.444** | 0.129 | 0.025 | **0.100** | 0.055 | 0.008 | 0.095 | -0.125 | **0.045** | 0.033 | -0.016 | 0.012 |
| Soda | -0.012 | -0.004 | -0.003 | 0.011 | 0.027 | 0.026 | 0.004 | -0.028 | 0.005 | 0.048 | -0.092 | 0.009 | -0.006 | 0.057 | 0.009 |
| Beer | -0.033 | -0.030 | 0.001 | -0.146 | **-0.211** | 0.022 | 0.000 | -0.088 | 0.011 | -0.070 | -0.085 | 0.029 | **0.042** | -0.018 | 0.006 |
| Smoke | 0.029 | 0.015 | 0.003 | -0.052 | 0.012 | **0.021** | -0.066 | -0.022 | **0.018** | **-0.080** | -0.025 | **0.022** | 0.014 | -0.014 | -0.005 |
| Toys | -0.021 | **0.074** | **0.013** | 0.012 | 0.089 | 0.003 | -0.007 | 0.044 | 0.003 | -0.003 | 0.046 | -0.003 | 0.009 | 0.013 | 0.002 |
| Fun | **0.018** | **0.037** | 0.000 | 0.046 | **0.193** | -0.012 | 0.040 | **0.224** | **0.025** | -0.022 | 0.062 | 0.009 | **-0.045** | -0.035 | 0.000 |
| Books | -0.055 | -0.053 | -0.003 | 0.324 | 0.329 | **-0.133** | **0.158** | **0.219** | **-0.054** | 0.177 | 0.163 | -0.047 | 0.021 | 0.015 | **0.011** |
| Hshld | -0.007 | -0.029 | **0.018** | 0.097 | -0.214 | **0.079** | **0.046** | 0.051 | 0.006 | **0.068** | -0.005 | **0.018** | -0.024 | 0.061 | **0.023** |
| Clths | **-0.082** | -0.046 | 0.003 | 0.290 | **-1.306** | **0.174** | 0.093 | -0.278 | **0.216** | 0.022 | -0.878 | **0.233** | -0.026 | **-0.070** | -0.008 |
| Hlth | 0.015 | 0.031 | -0.007 | 0.042 | **0.306** | 0.004 | 0.165 | **0.308** | -0.018 | 0.159 | **0.325** | -0.030 | 0.007 | -0.075 | 0.009 |
| MedEq | **-0.102** | **-0.099** | 0.013 | **0.866** | -0.288 | **-0.170** | **0.523** | 0.169 | **-0.115** | 0.099 | -0.244 | -0.022 | 0.026 | 0.010 | -0.002 |
| Drugs | **-0.171** | **-0.228** | 0.024 | **1.017** | -0.442 | -0.129 | 0.187 | -0.047 | 0.044 | 0.470 | -0.177 | -0.030 | -0.100 | -0.105 | -0.022 |
| Chems | 0.002 | 0.016 | 0.005 | -0.234 | -0.118 | 0.039 | -0.018 | 0.000 | -0.018 | -0.307 | -0.334 | 0.061 | -0.017 | -0.068 | 0.010 |
| Rubbr | -0.027 | **0.177** | -0.004 | **0.274** | **0.290** | **-0.073** | 0.060 | 0.183 | **-0.083** | 0.160 | 0.254 | **-0.096** | -0.024 | 0.013 | 0.004 |
| Txtls | -0.009 | 0.054 | 0.002 | 0.020 | 0.049 | -0.007 | 0.022 | 0.045 | -0.005 | 0.011 | 0.026 | -0.006 | -0.029 | **-0.236** | 0.002 |
| BldMt | **0.044** | -0.034 | 0.000 | **0.358** | **0.776** | -0.064 | **0.491** | **0.643** | -0.049 | **0.282** | **0.344** | 0.022 | -0.012 | 0.004 | 0.008 |
| Cnstr | 0.017 | -0.049 | 0.000 | -0.339 | 0.162 | **0.202** | 0.005 | **0.815** | 0.068 | -0.259 | -0.238 | 0.053 | -0.034 | -0.015 | 0.005 |
| Steel | 0.018 | -0.019 | 0.002 | **0.520** | **0.898** | 0.031 | **0.332** | **0.582** | 0.010 | **0.257** | **0.532** | 0.017 | -0.024 | -0.016 | 0.009 |
| FabPr | **0.033** | 0.024 | 0.001 | -0.098 | -0.196 | 0.014 | 0.001 | 0.155 | -0.010 | -0.107 | -0.205 | -0.004 | -0.027 | -0.053 | -0.005 |
| Mach | -0.007 | -0.045 | **0.015** | -0.177 | **-1.966** | **0.264** | 0.082 | 0.025 | 0.076 | -0.253 | -0.665 | **0.222** | -0.002 | **-0.072** | 0.002 |
| ElcEq | -0.010 | -0.076 | **0.018** | -0.043 | 0.164 | -0.024 | -0.056 | 0.286 | 0.018 | -0.148 | 0.056 | **0.125** | -0.052 | **-0.228** | -0.010 |
| Autos | **0.026** | **0.049** | 0.002 | 0.109 | 0.193 | -0.007 | **0.163** | **0.128** | -0.008 | **-0.112** | 0.035 | **0.033** | -0.008 | **-0.024** | 0.001 |
| Aero | **-0.058** | **-0.062** | 0.006 | **0.268** | **0.346** | -0.017 | 0.229 | 0.102 | 0.006 | **0.323** | **0.311** | -0.029 | 0.030 | 0.018 | 0.001 |
| Ships | 0.052 | 0.035 | **0.023** | 0.054 | 0.041 | **-0.015** | 0.032 | 0.030 | **-0.016** | 0.042 | 0.039 | -0.012 | -0.063 | **-0.153** | 0.004 |
| Guns | **-0.064** | -0.035 | 0.000 | **0.055** | 0.035 | **-0.009** | 0.037 | -0.041 | **-0.010** | 0.047 | -0.011 | **-0.008** | -0.042 | -0.015 | -0.008 |
| Gold | -0.131 | -0.198 | -0.006 | 0.011 | 0.076 | -0.065 | -0.012 | 0.416 | -0.069 | 0.047 | 0.274 | -0.082 | 0.131 | 0.077 | **-0.035** |
| Mines | -0.032 | -0.030 | 0.010 | -0.006 | -0.229 | **0.075** | 0.024 | -0.240 | **0.068** | -0.019 | **-0.306** | **0.058** | -0.032 | 0.002 | -0.008 |
| Coal | -0.003 | -0.023 | 0.003 | 0.011 | -0.079 | 0.013 | 0.024 | -0.028 | 0.003 | 0.031 | -0.042 | **0.026** | -0.020 | -0.054 | 0.007 |
| Oil | -0.009 | -0.027 | **0.010** | 0.190 | 0.498 | **-0.120** | **-0.705** | 0.739 | -0.019 | -0.974 | 1.270 | -0.030 | 0.026 | **0.168** | 0.004 |
| Util | 0.010 | 0.010 | 0.003 | 0.654 | 1.099 | 0.026 | **1.524** | **2.615** | -0.201 | **2.333** | 2.449 | 0.097 | **0.028** | **0.042** | **-0.007** |
| Telcm | 0.011 | -0.024 | 0.008 | **-0.444** | **-0.768** | **-0.108** | 0.140 | 0.143 | -0.042 | -0.311 | -0.084 | -0.019 | -0.101 | -0.087 | -0.023 |
| PerSv | -0.033 | -0.034 | -0.002 | 0.047 | **0.164** | **0.051** | **0.157** | **0.238** | 0.027 | **0.139** | **0.191** | **0.029** | -0.002 | 0.010 | 0.005 |
| BusSv | -0.070 | 0.016 | **0.021** | -0.313 | -0.138 | 0.076 | -0.227 | 0.217 | **0.106** | -0.348 | 0.036 | **0.135** | -0.006 | -0.018 | 0.005 |
| Hardw | **-0.064** | -0.041 | 0.005 | 0.148 | 0.134 | 0.000 | 0.203 | 0.052 | 0.052 | **-0.317** | -0.235 | 0.032 | -0.042 | 0.010 | 0.005 |
| Softw | -0.025 | 0.000 | 0.013 | -0.049 | 0.018 | **0.014** | -0.025 | 0.034 | 0.008 | **-0.041** | -0.002 | 0.009 | -0.019 | -0.019 | 0.000 |
| Chips | -0.007 | 0.027 | 0.005 | -0.193 | -0.008 | 0.071 | 0.361 | 0.584 | -0.012 | -0.030 | 0.044 | **0.023** | -0.043 | 0.024 | 0.015 |
| LabEq | -0.025 | 0.020 | 0.005 | **-0.188** | 0.119 | 0.056 | -0.047 | 0.149 | -0.033 | -0.182 | 0.074 | 0.044 | -0.083 | **-0.209** | 0.002 |
| Paper | -0.008 | -0.041 | **0.010** | 0.146 | **0.262** | -0.042 | 0.158 | -0.023 | -0.039 | **0.210** | **0.336** | -0.030 | 0.020 | -0.064 | -0.007 |
| Boxes | 0.024 | 0.009 | 0.000 | -0.137 | -0.049 | 0.003 | -0.131 | 0.015 | 0.010 | -0.022 | 0.038 | -0.007 | **-0.070** | -0.073 | -0.002 |
| Trans | 0.008 | **0.038** | -0.001 | -0.434 | **-1.585** | 0.079 | 0.113 | -0.438 | **0.085** | **-1.066** | -0.580 | **0.282** | 0.020 | -0.014 | 0.015 |
| Whlsl | -0.042 | -0.032 | **0.030** | **0.262** | **0.386** | **-0.077** | 0.629 | **1.099** | -0.024 | 0.286 | 0.429 | -0.013 | 0.092 | -0.014 | -0.003 |
| Rtail | -0.002 | **-0.127** | **0.015** | 0.131 | -0.348 | -0.101 | 0.239 | **-0.592** | 0.002 | 0.006 | -0.047 | **0.029** | 0.005 | **0.078** | 0.001 |
| Meals | -0.019 | 0.074 | 0.009 | -0.124 | -0.290 | **0.088** | -0.051 | **-0.125** | **0.022** | **-0.102** | -0.126 | **0.042** | -0.045 | 0.026 | 0.012 |
| Banks | **0.023** | **0.032** | **0.010** | **-0.400** | **-0.744** | **-0.160** | **-0.411** | **-0.738** | **-0.200** | **-0.355** | **-0.726** | **-0.173** | 0.027 | -0.053 | 0.011 |
| Insur | -0.006 | 0.039 | **0.015** | 0.065 | 0.222 | 0.134 | -0.170 | -0.468 | **-0.229** | 0.113 | -0.151 | -0.033 | 0.032 | **0.116** | **0.029** |
| RlEst | -0.008 | -0.002 | **0.010** | 0.018 | **-0.139** | 0.010 | 0.064 | -0.069 | **0.057** | **0.103** | -0.011 | 0.011 | -0.017 | -0.004 | **-0.006** |
| Fin | 0.009 | 0.025 | **0.007** | 0.244 | 0.110 | **0.104** | -0.099 | 0.005 | 0.030 | **0.221** | 0.085 | **0.054** | -0.016 | 0.007 | 0.006 |
| Other | **-0.061** | **-0.149** | **0.011** | **0.237** | 0.150 | -0.018 | -0.047 | **0.232** | 0.003 | **0.179** | 0.019 | **-0.057** | 0.003 | 0.018 | 0.002 |
| **Positive** | 5 | 6 | 15 | 10 | 9 | 11 | 9 | 12 | 8 | 10 | 6 | 16 | 2 | 4 | 3 |
| **Negative** | 7 | 6 | 0 | 3 | 7 | 9 | 2 | 3 | 7 | 7 | 2 | 4 | 2 | 7 | 3 |

Notes: Table 2.10 reports the $a_3$ coefficients from Equation 2.5, which runs a regression of excess industry returns on a constant, investor sentiment, industry characteristics, an interaction term of industry characteristics with investor sentiment, and the market-risk premium. Sentiment measures are from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). Bold indicates 10 percent or greater statistical significance estimated with White (1980) standard errors.

### 2.7.4 Regression of industry sentiment betas on industry characteristics

The analysis now takes a different approach, investigating the relationship between industry sensitivity to sentiment and industry characteristics. To accomplish that, the analysis first uses Equation 2.2 to estimate industry betas ($\beta_{i,s}$) on the AAII, II, and BW sentiment measures, over the full sample period from 24/07/1987 to 28/12/2007. The analysis then uses Equation 2.6 to run a regression of industry sentiment betas on a constant and each industry characteristic (*Char*$_c$). Bold indicates statistically significant coefficients at 10 percent or greater estimated with White (1980) standard errors. The table reports t-statistics directly beneath the $a_1$ coefficients.

**Table 2.11 Regressions for industry sentiment betas**

| Industry Characteristic | Expected Coefficient | | Investor Sentiment Betas ($\beta_s$) AAII | II | BW |
|---|---|---|---|---|---|
| Stdev | positive | coefficient | 0.087 | **0.330** | **-0.077** |
| | | t-statistic | 0.56 | 3.28 | -1.92 |
| Mom | positive | coefficient | **1.314** | -0.077 | 0.405 |
| | | t-statistic | 1.75 | -0.09 | 1.64 |
| Beta | positive | coefficient | **0.014** | 0.002 | **0.003** |
| | | t-statistic | 4.42 | 0.34 | 2.16 |
| Firms | positive | coefficient | 0.000 | -0.001 | **0.001** |
| | | t-statistic | 0.36 | -1.39 | 2.88 |
| Size | negative | coefficient | **-0.002** | **-0.002** | **0.000** |
| | | t-statistic | -3.66 | -2.45 | -2.04 |
| BE/ME | negative | coefficient | -0.006 | 0.000 | -0.002 |
| | | t-statistic | -1.35 | 0.04 | -1.59 |
| HH sales | negative | coefficient | 0.001 | -0.001 | **-0.003** |
| | | t-statistic | 0.16 | -0.10 | -3.89 |
| HH equity | negative | coefficient | 0.002 | 0.002 | **-0.004** |
| | | t-statistic | 0.29 | 0.21 | -3.09 |
| HH assets | negative | coefficient | 0.001 | -0.001 | **-0.003** |
| | | t-statistic | 0.25 | -0.12 | -2.61 |
| Sales σ | positive | coefficient | -0.007 | 0.144 | 0.000 |
| | | t-statistic | -0.10 | 1.33 | 0.01 |

Notes: Table 2.11 reports the $a_1$ coefficients from Equation 2.6. The analysis first uses Equation 2.2 to estimate industry sentiment betas for the indicated investor sentiment measures over the full sample from 24/07/1987–28/12/2007.The analysis then runs a cross-sectional univariate regression of industry sentiment betas on industry characteristic with Equation 2.6. The average industry characteristics evaluated are 12-week return volatility (stdev), 12-week return momentum (Mom), 26-week systematic market risk (Beta), number of firms (Firms), market capitalization (Size), book-to-market valuation ratios (BE/ME), Herfindahl sales (HH sales), Herfindahl book equity (HH equity), Herfindahl total assets (HH assets), and sales volatility (Sales σ). Sentiment measures come from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). The second column of Table 2.11 reports the expected sign of the $a_1$ regression coefficients. The table reports White (1980) standard errors beneath the regression coefficients. Bold indicates statistically significant coefficients at 10 percent or greater.

$$\beta_{s,i} = a_0 + a_1 Char_{c,i} + e_i \qquad \text{(Eq. 2.6)}$$

Table 2.11 reports the $a_1$ regression coefficients for the indicated sentiment measures and industry characteristics. The second column reports the expected sign of the $a_1$ coefficient. For instance, industry sentiment betas should positively increase with industry risk, as measured by standard deviation and a single-index beta. Indeed, the $a_1$ coefficient on beta is positive for all sentiment measures and statistically significant for

AAII and BW sentiment. The $a_1$ coefficient, overall, shows the correct sign about 60 percent of the time across all sentiment measures and industry characteristics. The $a_1$ coefficient for AAII and II sentiment generally lacks any statistical significance. However, results for BW sentiment are mostly significant and with the correct sign. Here again, the relationship between sentiment and industry characteristics appears to be weak and it varies substantially dependent on the measure of investor sentiment.

### 2.7.5 Regression of industry characteristics on investor sentiment

This section examines the interaction between investor sentiment and portfolios formed on decile sorts of industry characteristics. Similarly, Baker and Wurgler (2006) construct long-short portfolios to evaluate firm characteristics that are subject to investor speculation. Table 2.12 reports the $a_1$ regression coefficients from Equation 2.7. The interpretation of the $a_1$ coefficients is the sensitivity of industry characteristics to investor sentiment. The analysis first constructs portfolios long (short) in the five industries in the top (bottom) decile for each industry characterization ($r_c^l - r_c^s$). Equation 2.7 then runs a regression of the industry characteristic portfolios on a constant, the indicated investor sentiment measures ($Sent_s$), and the market-risk premium ($R_m$). The second column reports the expected sign of the $a_1$ regression coefficients. The table reports results for both bull and bear markets, in comparison with the full sample. Bull (bear) markets are periods that have a positive (negative) bull-bear sentiment spread, for each sentiment measure. Bold indicates statistical significance at 10 percent or greater estimated with White (1980) standard errors.

**Table 2.12 Regressions for industry characteristics**

| High - Low Decile | Expected | Full Sample | | | Bull Market | | | Bear Market | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Characteristic Portfolios** | **Coefficient** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Stdev | positive | 0.017 | 0.003 | -0.003 | 0.018 | 0.012 | -0.003 | 0.045 | -0.030 | -0.004 |
| Mom | positive | **0.035** | **0.037** | -0.003 | **0.060** | 0.041 | 0.008 | 0.003 | **0.093** | -0.013 |
| Beta | positive | 0.007 | -0.015 | **0.012** | 0.039 | 0.006 | 0.013 | **-0.091** | **-0.135** | **0.018** |
| Firms | positive | 0.006 | **-0.036** | **0.015** | 0.018 | **-0.060** | **0.010** | -0.026 | -0.002 | **0.027** |
| Size | negative | -0.017 | **-0.026** | -0.003 | -0.018 | -0.026 | -0.002 | -0.041 | **-0.076** | **-0.006** |
| BE/ME | negative | -0.027 | -0.023 | -0.006 | -0.035 | -0.016 | -0.008 | -0.043 | **-0.095** | -0.009 |
| HH sales | negative | **0.025** | 0.016 | -0.004 | **0.037** | 0.025 | 0.000 | 0.026 | 0.010 | **-0.010** |
| HH equity | negative | **0.025** | **0.023** | **-0.008** | **0.033** | **0.036** | -0.003 | 0.035 | 0.011 | **-0.016** |
| HH assets | negative | 0.014 | 0.007 | **-0.007** | 0.024 | 0.017 | -0.004 | 0.003 | -0.021 | **-0.015** |
| Sales σ | positive | -0.012 | -0.003 | -0.002 | -0.006 | -0.002 | -0.005 | **-0.049** | -0.009 | 0.001 |

Notes: Table 2.12 reports the $a_1$ coefficients from Equation 2.7. The analysis first constructs long-short portfolios based on the top-bottom deciles from sorts on each different industry's characteristics. The average industry characteristics evaluated are 12-week return volatility (stdev), 12-week return momentum (Mom), 26-week systematic market risk (Beta), number of firms (Firms), market capitalization (Size), book-to-market valuation ratios (BE/ME), Herfindahl sales (HH sales), Herfindahl book equity (HH equity), Herfindahl total assets (HH assets), and sales volatility (Sales σ). The analysis next uses Equation 2.7 to estimate the $a_1$ coefficients with a regression of long-short characteristic portfolios on a constant, the indicated investor sentiment measures, and the market-risk premium. The second column indicates the expected sign of the $a_1$ regression coefficients. Sentiment measures come from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). The table reports results for the full sample, bull markets and bear markets. Postive (negative) bull-bear spreads define bull (bear) markets,for each sentiment measure. Bold indicates statistical significance at 10 percent or greater, estimated with White (1980) standard errors.

$$r_{c,t}^{l} - r_{c,t}^{s} = a_0 + a_1 Sent_{s,t} + b_0 R_{m,t} + e_t \qquad \text{(Eq. 2.7)}$$

Table 2.12 reports mixed results. The $a_1$ coefficients have the correct sign approximately 56 percent of the time, for all measures and sample periods. However, the number of statistically significant coefficients with the correct sign drops dramatically to around 20 percent. For instance, industry capitalization and valuation (BE/ME) characteristics consistently have the correct sign, but mostly lack statistical significance. Overall, the BW index has the highest number of statistically significant $a_1$ coefficients with the correct sign, especially during periods of bearish sentiment. The results for AAII sentiment are overall the weakest. Generally, while the analysis indicates a link between industry characteristics and investor sentiment, the correlation is only weak, at best.

### 2.7.6 Fama and MacBeth regressions for industry characteristics

Lastly, the Fama and MacBeth (1973) regression analysis provides a final test of the interaction between investor sentiment and industry characteristics. First, Equation 2.8 runs a regression of excess industry returns ($R_i$) on a constant, investor sentiment ($Sent_s$), industry characteristics ($Char_c$), the interaction of investor sentiment with industry characteristics ($Sent_sChar_c$), and the market-risk premium ($R_m$). Equation 2.9 then estimates cross-sectional $\gamma_i$ coefficients for each time period. The variable of interest is the $\gamma_3$ coefficient.Table 2.13 reports the average $\gamma_3$ across bull and bear markets, in comparison with the full sample.The definition of bull (bear) markets are periods with a positive (negative) bull-bear sentiment spread, for each measure of investor sentiment. The second column reports the expected sign of the $\gamma_3$ coefficient. Bold indicates statistical significance at 10 percent or greater, estimated with Equation 2.11.

$$R_{i,t} = a_0 + a_1 Sent_{s,t} + a_2 Char_{c,t} + a_3 Sent_{s,t} * Char_{c,t} + b_0 R_{m,t} + e_t \qquad \text{(Eq. 2.8)}$$

$$R_i = \gamma_0 + \gamma_1 a_{1,i} + \gamma_2 a_{2,i} + \gamma_3 a_{3,i} + \gamma_4 b_{0,i} + e_i \qquad \text{(Eq. 2.9)}$$

$$\overline{\gamma}_3 = \frac{1}{T}\sum_{t=1}^{T}\gamma_3 \qquad \text{(Eq. 2.10)}$$

$$t = \frac{\overline{\gamma}_3}{\sigma(\gamma_3)/\sqrt{T}} \qquad \text{(Eq. 2.11)}$$

The Fama and MacBeth (1973) results reported in Table 2.13 corroborate the earlier findings. The results document only limited evidence of industry characteristics that systematically attract investor sentiment-driven mispricing. Only 23 percent of the Fama and MacBeth (1973) $\gamma_3$coefficients are statistically significant and have the correct sign. Now, however, BW results show the weakest statistical significance, while AAII sentiment shows the strongest. In further contrast, results are now stronger during periods of bullish sentiment when estimated with the Fama and MacBeth (1973) regressions. Overall, the relationship between investor sentiment and industry characteristics lacks robustness across sentiment measures, samples periods, and estimations.

**Table 2.13 Fama and MacBeth coefficients for industry characteristics**

| Industry Characteristic | Expected Coefficient | Full Period AAII | Full Period II | Full Period BW | Bull Market AAII | Bull Market II | Bull Market BW | Bear Market AAII | Bear Market II | Bear Market BW |
|---|---|---|---|---|---|---|---|---|---|---|
| Stdev | positive | 0.001 | 0.000 | **0.008** | 0.000 | **-0.001** | -0.001 | **0.014** | 0.000 | 0.001 |
| Mom | positive | 0.000 | 0.000 | -0.001 | 0.000 | 0.001 | **-0.004** | 0.001 | 0.000 | -0.003 |
| Beta | positive | **0.035** | -0.003 | 0.154 | **0.038** | 0.006 | **0.123** | 0.003 | 0.005 | 0.010 |
| Firms | positive | 0.007 | 0.001 | 0.006 | 0.014 | 0.005 | -0.028 | **-0.005** | **0.016** | 0.153 |
| Size | negative | **0.357** | 0.117 | **-0.632** | 0.067 | 0.112 | **-0.575** | **0.003** | -0.002 | -0.429 |
| BE/ME | negative | 0.004 | 0.004 | **0.080** | -0.005 | **0.005** | **0.075** | **0.002** | 0.002 | 0.022 |
| HH sales | negative | -0.001 | **-0.001** | **0.004** | **-0.001** | **-0.001** | 0.002 | **0.000** | **0.000** | -0.002 |
| HH equity | negative | -0.001 | **0.000** | **0.005** | 0.000 | **0.000** | **-0.003** | **-0.004** | **0.001** | 0.000 |
| HH assets | negative | **-0.001** | **-0.001** | 0.001 | **-0.002** | **-0.001** | 0.000 | -0.001 | 0.000 | -0.004 |
| Sales $\sigma$ | positive | **0.011** | **0.003** | -0.018 | 0.001 | **0.002** | -0.004 | **0.004** | 0.000 | -0.001 |

Notes: Table 2.13 reports the average $\gamma_3$ time series coefficients from Equation 2.10 following the methodology discussed in Fama and MacBeth (1973). Equation 2.8 first estimates time-series coefficients, regressing excess industry returns ($R_i$) on a constant investor sentiment ($Sent_s$), industry characteristics ($Char_c$), the interaction of investor sentiment with industry characteristics ($Sent_sChar_c$), and the market-risk premium. The average industry characteristics evaluated are 12-week return volatility (stdev), 12-week return momentum (Mom), 26-week systematic market risk (Beta), number of firms (Firms), market capitalization (Size), book-to-market valuation ratios (BE/ME), Herfindahl sales (HH sales), Herfindahl book equity (HH equity), Herfindahl total assets (HH assets), and sales volatility (Sales $\sigma$). Equation 2.9 then estimates cross-sectional $\gamma_i$ coefficients for each period. Table 2.13 reports the $\gamma_3$ time-series averages estimated with Equation 2.10, for the full sample, bull markets, and bear markets. Periods of positive (negative) bull-bear spreads define bull (bear) markets, for each sentiment measure. Bold indicates t-statistics estimated with Equation 2.11 that are statistically significant at 10 percent or greater.

The conclusion that ultimately emerges from the preceding analysis is that measures of industry characteristics only marginally explain the effect of investor sentiment on industry performance. This results contrast with previous firm-level studies that document a relationship between speculative mispricing and firm-level characteristics that cause valuation difficulties. It may be that the industry characteristics identified only provide a crude proxy for cash flow uncertainty. As such, they may fail to distinguish sufficiently industries that are most susceptible to speculative pricing. Alternatively, the effect of investor sentiment may represent a market-wide phenomenon, which extends to all industries. As a final test, the next section examines whether investor sentiment provides a practical signal that investors can use to profitably time industry investments.

## 2.8 Investor Sentiment Strategy Returns

Does investor sentiment provide the opportunity for profitable industry rotation? This section investigates a strategy that rotates industries with investor sentiment. Evidence of a profitable investor sentiment strategy would be interesting, not only from a practical perspective, but also from a market efficiency perspective. Predictable strategy performance would violate the efficient markets hypothesis, which states that returns follow a random walk and that prices reflect fundamental value. Both short-term mispricing and predictable long-term reversals are necessary for a profitable rotation strategy. While investor sentiment predicts short-term industry mispricing, the results provide limited evidence of significant long-term reversals. Nonetheless, the previous results show that industry sentiment alphas vary across periods of bullish and bearish sentiment. Time-variant industry exposure to investor sentiment suggests a profitable rotation strategy. Barberis and Shleifer (2003) and Peng and Xiong (2006) provide the theoretical basis for a style-rotation model. The Barberis and Shleifer (2003) and Peng and Xiong (2006) models theorize that profitable trading strategies result from shifts in investor style preferences, including industry styles. For robustness, the analysis investigates sentiment rotation strategies for different holding periods, risk corrections, and sub-periods.

Table 2.14 reports returns for a strategy that rotates industry allocations based on their time-variant sentiment alphas. First, Equation 2.2 estimates industry $a_1$ regression coefficients, estimated over 26-week and 52-week rolling windows. After allowing for the initial 26-week and 52-week alpha estimations, the first strategy holding periods start on 15/01/1988 and 18/07/1988. The interpretation of the $a_1$ coefficients is the portion of industry excess returns, or alpha performance, attributable to time-variant investor sentiment. Next, the analysis constructs self-financing strategy portfolios ($r^l$-$r^s$), which are long (short) in the 15 of 49 industries with the lowest (highest) $a_1$ regression coefficients. The table then evaluates strategy performance over different holding periods from four to 52 weeks. The strategy performance evaluation largely follows Moskowitz and Grinblatt (1999) and Brown and Cliff (2005). Those studies similarly construct and evaluate self-financing portfolios to evaluate strategy performance over different holding periods. Panel A and Panel B report strategy returns for portfolios formed on industry sentiment alphas, estimated over 26-week and 52-week rolling windows, for the indicated holding periods.[34] Table 2.14 reports annualized Jensen's alphas ($\alpha_J$), Fama and French alphas ($\alpha_F$), and Carhart alphas ($\alpha_C$), estimated with Equations 2.12–2.14 to measure risk-adjusted strategy performance. Bold indicates

[34] The study reports strategy results for non-overlapping holding periods. Unreported analysis also evaluates strategy returns with overlapping holding periods, similar to Brown and Cliff (2005). The use of overlapping periods results in overestimated statistical significance, which requires correcting t-statistics following the methodology of Valkanov (2003). Results for overlapping regressions are quantitatively similar to non-overlapping regressions.

statistical significance of 10 percent or greater estimated with White (1980) standard errors.

**Table 2.14 Investor sentiment strategy performance**

**Panel A: Portfolios formed on sentiment alphas estimated with 26-week rolling regressions**

| | | 04 Week | 08 Week | 13 Week | 26 Week | 52 Week |
|---|---|---|---|---|---|---|
| **AAII** | Jensen's alpha | 0.020 | 0.029 | **0.043** | **0.053** | **0.057** |
| | t-statistic | 1.16 | 1.62 | 2.38 | 2.66 | 2.56 |
| | Fama & French alpha | 0.007 | 0.009 | 0.023 | 0.024 | 0.021 |
| | t-statistic | 0.41 | 0.52 | 1.29 | 1.33 | 1.03 |
| | Carhart alpha | 0.010 | 0.024 | **0.033** | 0.023 | 0.014 |
| | t-statistic | 0.54 | 1.33 | 1.75 | 1.14 | 0.63 |
| **II** | Jensen's alpha | 0.007 | 0.005 | -0.018 | -0.016 | 0.007 |
| | t-statistic | 0.40 | 0.25 | -0.96 | -0.74 | 0.32 |
| | Fama & French alpha | -0.009 | -0.013 | **-0.034** | **-0.041** | -0.019 |
| | t-statistic | -0.52 | -0.69 | -1.85 | -2.09 | -0.91 |
| | Carhart alpha | 0.009 | 0.009 | -0.016 | -0.012 | 0.022 |
| | t-statistic | 0.51 | 0.48 | -0.88 | -0.62 | 1.18 |
| **BW** | Jensen's alpha | -0.024 | -0.007 | -0.017 | 0.004 | **0.068** |
| | t-statistic | -1.07 | -0.38 | -0.83 | 0.26 | 3.79 |
| | Fama & French alpha | -0.020 | -0.007 | -0.018 | -0.016 | **0.044** |
| | t-statistic | -0.98 | -0.34 | -0.95 | -1.00 | 2.47 |
| | Carhart alpha | **-0.053** | -0.027 | **-0.050** | -0.023 | **0.035** |
| | t-statistic | -2.57 | -1.45 | -2.48 | -1.37 | 1.94 |

**Panel B: Portfolios formed on sentiment alphas estimated with 52-week rolling regressions**

| | | 04 Week | 08 Week | 13 Week | 26 Week | 52 Week |
|---|---|---|---|---|---|---|
| **AAII** | Jensen's alpha | -0.003 | 0.004 | 0.019 | 0.036 | 0.011 |
| | t-statistic | -0.13 | 0.22 | 0.93 | 1.62 | 0.52 |
| | Fama & French alpha | -0.028 | -0.023 | -0.010 | -0.002 | -0.022 |
| | t-statistic | -1.62 | -1.32 | -0.58 | -0.09 | -1.19 |
| | Carhart alpha | -0.010 | -0.005 | 0.009 | 0.006 | -0.019 |
| | t-statistic | -0.57 | -0.29 | 0.47 | 0.29 | -0.94 |
| **II** | Jensen's alpha | **-0.043** | -0.028 | **-0.035** | **-0.031** | 0.000 |
| | t-statistic | -2.40 | -1.53 | -2.04 | -1.85 | -0.02 |
| | Fama & French alpha | **-0.057** | **-0.044** | **-0.049** | **-0.045** | -0.024 |
| | t-statistic | -3.11 | -2.47 | -2.77 | -2.62 | -1.35 |
| | Carhart alpha | **-0.044** | -0.028 | **-0.037** | **-0.033** | -0.001 |
| | t-statistic | -2.41 | -1.54 | -2.07 | -1.88 | -0.03 |
| **BW** | Jensen's alpha | -0.020 | 0.006 | -0.002 | **0.041** | **0.033** |
| | t-statistic | -1.03 | 0.30 | -0.07 | 2.30 | 1.76 |
| | Fama & French alpha | **-0.035** | -0.018 | -0.004 | 0.019 | **0.034** |
| | t-statistic | -1.89 | -0.99 | -0.21 | 1.08 | 1.78 |
| | Carhart alpha | **-0.062** | -0.033 | **-0.036** | 0.003 | 0.002 |
| | t-statistic | -3.28 | -1.64 | -1.75 | 0.16 | 0.13 |

Notes: Table 2.14 reports annualised returns for an investment strategy that uses time-variant sentiment alphas to allocate industry investments. The analysis first uses Equation 2.2 to estimate time-variant industry sentiment alphas ($a_1$) over 26- and 52-week rolling windows. Next, the analysis then constructs self-financing portfolios that are long (short) in the 15 lowest (highest) sentiment alpha industries. The table reports annualized Jensen's ($\alpha_J$), Fama and French ($\alpha_F$), and Carhart alphas ($\alpha_C$), estimated with Equations 2.12–2.14, for the indicated weekly holding periods. Panel A and Panel B report results for strategies based on 26-week and 52-week rolling window alpha estimations. Bold indicates statistical significance at 10 percent or greater estiamted with White (1980) standard errors.

$$r_{i,t}^{l} - r_{i,t}^{s} = \alpha_J + b_1 R_{m,t} + e_t \qquad \text{(Eq. 2.12)}$$

$$r_{i,t}^{l} - r_{i,t}^{s} = \alpha_F + b_1 R_{m,t} + b_2 SMB_t + b_3 HML_t + e_t \qquad \text{(Eq. 2.13)}$$

$$r_{i,t}^{l} - r_{i,t}^{s} = \alpha_C + b_1 R_{m,t} + b_2 SMB_t + b_3 HML_t + b_4 UMD_t + e_t \qquad \text{(Eq. 2.14)}$$

Strategy performance varies substantially across all dimensions: portfolio formation, sentiment measures, and risk adjustment. Prior research, such as Fisher and Statman (2000), Brown and Cliff (2005), and Baker and Wurgler (2006), observes that investor sentiment-driven under-reaction (overreaction) leads to later momentum (reversals). As such, the expectation is to observe positive strategy returns for portfolios long (short) in industries with low (high) investor sentiment alphas. Portfolios formed on 26-week alpha estimations, as Panel A reports, show the least significant return performance. Overall, BW sentiment portfolios have the highest statistical and economic significance. For instance, with a 52-week holding period, the BW strategy generates a 6.8 percent Jensen's alpha, which has a highly significant 3.79 t-statistic. Portfolios formed on AAII sentiment have positively significant Jensen's alphas at longer horizons of 13–26 weeks. However, statistical significance dissipates for AAII sentiment after three-factor and four-factor risk corrections. Results for portfolios formed on 52-week alpha forecasts have the greatest overall statistical significance. However, with 52-week estimations, while II portfolio performance is now stronger, AAII portfolio performance is weaker. Interestingly, II portfolio performance is significantly negative, for all holding periods. Negative strategy performance indicates continued momentum for high-alpha industries, which the strategy portfolios hold short.

Table 2.14 reports strategy performance before an allowance for transaction costs. Thus, inclusion of transaction costs would partially explain portfolio return performance. Transaction costs are both explicit and implicit; including commissions, bid-ask spread, and price impact. [35] Total transaction costs would also have varied greatly over the sample period from 1968 to 2007. An industry rotation strategy based on investor sentiment would have extremely high turnover and related transaction costs.

[35] See, for example, Goyenko, Holden, and Trzcinka (2009).

For instance, portfolios formed on 52-week alphas and updated every four weeks turn over approximately four times per annum. Round-trip transaction costs would amount to a minimum 4 percent a year, assuming modest transaction costs of 1 percent per turnover over the full sample. Of course, transaction costs decrease with an increase in holding periods. Portfolios held for 52 weeks, for instance, turn over on average once a year.

Table 2.15 compares strategy return performance across two sub-periods. The AAII survey changed its sampling methodology from a direct mail survey to an online survey in 2000. Subsequent surveys, thus, potentially sample a different population of investors. Additionally, AAII and II surveys results are now readily available online. The consequent greater dissemination of the survey results has potentially limited their practical usefulness in recent years. The analysis considers two equal sub-periods. The first sub-period runs from 15/07/1988 to 24/04/1998 and the second from 01/05/1998 to 01/02/2008. Sub-period analysis focuses on portfolios formed with sentiment alphas estimated over 52-week rolling windows.

Strategy performance is more apparent in the first sub-period than in the second. In the earlier period, II sentiment portfolios are all statistically significant, regardless of the holding periods or the risk correction. However, as with the full sample, the II strategy again generates negative return performance. Statistical significance of the II strategy, with one exception, all but disappears in the later sub-period. The results are opposite for the BW strategy portfolios. Results for BW sentiment show greater statistical and economic significance in the later period. For instance, the BW portfolio has an annualized 8.2 percent Jensen's alpha over a 52-week holding period. However, that performance decreases to a statistically significant 5.4 percent annual return with a four-factor risk correction. The AAII portfolio performance is now statistically significant over long horizons in the early period and short horizons in the later period, whereas previously, performance was statistically insignificant for the entire period.

**Table 2.15 Sub-period strategy performance**

| Panel A: | Portfolios formed on sentiment alphas estimated with 52-week rolling regressions *Sample period - 15/07/1988 to 24/04/1998* | | | | | |
|---|---|---|---|---|---|---|
| | | 04 Week | 08 Week | 13 Week | 26 Week | 52 Week |
| AAII | Jensen's alpha | 0.000 | -0.002 | 0.014 | 0.010 | **-0.041** |
| | t-statistic | 0.00 | -0.13 | 0.74 | 0.51 | -2.07 |
| | Fama & French alpha | 0.015 | 0.010 | 0.025 | 0.020 | **-0.035** |
| | t-statistic | 0.80 | 0.50 | 1.29 | 1.02 | -1.73 |
| | Carhart alpha | 0.018 | 0.011 | 0.025 | 0.017 | **-0.040** |
| | t-statistic | 0.92 | 0.54 | 1.22 | 0.81 | -1.86 |
| II | Jensen's alpha | **-0.059** | **-0.056** | **-0.065** | **-0.052** | **-0.047** |
| | t-statistic | -3.34 | -3.17 | -3.64 | -2.96 | -2.61 |
| | Fama & French alpha | **-0.056** | **-0.058** | **-0.064** | **-0.055** | **-0.049** |
| | t-statistic | -2.92 | -3.09 | -3.40 | -2.99 | -2.58 |
| | Carhart alpha | **-0.051** | **-0.058** | **-0.059** | **-0.050** | **-0.045** |
| | t-statistic | -2.57 | -2.97 | -2.97 | -2.63 | -2.27 |
| BW | Jensen's alpha | -0.017 | -0.009 | -0.012 | 0.011 | -0.009 |
| | t-statistic | -0.93 | -0.53 | -0.65 | 0.63 | -0.47 |
| | Fama & French alpha | **-0.035** | -0.028 | -0.027 | -0.005 | **-0.031** |
| | t-statistic | -1.93 | -1.60 | -1.51 | -0.25 | -1.65 |
| | Carhart alpha | -0.031 | -0.025 | -0.024 | 0.000 | **-0.036** |
| | t-statistic | -1.61 | -1.34 | -1.24 | 0.00 | -1.87 |

| Panel B: | Portfolios formed on sentiment alphas estimated with 52-week rolling regressions *Sample period - 01/05/1998 to 01/02/2008* | | | | | |
|---|---|---|---|---|---|---|
| | | 04 Week | 08 Week | 13 Week | 26 Week | 52 Week |
| AAII | Jensen's alpha | -0.038 | -0.019 | -0.009 | 0.024 | 0.023 |
| | t-statistic | -1.21 | -0.59 | -0.29 | 0.67 | 0.70 |
| | Fama & French alpha | **-0.066** | **-0.049** | -0.040 | -0.018 | -0.014 |
| | t-statistic | -2.53 | -1.85 | -1.49 | -0.65 | -0.51 |
| | Carhart alpha | **-0.048** | -0.031 | -0.021 | -0.011 | -0.010 |
| | t-statistic | -1.84 | -1.16 | -0.78 | -0.37 | -0.35 |
| II | Jensen's alpha | -0.041 | -0.016 | -0.016 | -0.012 | 0.033 |
| | t-statistic | -1.38 | -0.55 | -0.57 | -0.44 | 1.03 |
| | Fama & French alpha | **-0.055** | -0.031 | -0.030 | -0.026 | 0.010 |
| | t-statistic | -1.90 | -1.09 | -1.08 | -0.93 | 0.35 |
| | Carhart alpha | -0.042 | -0.013 | -0.018 | -0.014 | 0.034 |
| | t-statistic | -1.46 | -0.46 | -0.65 | -0.49 | 1.21 |
| BW | Jensen's alpha | -0.007 | 0.024 | 0.027 | **0.068** | **0.082** |
| | t-statistic | -0.21 | 0.73 | 0.78 | 2.31 | 2.75 |
| | Fama & French alpha | -0.019 | 0.002 | 0.025 | 0.046 | **0.085** |
| | t-statistic | -0.61 | 0.06 | 0.76 | 1.60 | 2.83 |
| | Carhart alpha | **-0.051** | -0.015 | -0.010 | 0.027 | **0.054** |
| | t-statistic | -1.71 | -0.48 | -0.31 | 0.96 | 1.93 |

Notes: Table 2.15 compares annualized returns for an investment strategy that rotates industry investments with time-variant sentiment alphas. The analysis first uses Equation 2.2 to estimate time-variant industry sentiment alphas estimated over 52-week rolling windows. Next, the analysis constructs self-financing portfolios that are long (short) the 15 lowest (highest) sentiment-alpha industries. The table reports annualized Jensen's, Fama and French, and Carhart alphas from Equations 2.12–2.14 for the indicated holding periods. Panel A and Panel B report the indicated sub-period results. Bold indicates significance at 10 percent or greater estimated with White (1980) standard errors.

Overall, timing industry allocations with investment sentiment measures do not produce systematic performance. Statistically significant performance for the full sample ranges, in absolute annual terms, from 3.1 to 6.8 percent. To put that performance in perspective, Moskowitz and Grinblatt (1999) estimate 12 percent annual returns for an industry rotation strategy based on return momentum. However, the performance documented varies substantially, dependent on the investor sentiment measure, risk correction, and sub-period. The results also document less statistically significant strategy performances in recent years, even before the inclusion of transaction costs. The results bring into doubt the practical application of using time-variant investor sentiment to allocate industry investments. As such, one can question whether investors systematically price the announcement of sentiment surveys in industry returns, as examined next.

## 2.9 Event Study with Extreme Bullish and Bearish Sentiment

This section investigates industry response to the release of extreme sentiment survey measures. The earlier results show that, while investor sentiment positively predicts short-term industry mispricing, it provides limited predictability of price reversals. Moreover, a strategy that allocates industry investments based on time-variant investor sentiment generates only marginal and unsystematic outperformance. The results run contrary to the Barberis and Shleifer (2003) theoretical model and empirical findings of Jame and Tong (2009), among others. According to such studies, short-term mispricing should result in predictable long-term price reversals. There are, at least, two explanations for the results. The first is that short-term predictability, absent long-term reversals, indicates rational investor sentiment regarding industry values. Alternatively, short-term industry mispricing may gradually reverse over more extended periods.

In the spirit of an event study, the analysis investigates industry response to the release of extreme investor sentiment news. Industry response to the release of AAII and II survey results indicates whether investors systematically price investor sentiment. To minimize the effect of noisy investor sentiment, and to accurately measure industry response, the analysis considers extreme measures of investor sentiment. Nofsinger and Sias (1999) and Lemmon and Portniaguina (2006) document that institutional and retail investor herding leads to mispricing. Moreover, extreme investor sentiment potentially captures a greater degree of investor herding. As such, extreme investor sentiment is more likely to have an observable and immediate effect on industry performance.

Bullish or bearish sentiment that is one standard deviation above average defines extreme. There are roughly 200 weeks each with extreme bullish and bearish sentiment, for both the AAII and II sentiment measures. Interestingly, the correlation between extreme AAII and II bullish sentiment is relatively low at 35 percent, and lower yet for bearish sentiment at -17 percent. The analysis uses daily industry returns over the sample period 24/07/1987 to 28/12/2007, with data from the Kenneth French website.[36]

Table 2.16 reports industry returns immediately following the announcement of extreme bullish or bearish investor sentiment. Equation 2.15 estimates industry response to bullish or bearish sentiment, with a regression of excess industry returns ($R_i$) on a constant daily dummy variables (*dayN*), and the market-risk premium ($R_m$). For bullish sentiment, the *day0* dummy variables equals one on Thursday survey release days, when bull sentiment exceeds one standard deviation above average, and zero otherwise. The *day1* and *day2* dummy variables take the value of one on the first and second days subsequent to the release of extreme bullish sentiment and zero otherwise. Construction of the bearish sentiment dummy variables is similar.[37] The analysis is limited to the AAII and II sentiment measures, which have weekly release dates whereas Baker and Wurgler (2006) construct their sentiment index from historical data and do not provide regular updates. Bold indicates statistical significance at 10 percent or greater estimated with White (1980) standard errors. The bottom two rows of the table report the total number of statistically significant positive and negative coefficients.

$$R_{i,t} = a_0 + AR_0 day0_t + AR_1 day1_t + AR_2 day2_t + b_0 R_{m,t} + e_t \qquad \text{(Eq. 2.15)}$$

[36] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[37] The release of AAII and II surveys occurs on Wednesdays. The study counts Thursday as the first full release day, or *day0*.

## Table 2.16 Event study results for extreme investor sentiment

| | AAII Sentiment | | | | | | II Sentiment | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bullish Sentiment (+σ) | | | Bearish Sentiment (+σ) | | | Bullish Sentiment (+σ) | | | Bearish Sentiment (+σ) | | |
| **Industry** | $AR_{00}$ | $AR_{01}$ | $AR_{02}$ | $AR_{00}$ | $AR_{01}$ | $AR_{02}$ | $AR_{00}$ | $AR_{01}$ | $AR_{02}$ | $AR_{00}$ | $AR_{01}$ | $AR_{02}$ |
| Agric | 0.0014 | **0.0018** | -0.0008 | 0.0005 | 0.0003 | **-0.0022** | 0.0009 | **0.0017** | -0.0007 | 0.0008 | -0.0006 | -0.0017 |
| Food | **0.0009** | **0.0012** | -0.0004 | 0.0002 | 0.0001 | **-0.0018** | **0.0007** | 0.0005 | -0.0005 | 0.0003 | -0.0001 | **-0.0023** |
| Soda | 0.0006 | **0.0020** | -0.0007 | -0.0014 | -0.0011 | -0.0016 | 0.0006 | 0.0008 | 0.0003 | -0.0008 | 0.0009 | **-0.0034** |
| Beer | **0.0018** | **0.0012** | 0.0001 | **-0.0013** | 0.0006 | -0.0004 | -0.0003 | 0.0006 | 0.0006 | **-0.0013** | 0.0009 | -0.0002 |
| Smoke | **0.0037** | 0.0006 | -0.0012 | -0.0007 | 0.0014 | 0.0001 | **0.0019** | 0.0004 | 0.0000 | 0.0002 | **0.0029** | -0.0002 |
| Toys | **0.0021** | **0.0014** | -0.0008 | -0.0009 | -0.0005 | **-0.0023** | **0.0016** | **0.0018** | **-0.0015** | 0.0000 | 0.0003 | **-0.0028** |
| Fun | **0.0016** | **0.0025** | -0.0007 | -0.0010 | 0.0006 | **-0.0027** | **0.0014** | **0.0022** | -0.0005 | -0.0011 | **0.0015** | **-0.0038** |
| Books | **0.0012** | **0.0011** | 0.0000 | -0.0003 | 0.0005 | **-0.0020** | **0.0014** | 0.0000 | -0.0002 | **-0.0014** | 0.0007 | **-0.0019** |
| Hshld | 0.0008 | **0.0014** | 0.0005 | 0.0004 | -0.0004 | **-0.0017** | **0.0014** | **0.0013** | 0.0004 | **-0.0010** | 0.0002 | **-0.0025** |
| Clths | **0.0009** | **0.0018** | -0.0004 | 0.0000 | 0.0000 | **-0.0030** | **0.0012** | **0.0013** | 0.0003 | -0.0009 | -0.0003 | **-0.0034** |
| Hlth | 0.0005 | **0.0021** | 0.0005 | -0.0003 | -0.0006 | **-0.0027** | 0.0002 | **0.0023** | -0.0007 | 0.0001 | **0.0018** | **-0.0027** |
| MedEq | **0.0018** | **0.0026** | 0.0000 | -0.0006 | 0.0006 | **-0.0024** | **0.0015** | **0.0021** | **-0.0010** | 0.0000 | **0.0013** | **-0.0029** |
| Drugs | **0.0022** | **0.0029** | -0.0005 | -0.0004 | **0.0012** | **-0.0026** | **0.0015** | **0.0025** | **-0.0015** | 0.0002 | **0.0012** | **-0.0029** |
| Chems | **0.0009** | **0.0008** | 0.0004 | -0.0009 | -0.0001 | **-0.0018** | 0.0010 | **0.0009** | 0.0006 | -0.0007 | -0.0005 | **-0.0026** |
| Rubbr | **0.0016** | **0.0026** | -0.0008 | -0.0007 | -0.0008 | **-0.0025** | **0.0011** | **0.0015** | 0.0000 | 0.0000 | -0.0001 | **-0.0021** |
| Txtls | 0.0004 | 0.0011 | 0.0004 | 0.0012 | 0.0006 | **-0.0019** | **0.0022** | 0.0005 | 0.0001 | 0.0000 | -0.0003 | **-0.0024** |
| BldMt | **0.0014** | **0.0009** | 0.0002 | -0.0010 | -0.0009 | **-0.0018** | **0.0012** | 0.0005 | 0.0002 | **-0.0015** | 0.0003 | **-0.0016** |
| Cnstr | 0.0006 | **0.0022** | -0.0001 | 0.0004 | 0.0004 | **-0.0028** | **0.0020** | **0.0017** | 0.0004 | 0.0013 | 0.0006 | **-0.0023** |
| Steel | **0.0012** | **0.0022** | 0.0000 | -0.0015 | **0.0015** | **-0.0031** | **0.0018** | **0.0033** | 0.0002 | -0.0008 | 0.0005 | **-0.0025** |
| FabPr | 0.0010 | **0.0021** | -0.0001 | **-0.0027** | 0.0018 | **-0.0044** | 0.0011 | 0.0008 | -0.0004 | -0.0012 | 0.0013 | **-0.0031** |
| Mach | **0.0010** | **0.0013** | 0.0001 | -0.0003 | 0.0000 | **-0.0020** | **0.0015** | **0.0017** | 0.0003 | -0.0001 | 0.0003 | **-0.0024** |
| ElcEq | **0.0011** | **0.0017** | 0.0003 | **-0.0013** | 0.0004 | **-0.0021** | 0.0009 | **0.0012** | 0.0001 | -0.0011 | **0.0015** | **-0.0028** |
| Autos | 0.0005 | **0.0011** | -0.0001 | -0.0001 | 0.0003 | -0.0009 | **0.0011** | 0.0009 | 0.0003 | **-0.0014** | 0.0005 | **-0.0025** |
| Aero | 0.0012 | **0.0016** | 0.0003 | -0.0006 | -0.0008 | **-0.0029** | **0.0015** | 0.0010 | 0.0010 | **-0.0016** | -0.0006 | **-0.0019** |
| Ships | **0.0019** | 0.0012 | **0.0021** | -0.0009 | -0.0010 | **-0.0027** | **0.0027** | 0.0010 | 0.0007 | **-0.0029** | 0.0004 | -0.0009 |
| Guns | 0.0018 | **0.0031** | 0.0011 | **-0.0028** | -0.0005 | 0.0001 | 0.0014 | 0.0014 | 0.0018 | -0.0010 | -0.0001 | 0.0001 |
| Gold | 0.0019 | **0.0044** | -0.0001 | -0.0015 | 0.0023 | **-0.0047** | 0.0009 | **0.0050** | -0.0016 | -0.0007 | **0.0043** | **-0.0055** |
| Mines | 0.0006 | 0.0019 | 0.0007 | 0.0002 | 0.0019 | **-0.0025** | **0.0021** | **0.0034** | 0.0010 | -0.0004 | 0.0009 | **-0.0040** |
| Coal | 0.0013 | **0.0035** | **0.0034** | -0.0004 | **0.0035** | -0.0029 | **0.0034** | **0.0034** | 0.0015 | -0.0009 | 0.0004 | -0.0038 |
| Oil | -0.0002 | **0.0029** | 0.0004 | -0.0019 | 0.0010 | -0.0022 | **0.0017** | **0.0030** | 0.0000 | -0.0007 | 0.0005 | **-0.0035** |
| Util | 0.0002 | 0.0006 | 0.0004 | -0.0001 | -0.0006 | 0.0003 | 0.0000 | 0.0006 | 0.0005 | 0.0003 | -0.0002 | -0.0003 |
| Telcm | 0.0000 | **0.0022** | -0.0004 | -0.0003 | 0.0007 | **-0.0018** | 0.0005 | **0.0019** | -0.0006 | 0.0000 | **0.0014** | **-0.0021** |
| PerSv | **0.0014** | **0.0024** | 0.0002 | -0.0012 | 0.0005 | **-0.0031** | **0.0010** | 0.0007 | -0.0002 | **-0.0015** | **0.0022** | **-0.0040** |
| BusSv | **0.0015** | **0.0020** | -0.0004 | -0.0002 | 0.0002 | **-0.0032** | **0.0011** | **0.0015** | **-0.0009** | -0.0002 | 0.0009 | **-0.0030** |
| Hardw | **0.0015** | **0.0021** | -0.0004 | -0.0004 | 0.0005 | **-0.0024** | 0.0010 | **0.0019** | -0.0007 | 0.0011 | **0.0011** | **-0.0025** |
| Softw | **0.0012** | **0.0016** | -0.0010 | 0.0000 | 0.0007 | **-0.0033** | 0.0009 | **0.0015** | **-0.0016** | 0.0008 | 0.0009 | **-0.0030** |
| Chips | **0.0018** | **0.0022** | -0.0001 | -0.0003 | -0.0001 | **-0.0031** | **0.0013** | **0.0017** | -0.0004 | 0.0009 | 0.0006 | **-0.0031** |
| LabEq | 0.0007 | **0.0024** | 0.0002 | -0.0001 | 0.0003 | **-0.0031** | 0.0007 | **0.0020** | -0.0002 | -0.0004 | 0.0007 | **-0.0019** |
| Paper | **0.0009** | **0.0011** | -0.0002 | 0.0002 | 0.0008 | **-0.0021** | **0.0010** | 0.0002 | -0.0002 | -0.0004 | **0.0017** | **-0.0018** |
| Boxes | **0.0019** | 0.0002 | 0.0014 | 0.0010 | **0.0020** | **-0.0017** | 0.0007 | -0.0004 | 0.0006 | 0.0012 | 0.0008 | -0.0010 |
| Trans | **0.0009** | **0.0016** | -0.0006 | 0.0002 | -0.0002 | **-0.0023** | **0.0009** | 0.0006 | -0.0001 | -0.0007 | 0.0003 | **-0.0018** |
| Whlsl | **0.0012** | **0.0025** | -0.0001 | -0.0006 | 0.0002 | **-0.0028** | **0.0013** | **0.0015** | -0.0001 | -0.0001 | 0.0008 | **-0.0028** |
| Rtail | 0.0002 | **0.0014** | -0.0006 | 0.0007 | -0.0004 | **-0.0015** | 0.0006 | 0.0007 | -0.0003 | -0.0005 | 0.0001 | **-0.0021** |
| Meals | **0.0011** | **0.0017** | 0.0001 | 0.0002 | -0.0005 | **-0.0019** | **0.0009** | **0.0013** | -0.0001 | -0.0007 | 0.0005 | **-0.0026** |
| Banks | **0.0006** | **0.0005** | -0.0002 | -0.0002 | 0.0001 | **-0.0021** | 0.0003 | 0.0003 | -0.0003 | -0.0007 | 0.0004 | **-0.0017** |
| Insur | 0.0006 | **0.0009** | 0.0002 | -0.0008 | **0.0012** | -0.0012 | -0.0002 | 0.0001 | 0.0003 | -0.0005 | **0.0011** | **-0.0016** |
| RlEst | 0.0000 | **0.0024** | 0.0000 | 0.0003 | -0.0011 | **-0.0023** | 0.0007 | **0.0020** | -0.0010 | **-0.0022** | 0.0005 | -0.0016 |
| Fin | **0.0007** | **0.0010** | -0.0006 | 0.0005 | **0.0013** | **-0.0025** | **0.0007** | **0.0008** | -0.0004 | -0.0004 | 0.0001 | **-0.0023** |
| Other | **0.0019** | **0.0021** | -0.0005 | **-0.0011** | 0.0000 | **-0.0021** | **0.0011** | **0.0025** | -0.0008 | 0.0005 | -0.0001 | **-0.0023** |
| Positive | 29 | 43 | 2 | 0 | 6 | 0 | 30 | 29 | 0 | 0 | 12 | 0 |
| Negative | 0 | 0 | 0 | 5 | 0 | 41 | 0 | 0 | 5 | 9 | 0 | 40 |

Notes: Table 2.16 reports industry returns in response to the release of investor sentiment measures greater than one standard deviation above average. Equation 2.15 estimates abnormal returns (AR) with a regression of excess industry returns on event-day dummy variables and the market-risk premium. Bull sentiment denotes investor sentiment greater than one standard deviation above average, and likewise for bear sentiment. Bold indicates statistically significant abnormal returns at 10 percent or greater estimated with White (1980) standard errors. The bottom rows report the total number of statistically significant positive and negative coefficients.

Industry response to the announcement of extreme bullish and bearish sentiment is mostly significant with the correct sign. The results show significant and positive *day0* and *day1* industry performance following the release of extreme AAII and II bullish sentiment measures. For instance, there are 29 and 43 industries with significant *day0* and *day1* performance following extreme AAII bullish sentiment. The average AAII *day1* response (.0018) shows slightly greater economic significance than *day0* (.0011). Results for II sentiment are comparable with AAII sentiment. Notably, there is only weak evidence of statistically significant *day2* reversals, for either measure. More interestingly, the results document an opposite effect following the release of extremely bearish sentiment, except with a two-day delay. There is only negligible evidence of *day0* or *day1* excess industry returns in response to extreme bearish sentiment announcements. However, there is a highly significant and negative *day2* industry response for both measures. There are 41 and 40 industries with significantly negative *day2* returns following the release of extreme bearish AAII and II sentiment, averaging -.0022 and -.0024 for each measure. The results indicate investors respond more quickly to extreme bullish sentiment than to bearish sentiment. Such results align with Hong, Lim, and Stein (2000), who similarly document that investors process bad news more slowly than good news.

Generally, the immediate effect of extreme investor sentiment on industry performance is significant and widespread. Here again, the effect of sentiment appears to be market wide rather than industry specific. Investor response to extreme bullish and bearish sentiment suggests that investors believe that sentiment projects a continuation of prevailing market direction. This belief runs counter to prior market studies, including the industry analysis, which shows that initial investor sentiment-driven mispricing leads to predictable price reversals. To that end, excess returns following the announcement of extreme bullish and bear sentiment appear to reflect an element of rational industry performance expectations.

### 2.10 Robustness Checks

The results provide evidence that investor sentiment systematically predicts industry returns. However, the results are subject to potential criticisms. First, the sample period may drive the findings. A robustness test thus splits the sample and examines two equal sub-periods. Second, industry return predictability may simply reflect additional risk compensation. Therefore, another robustness test investigates investor sentiment predictability of risk-adjusted industry returns. The risk adjustment uses the well-known Fama and French three-factor and Carhart four-factor risk-correction models. Lastly, the results are potentially specific to the Fama and French industry portfolios. Therefore, as a further precaution, a robustness test examines return predictability using three alternative sector and industry classifications. Nevertheless, these additional results remain fundamentally unaltered, even after considering alternative sample periods, risk corrections, and industry classifications.

### 2.10.1 Sub-period comparison

The effect of investor sentiment on industry performance potentially varies across different sub-periods. Brown and Cliff (2005), for instance, show that the effect of investor sentiment on the market was greater prior to 1990. More recently, Brown and Cliff (2005) argue that the effect of sentiment on returns has declined due to a greater dissemination of investor sentiment measures. Thus, for robustness, the analysis examines two equal sub-periods, from 24/07/87 to 03/10/1997 and from 10/10/1997 to 28/12/2007.

Table 2.17 summarizes and compares the ability of investor sentiment to predict industry returns for the full sample with two sub-periods. The table compares results for bullish and bearish periods of sentiment. The table also reports the total number of statistically significant $a_1$ regression coefficients from Equation 2.2. The $a_1$ regression coefficients measure unconditional sentiment predictability of industry returns. Additionally, the table reports the total number of statistically significant $a_2$ and $a_3$ regression coefficients from Equation 2.3. The $a_2$ and $a_3$ regression coefficients measure sentiment predictability of industry returns for periods of bullish and bearish sentiment. Table 2.17 reports the total number of statistically significant coefficients at 10 percent or greater estimated with White (1980) standard errors for the indicated investor sentiment measures at $k$-week lags.

**Table 2.17 Sub-period comparison of investor sentiment predictability**

| lag | Sentiment Measure | Sample Period | Full Sample positive | Full Sample negative | Bullish Sentiment positive | Bullish Sentiment negative | Bearish Sentiment positive | Bearish Sentiment negative |
|---|---|---|---|---|---|---|---|---|
| 1 week | AAII | 1987-2007 | 48 | 0 | 45 | 0 | 33 | 0 |
| | | 1987-1997 | 43 | 0 | 33 | 0 | 20 | 0 |
| | | 1997-2007 | 46 | 0 | 40 | 0 | 32 | 0 |
| | II | 1987-2007 | 46 | 0 | 37 | 0 | 22 | 0 |
| | | 1987-1997 | 42 | 0 | 12 | 0 | 39 | 0 |
| | | 1997-2007 | 44 | 0 | 43 | 0 | 21 | 0 |
| | BW | 1987-2007 | 28 | 1 | 15 | 0 | 11 | 4 |
| | | 1987-1997 | 43 | 0 | 43 | 0 | 7 | 0 |
| | | 1997-2007 | 4 | 2 | 3 | 0 | 4 | 5 |
| 8 weeks | AAII | 1987-2007 | 11 | 2 | 33 | 0 | 0 | 25 |
| | | 1987-1997 | 2 | 3 | 9 | 0 | 1 | 4 |
| | | 1997-2007 | 16 | 0 | 32 | 0 | 0 | 18 |
| | II | 1987-2007 | 4 | 10 | 2 | 5 | 1 | 1 |
| | | 1987-1997 | 2 | 8 | 0 | 22 | 10 | 0 |
| | | 1997-2007 | 5 | 4 | 15 | 0 | 0 | 32 |
| | BW | 1987-2007 | 0 | 12 | 9 | 1 | 0 | 31 |
| | | 1987-1997 | 12 | 0 | 2 | 1 | 9 | 0 |
| | | 1997-2007 | 0 | 24 | 13 | 1 | 0 | 38 |
| 13 weeks | AAII | 1987-2007 | 3 | 8 | 8 | 1 | 0 | 18 |
| | | 1987-1997 | 2 | 18 | 1 | 1 | 0 | 18 |
| | | 1997-2007 | 6 | 2 | 10 | 1 | 0 | 1 |
| | II | 1987-2007 | 3 | 13 | 3 | 26 | 9 | 0 |
| | | 1987-1997 | 1 | 7 | 0 | 8 | 8 | 0 |
| | | 1997-2007 | 4 | 10 | 2 | 17 | 13 | 0 |
| | BW | 1987-2007 | 0 | 10 | 1 | 3 | 1 | 11 |
| | | 1987-1997 | 0 | 7 | 3 | 5 | 0 | 4 |
| | | 1997-2007 | 2 | 8 | 1 | 4 | 1 | 10 |
| 26 weeks | AAII | 1987-2007 | 2 | 2 | 2 | 0 | 0 | 11 |
| | | 1987-1997 | 1 | 2 | 1 | 0 | 1 | 12 |
| | | 1997-2007 | 1 | 0 | 2 | 0 | 1 | 3 |
| | II | 1987-2007 | 2 | 1 | 3 | 3 | 4 | 2 |
| | | 1987-1997 | 15 | 1 | 12 | 2 | 0 | 2 |
| | | 1997-2007 | 2 | 3 | 2 | 5 | 0 | 1 |
| | BW | 1987-2007 | 6 | 0 | 1 | 2 | 2 | 0 |
| | | 1987-1997 | 2 | 16 | 11 | 1 | 1 | 0 |
| | | 1997-2007 | 6 | 0 | 0 | 4 | 0 | 2 |
| 52 weeks | AAII | 1987-2007 | 0 | 13 | 0 | 0 | 0 | 18 |
| | | 1987-1997 | 0 | 11 | 8 | 1 | 1 | 21 |
| | | 1997-2007 | 0 | 5 | 0 | 1 | 0 | 3 |
| | II | 1987-2007 | 2 | 6 | 2 | 4 | 3 | 4 |
| | | 1987-1997 | 1 | 5 | 3 | 8 | 2 | 4 |
| | | 1997-2007 | 3 | 1 | 1 | 1 | 2 | 1 |
| | BW | 1987-2007 | 0 | 5 | 7 | 0 | 0 | 23 |
| | | 1987-1997 | 6 | 1 | 1 | 3 | 4 | 1 |
| | | 1997-2007 | 1 | 5 | 7 | 0 | 0 | 29 |

Notes: Table 2.17 summarizes and compares the number of industries that investor sentiment predicts at 10 percent or greater statistical significance over the full sample and two equal sub-periods. The sub-periods are from 07/87 to 10/97 and 10/97 to 12/07. The table reports the number of statistically significant $a_1$ coefficients from Equation 2.2 and the statistically significant $a_2$ and $a_3$ coefficients for bullish and bearish sentiment periods from Equation 2.3. Sentiment measures are from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). The analysis estimates statistical significance using White (1980) standard errors.

The study's general results remain largely unchanged for the two sub-periods. Investor sentiment systematically predicts returns for most industries at a one-week lag. AAII sentiment remains the best predictor of industry returns at a one-week horizon, followed by II, and then the BW sentiment measure. Again, predictability quickly diminishes for all measures, at longer horizons, especially at 26 and 52 weeks. For those horizons, statistical significance occurs only slightly more than expected by random chance, in the absence of true return predictability. Overall, the biggest change is substantially greater short-horizon and long-horizon predictability for BW sentiment during the earlier sub-period. Alternatively, AAII sentiment predictability is slightly more significant in more recent years, for all horizons, which runs contrary to the findings of Brown and Cliff (2005) for the market.

### 2.10.2 Controls for risk factors

This section examines whether investor sentiment predictability remains after controlling industry returns for additional risk sources. Baker and Wurgler (2006), for instance, provide evidence that sentiment affects the returns of small-cap and growth stocks. Prior research, such as Fama and French (1993), also identifies small-cap and growth premiums. As such, the investor sentiment predictability observed may merely represent expected investor compensation for bearing systematic risk. Equally, Moskowitz and Grinblatt (1999) identify industry returns as a source of momentum profits. The Carhart (1997) four-factor model identifies momentum as an additional source of systematic risk. The analysis controls industry returns for these well-known risk factors using the Fama and French (1993) three-factor and Carhart (1997) four-factor risk-correction models. The three-factor model includes corrections for a size factor (*SMB*) and a growth factor (*HML*), in addition to the market. Additionally, the four-factor model includes a momentum factor (*UMD*). The size factor measures the return premium between small-cap and large-cap stocks. The growth factor measures the return premium between growth and value stocks. The momentum factor measures the return premium between high-return and low-return stocks. The *SMB*, *HML*, and

*UMD* risk factors come from the Kenneth French website, where complete details are available on the construction of these risk factors.[38]

$$R_{i,t} = a_0 + a_1 Sent_{s,t-k} + b_0 R_{m,t} + e_t \quad \text{(Eq. 2.2)}$$

$$R_{i,t} = a_0 + a_1 Sent_{s,t-k} + b_0 R_{m,t} + b_1 SMB_t + b_2 HML_t + e_t \quad \text{(Eq. 2.16)}$$

$$R_{i,t} = a_0 + a_1 Sent_{s,t-k} + b_0 R_{m,t} + b_1 SMB_t + b_2 HML_t + b_3 UMD_t + e_t \quad \text{(Eq. 2.17)}$$

Table 2.18 compares investor sentiment predictability of industry returns after corrections for different sources of systematic risk. The table summarizes the number of positive and negative $a_1$ coefficient from single index (Eq. 2.2), Fama and French three-factor (Eq. 2.16), and Carhart four-factor (Eq. 2.17) models, with statistical significance estimated with White (1980) corrected standard errors. Table 2.18 reports summary results for the indicated sentiment measure at a *k*-week lag and the indicated risk-correction model. The table reports results for the full sample, bullish sentiment, and bearish sentiment. Additionally, Table 2.19 provides the complete results for investor sentiment predictability of industry returns corrected with a Carhart four-factor model over the full sample.

[38] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

**Table 2.18 Risk adjusted comparison of investor sentiment predictability**

| lag | Sentiment Measure | Risk Correction | Full sample positive | Full sample negative | Bullish Sentiment positive | Bullish Sentiment negative | Bearish Sentiment positive | Bearish Sentiment negative |
|---|---|---|---|---|---|---|---|---|
| 1 week | AAII | Single-index model | 48 | 0 | 33 | 0 | 20 | 0 |
| | | Fama & French 3-factor | 34 | 0 | 23 | 1 | 8 | 0 |
| | | Carhart 4-factor | 32 | 0 | 25 | 1 | 5 | 2 |
| | II | Single-index model | 46 | 0 | 12 | 0 | 39 | 0 |
| | | Fama & French 3-factor | 19 | 0 | 13 | 1 | 9 | 1 |
| | | Carhart 4-factor | 19 | 0 | 10 | 1 | 9 | 2 |
| | BW | Single-index model | 28 | 1 | 43 | 0 | 7 | 0 |
| | | Fama & French 3-factor | 29 | 1 | 19 | 0 | 11 | 4 |
| | | Carhart 4-factor | 28 | 1 | 22 | 0 | 10 | 4 |
| 8 weeks | AAII | Single-index model | 11 | 2 | 9 | 0 | 1 | 4 |
| | | Fama & French 3-factor | 2 | 10 | 2 | 1 | 1 | 17 |
| | | Carhart 4-factor | 2 | 4 | 5 | 1 | 1 | 14 |
| | II | Single-index model | 4 | 10 | 0 | 22 | 10 | 0 |
| | | Fama & French 3-factor | 4 | 17 | 2 | 11 | 1 | 5 |
| | | Carhart 4-factor | 3 | 14 | 2 | 11 | 1 | 5 |
| | BW | Single-index model | 0 | 13 | 2 | 1 | 9 | 0 |
| | | Fama & French 3-factor | 1 | 11 | 4 | 1 | 0 | 10 |
| | | Carhart 4-factor | 1 | 7 | 6 | 1 | 0 | 10 |
| 13 weeks | AAII | Single-index model | 3 | 8 | 1 | 1 | 0 | 18 |
| | | Fama & French 3-factor | 2 | 7 | 3 | 1 | 0 | 18 |
| | | Carhart 4-factor | 2 | 6 | 6 | 1 | 0 | 16 |
| | II | Single-index model | 3 | 13 | 0 | 8 | 8 | 0 |
| | | Fama & French 3-factor | 3 | 22 | 3 | 28 | 10 | 0 |
| | | Carhart 4-factor | 3 | 18 | 4 | 27 | 10 | 0 |
| | BW | Single-index model | 0 | 10 | 3 | 5 | 0 | 4 |
| | | Fama & French 3-factor | 4 | 5 | 3 | 3 | 1 | 11 |
| | | Carhart 4-factor | 4 | 12 | 3 | 5 | 1 | 12 |
| 26 weeks | AAII | Single-index model | 2 | 2 | 1 | 0 | 1 | 12 |
| | | Fama & French 3-factor | 2 | 3 | 1 | 0 | 0 | 8 |
| | | Carhart 4-factor | 2 | 4 | 1 | 0 | 0 | 6 |
| | II | Single-index model | 2 | 1 | 12 | 2 | 0 | 2 |
| | | Fama & French 3-factor | 2 | 11 | 2 | 12 | 5 | 5 |
| | | Carhart 4-factor | 1 | 11 | 2 | 15 | 5 | 4 |
| | BW | Single-index model | 6 | 0 | 11 | 1 | 1 | 0 |
| | | Fama & French 3-factor | 8 | 0 | 8 | 3 | 6 | 2 |
| | | Carhart 4-factor | 6 | 0 | 8 | 3 | 6 | 3 |
| 52 weeks | AAII | Single-index model | 0 | 13 | 8 | 1 | 1 | 21 |
| | | Fama & French 3-factor | 0 | 8 | 2 | 2 | 0 | 13 |
| | | Carhart 4-factor | 0 | 11 | 2 | 3 | 0 | 11 |
| | II | Single-index model | 2 | 6 | 3 | 8 | 2 | 4 |
| | | Fama & French 3-factor | 0 | 14 | 0 | 21 | 6 | 2 |
| | | Carhart 4-factor | 0 | 15 | 0 | 24 | 8 | 1 |
| | BW | Single-index model | 0 | 5 | 1 | 3 | 4 | 1 |
| | | Fama & French 3-factor | 1 | 5 | 3 | 1 | 1 | 8 |
| | | Carhart 4-factor | 1 | 5 | 4 | 3 | 1 | 8 |

Notes: Table 2.18 summarizes the number of positive and negative $\alpha_1$ regression coefficients statistically significant at 10 percent or greater. The table reports results for the indicated sentiment measures at various *k*-week lags, risk corrections, and periods of market sentiment. Sentiment measures come from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). The analysis estimates risk-corrected industry returns using the single-index (Eq. 2.2), Fama and French (1993) three-factor (Eq. 2.16), and Carhart (1997) four-factor (Eq. 2.17) models and statistical significance using White (1980) standard errors.

## Table 2.19 Four-factor risk adjusted investor sentiment predictability

| | 1 week | | | 8 week | | | 13 week | | | 26 week | | | 52 week | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| Agric | **0.009** | **0.009** | 0.000 | **0.010** | 0.006 | 0.001 | 0.001 | 0.002 | -0.001 | **0.008** | 0.001 | 0.001 | 0.004 | -0.002 | 0.001 |
| Food | 0.003 | **0.004** | 0.000 | 0.000 | -0.003 | **-0.001** | 0.000 | -0.003 | 0.000 | 0.001 | 0.001 | 0.000 | **-0.003** | -0.003 | 0.000 |
| Soda | **0.008** | 0.004 | 0.001 | 0.007 | 0.000 | **-0.002** | 0.005 | 0.003 | 0.000 | -0.001 | 0.001 | 0.000 | 0.001 | -0.001 | 0.001 |
| Beer | **0.006** | **0.007** | 0.000 | 0.000 | -0.001 | 0.000 | 0.002 | 0.004 | **-0.001** | 0.003 | **0.007** | 0.000 | 0.001 | 0.002 | -0.001 |
| Smoke | 0.006 | -0.002 | -0.002 | -0.008 | **-0.013** | 0.000 | -0.002 | -0.009 | 0.000 | 0.004 | -0.005 | -0.002 | 0.003 | -0.004 | -0.001 |
| Toys | **0.010** | **0.008** | **0.002** | 0.002 | -0.005 | 0.000 | -0.001 | -0.003 | 0.000 | -0.001 | -0.006 | 0.000 | **-0.007** | **-0.009** | **-0.001** |
| Fun | **0.010** | **0.008** | **0.002** | 0.001 | -0.002 | -0.001 | 0.003 | -0.003 | -0.001 | 0.001 | -0.004 | 0.000 | 0.003 | 0.000 | **-0.001** |
| Books | **0.008** | **0.005** | **0.001** | 0.000 | **-0.005** | -0.001 | -0.002 | **-0.005** | 0.000 | **0.004** | 0.001 | 0.000 | -0.002 | -0.002 | **-0.001** |
| Hshld | **0.008** | **0.009** | **0.001** | 0.000 | -0.001 | 0.000 | -0.002 | -0.002 | -0.001 | **-0.005** | -0.004 | 0.000 | -0.001 | -0.003 | 0.000 |
| Clths | **0.007** | **0.012** | **0.002** | -0.002 | 0.000 | **-0.001** | -0.003 | -0.004 | -0.001 | -0.003 | -0.003 | 0.000 | 0.002 | -0.003 | 0.000 |
| Hlth | 0.004 | 0.003 | 0.001 | -0.001 | **-0.010** | -0.001 | -0.002 | **-0.010** | -0.001 | -0.001 | -0.005 | 0.000 | **-0.005** | **-0.010** | 0.000 |
| MedEq | **0.010** | 0.003 | **0.002** | -0.001 | **-0.006** | 0.000 | -0.003 | **-0.008** | **-0.001** | -0.002 | **-0.006** | 0.000 | **-0.006** | **-0.010** | -0.001 |
| Drugs | **0.013** | **0.006** | **0.002** | 0.000 | -0.003 | 0.001 | -0.005 | -0.002 | 0.000 | -0.001 | -0.002 | 0.000 | **-0.010** | **-0.014** | -0.001 |
| Chems | 0.001 | 0.001 | 0.000 | -0.001 | -0.001 | 0.000 | 0.003 | 0.002 | 0.000 | -0.002 | 0.000 | 0.000 | -0.003 | 0.000 | 0.000 |
| Rubbr | **0.008** | 0.004 | **0.001** | -0.003 | -0.004 | -0.001 | -0.002 | -0.003 | 0.000 | -0.003 | -0.004 | 0.000 | -0.002 | -0.002 | -0.001 |
| Txtls | 0.004 | 0.002 | **0.002** | -0.002 | -0.006 | -0.001 | 0.000 | **-0.008** | -0.001 | **-0.008** | **-0.007** | 0.000 | -0.006 | -0.005 | -0.001 |
| BldMt | **0.006** | 0.001 | **0.001** | 0.002 | 0.001 | 0.000 | 0.003 | 0.000 | 0.000 | -0.002 | -0.003 | 0.000 | -0.001 | **-0.004** | 0.000 |
| Cnstr | **0.008** | **0.012** | 0.001 | -0.002 | -0.003 | 0.001 | -0.003 | -0.001 | **-0.001** | -0.003 | -0.005 | -0.001 | **-0.005** | **-0.010** | -0.001 |
| Steel | 0.001 | 0.002 | **0.001** | 0.002 | 0.003 | 0.000 | -0.001 | 0.004 | 0.000 | -0.004 | 0.005 | **0.001** | -0.003 | 0.003 | 0.000 |
| FabPr | 0.004 | -0.003 | 0.001 | -0.001 | -0.005 | -0.001 | -0.004 | **-0.007** | 0.000 | 0.000 | 0.002 | 0.001 | -0.005 | -0.002 | 0.001 |
| Mach | **0.003** | 0.002 | **0.001** | 0.001 | -0.001 | 0.000 | -0.002 | **-0.005** | 0.000 | -0.003 | -0.002 | 0.000 | -0.003 | -0.001 | 0.000 |
| ElcEq | **0.008** | -0.004 | **0.002** | -0.001 | **-0.008** | **0.001** | -0.001 | **-0.007** | **0.001** | -0.004 | **-0.009** | 0.000 | **-0.004** | **-0.007** | 0.001 |
| Autos | **0.006** | 0.004 | **0.001** | -0.002 | **-0.005** | 0.000 | 0.000 | -0.004 | **-0.001** | -0.001 | -0.001 | 0.000 | -0.004 | **-0.006** | 0.000 |
| Aero | **0.010** | **0.012** | **0.001** | 0.002 | 0.003 | 0.000 | **0.011** | 0.004 | 0.000 | 0.003 | 0.002 | 0.001 | -0.004 | 0.000 | 0.000 |
| Ships | **0.012** | **0.013** | 0.000 | 0.002 | 0.003 | 0.000 | -0.001 | 0.007 | -0.001 | **-0.008** | 0.000 | -0.001 | -0.004 | -0.005 | 0.000 |
| Guns | **0.012** | 0.008 | 0.000 | 0.003 | 0.004 | -0.001 | 0.005 | 0.006 | 0.000 | -0.001 | 0.001 | -0.001 | -0.003 | -0.002 | 0.000 |
| Gold | -0.004 | 0.012 | -0.002 | 0.009 | **0.018** | 0.001 | 0.005 | 0.006 | -0.001 | -0.014 | -0.003 | **0.004** | -0.002 | -0.011 | **0.004** |
| Mines | 0.002 | 0.005 | 0.001 | 0.005 | **0.010** | 0.000 | 0.000 | 0.008 | 0.000 | -0.005 | -0.004 | 0.001 | -0.009 | -0.001 | 0.001 |
| Coal | 0.002 | 0.008 | **-0.004** | 0.007 | 0.011 | 0.000 | **0.013** | **0.020** | 0.000 | 0.011 | 0.007 | **0.003** | 0.000 | 0.002 | 0.002 |
| Oil | 0.000 | -0.002 | -0.001 | **0.009** | **0.008** | 0.001 | 0.006 | **0.008** | **0.002** | -0.001 | -0.004 | **0.002** | -0.002 | -0.003 | 0.000 |
| Util | -0.002 | -0.001 | 0.000 | -0.002 | 0.001 | 0.000 | 0.000 | **0.003** | 0.000 | 0.002 | 0.002 | 0.000 | -0.001 | 0.001 | 0.000 |
| Whlsl | **0.006** | 0.002 | **0.003** | **-0.006** | **-0.007** | 0.000 | -0.004 | **-0.010** | **0.001** | -0.002 | -0.004 | 0.001 | -0.001 | 0.000 | 0.000 |
| PerSv | **0.009** | **0.007** | **0.002** | -0.005 | -0.004 | -0.001 | **-0.007** | **-0.006** | **-0.001** | -0.001 | 0.001 | 0.000 | **-0.005** | **-0.006** | 0.000 |
| BusSv | **0.010** | **0.004** | **0.002** | -0.002 | **-0.006** | 0.000 | -0.002 | **-0.007** | 0.000 | -0.001 | **-0.005** | 0.000 | -0.002 | **-0.005** | 0.000 |
| Hardw | **0.010** | -0.001 | **0.003** | **-0.006** | **-0.008** | 0.001 | **-0.006** | **-0.011** | 0.000 | -0.004 | **-0.008** | 0.000 | -0.003 | -0.005 | 0.000 |
| Softw | **0.012** | 0.002 | **0.003** | -0.004 | **-0.008** | 0.000 | **-0.009** | **-0.010** | -0.001 | -0.001 | -0.005 | 0.000 | -0.002 | -0.003 | -0.001 |
| Chips | **0.011** | 0.002 | **0.003** | 0.000 | 0.000 | 0.001 | -0.002 | -0.004 | 0.001 | -0.004 | **-0.006** | 0.001 | -0.002 | -0.001 | 0.001 |
| LabEq | **0.012** | -0.003 | **0.002** | 0.002 | **-0.007** | 0.001 | -0.001 | **-0.011** | **0.001** | 0.000 | **-0.009** | 0.001 | **-0.005** | **-0.007** | 0.000 |
| Paper | 0.002 | 0.001 | 0.000 | 0.000 | -0.002 | 0.000 | -0.001 | **-0.004** | 0.000 | -0.001 | -0.003 | 0.000 | -0.001 | -0.003 | 0.000 |
| Boxes | 0.003 | -0.004 | 0.001 | **-0.012** | **-0.012** | **-0.001** | -0.002 | **-0.008** | -0.001 | -0.002 | **-0.009** | -0.001 | 0.000 | -0.007 | -0.001 |
| Trans | **0.004** | 0.002 | **0.001** | 0.002 | -0.002 | **-0.001** | 0.002 | -0.003 | **-0.001** | -0.003 | -0.002 | **0.001** | -0.002 | -0.001 | 0.000 |
| Whlsl | **0.008** | **0.006** | **0.002** | 0.002 | 0.000 | 0.000 | 0.000 | -0.002 | -0.001 | -0.001 | 0.001 | 0.000 | -0.001 | -0.002 | 0.000 |
| Rtail | **0.004** | **0.007** | 0.001 | -0.002 | **-0.004** | **-0.001** | -0.002 | -0.003 | **-0.002** | -0.001 | **-0.004** | -0.001 | 0.000 | -0.002 | 0.000 |
| Meals | **0.010** | **0.010** | **0.001** | 0.000 | -0.001 | 0.000 | 0.001 | -0.004 | **-0.001** | -0.002 | -0.003 | 0.000 | -0.001 | -0.004 | **-0.001** |
| Banks | 0.000 | 0.000 | 0.000 | -0.003 | **-0.005** | 0.000 | **-0.004** | **-0.005** | **-0.001** | -0.002 | **-0.004** | 0.000 | **-0.005** | **-0.009** | 0.000 |
| Insur | 0.001 | 0.002 | 0.000 | -0.001 | -0.003 | 0.000 | **-0.004** | **-0.004** | **-0.001** | -0.001 | -0.003 | -0.001 | -0.002 | **-0.005** | **-0.001** |
| RlEst | **0.010** | **0.009** | **0.002** | 0.000 | -0.004 | **-0.001** | -0.003 | -0.002 | 0.000 | -0.002 | 0.000 | -0.001 | -0.004 | -0.005 | 0.000 |
| Fin | 0.003 | 0.002 | **0.001** | **-0.004** | -0.002 | 0.000 | **-0.005** | **-0.004** | **-0.001** | **-0.006** | **-0.005** | **0.001** | **-0.005** | **-0.003** | 0.000 |
| Other | **0.009** | **0.006** | **0.002** | 0.001 | -0.002 | 0.000 | 0.003 | 0.000 | **-0.001** | 0.001 | -0.002 | 0.000 | -0.003 | **-0.005** | 0.000 |
| Positive | 32 | 19 | 28 | 2 | 3 | 1 | 2 | 3 | 4 | 2 | 1 | 6 | 0 | 0 | 1 |
| Negative | 0 | 0 | 1 | 4 | 14 | 7 | 6 | 18 | 12 | 4 | 11 | 0 | 11 | 15 | 5 |

Notes: Table 2.19 reports the $a_1$ slope coefficients estimated with Equation 2.17. The equation runs a regression of industry returns on a constant investor sentiment at different *k*-week lags, and a Carhart (1997) four-factor risk correction. The Carhart (1997) four-factors are the market ($R_m$), size (*SMB*), value (*HML*), and momentum (*UMD*) risk premiums. Investor sentiment measures come from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). Bold indicates 10 percent or greater statistical significance estimated with White (1980) standard errors. The bottom two rows report the total positive and negative significant coefficients.

The results provide evidence that well-known risk factors at least partially explain investor sentiment predictability, at both short horizons and long horizons. For instance, at a one-week horizon, statistically significant and positive AAII predictability drops from 48 to 34 for industries after a three-factor risk correction. The results are more striking for AAII positive predictability at a one-week lag for periods of bearish sentiment. Significant and positive predictability drops from 20 to five industries after a four-factor risk correction. More interestingly, the economic significance of investor sentiment predictability drops noticeably. For instance, AAII sentiment has an average $a_1$ regression coefficient of 0.017 for industry returns corrected for the market at a one-week lag. In comparison, the average $a_1$ regression coefficient for AAII sentiment is 0.006 for industry returns corrected with a four-factor model at a one-week lag. The statistical significance of risk-adjusted return predictability increases at longer horizons, especially for II sentiment and during periods of bullish sentiment. For instance, II sentiment significantly predicts four-factor adjusted returns for 24 industries at a 52-week lag with bullish sentiment. That directly compares with the predictability of market-adjusted returns for eight industries. The absolute economic value of significant and negative predictability also increases for risk-adjusted returns at longer horizons. While short-term positive predictability decreases somewhat, the results for negative long-term reversals strengthen after three-factor and four-factor risk corrections. Consequently, the predictability of industry returns actually strengthens after correcting for well-known sources, particularly bullish II sentiment at all horizons.

### 2.10.3 Alternative industry portfolios

The choice of industrial classification scheme can determine the outcomes of empirical research (Bhojraj, Lee, and Oler (2003)). Additionally, the returns of industry portfolios comprising a few firms or a few dominant firms may merely represent idiosyncratic risk. The results may therefore misestimate the effect of investor sentiment predictability on industry values. For additional robustness, the analysis compares results for the Fama and French industries with results for alternative sector and industry groups. Specifically, the analysis maps the Fama and French 49 industry portfolios to the Kacperczyk, Sialm, and Zheng (2005) and GICS sector and industry classifications. Kacperczyk, Sialm, and Zheng (2005) map the Fama and French 48 industry portfolios to one of 10 sector portfolios. Additionally, the analysis maps the extra software industry included in the Fama and French 49 industry classification to the Kacperczyk, Sialm, and Zheng (2005) business equipment and services sector. The analysis also uses the GICS 10 sector and 24 industry mappings. Analysts widely follow the GICS classification. Bhojraj, Lee, and Oler (2003) find that intra-industry return correlations are higher for the GICS classification than other popular industry classifications, such as the Standard Industrial Classification (SIC). Table 2.20 details the mapping of the original Fama and French 49 industry portfolios to the Kacperczyk, Sialm, and Zheng (2005) and GICS sector and industry portfolios.

**Table 2.20 Alternative sector and industry mappings**

| Fama & French 49 Industries | | Kacperczyk, Sialm, Zheng 10 Sectors | | GICS 10 Sector Groups | | GICS 24 Industry Groups | |
|---|---|---|---|---|---|---|---|
| Group | Description | Group | Description | Group | Description | Group | Description |
| 01 | Agriculture | 01 | Consumer Non-Durable | 30 | Consumer Staples | 3020 | Food, Beverages, & Tobacco |
| 02 | Food Products | 01 | Consumer Non-Durable | 30 | Consumer Staples | 3010 | Food & Staples Retailing |
| 03 | Candy & Soda | 01 | Consumer Non-Durable | 30 | Consumer Staples | 3020 | Food, Beverages, & Tobacco |
| 04 | Beer & Liquor | 01 | Consumer Non-Durable | 30 | Consumer Staples | 3020 | Food, Beverages, & Tobacco |
| 05 | Tobacco Products | 01 | Consumer Non-Durable | 30 | Consumer Staples | 3020 | Food, Beverages, & Tobacco |
| 06 | Recreation | 02 | Consumer Durable | 25 | Consumer Discretionary | 2520 | Consumer Durables & Apparel |
| 07 | Entertainment | 01 | Consumer Non-Durable | 25 | Consumer Discretionary | 2540 | Media |
| 08 | Printing & Publishing | 01 | Consumer Non-Durable | 25 | Consumer Discretionary | 2540 | Media |
| 09 | Consumer Goods | 02 | Consumer Durable | 25 | Consumer Discretionary | 2530 | Consumer Services |
| 10 | Apparel | 01 | Consumer Non-Durable | 25 | Consumer Discretionary | 2520 | Consumer Durables & Apparel |
| 11 | Healthcare | 03 | Healthcare | 35 | Healthcare | 3510 | Healthcare |
| 12 | Medical Equipment | 03 | Healthcare | 35 | Healthcare | 3510 | Healthcare |
| 13 | Pharmaceutical | 03 | Healthcare | 35 | Healthcare | 3520 | Pharmaceuticals |
| 14 | Chemicals | 04 | Manufacturing | 15 | Materials | 1510 | Materials |
| 15 | Rubber & Plastic | 04 | Manufacturing | 25 | Consumer Discretionary | 2550 | Retailing |
| 16 | Textiles | 01 | Consumer Non-Durable | 25 | Consumer Discretionary | 2520 | Consumer Durables & Apparel |
| 17 | Construction Material | 04 | Manufacturing | 15 | Materials | 1510 | Materials |
| 18 | Construction | 04 | Manufacturing | 25 | Consumer Discretionary | 2550 | Retailing |
| 19 | Steel Works | 04 | Manufacturing | 15 | Materials | 1510 | Materials |
| 20 | Fabricated Products | 04 | Manufacturing | 20 | Industrials | 2010 | Capital Goods |
| 21 | Machinery | 04 | Manufacturing | 20 | Industrials | 2010 | Capital Goods |
| 22 | Electrical Equipment | 04 | Manufacturing | 20 | Industrials | 2010 | Capital Goods |
| 23 | Automobiles & Truck | 02 | Consumer Durable | 25 | Consumer Discretionary | 2510 | Automobiles & Components |
| 24 | Aircraft | 04 | Manufacturing | 20 | Industrials | 2010 | Capital Goods |
| 25 | Shipbuilding & Railroad | 04 | Manufacturing | 20 | Industrials | 2010 | Capital Goods |
| 26 | Defence | 04 | Manufacturing | 20 | Industrials | 2010 | Capital Goods |
| 27 | Precious Metals | 05 | Energy | 15 | Materials | 1510 | Materials |
| 28 | Mining | 05 | Energy | 15 | Materials | 1510 | Materials |
| 29 | Coal | 05 | Energy | 10 | Energy | 1010 | Energy |
| 30 | Petroleum & Natural | 05 | Energy | 10 | Energy | 1010 | Energy |
| 31 | Utilities | 06 | Utilites | 55 | Utilities | 5510 | Utilities |
| 32 | Communication | 07 | Telecom | 50 | Telecommunication Services | 5010 | Telecommunication Services |
| 33 | Personal Services | 01 | Consumer Non-Durable | 25 | Consumer Discretionary | 2530 | Consumer Services |
| 34 | Business Services | 08 | Business Equipment & Services | 20 | Industrials | 2020 | Commercial Services & Supplies |
| 35 | Computers | 08 | Business Equipment & Services | 45 | Information Technology | 4520 | Technology Hardware & Equipment |
| 36 | Computer Software | 08 | Business Equipment & Services | 45 | Information Technology | 4510 | Software & Services |
| 37 | Electronic Equipment | 08 | Business Equipment & Services | 45 | Information Technology | 4530 | Semiconductors & Equipment |
| 38 | Measuring & Control | 08 | Business Equipment & Services | 45 | Information Technology | 4520 | Technology Hardware & Equipment |
| 39 | Business Supplies | 04 | Manufacturing | 20 | Industrials | 2020 | Commercial Services & Supplies |
| 40 | Shipping Containers | 04 | Manufacturing | 20 | Industrials | 2030 | Transportation |
| 41 | Transportation | 04 | Manufacturing | 20 | Industrials | 2030 | Transportation |
| 42 | Wholesale | 09 | Wholesale & Retail | 25 | Consumer Discretionary | 2550 | Retailing |
| 43 | Retail | 09 | Wholesale & Retail | 25 | Consumer Discretionary | 2550 | Retailing |
| 44 | Restaurants & Hotels | 09 | Wholesale & Retail | 25 | Consumer Discretionary | 2530 | Consumer Services |
| 45 | Banking | 10 | Finance | 40 | Financials | 4010 | Banks |
| 46 | Insurance | 10 | Finance | 40 | Financials | 4030 | Insurance |
| 47 | Real Estate | 10 | Finance | 40 | Financials | 4040 | Real Estate |
| 48 | Trading | 10 | Finance | 40 | Financials | 4020 | Diversified Financials |
| 49 | Miscellaneous | 04 | Manufacturing | 99 | Miscellaneous | 9999 | Miscellaneous |

Notes: Table 2.20 provides a mapping of the Fama and French 49 industry portfolios to Kacperczyk, Sialm, and Zheng (2005) 10 sector, GICS 10 sector, and GICS 24 industry portfolios.

Table 2.21 reports investor sentiment predictability of alternative sector and industry portfolio returns. Equation 2.2 runs a regression of excess industry returns on a constant, investor sentiment, and the market-risk premium. The table reports the $a_1$ regression coefficients from Equation 2.2 for the indicated *k*-week lags. Bold indicates statistical significance of 10 percent or greater estimated with White (1980) standard errors. The bottom two rows of the table report the total number of statistically significant coefficients for all sector and industry groups. The results reported in Table 2.21 compare directly with results previously reported for the Fama and French 49 industries in Table 2.4. Results for investor sentiment predictability of alternative industry returns remain fundamentally unaltered from the previous analysis. All sector and industry groups have significantly positive predictability at a one-week lag. Predictability at 8-week and 13-week lags remains mostly negative. Longer-term predictability at 26 and 52 weeks is almost non-existent. Analysis of alternative industry classifications continues to support the main results.

**Table 2.21 Investor sentiment predictability using alternative industries**

| | 1 week | | | 8 week | | | 13 week | | | 26 week | | | 52 week | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** | **AAII** | **II** | **BW** |
| **Kacperczyk, Sialm, Zheng (2005):** | | | | | | | | | | | | | | | |
| Consumer Staples | **0.016** | **0.014** | **0.001** | 0.002 | -0.002 | **-0.001** | 0.000 | -0.003 | -0.001 | 0.001 | 0.001 | 0.000 | -0.001 | 0.000 | 0.000 |
| Consumer Durables | **0.020** | **0.019** | **0.002** | 0.003 | -0.003 | **-0.001** | -0.002 | -0.003 | -0.001 | -0.002 | -0.001 | 0.000 | **-0.005** | -0.004 | -0.001 |
| Healthcare | **0.020** | **0.016** | **0.002** | 0.002 | **-0.006** | 0.000 | **-0.007** | **-0.007** | -0.001 | -0.001 | 0.000 | 0.000 | **-0.010** | **-0.011** | -0.001 |
| Manufacturing | **0.018** | **0.016** | **0.001** | 0.003 | 0.000 | -0.001 | 0.001 | -0.001 | 0.000 | -0.002 | 0.001 | 0.000 | -0.004 | 0.000 | 0.000 |
| Energy | **0.013** | **0.019** | -0.001 | **0.014** | **0.014** | 0.000 | **0.008** | **0.012** | 0.000 | -0.002 | 0.002 | **0.003** | -0.004 | 0.001 | 0.002 |
| Utilites | **0.005** | **0.005** | 0.000 | 0.002 | 0.003 | 0.000 | 0.003 | **0.005** | 0.000 | 0.002 | 0.002 | -0.001 | 0.000 | **0.004** | 0.000 |
| Telecom | **0.015** | **0.012** | **0.003** | **-0.006** | **-0.008** | -0.001 | **-0.009** | **-0.012** | 0.001 | 0.000 | 0.000 | 0.002 | -0.004 | 0.000 | 0.000 |
| Business Equip & Services | **0.021** | **0.012** | **0.003** | -0.002 | **-0.007** | 0.000 | **-0.010** | **-0.011** | 0.000 | -0.001 | -0.002 | 0.001 | **-0.007** | -0.006 | -0.001 |
| Wholesale & Retail | **0.018** | **0.019** | **0.001** | 0.002 | -0.001 | **-0.001** | -0.001 | -0.003 | **-0.001** | -0.001 | 0.001 | 0.000 | -0.002 | -0.001 | -0.001 |
| Finance | **0.013** | **0.012** | **0.001** | 0.001 | -0.003 | **-0.001** | **-0.003** | -0.003 | **-0.001** | -0.002 | -0.001 | 0.000 | **-0.004** | -0.003 | 0.000 |
| **GICS Sector Classification:** | | | | | | | | | | | | | | | |
| Energy | **0.015** | **0.017** | **-0.002** | **0.015** | **0.012** | 0.000 | **0.012** | **0.016** | 0.000 | 0.005 | 0.004 | **0.002** | -0.001 | 0.003 | 0.001 |
| Materials | **0.015** | **0.017** | 0.001 | **0.008** | **0.008** | 0.000 | 0.003 | 0.005 | -0.001 | -0.005 | 0.002 | **0.001** | -0.004 | 0.001 | 0.001 |
| Industrials | **0.018** | **0.015** | **0.001** | 0.003 | -0.001 | -0.001 | 0.000 | -0.002 | 0.000 | -0.001 | 0.000 | 0.000 | **-0.004** | -0.001 | 0.000 |
| Consumer Durables | **0.019** | **0.019** | **0.002** | 0.002 | -0.002 | **-0.001** | -0.002 | -0.004 | **-0.001** | -0.001 | 0.000 | 0.000 | -0.003 | -0.002 | **-0.001** |
| Consumer Staples | **0.013** | **0.011** | 0.000 | 0.004 | -0.001 | -0.001 | 0.002 | 0.000 | -0.001 | 0.003 | 0.002 | 0.000 | 0.001 | 0.000 | 0.000 |
| Healthcare | **0.020** | **0.016** | **0.002** | 0.002 | **-0.006** | 0.000 | **-0.007** | **-0.007** | -0.001 | -0.001 | 0.000 | 0.000 | **-0.010** | **-0.011** | -0.001 |
| Financials | **0.013** | **0.012** | **0.001** | 0.001 | -0.003 | **-0.001** | -0.003 | -0.003 | **-0.001** | -0.002 | -0.001 | 0.000 | **-0.004** | -0.003 | 0.000 |
| Information Technology | **0.022** | **0.012** | **0.003** | -0.003 | **-0.007** | 0.000 | **-0.011** | **-0.011** | 0.000 | -0.001 | -0.002 | 0.001 | **-0.007** | -0.006 | -0.001 |
| Telecom | **0.015** | **0.012** | **0.003** | **-0.006** | **-0.008** | -0.001 | **-0.009** | **-0.012** | 0.001 | 0.000 | 0.000 | 0.002 | -0.004 | 0.000 | 0.000 |
| Utilities | **0.005** | **0.005** | 0.000 | 0.002 | 0.003 | 0.000 | 0.003 | **0.005** | 0.000 | 0.002 | 0.002 | -0.001 | 0.000 | **0.004** | 0.000 |
| **GICS Industry Classification:** | | | | | | | | | | | | | | | |
| Energy | **0.015** | **0.017** | **-0.002** | **0.015** | **0.012** | 0.000 | **0.012** | **0.016** | 0.000 | 0.005 | 0.004 | **0.002** | -0.001 | 0.003 | 0.001 |
| Materials | **0.015** | **0.017** | 0.001 | **0.008** | **0.008** | 0.000 | 0.003 | 0.005 | -0.001 | -0.005 | 0.002 | **0.001** | -0.004 | 0.001 | 0.001 |
| Capital Goods | **0.020** | **0.017** | **0.001** | **0.005** | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 | -0.002 | 0.002 | 0.000 | **-0.005** | 0.000 | 0.000 |
| Commercial Services | **0.016** | **0.013** | **0.001** | 0.002 | -0.003 | 0.000 | -0.002 | **-0.006** | 0.000 | 0.000 | -0.001 | 0.000 | -0.003 | -0.002 | 0.000 |
| Transportation | **0.016** | **0.011** | **0.001** | -0.002 | **-0.006** | **-0.002** | 0.000 | **-0.005** | -0.001 | -0.002 | -0.003 | 0.000 | -0.002 | -0.001 | 0.000 |
| Automobiles & Components | **0.020** | **0.018** | **0.002** | 0.002 | -0.004 | **-0.001** | 0.000 | -0.003 | -0.001 | -0.001 | 0.001 | 0.000 | -0.004 | -0.002 | 0.000 |
| Consumer Durables & Apparel | **0.020** | **0.020** | **0.002** | 0.002 | -0.003 | **-0.001** | -0.002 | -0.005 | -0.001 | -0.003 | -0.002 | 0.000 | -0.004 | -0.003 | -0.001 |
| Consumer Services | **0.019** | **0.019** | **0.001** | 0.001 | -0.001 | **-0.001** | -0.003 | **-0.004** | **-0.001** | -0.002 | 0.001 | 0.000 | -0.003 | -0.003 | -0.001 |
| Media | **0.018** | **0.016** | **0.002** | 0.002 | -0.003 | **-0.001** | 0.000 | **-0.004** | 0.000 | 0.003 | 0.001 | 0.000 | 0.000 | 0.001 | **-0.001** |
| Retailing | **0.020** | **0.020** | **0.001** | 0.002 | -0.002 | **-0.001** | -0.002 | -0.002 | **-0.001** | -0.001 | 0.000 | 0.000 | -0.003 | -0.002 | -0.001 |
| Food & Staples Retailing | **0.010** | **0.011** | 0.001 | 0.002 | -0.002 | **-0.001** | 0.000 | -0.003 | 0.000 | 0.001 | 0.002 | 0.000 | **-0.003** | -0.002 | 0.000 |
| Food, Beverages, & Tobacco | **0.013** | **0.011** | 0.000 | 0.004 | -0.001 | -0.001 | 0.002 | 0.000 | -0.001 | 0.004 | 0.002 | 0.000 | 0.002 | 0.000 | 0.000 |
| Healthcare | **0.018** | **0.015** | **0.002** | 0.002 | **-0.007** | -0.001 | **-0.005** | **-0.010** | **-0.001** | -0.001 | -0.002 | 0.000 | **-0.008** | **-0.009** | -0.001 |
| Pharmaceuticals | **0.024** | **0.018** | 0.002 | 0.002 | -0.003 | 0.000 | **-0.010** | -0.003 | -0.001 | -0.001 | 0.003 | 0.001 | **-0.015** | **-0.016** | -0.002 |
| Banks | **0.009** | **0.009** | 0.000 | 0.000 | **-0.004** | **-0.001** | -0.003 | **-0.004** | **-0.001** | -0.002 | -0.003 | 0.000 | **-0.005** | **-0.007** | 0.000 |
| Diversified Financials | **0.012** | **0.011** | **0.001** | -0.002 | -0.001 | 0.000 | **-0.005** | -0.004 | **-0.001** | **-0.005** | -0.003 | **0.001** | **-0.005** | -0.001 | 0.000 |
| Insurance | **0.010** | **0.010** | 0.000 | 0.002 | -0.001 | **-0.001** | -0.003 | -0.003 | **-0.001** | -0.001 | -0.002 | -0.001 | -0.001 | -0.003 | -0.001 |
| Real Estate | **0.020** | **0.019** | **0.002** | 0.003 | -0.003 | **-0.002** | -0.003 | -0.002 | 0.000 | -0.002 | 0.002 | 0.000 | -0.005 | -0.003 | 0.000 |
| Software & Services | **0.021** | **0.012** | **0.004** | -0.006 | **-0.010** | 0.000 | **-0.016** | **-0.012** | -0.001 | 0.001 | 0.001 | 0.001 | **-0.007** | -0.006 | **-0.002** |
| Technology Hardware & Equipment | **0.022** | **0.010** | **0.003** | -0.002 | **-0.009** | 0.000 | **-0.009** | **-0.013** | 0.000 | -0.001 | -0.004 | 0.001 | **-0.008** | **-0.008** | -0.001 |
| Semiconductors & Equipment | **0.022** | **0.014** | **0.003** | -0.001 | -0.001 | 0.000 | **-0.009** | -0.007 | 0.001 | -0.002 | 0.000 | 0.002 | -0.006 | -0.003 | 0.000 |
| Telecommunication Services | **0.015** | **0.012** | **0.003** | **-0.006** | **-0.008** | -0.001 | **-0.009** | **-0.012** | 0.001 | 0.000 | 0.000 | 0.002 | -0.004 | 0.000 | 0.000 |
| Utilities | **0.005** | **0.005** | 0.000 | 0.002 | 0.003 | 0.000 | 0.003 | **0.005** | 0.000 | 0.002 | 0.002 | -0.001 | 0.000 | **0.004** | 0.000 |
| Other | **0.021** | **0.019** | **0.002** | 0.004 | -0.001 | 0.000 | 0.001 | 0.000 | **-0.001** | 0.002 | 0.002 | 0.001 | -0.004 | -0.004 | 0.000 |
| **Total Significant Positive** | 44 | 44 | 30 | 6 | 5 | 0 | 3 | 6 | 0 | 0 | 0 | 6 | 0 | 3 | 0 |
| **Total Significant Negative** | 0 | 0 | 2 | 3 | 12 | 16 | 14 | 15 | 11 | 1 | 0 | 0 | 16 | 6 | 3 |

Notes: Table 2.21 reports the a1 slope coefficients estimated with Equation 2.2. The analysis runs a regression of excess sector/industry returns on a constant, the indicated sentiment measures at different k-week lags, and the market-risk premium. The table reports results for sector and industry groups formed by mapping the Fama and French 49 industries alternatively to the Kacperczyk, Sialm, and Zheng (2005), GICS sector and GICS industry classifications, as Table 2.20 details. Sentiment measures are from the American Association of Independent Investors (AAII), Investors Intelligence (II), and Baker and Wurgler (BW). Bold indicates 10 percent or greater statistical significance estimated with White (1980) standard errors.

## 2.11 Conclusion

This study examines the interaction between investor sentiment and industry performance. As no universally accepted measure exists, the study examines return predictability using three popular investor sentiment measures. These measures are from the American Association of Independent Investors, Investors Intelligence and Baker and Wurgler (2006). First, the results confirm that investor sentiment positively predicts short-term and negatively predicts long-term market returns. The results also confirm that equal-weighted indices, in which small-cap stocks have a greater weight, are more susceptible to investor sentiment. Next, the results document widespread investor sentiment predictability of industry performance. At a one-week horizon, investor sentiment positively predicts performance for most industries. As expected, at long horizons, investor sentiment predicts negative industry performance. Interestingly, predictable performance differs between bull and bear markets, with greater predictability of reversals during bear markets. Additionally, in contrast to previous market studies, there is no evidence that industry-wide characteristics, which act as a proxy for valuation uncertainty, attract investor sentiment. Lastly, the study evaluates the practical application of an industry rotation strategy using investor sentiment. The strategy holds self-financing portfolios that are long (short) industries with the least (greatest) exposure to time-variant investor sentiment. Strategy performance ranges from 3 to 6 percent for different holding periods, which turnover and transaction costs would quickly dissipate.

Overall, the study provides limited evidence of cross-sectional differences in investor sentiment predictability of industry performance and questions the practical application of investor sentiment in industry allocations. Better understanding how investor sentiment drives industry performance would require industry-specific measures of investor sentiment. For now, this remains a topic for further research.

# Chapter 3 Political Cycles in U.S. Industry Returns

## 3.1 Introduction

The popular press regularly features articles on the outlook for financial markets prior to U.S. presidential elections. A common perception is that stocks perform better under Republican presidents. In a seminal study, Hibbs (1977) states, “the Republican Party is generally viewed as being responsive to the interests of capital or business,” while “the Democratic Party has relatively close connections to organized labor and lower-income [groups].” Characteristic of that view, financial analysts regarded the 2004 Republican presidential candidate as “very pro-investment” and the Democratic candidate as negative for “market psychology.”[39] Investor response to election news adds support to the popular belief that stocks perform best under Republican mandates. A study by Snowberg, Wolfers, and Zitzewitz (2008) provides evidence that “Republicans have consistently been the party of capital.” Analyzing presidential elections from 1880–2004, they find that the stock market increases in value 2 percent more with news of a Republican victory than following news of a Democratic victory.

However, empirical studies of political cycles in the U.S. stock market observe two important stylized facts. First, in presidential cycles,[40] the stock market performs better under Democratic presidents. Empirical research, since Herbst and Slinkman (1984) and most recently Santa-Clara and Valkanov (2003), documents systematic stock market underperformance for Republican presidents. Second, in quadrennial cycles,[41] the stock market performs better in the latter half of a four-year presidential term, irrespective of a president’s political affiliation. Politicians seeking reelection seemingly manipulate the economy to bolster investor support before elections. Since Nordhaus (1975) and Hibbs (1977), empirical research has documented four-year stock market cycles centered on presidential elections.[42]

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[39] http://www.businessweek.com/bwdaily/dnflash/jul2004/nf2004079_2333_db035.htm
http://money.cnn.com/2004/01/29/markets/election_kerrystocks/

[40] Also referred to in the literature as partisan cycles

[41] Also referred to in the literature as opportunistic cycles

[42] The “Stock Trader’s Almanac,” published by Yale Hirsch, originally popularized the “Presidential Cycle” trading strategy. http://www.investopedia.com/articles/financial-theory/08/presidential-election-cycle.asp

While the literature extensively documents political cycles, systematic patterns in financial assets pose a challenge to market efficiency. Santa-Clara and Valkanov (2003) thoroughly investigate whether political cycles in the general stock market serve as a proxy for business cycles, but find the two cycles unrelated. Additionally, Santa-Clara and Valkanov (2003) examine whether expected returns explain political stock market cycles, concluding that higher returns during Democratic administrations systematically surprise investors. Cooper, McConnell, and Ovtchinnikov (2006) investigate the relationship between the January effect and political stock market cycles, finding no relationship between the two anomalies. Political stock market cycles, and the mechanism through which politics affects stock returns, remain an unresolved puzzle.

This study investigates industry returns for evidence of political cycles, which potentially will explain documented evidence of political stock market cycles. As Santa-Clara and Valkanov (2003) observe, political stock market cycles can comprise both unexpected and expected elements. Initially, the analysis examines realized industry returns for evidence of presidential and quadrennial cycles. The data covers 21 presidencies from 1926–2006. Unexpected stock market performance can occur over time when Democratic or Republican policies positively or negatively surprise investors (Santa-Clara and Valkanov (2003)). For instance, a positive surprise would result if investors anticipate Democratic investment taxes that ultimately fail to materialize. Dominant industries, with cash flow sensitivity to policy surprises, in turn could potentially explain political cycles, which previous studies attribute to the general stock market. The analysis also includes an event study, to provide insight into whether the election of a Democratic or Republican president causes differences in expected industry performance. In efficient markets, stock prices should immediately reflect expected returns. Therefore, if investors anticipate differential industry performance between Democratic and Republican presidents, stock prices will reflect that difference upon election resolution. Differences in expected returns can arise due to a political risk premium, changes in expected [industry] cash flows, or both (Santa-Clara and Valkanov (2003)). As an illustration, if defense industry cash flows systematically increase under Republicans, then defense stock prices should increase with the election of a Republican president. Alternatively, differences in expected returns might merely reflect unsubstantiated beliefs on politically driven industry performance. To measure how political cycles affect expected industry returns, the analysis examines industry performance surrounding the closely contested and politically divergent 2004 Bush-Kerry election.

The results document the absence of political cycles in industry returns. The results confirm prior empirical studies, which document that the stock market performs better for Democrats and in the latter half of any presidency. In line with Santa-Clara and Valkanov (2003), stock market returns are 8.6 percent higher under Democratic presidents. Stock market returns are 10 percent higher in the second half of any presidency. Similar to the market, unadjusted industry returns are also higher under Democrats and the second half of any presidency. However, after correcting industry returns for risk with a Fama and French three-factor model, industry returns do not exhibit statistically significant returns over presidential or quadrennial cycles. There is also no evidence of significant differences in expected industry performance over the days immediately surrounding the 2004 election of a Republican president. The event-study analysis groups industries by political orientation based on past performance, political campaign contributions, and analyst recommendations. No matter the grouping, there is only scant evidence of statistically significant differences in expected industry returns following the 2004 election. Industries that have previously performed better under Republican presidents generate the highest excess returns – but only insignificantly so. The overall lack of statistically significant excess returns surrounding the election indicates that investors do not take political outcomes as a signal of expected industry performance.

The results question the popular belief that political cycles drive industry performance and provide evidence that political cycles are solely market-wide phenomena, best explained at the macroeconomic level. Systematic differences in macroeconomic policies between Democrats and Republicans may provide an answer to the puzzling feature of political business cycles in the data.

### 3.2 Literature Review and Hypotheses Development

The literature documents two political stock market cycles: presidential cycles and quadrennial cycles.[43] Presidential cycles depend on a president's political party. Democratic and Republican Party social and economic agendas determine presidential cycles. Figure 3.1 illustrates average market returns for the past 21 presidential administrations. Stock market returns are above average for 80 percent of Democratic presidencies. In contrast, stock market returns are below average for 65 percent of Republican presidencies. A Republican was president during the 1929 and 1987 stock market crashes. The 1969–1974 bear market also occurred under a Republican president. Conversely, a Democrat was president during the 1960s and 1990s bull markets (Gross (2004)). Niederhoffer, Gibbs, and Bullock (1970) provide evidence of systematic and statistically significant Democratic outperformance.

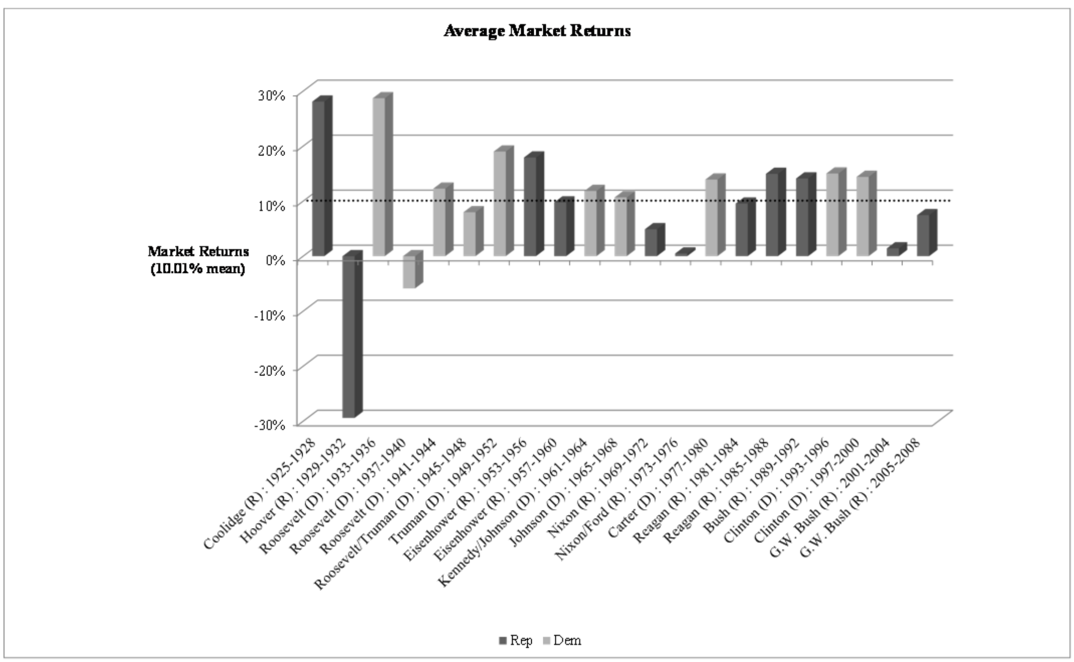
An influential study by Santa-Clara and Valkanov (2003) investigates election cycles in the U.S. stock market across 18 presidential elections from 1927 to 1998. The central finding of Santa-Clara and Valkanov (2003) is that the stock market performs systematically better during Democratic presidencies. As a possible explanation, Santa-Clara and Valkanov (2003, pg. 1842) investigate whether the difference in market outperformance is due to a "Democratic risk premium." Higher market volatility during Democratic presidencies would indicate that excess returns were merely rational compensation for risk. However, Santa-Clara and Valkanov (2003) observe that stock market volatility actually decreases under Democrats. Santa-Clara and Valkanov (2003) confirm that presidential cycles are independent of normal business cycles. Lastly, Santa-Clara and Valkanov (2003) examine the response of investors to election outcomes, documenting no difference in expected returns with the election of a Democratic president. Santa-Clara and Valkanov (2003, pg. 1870) conclude, "The small market reaction to election news is difficult to reconcile in a rational-expectations framework."

Quadrennial cycles depend on the year of a four-year presidential term**.** Self-serving political agendas determine quadrennial cycles. Booth and Booth (2003) and Gärtner

[43] Alesina, Roubini, and Cohen (1997) and Drazen (2000) provide good surveys of political stock market cycles.

and Wellershoff (1995) document higher stock market returns in the latter half of any presidential term. Nordhaus (1975) and Alesina (1989) conjecture that politicians, motivated by reelection desires, generate political cycles through manipulative economic policies. For instance, politicians seeking reelection lower interest rates to increase employment. After the election, they then increase interest rates to restore the economy to sustainable growth levels. Ideologically, investors view Democrats as favoring low unemployment at the expense of higher inflation and Republicans as doing the opposite (Hibbs (1977)). A number of studies provide empirical evidence of quadrennial cycles. Allvine and O'Neil (1980) use Standard & Poor's 400 data from 1948 to 1978. Their study documents stronger evidence of quadrennial cycles in the latter half of their sample, attributed to more adroit political macroeconomic manipulation. A later study by Beyer, Jensen, and Johnson (2008) confirms quadrennial cycles in small-cap and large-cap market indices with data from 1957 to 2004. Most recently, Beyer, Jensen, and Johnson (2008) show that quadrennial cycles are most evident in small-cap stocks and during the third year of a presidency.

**Figure 3.1 Value-weighted market returns by U.S. presidential administration**




Notes: Figure 3.1 depicts market performance reported for presidential administrations over the sample period from July 1927 to June 2006.

The mechanism through which political cycles act on stock market returns remains an open question.[44] Investors systematically appear to ignore the empirical fact that stocks perform better under Democrats. Santa-Clara and Valkanov (2003) find no significant difference in expected market returns resulting from presidential elections. Additionally, they find no evidence that political stock cycles reflect differences in expected returns related to business cycle fluctuations. Rather, Santa-Clara and Valkanov (2003) observe that unexpected returns fully explain the return differential between Democratic and Republican administrations. Unexpected returns can result from political agendas that surprise the market or from investor inattention to previous political stock cycles. A logical question one could then ask is why investors fail to anticipate the impact of presidential elections on the stock market. A political risk premium could potentially account for systematically higher market performance under Democrats. However, counter to that argument, Leblang and Mukherjee (2004) and Santa-Clara and Valkanov (2003) actually document lower stock market volatility when a Democrat holds office. In the absence of a risk premium explanation, systematically higher market returns under Democrats leave an unanswered puzzle and a gap in the literature. This study attempts to fill that gap, by investigating whether industry performance provides any additional insight into political stock cycles.

Industry cash flows can provide a direct mechanism for political cycles to act on stock returns. Certain industries, with cash flow sensitivity to political agendas, can potentially drive political stock market cycles. Democrats and Republicans, for instance, have distinctive agendas for health care and national defense. Political agendas, thus, can significantly affect the profitability of those highly capitalized industries. As an example, defense spending increased by 40 percent under a Republican president from 1981–1989.[45] Similarly, quadrennial cycles potentially affect the cash flows of industries most sensitive to interest rate adjustments, such as the finance and construction industries. Herron, Lavin, Cram, and Silver (1999), observing the 1992 election, find investors capitalize election probabilities differently across industries. Defense, aerospace, finance, and pharmaceuticals were the most politically sensitive

[44] See the conclusions of Santa-Clara and Valkanov (2003) for a complete discussion.
[45] http://en.wikipedia.org/wiki/Ronald_Reagan

industries at that time. Industry returns around key election events reflect changes in expected returns. For example, financial analysts considered a 2004 Republican victory positive for energy, utilities, and pharmaceuticals.[46] Those industries surged in value an average 4.5 percent following the Republican convention and renomination of George W. Bush.[47] Industry cash flow sensitivity to political agendas suggests a role for industries in describing political stock market cycles.

The above discussion leads to a formal statement of this study's null and alternative hypotheses.

**$H_0$**: There is no relationship between presidential election cycles and industry returns.
**$H_1$**: The political affiliation of a president determines industry returns.
**$H_2$**: The year of a presidential term in office determines industry returns.
**$H_3$**: Presidential elections determine investor expectations of future industry returns.

### 3.3 Results for the General Market

The principal purpose of this section is to replicate and verify prior research, such as Santa-Clara and Valkanov (2003), documenting political cycles in US stock market indices. Santa-Clara and Valkanov (2003) document three central findings: market returns are higher under Democrats; there is a small capitalization stock premium under Democratic presidents; and market returns are higher the second half of any presidential term.

If stock markets follow a random walk, information on whether a president is a Democrat or Republican or the year of a presidential term should have no effect on expected returns. Therefore, empirical studies, such as Santa-Clara and Valkanov (2003), that document a correlation between political election cycles and general stock market returns contradict financial theory. Consider, for instance, the simple regression equation

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[46] As a further illustration, the largest Swiss bank, Banque Vontobel, introduced two mutual funds in 2000. The Bush fund held stocks in industries expected to benefit under Republicans: Philip Morris, Pfizer, Microsoft, General Dynamics, Lockheed Martin and International Paper. The Gore fund held stock in industries expected to benefit under Democrats: Merck, Fannie Mae, Freddie Mac, Devry Inc, Ballard and United Technologies.
[47] CNN Money provides a detailed account of market expectations for a Republican victory. http://money.cnn.com/2004/08/30/markets/election_stocks/index.htm\

$$R_t = \alpha_0 + \alpha_1 RPD_t + \varepsilon_t \tag{Eq. 3.1}$$

where excess market returns ($R$) are regressed on a constant and a presidential cycle dummy variable ($RPD$), with the usual white-noise error term ($\varepsilon$) controlled for heteroskedasticity and autocorrelation following Newey and West (1987). The presidential cycle dummy variable ($RPD$) takes the value of one under a Republican president and zero otherwise. The intercept $\alpha_0$ represents average returns under Democrats and the $\alpha_1$ coefficient represents the marginal difference in returns between Republicans and Democrats. If the simple regression equation holds, whether a president is a Republican or Democrat should not have a systematic effect on stock returns and $\alpha_1$ should equal zero. In efficient markets, returns should follow a random walk. Consequently, political variables should contain no explanatory power. Similarly, consider the regression equation

$$R_t = \alpha_0 + \alpha_1 H2D_t + \varepsilon_t \tag{Eq. 3.2}$$

where excess market returns ($R$) are regressed on a constant and the quadrennial cycle dummy variable ($H2D$) with the same Newey and West (1987) adjusted standard errors as above. The quadrennial cycle dummy variable ($H2D$) takes the value one during the second half of any presidential administration and zero otherwise. Here, the intercept $\alpha_0$ represents average first-half returns and the $\alpha_1$ coefficient represents the marginal difference in returns between the first and second half of a four-year U.S. presidential term. Again, in the absence of a quadrennial cycle, the year of a presidential term should not have a predictable effect on stock returns and the $\alpha_1$ coefficient should equal zero. Nevertheless, the empirical financial literature documents both presidential and quadrennial cycles in the general stock market.

The analysis of political business cycles in the general stock market covers 80 years or 21 presidential administrations, spanning 1926–2006. Panel A of Table 3.1 reports results from Equation 3.1 for the value-weighted general market index, Fama-French size and value factors, and short-term interest rates. The one-month Treasury bill from Ibbotson Associates proxies the risk free rate. The size factor SMB (small minus big) and value factor HML (high minus low) are well-known risk factors described by Fama and French (1993). The value-weighted market and industry returns, the one-month Treasury bill rate, size factor, and value factor come from the Kenneth French website.[48]

**Table 3.1 Market descriptive statistics for presidential and quadrennial cycles**

| **Panel A: Presidential Cycle** | | | | | | |
|---|---|---|---|---|---|---|
| **Description** | **Mean** | **Std.Dev.** | **REP** | **DEM** | **DIF** | |
| Excess value-weighted market return | 6.2% | 18.9% | 1.9% | 10.6% | -8.6% | ** |
| Size factor (SMB) | 2.2% | 11.3% | -0.8% | 5.4% | -6.2% | ** |
| Value factor (HML) | 4.3% | 12.1% | 4.5% | 4.1% | 0.3% | |
| Treaury bill | 3.7% | 0.9% | 4.7% | 2.7% | 1.9% | *** |

| **Panel B: Quadrennial Cycle** | | | | | | |
|---|---|---|---|---|---|---|
| **Description** | **Mean** | **Std.Dev.** | **HLF1** | **HLF2** | **DIF** | |
| Excess value-weighted market return | 6.2% | 18.9% | 1.3% | 11.3% | -10.0% | ** |
| Size factor (SMB) | 2.2% | 11.3% | -0.1% | 4.7% | -4.8% | * |
| Value factor (HML) | 4.3% | 12.1% | 4.8% | 3.8% | 0.9% | |
| Treaury bill | 3.7% | 0.9% | 3.9% | 3.5% | 0.3% | |

Notes: Panel A of Table 3.1 reports annualized means, standard deviations, and presidential cycle results for excess value-weighted market returns, size factor (*SMB*), value factor (*HML*), and the one-month Treasury bill.[49] The sample period covers 1926–2006. Equation 3.1 estimates average excess returns for Republican (*REP*) or Democratic (*DEM*) presidencies, with a regression of excess returns (*R*) on a constant and the Republican dummy variable (*RPD*). The presidential cycle dummy variable (*RPD*) takes the value of one under a Republican president and zero otherwise. The $\alpha_0$ intercept measures Democratic (*DEM*) performance, $\alpha_1$ measures marginal Republican performance (*DIF*), and ($\alpha_0 + \alpha_1$) measures Republican (*REP*) performance. Panel B reports annualized means, standard deviations, and quadrennial cycle results for excess value-weighted market returns, size factor (*SMB*), value factor (*HML*), and the one-month Treasury bill. The sample period covers 1926–2006. Equation 3.2 estimates average returns excess for the first half (*HLF1*) or second half (*HLF2*) of a four-year U.S. presidential cycle, with a regression of excess returns (*R*) on a constant and the timing variable (*H2D*). The quadrennial cycle variable (*H2D*) takes the value of one during the second half of a four-year U.S. presidential cycle and zero otherwise. The intercept $\alpha_0$ measures average first-half performance, $\alpha_1$ measures the marginal difference (*DIF*) in returns between first-half and second-half performance, and ($\alpha_0 + \alpha_1$) measures second-half (*HLF2*) performance. Panel A and Panel B indicate statistically significant differences (*DIF*) at 1%***, 5%**, and 10%* based on Newey and West (1987) heteroskedasticity and autocorrelation corrected test-statistics.

For the entire period, excess market returns over the one-month Treasury-bill rate average 6.2 percent per annum. However, average excess returns of 10.6 percent for Democrats are much higher than average excess returns of 1.9 percent for Republicans. The difference represents an economically large and statistically significant outperformance of 8.6 percent for Democrats. Similarly, Santa-Clara and Valkanov (2003) document a 9 percent difference in returns between Democrats and Republicans using monthly returns for the AMEX, NYSE, and NASDAQ indexes from 1926 to 1998. Swensen and Patel (2004) observe annual returns from 1969-2000 for the NYSE composite and industrial, transportation, utility, and financial sub-indexes. Swensen and

[48] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[49] See Fama and French (1993) for a discussion of the (SMB) size and (HML) value factors.

Patel (2004) find average returns to the NYSE composite are 5 percent greater under Democratic administrations. Likewise, Swensen and Patel (2004) show returns for industrials (5.3%), financials (7.0%), transportation (7.2%), and utilities (10.3%) sub-indices are uniformly higher for Democratic administrations.

The results confirm that small-cap firms have higher returns under Democrats, as previous studies also show. As indicated by the SMB factor, excess returns to small-cap firms earn a 5.4 percent premium under Democrats compared with a 0.8 percent discount under Republicans. The 6.2 percent difference is economically and statistically significant. Likewise, Hensel and Ziemba (1995) find higher returns for small-cap NYSE stocks under Democratic presidents for the years 1928 to 1993. Similarly, Santa-Clara and Valkanov (2003) observe the difference in returns to size-decile portfolios between Republican and Democratic administrations. Santa-Clara and Valkanov (2003) show that, while all decile portfolios have higher returns under Democrats, relative outperformance increases monotonically from large to small capitalization. While one can argue that small-cap firms are typically more risky than large-cap firms are, any capitalization premium should be independent of a president's political affiliation. However, Santa-Clara and Valkanov (2003) show presidential cycle effects are most pronounced in small-cap firms.

The results show no indication of a glamour stock effect between Republicans and Democrats in the general stock market. A glamour effect would be evident if high-growth firms, with large market-value-to-book-value ratios, performed better under a given political party. However, a look at the HML value factor shows similar returns across administrations for Republicans (4.5%) and Democrats (4.1%).

A look at Treasury bill rates reveals slightly higher interest rates under Republican administrations. The observation comes as no surprise given Republican administrations typically pursue tighter monetary policy. Over the last 80 years, short-term interest rates average 4.7 percent under Republicans and 2.7 percent under Democrats, for an approximate 200-basis-point difference. A study by Johnson and Chittenden (1999), which covers the 1929–1996 period, likewise documents a 2.7 percent difference in interest rates favoring Republicans. Considering average market volatility of approximately 19 percent over the past eight decades, it seems unlikely, however, that such a relatively small difference in interest rates between political parties would influence stock returns. A study by Durham (2005) also concludes that the impact of "surprises" in monetary policy on stock returns is minimal compared with overall equity return volatility. Nonetheless, regardless of any marginal difference in interest rate levels between administrations, investors would have been better off investing in the general market rather than short-term Treasury bills under either Democrats or Republicans.

Additionally, the analysis investigates the general stock market index for evidence of quadrennial cycles. Systematically different returns over presidential terms could indicate that incumbent presidents, irrespective of political party, manipulate the economy to improve chances for reelection. Panel B of Table 3.1 reports results from Equation 3.2 for the general market index, the Fama-French factors, and interest rates. While excess market returns average 6.2 percent from 1926 to 2006, most appreciation occurs during the second half of a presidential term. The results show an economically and statistically significant 10 percent difference in excess returns between the first (1.3%) and second half (11.3%) of a presidential term.

The results confirm the work of previous studies that document quadrennial cycles in stock returns. Research by Allvine and O'Neil (1980), Huang (1985), Johnson and Chittenden (1999), and Booth and Booth (2003), among others, find four-year asset return cycles coinciding with presidential administrations for the general market. Swensen and Patel (2004) observe quadrennial cycles in the NYSE composite index, as do Hensel and Ziemba (1995) in large-cap and small-cap stocks.

While most previous research finds evidence of a quadrennial cycle in asset returns, there are exceptions. In his study, Banning (2002) finds no statistically significant difference between first- and second-half returns using daily data for the Dow Jones Industrial Average covering the 1897–2000 period. The choice of short-frequency data perhaps explains the inconsistency with other studies, which typically use less noisy longer horizon monthly or quarterly data. Interestingly, the Banning (2002) study finds a statistically significant difference in returns during a president's first complete term in office compared with subsequent terms.

As with the investigation of presidential cycles, this study also considers the correlation between quadrennial cycle and market cap, market values, and Treasury bill rates. The SMB size-factor confirms a statistically significant 4.8 percent higher second-half return to small stocks. However, as with presidential cycles, no value effect is evident in quadrennial cycles. Treasury bill rates are constant across presidential terms, at 3.9 percent and 3.5 percent for the first and second half.

To summarize, the empirical results to this point confirm a systematic relationship between market performance and both a president's political affiliation and the year of a president's term. Notably, contrary to popular belief, general stock market indices perform better under a Democratic president. A political effect is even more evident with small-cap stocks than large-cap stocks. As previous studies also show, interest rates are higher with a Republican in the White House. Additionally, stock market returns are higher during the second half of a four-year presidential term, regardless of political affiliation.

While the literature documents presidential and quadrennial cycles, financial theory fails adequately to explain the existence of these political cycles. Studies put forth a number of different theories as explanations. One possible explanation is that political cycles may simply track business cycles. To correct for this possibility, Santa-Clara and Valkanov (2003) include well-known business-cycle variables in their model. Surprisingly, even with the addition of dividend yield, term-spread, default-spread, and relative interest rate variables, Santa-Clara and Valkanov (2003) find results for presidential cycles are more robust. They conclude that political cycles are unrelated to recurring business cycles.

Another argument, in a risk and return paradigm, is that higher returns under Democratic administrations are simply compensation for additional risk, as measured by increased stock volatility. However, in contrast to the expected higher volatility under Democrats required to substantiate this argument, Santa-Clara and Valkanov (2003) actually observe higher variance in stock returns under Republicans. They argue higher volatility possibly results from increased market liquidity under Republicans, given investor expectations of higher returns. A study of the 2000 U.S. presidential election

(Leblang and Mukherjee (2004)) concludes markets are less volatile when it appears a Democrat will become president.

Campbell and Li (2004) observe differences in volatility as an explanation for the presidential premium. While typically political cycle studies use OLS regressions with HAC adjusted standard errors, Campbell and Li (2004) question the validity and efficiency of OLS parameter estimates in calculating presidential cycle premiums. Alternatively, Campbell and Li (2004) use a variety of methods, such as weighted least squares (WLS) and GARCH models, to account for time variant market volatility. Generally, they conclude that the differences in returns to large stocks between Republicans and Democrats, although still persistent, are smaller than OLS estimates and lack statistical significance. However, even with different methodologies, a small-cap stock premium of 6.1 percent to 11.9 percent, depending respectively on GARCH or WLS estimates, remains relatively large and statistically significant under Democratic administrations.

Other studies consider whether differences in excess returns between political parties represent conditional differences in investor expectations. Riley and Luksetich (1980) use Standard & Poor’s 500 return data from 1900 to 1976 to conduct an event study surrounding key election days. Riley and Luksetich (1980) observe that although the market responds favorably in the short term to a Republican victory, investors show no long-term political preference except possibly for an incumbent. Similarly, Santa-Clara and Valkanov (2003) look at market reaction in the days surrounding presidential elections from 1926 to 1998. They conclude the market does not price election outcomes. Differences in investor expectations, given the party in power, inadequately explain the systematically large and seemingly unexpected general stock market returns that favor Democratic administrations.

The literature provides few alternative explanations of what might cause documented quadrennial cycles. Allvine and O'Neil (1980) argue that partially efficient markets explain the persistence of four-year cycles. They suggest short-sale restrictions faced by institutional investors limit the ability to exploit downside opportunities during the first half of an administration. Moreover, they argue that investor limitations in processing copious amounts of political information distort otherwise efficient markets. Swensen and Patel (2004) look at inflation rates and required real rates of returns. While inflation rates are higher in the last two years of a presidency, particularly during Republican administrations, they find real returns remain larger and statistically significant. Lastly, Swensen and Patel (2004) suggest quadrennial cycles may partially be explained by control of the Congress. However, the presence of quadrennial cycles, like presidential cycles, in the data remains largely unexplained.

The above analysis confirms the presence of political stocks previously documented in the literature. In the sections that follow, the analysis investigates industry returns as a possible explanation for political cycles in the general stock market. If political effects are exceptionally strong in dominant industries, the observed market-wide phenomenon might be only industry specific. If political effects were industry specific, industry returns should remain significant after correcting for general market movements and should persist across sub-periods. Otherwise, general macroeconomic determinants might provide a more likely explanation. Therefore, the analysis first tests whether political and quadrennial cycles are present in industry returns after adjusting for general market movements. The initial test simply uses a single-index model. Moreover, as other studies observe that differences in returns under Democrats and Republicans are particularly large for smaller firms, additional analysis adjusts industry outperformance with the Fama-French three-factor model.

### 3.4 Industry Presidential Cycles

The industry data covers the same 1926 to 2006 period, spanning eight decades and 21 presidential administrations. The 48 industry portfolios represent all stocks included in the NYSE, AMEX, and NASDAQ indices grouped by standard industrial classifications, as the Kenneth French website describes in detail.[50]

Table 3.2 reports the basic characteristics of all 48 industries for returns in excess of the Treasury bill rate reported as annualized returns. The highest unconditional return is banking (9.3%) followed by aircraft (8.8%), beer & liquor (8.3%) and tobacco (8.3%). It is interesting to observe that within a risk and return paradigm, tobacco has the third-

[50] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html

highest return of all industries, yet it has the eighth smallest return variance and the smallest systematic risk. Conversely, real estate has the second-lowest return for all industries (0.6 percent) but a relatively large market beta.

**Table 3.2 Industry summary statistics for presidential and quadrennial cycles**

| Industry | Size | Mean | Std. Dev. | Beta | REP | DEM | DIF | | HLF1 | HLF2 | DIF | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Agriculture | 219 | 4.3% | 25.9% | 0.92 | -2.3% | 11.3% | -13.6% | ** | 0.8% | 7.9% | 7.1% | |
| Food Products | 718 | 7.1% | 17.0% | 0.74 | 7.7% | 6.6% | 1.1% | | 4.1% | 10.2% | 6.1% | |
| Beer & Liquor | 2,388 | 8.3% | 25.2% | 0.97 | 4.0% | 12.8% | -8.8% | | 7.3% | 9.3% | 2.0% | |
| Tobacco Products | 3,695 | 8.3% | 20.3% | 0.63 | 10.7% | 6.0% | 4.7% | | 6.8% | 9.9% | 3.1% | |
| Recreation | 136 | 3.4% | 33.5% | 1.21 | 1.2% | 5.7% | -4.6% | | -6.4% | 14.2% | 20.5% | ** |
| Entertainment | 347 | 6.6% | 32.2% | 1.39 | 0.9% | 12.5% | -11.6% | | 3.1% | 10.1% | 7.0% | |
| Printing and Publishing | 505 | 6.1% | 26.2% | 1.06 | 3.1% | 9.1% | -6.1% | | 4.3% | 7.9% | 3.6% | |
| Consumer Goods | 700 | 5.5% | 19.6% | 0.85 | 2.2% | 8.9% | -6.6% | | 2.0% | 9.1% | 7.1% | |
| Apparel | 162 | 6.6% | 23.8% | 0.99 | 2.1% | 11.4% | -9.3% | | 0.8% | 12.8% | 12.0% | * |
| Medical Equipment | 248 | 7.6% | 22.1% | 0.85 | 4.3% | 11.0% | -6.7% | | 6.7% | 8.5% | 1.8% | |
| Pharmaceutical Products | 879 | 7.9% | 20.5% | 0.85 | 5.5% | 10.3% | -4.8% | | 7.2% | 8.6% | 1.4% | |
| Chemicals | 723 | 6.8% | 21.7% | 1.02 | 4.1% | 9.6% | -5.5% | | 2.7% | 11.1% | 8.3% | |
| Textiles | 142 | 4.4% | 26.1% | 1.14 | -0.5% | 9.6% | -10.1% | | 0.2% | 8.8% | 8.6% | |
| Construction Materials | 267 | 5.7% | 23.3% | 1.12 | 1.6% | 10.0% | -8.4% | | 1.4% | 10.3% | 8.9% | |
| Construction | 170 | 3.8% | 32.8% | 1.35 | -5.8% | 14.4% | -20.3% | *** | -3.3% | 11.4% | 14.7% | * |
| Steel Works Etc | 311 | 4.3% | 28.0% | 1.29 | -0.6% | 9.5% | -10.0% | | -2.0% | 11.1% | 13.1% | ** |
| Machinery | 260 | 6.4% | 24.9% | 1.22 | 0.4% | 12.7% | -12.3% | ** | 0.3% | 12.9% | 12.6% | ** |
| Electrical Equipment | 522 | 7.7% | 26.5% | 1.27 | 2.9% | 12.7% | -9.8% | | 2.0% | 13.8% | 11.8% | * |
| Automobiles and Trucks | 682 | 6.4% | 26.7% | 1.19 | 1.5% | 11.5% | -10.0% | | 0.0% | 13.1% | 13.2% | * |
| Aircraft | 1,121 | 8.8% | 32.6% | 1.32 | 3.2% | 14.7% | -11.5% | | -2.6% | 21.4% | 24.0% | *** |
| Shipbuilding, Railroad Equipment | 357 | 4.5% | 27.2% | 1.12 | -2.2% | 11.5% | -13.6% | ** | -0.9% | 10.0% | 10.9% | |
| Non-Metallic & Industrial Metal Mining | 298 | 5.8% | 23.4% | 0.95 | 1.6% | 10.2% | -8.7% | | -1.5% | 13.6% | 15.2% | *** |
| Coal | 371 | 7.3% | 29.4% | 0.78 | 0.8% | 14.1% | -13.3% | ** | -0.3% | 15.4% | 15.6% | ** |
| Petroleum and Natural Gas | 1,008 | 7.5% | 21.0% | 0.86 | 1.4% | 13.8% | -12.4% | ** | 1.7% | 13.6% | 11.9% | ** |
| Utilities | 761 | 5.2% | 19.8% | 0.80 | 4.9% | 5.6% | -0.7% | | -0.1% | 10.8% | 10.9% | ** |
| Communication | 1,772 | 5.4% | 15.9% | 0.64 | 5.3% | 5.6% | -0.3% | | 2.9% | 8.0% | 5.2% | |
| Business Services | 265 | 5.9% | 26.5% | 0.96 | -1.2% | 13.5% | -14.7% | ** | 2.3% | 9.6% | 7.4% | |
| Computers | 769 | 8.1% | 25.7% | 1.10 | 2.3% | 14.2% | -11.8% | * | 3.3% | 13.1% | 9.7% | |
| Electronic Equipment | 376 | 6.0% | 30.8% | 1.37 | -4.2% | 17.2% | -21.4% | *** | 0.2% | 12.1% | 11.9% | |
| Measuring and Control Equipment | 334 | 6.6% | 24.6% | 1.01 | 0.9% | 12.7% | -11.8% | ** | 2.2% | 11.3% | 9.1% | |
| Shipping Containers | 410 | 6.9% | 21.3% | 0.94 | 7.1% | 6.7% | 0.4% | | 5.1% | 8.7% | 3.6% | |
| Transportation | 380 | 4.6% | 24.6% | 1.12 | -0.1% | 9.5% | -9.6% | | 0.4% | 9.0% | 8.6% | |
| Wholesale | 157 | 2.7% | 26.4% | 1.10 | -6.2% | 12.5% | -18.7% | *** | -1.1% | 6.7% | 7.7% | |
| Retail | 550 | 6.6% | 21.1% | 0.96 | 4.1% | 9.2% | -5.1% | | 1.5% | 11.9% | 10.4% | * |
| Restaurants, Hotels, Motels | 221 | 6.8% | 24.5% | 1.00 | 3.3% | 10.4% | -7.2% | | 0.2% | 13.8% | 13.6% | ** |
| Banking | 356 | 9.3% | 24.6% | 1.03 | 4.5% | 14.4% | -9.8% | | 4.6% | 14.3% | 9.6% | |
| Insurance | 691 | 6.3% | 25.9% | 1.10 | 1.1% | 11.8% | -10.8% | ** | 2.9% | 9.9% | 7.0% | |
| Real Estate | 78 | 0.6% | 33.2% | 1.25 | -7.5% | 9.4% | -16.8% | ** | -7.0% | 8.9% | 15.9% | * |
| Trading | 479 | 6.6% | 26.3% | 1.26 | 1.2% | 12.1% | -10.9% | * | -2.3% | 16.2% | 18.5% | *** |
| Other | 797 | 1.7% | 25.9% | 1.06 | -6.8% | 11.0% | -17.7% | *** | -4.2% | 8.0% | 12.2% | * |
| Personal Services | 147 | 3.2% | 32.3% | 1.12 | -3.4% | 10.2% | -13.6% | * | -3.8% | 10.7% | 14.5% | * |
| Rubber and Plastic Products | 108 | 6.9% | 27.0% | 1.14 | 0.9% | 12.6% | -11.7% | * | 3.2% | 10.8% | 7.6% | |
| Candy & Soda | 692 | 7.6% | 23.7% | 0.88 | 7.2% | 8.0% | -0.9% | | 5.0% | 10.4% | 5.4% | |
| Business Supplies | 631 | 3.6% | 43.0% | 1.47 | -5.5% | 12.9% | -18.4% | * | 0.9% | 6.6% | 5.7% | |
| Healthcare | 314 | 0.8% | 36.1% | 1.25 | -8.2% | 15.6% | -23.8% | * | -15.3% | 19.8% | 35.0% | *** |
| Fabricated Products | 110 | -1.0% | 24.2% | 1.10 | -5.4% | 5.7% | -11.1% | | -11.9% | 11.2% | 23.0% | *** |
| Defense | 1,121 | 5.4% | 23.6% | 0.83 | 3.6% | 8.2% | -4.6% | | 0.1% | 11.0% | 10.9% | |
| Precious Metals | 435 | 2.9% | 35.3% | 0.68 | 0.6% | 6.4% | -5.9% | | -0.1% | 6.0% | 6.1% | |

Notes: Table 3.2 reports average firm size (million USD), excess returns, standard deviation, and market beta for the full period. Equation 3.1 estimates industry performance for presidential cycles under Republican (*REP*) and Democratic (*DEM*) administrations. Equation 3.2 estimates industry performance for quadrennial cycles over the first half (*HLF1*) or second half (*HLF2*) of a four-year U.S. presidential term. The table indicates statistically significant differences (*DIF*) for presidential and quadrennial cycles at 1%***, 5%**, and 10%*, based on Newey and West (1987) heteroskedasticity and autocorrelation corrected test-statistics.

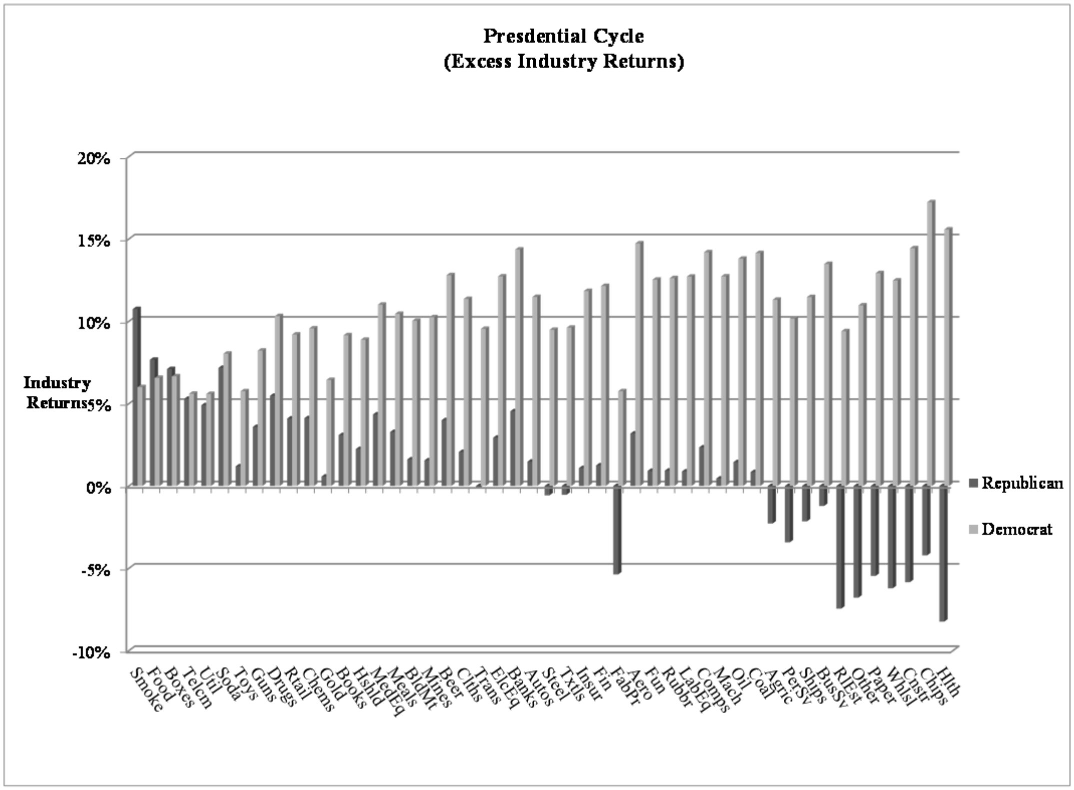
$$R_t = \alpha_0 + \alpha_1 RPD_t + \varepsilon_t \quad \text{(Eq. 3.1)}$$

Equation 3.1 runs a regression of excess returns for each of the 48 industry portfolios (*R*) on the presidential cycle dummy variable (*RPD*) previously described.

Observing conditional excess industry returns for Republicans (REP) and Democrats (DEM), reported in Table 3.2, the results – not surprisingly – show a strong outperformance of most industries under Democrats. There are notable exceptions. The largest relative outperformance in returns between administrations is tobacco (4.7%) and food products (1.1%) under Republicans. In comparison, industries with the largest relative outperformance under Democrats are healthcare (35%) and aircraft (24%). Another strong performer for Democrats, the construction industry, typified by small contractors, shows a 20.3 percent difference (DIF) over Republicans. These initial observations support conventional wisdom, which holds that Republican policies support tobacco interests and big industries such as food processing and that Democratic policies support healthcare, technology, and small-scale industries.[51] There are some surprises, however, that contradict popular perceptions. Perhaps most notably, defense shows a 4.6 percent outperformance when Democrats hold office. Likewise, natural resource extraction industries, such as coal and petroleum, show a strong performance under Democrats. Figure 3.2 illustrates industry returns sorted left to right from highest Republican outperformance to highest Democratic outperformance.

[51] "Words from the Trading Floor," CNN financial, Christine Romans, 01 September, 2004.

**Figure 3.2 Industry returns over presidential cycles**




Notes: Figure 3.2 illustrates excess industry returns over presidential cycles for Republican and Democratic presidencies estimated with Equation 3.1. The presidential cycle dummy variable (*RPD*) takes the value of one if a Republican is president and zero otherwise. The table sorts returns from left to right by the largest difference in returns between Republican administrations and Democratic administrations. The $\alpha_0$ intercept measures average returns under Democratic administrations and ($\alpha_0$ + $\alpha_1$) measures average industry returns under Republican administrations.

Market-wide political cycles may explain the industry results. To correct for this possibility, Equation 3.3 adjusts for industry returns with the inclusion of a term for relative market movements, using a modified single-index model. The model now becomes a market model with the inclusion of a political variable, which effectively divides alpha returns between Democratic and Republican administrations.

$$R_t = \alpha_0 + \alpha_1 RPD_t + \beta_1 (r_{mt} - rf_t) + \varepsilon_t \qquad \text{(Eq. 3.3)}$$

Table 3.3 reports the results from Equation 3.3. Relative to the market, there are six industries with positive outperformance and seven industries with negative outperformance for Republicans that are statistically significant at a level of 10 percent or greater. After a market correction, industries with large capitalization, such as tobacco, continue to provide Republicans the best performance. Small-scale industries, such as healthcare and construction, provide Republicans the least performance. Relative to the market, there is a substantial change in the number of excess industry returns that remain statistically significant for Democrats. The petroleum industry is now the sole industry with significantly positive returns for Democrats, while returns to the steel industry turn significantly negative. Statistically significant positive differences increase from virtually none to five industries for Republicans and decrease from 20 to four industries for Democrats. The largest difference in statistically significant returns remains tobacco (10.0%) for Republicans and wholesale (8.8%) and electronic equipment (8.8%) for Democrats.

As a robustness check, the analysis divides the full time period in half to observe if results are persistent across sub-periods. Only one industry, food products, has a statistically significant difference in returns between Republican and Democratic administrations for all periods. Even tobacco, which had a highly significant outperformance for Republicans, is not statistically significant in the sub-periods. The results, to this point, indicate industry returns conditional on political control provide no relative outperformance for investors, once controlled for general market movements.

**Table 3.3 Industry presidential cycles with a market correction**

| | 1926:07 to 2006:06 | | | 1926:07 to 1966:06 | | | 1966:07 to 2006:06 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **REP** | **DEM** | **DIF** | **REP** | **DEM** | **DIF** | **REP** | **DEM** | **DIF** |
| Agriculture | -3.9% | 1.5% | -5.4% | -6.7% | 1.0% | -7.6% | -2.3% | 2.5% | -4.8% |
| Food Products | 6.2% *** | -1.2% | 7.4% *** | 4.3% * | -0.8% | 5.1% * | 7.4% *** | -1.9% | 9.3% ** |
| Beer & Liquor | 2.2% | 2.4% | -0.2% | -0.6% | 3.2% | -3.8% | 4.0% | 0.7% | 3.3% |
| Tobacco Products | 9.5% *** | -0.6% | 10.0% ** | 7.7% * | -0.7% | 8.4% | 10.5% *** | -0.3% | 10.8% |
| Recreation | -1.0% | -6.4% | 5.4% | -2.8% | -2.8% | 0.0% | 0.1% | -12.5% *** | 12.6% ** |
| Entertainment | -1.6% | -2.1% | 0.5% | -8.6% * | -4.7% | -3.9% | 2.7% | 2.5% | 0.3% |
| Printing and Publishing | 1.1% | -1.9% | 3.0% | 4.8% | -3.8% | 8.5% | -0.8% | 1.4% | -2.2% |
| Consumer Goods | 0.7% | 0.0% | 0.7% | -1.0% | 1.7% | -2.7% | 1.7% | -3.1% | 4.7% |
| Apparel | 0.3% | 0.8% | -0.5% | -0.8% | 2.8% | -3.6% | 0.7% | -2.5% | 3.2% |
| Medical Equipment | 2.8% | 1.9% | 0.8% | 4.0% | 2.0% | 2.0% | 2.0% | 1.9% | 0.1% |
| Pharmaceutical Products | 3.9% * | 1.3% | 2.6% | 8.8% ** | -0.4% | 9.1% ** | 1.2% | 4.2% | -3.0% |
| Chemicals | 2.2% | -1.1% | 3.3% | 2.9% | 1.2% | 1.8% | 1.9% | -4.9% | 6.8% * |
| Textiles | -2.5% | -2.2% | -0.3% | -11.5% ** | 2.4% | -13.9% *** | 3.1% | -10.1% ** | 13.2% *** |
| Construction Materials | -0.4% | -1.7% | 1.3% | -4.1% * | -2.1% | -2.0% | 1.8% | -1.1% | 2.9% |
| Construction | -8.1% *** | 0.0% | -8.1% * | -12.8% ** | -3.7% | -9.1% | -5.3% * | 6.7% | -12.0% ** |
| Steel Works Etc | -2.8% | -3.8% * | 1.0% | -4.2% | -2.0% | -2.2% | -2.0% | -7.0% * | 5.0% |
| Machinery | -1.7% | -0.2% | -1.5% | -1.8% | 0.1% | -1.9% | -1.7% | -0.8% | -0.8% |
| Electrical Equipment | 0.6% | -0.8% | 1.4% | 0.5% | -3.4% | 3.9% | 0.8% | 3.8% | -3.0% |
| Automobiles and Trucks | -0.7% | -1.1% | 0.4% | -2.1% | 2.1% | -4.2% | 0.3% | -6.8% ** | 7.1% |
| Aircraft | 0.8% | 0.5% | 0.3% | 7.1% | -1.6% | 8.7% | -2.5% | 4.0% | -6.5% |
| Shipbuilding, Railroad Equipment | -4.1% | -0.4% | -3.7% | -5.2% | -3.0% | -2.2% | -3.4% | 4.1% | -7.5% |
| Non-Metallic and Industrial Metal Mining | -0.2% | 0.2% | -0.4% | -2.3% | 2.5% | -4.9% | 1.0% | -3.8% | 4.8% |
| Coal | -0.6% | 5.6% | -6.1% | -5.6% | 5.8% | -11.4% * | 2.1% | 5.6% | -3.5% |
| Petroleum and Natural Gas | -0.1% | 4.4% ** | -4.5% | -2.7% | 3.3% | -5.9% | 1.5% | 6.3% * | -4.8% |
| Utilities | 3.4% * | -2.6% | 6.0% * | 4.8% | -4.4% | 9.1% ** | 2.9% | 0.1% | 2.9% |
| Communication | 4.1% ** | -1.1% | 5.1% ** | 6.2% *** | 0.2% | 6.0% ** | 2.8% | -3.1% | 5.9% |
| Business Services | -2.9% | 3.1% | -6.0% | -2.7% | 2.7% | -5.4% | -3.4% * | 4.5% | -7.9% ** |
| Computers | 0.3% | 2.3% | -1.9% | 14.7% *** | 0.9% | 13.8% *** | -7.2% ** | 4.9% | -12.1% ** |
| Electronic Equipment | -6.5% *** | 2.3% | -8.8% ** | -6.9% | 2.6% | -9.6% * | -6.4% *** | 1.9% | -8.3% |
| Measuring and Control Equipment | -0.9% | 1.8% | -2.8% | 7.7% | 2.1% | 5.6% | -5.9% ** | 1.9% | -7.9% * |
| Shipping Containers | 5.3% *** | -3.0% | 8.3% *** | 5.1% * | 0.9% | 4.3% | 5.4% ** | -9.5% ** | 14.9% *** |
| Transportation | -2.1% | -2.2% | 0.1% | -6.6% ** | -0.8% | -5.8% | 0.6% | -4.7% | 5.3% |
| Wholesale | -8.1% *** | 0.7% | -8.8% ** | -19.6% *** | 0.3% | -19.9% *** | -0.8% | 1.5% | -2.3% |
| Retail | 2.3% | -0.9% | 3.2% | -1.6% | 1.2% | -2.8% | 4.5% ** | -4.4% | 8.9% ** |
| Restaurants, Hotels, Motels | 1.4% | -0.1% | 1.5% | 1.8% | -1.1% | 3.0% | 1.1% | 2.0% | -0.9% |
| Banking | 2.6% | 3.1% | -0.5% | 2.7% | 2.7% | 0.0% | 2.6% | 3.8% | -1.2% |
| Insurance | -0.9% | 0.2% | -1.1% | -4.5% | -2.5% | -1.9% | 1.4% | 4.8% | -3.4% |
| Real Estate | -9.5% *** | -3.5% | -6.0% | -13.2% ** | -6.6% | -6.6% | -7.2% ** | 1.9% | -9.1% |
| Trading | -1.0% | -1.2% | 0.2% | -4.7% | -4.6% ** | 0.0% | 1.3% | 4.9% | -3.6% |
| Other | -8.6% *** | -0.2% | -8.3% ** | -8.1% | 2.6% | -10.8% * | -8.9% *** | -4.8% | -4.1% |
| Personal Services | -5.0% | -1.6% | -3.4% | -3.0% | -1.8% | -1.2% | -6.1% | -1.1% | -5.0% |
| Rubber and Plastic Products | -0.2% | 0.4% | -0.7% | -1.4% | 1.3% | -2.7% | 0.4% | -1.2% | 1.6% |
| Candy & Soda | 3.4% | 0.3% | 3.1% | 4.1% | -0.7% | 4.7% | 3.0% | 1.3% | 1.7% |
| Business Supplies | -5.6% | -1.9% | -3.7% | -21.6% ** | -1.9% | -19.7% * | 4.0% * | -2.2% | 6.3% |
| Healthcare | -10.1% * | 4.3% | -14.4% | | | | -10.1% * | 4.9% | -15.0% |
| Fabricated Products | -7.1% ** | -3.5% | -3.5% | | | | -7.1% ** | -4.5% | -2.6% |
| Defense | 2.2% | 0.9% | 1.2% | | | | 2.2% | 2.7% | -0.6% |
| Precious Metals | -0.6% | 0.6% | -1.1% | | | | -0.6% | -1.5% | 0.9% |
| **Significant at >10%** | **13** | **2** | **9** | **14** | **1** | **11** | **14** | **6** | **10** |

Notes: Table 3.3 reports regression results estimated with Equation 3.3 for industry outperformance over presidential cycles corrected for general market movement. The model equates to a single-index model with the inclusion of a political dummy variable (*RPD*) that takes the value of one if a Republican is president and zero otherwise. The $\alpha_0$ intercept measures Democratic (*DEM*) outperformance, $\alpha_1$ measures marginal Republican outperformance (*DIF*), and ($\alpha_0 + \alpha_1$) measures Republican (*REP*) outperformance. The table reports results for the full period and two equal sub-periods and indicates statistical significance at 1%***, 5%**, and 10%* based on Newey and West (1987) heteroskedasticity and autocorrelation corrected test-statistics.

As a final exercise, the analysis investigates if sensitivities to industry size and value risk factors explain excess returns. With the inclusion of size (*SMB*) and value factors (*HML*), discussed in Fama and French (1993), the model becomes a modified Fama-French three-factor model. Table 3.4 reports the estimation results from Equation 3.4.

**Table 3.4 Industry presidential cycles with a three-factor correction**

| | 1926:07 to 2006:06 | | | 1926:07 to 1966:06 | | | 1966:07 to 2006:06 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Industry** | **REP** | **DEM** | **DIF** | **REP** | **DEM** | **DIF** | **REP** | **DEM** | **DIF** |
| Agriculture | -4.0% * | 0.6% | -4.5% * | -6.8% | 1.1% | -7.8% | -4.2% | -0.5% | -3.8% |
| Food Products | 5.8% *** | -1.0% | 6.8% | 4.2% * | -0.6% | 4.7% * | 5.2% ** | -2.1% | 7.4% * |
| Beer & Liquor | 1.8% | 1.3% | 0.5% | 0.8% | 1.8% | -1.0% | 2.2% | 0.4% | 1.8% |
| Tobacco Products | 8.9% *** | -0.3% | 9.2% | 7.5% * | -0.5% | 8.0% | 8.1% ** | -0.4% | 8.5% |
| Recreation | -0.5% | -8.8% ** | 8.3% | -0.3% | -5.5% | 5.2% | -1.2% | -14.6% *** | 13.4% *** |
| Entertainment | -1.8% | -3.6% | 1.9% | -7.8% * | -5.8% | -2.0% | 1.9% | 0.5% | 1.5% |
| Printing and Publishing | 0.9% | -3.4% | 4.3% | 6.3% | -5.5% | 11.8% | -2.3% | 0.1% | -2.4% |
| Consumer Goods | 1.2% | 0.3% | 0.9% | -0.7% | 1.7% | -2.4% | 1.7% | -2.5% | 4.1% |
| Apparel | 0.2% | -1.2% | 1.4% | 0.9% | 0.8% | 0.1% | -2.7% | -5.4% | 2.7% |
| Medical Equipment | 3.4% | 1.7% | 1.7% | 4.7% | 1.2% | 3.6% | 4.7% * | 3.0% | 1.7% |
| Pharmaceutical Products | 4.5% ** | 2.4% | 2.1% | 8.6% ** | 0.1% | 8.6% * | 3.9% * | 6.9% ** | -3.0% |
| Chemicals | 2.0% | -0.5% | 2.5% | 2.2% | 2.3% * | -0.1% | -1.0% | -5.8% ** | 4.7% |
| Textiles | -3.4% | -5.0% *** | 1.6% | -9.8% *** | 0.1% | -9.9% ** | -1.7% | -13.8% *** | 12.1% *** |
| Construction Materials | -0.6% | -2.6% * | 2.0% | -3.5% | -2.7% * | -0.9% | -1.3% | -3.1% | 1.8% |
| Construction | -8.9% *** | -2.9% | -6.0% * | -10.7% * | -6.7% | -4.0% | -7.7% *** | 3.9% | -11.6% ** |
| Steel Works Etc | -3.9% * | -5.5% *** | 1.6% | -3.6% | -3.2% | -0.3% | -4.3% | -9.3% *** | 5.0% |
| Machinery | -1.9% | -1.4% | -0.5% | -1.2% | -0.8% | -0.4% | -2.4% | -2.3% | -0.1% |
| Electrical Equipment | 0.5% | -0.5% | 1.0% | 0.1% | -2.8% | 2.9% | 0.9% | 4.0% | -3.1% |
| Automobiles and Trucks | -1.7% | -1.9% | 0.2% | -2.0% | 2.1% | -4.1% | -4.6% | -9.1% *** | 4.5% |
| Aircraft | -0.1% | -1.1% | 1.0% | 8.3% | -3.0% | 11.3% | -5.6% * | 1.8% | -7.5% |
| Shipbuilding, Railroad Equipment | -5.7% ** | -2.3% | -3.4% * | -3.9% | -4.9% * | 0.9% | -6.7% * | 2.2% | -8.9% |
| Non-Metallic and Industrial Metal Mining | -0.5% | -1.1% | 0.6% | -1.7% | 1.7% | -3.4% | -2.3% | -6.5% * | 4.1% |
| Coal | -0.9% | 4.1% | -5.0% | -4.7% | 4.1% | -8.8% | -0.5% | 3.2% | -3.7% |
| Petroleum and Natural Gas | -1.4% | 4.4% ** | -5.8% ** | -2.9% | 3.4% | -6.3% | -1.2% | 6.1% * | -7.3% * |
| Utilities | 1.8% | -3.0% | 4.9% | 4.7% | -4.2% | 8.9% ** | -1.6% | -1.1% | -0.5% |
| Communication | 4.3% ** | -0.4% | 4.6% | 6.0% ** | 0.6% | 5.4% * | 2.1% | -2.6% | 4.7% |
| Business Services | -1.2% | 2.8% | -4.0% | -2.0% | 1.8% | -3.7% | -0.1% | 4.4% * | -4.5% |
| Computers | 2.4% | 3.3% | -0.9% | 14.3% *** | 1.6% | 12.7% *** | -1.8% | 6.8% | -8.5% * |
| Electronic Equipment | -5.3% ** | 1.5% | -6.8% ** | -6.0% | 1.5% | -7.5% | -2.8% | 2.0% | -4.8% |
| Measuring and Control Equipment | 1.5% | 2.7% | -1.2% | 7.1% | 3.2% | 3.9% | -3.0% | 1.4% | -4.4% |
| Shipping Containers | 5.4% *** | -2.8% | 8.1% | 5.1% * | 1.1% | 4.0% | 4.5% ** | -9.4% ** | 13.9% *** |
| Transportation | -3.9% ** | -4.0% ** | 0.1% | -5.7% * | -2.5% | -3.2% | -2.3% | -6.4% ** | 4.1% |
| Wholesale | -8.0% *** | -1.0% | -6.9% ** | -18.3% *** | -1.5% | -16.9% *** | -2.6% | -0.6% | -2.0% |
| Retail | 2.9% | -0.7% | 3.6% | -1.7% | 1.6% | -3.3% | 3.7% * | -5.1% * | 8.8% ** |
| Restaurants, Hotels, Motels | 1.7% | -1.1% | 2.8% | 2.7% | -2.1% | 4.8% | -1.2% | -0.1% | -1.1% |
| Banking | 2.2% | 3.1% | -1.0% | 2.9% | 2.8% | 0.0% | -1.4% | 2.8% | -4.2% |
| Insurance | -1.9% | 0.3% | -2.2% | -4.9% | -1.9% | -3.0% | -1.8% | 4.1% | -5.9% |
| Real Estate | -10.3% *** | -6.8% ** | -3.5% | -11.6% * | -8.7% ** | -2.9% | -12.0% *** | -3.7% | -8.3% * |
| Trading | -2.2% | -2.1% | 0.0% | -4.2% | -5.3% ** | 1.1% | -1.4% | 3.7% | -5.1% * |
| Other | -7.7% *** | -1.1% | -6.6% ** | -7.1% | 1.6% | -8.8% | -9.9% *** | -6.4% | -3.5% |
| Personal Services | -4.7% | -4.1% | -0.6% | -0.8% | -4.7% | 3.9% | -7.8% ** | -3.6% | -4.2% |
| Rubber and Plastic Products | -1.4% | -1.9% | 0.5% | -1.7% | -0.4% | -1.2% | -1.8% | -4.4% | 2.7% |
| Candy & Soda | 2.1% | -0.8% | 2.9% | 5.5% | -0.9% | 6.3% | 0.9% | 0.9% | -0.1% |
| Business Supplies | -8.1% * | -5.6% | -2.5% | -21.1% * | -6.7% | -14.3% | 1.3% | -3.4% | 4.7% |
| Healthcare | -12.1% ** | -0.4% | -11.7% | | | | -11.8% ** | 0.7% | -12.5% |
| Fabricated Products | -8.7% ** | -6.5% | -2.3% | | | | -8.7% ** | -7.1% | -1.5% |
| Defense | -2.6% | -2.6% | 0.0% | | | | -2.5% | -0.2% | -2.3% |
| Precious Metals | -2.8% | -2.6% | -0.1% | | | | -3.0% | -4.5% | 1.5% |
| **Significant at >10%** | **17** | **7** | **7** | **13** | **5** | **7** | **14** | **12** | **10** |

Notes: Table 3.4 reports regression results estimated with Equation 3.4 for industry outperformance over presidential cycles with a correction for general market movement, size (*SMB*), and value (*HML*) factors. The model equates to the Fama-French three-factor model with the inclusion of a political dummy variable. The political dummy variable (*RPD*) takes the value of one if a Republican is president and zero otherwise. The $\alpha_0$ intercept measures Democratic (*DEM*) outperformance, $\alpha_1$ measures marginal Republican outperformance (*DIF*), and $(\alpha_0 + \alpha_1)$ measures Republican (*REP*) outperformance. The table reports results for the full period and two equal sub-periods. The table indicates statistical significance at 1%***, 5%**, and 10%* based on Newey and West (1987) heteroskedasticity and autocorrelation corrected test-statistics.

$$R_t = \alpha_0 + \alpha_1 RPD_t + \beta_1 (r_{mt} - rf_t) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \qquad \text{(Eq. 3.4)}$$

After factor adjustments and sub-period comparisons, relative industry outperformance between Republicans and Democrats dissipates entirely, with no industry showing consistent outperformance by political party across all periods. In particular, industry returns are highly sensitive to firm size under Democrats. This result is not surprising, given previous studies, such as Santa-Clara and Valkanov (2003), that document a pronounced small-firm effect under Democratic administrations.

The study concludes that all remaining evidence of presidential cycles in industry returns disappears after correcting for industry sensitivity to size and value factors. Table 3.5 visually compares the statistical significance of industry performance estimated for all three models and for different sub-periods. It is clear from Panel A that a correction for relative market movement, with the modified single-index model, largely explains excess industry performance attributable to presidential cycles. Size and value factor sensitivity, controlled with a modified three-factor model, accounts for any remaining industry presidential cycle. Further, returns are not persistent across sub-periods, as Panel B indicates.

**Table 3.5 Presidential cycle summary for different models and sub-periods**

| | Panel A: | Agric | Food | Beer | Smoke | Toys | Fun | Books | Hshld | Clths | MedEq | Drugs | Chems | Txtls | BldMt | Cnstr | Steel | Mach | ElcEq | Autos | Aero | Ships | Mines | Coal | Oil | Util | Telcm | BusSv | Comps | Chips | LabEq | Boxes | Trans | Whlsl | Rtail | Meals | Banks | Insur | RlEst | Fin | Other | PerSv | Rubbr | Soda | Paper | Hlth | FabPr | Guns | Gold |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eq. 3.1 | RP | | + | | + | | | | | | | | | | | | | | | | | | | | | | + | | | | | + | | | | | | | | | | | | + | | | | | |
| | DP | + | + | + | + | | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | | + | + | + | + | + | + | | | | |
| | DIF | - | | | | | | | | | | | | | | - | | - | | | | - | | - | - | | | - | - | - | - | | | - | | | | - | - | - | - | - | - | | - | - | | | |
| Eq. 3.3 | RP | | + | | + | | | | | | | + | | | | - | | | | | | | | | | + | + | | | - | | + | | - | | | | | - | | - | | | | | - | - | | |
| | DP | | | | | | | | | | | | | | | | - | | | | | | | | + | | | | | | | | | | | | | | | | | | | | | | | | |
| | DIF | | + | | + | | | | | | | | | | | - | | | | | | | | | | + | + | | | - | | + | | - | | | | | | | - | | | | | | | | |
| Eq. 3.4 | RP | - | + | | + | | | | | | | + | | | | - | - | | | | | - | | | | | + | | | - | | + | - | - | | | | | - | | - | | | | - | - | - | | |
| | DP | | | | | - | | | | | | | | - | - | | - | | | | | | | | + | | | | | | | | - | | | | | | - | | | | | | | | | | |
| | DIF | | + | | + | + | | | | | | | | | | | | | | | | | | | - | | + | | | - | | + | | - | | | | | | | - | | | | | | | | |

plus/minus denotes positive/negative significance at a level of 10% or greater

| | Panel B: | Agric | Food | Beer | Smoke | Toys | Fun | Books | Hshld | Clths | MedEq | Drugs | Chems | Txtls | BldMt | Cnstr | Steel | Mach | ElcEq | Autos | Aero | Ships | Mines | Coal | Oil | Util | Telcm | BusSv | Comps | Chips | LabEq | Boxes | Trans | Whlsl | Rtail | Meals | Banks | Insur | RlEst | Fin | Other | PerSv | Rubbr | Soda | Paper | Hlth | FabPr | Guns | Gold |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RP | 1926-2006 | | + | | + | | | | | | | + | | | | - | | | | | | | | | | + | + | | | - | | + | | - | | | | | - | | - | | | | | - | - | | |
| | 1926-1966 | | + | | + | | - | | | | | + | | - | | - | | | | | | | | | | | + | | + | | | + | - | - | | | | | - | | | | | | - | | | | |
| | 1966-2006 | | + | | + | | | | | | + | + | | | | - | | | | | - | - | | | | | | | | | | + | | | + | | | | - | | - | - | | | | - | - | | |
| DP | 1926-2006 | | | | | | | | | | | | | | | | - | | | | | | | | + | | | | | | | | | | | | | | | | | | | | | | | | |
| | 1926-1966 | | | | | | | | | | | | + | | - | | | | | | | - | | | | | | | | | | | | | | | | | - | - | | | | | | | | | |
| | 1966-2006 | | | | | - | | | | | | + | - | - | | | - | | | - | | | - | | + | | | + | | | | - | - | | - | | | | | | | | | | | | | | |
| DIF | 1926-2006 | | + | | + | | | | | | | | | | | - | | | | | | | | | | + | + | | | - | | + | | - | | | | | | | - | | | | | | | | |
| | 1926-1966 | | + | | | | | | | | | + | | - | | | | | | | | | | | | + | + | | + | | | | | - | | | | | | | | | | | | | | | |
| | 1966-2006 | | + | | | + | | | | | | | | + | | - | | | | | | | | | - | | | | - | | | + | | | + | | | | - | - | | | | | | | | | |

plus/minus denotes positive/negative significance at a level of 10% or greater

Notes: Panel A of Table 3.5 reports a summary of statistically significant industry performance over presidential cycles for Republicans (*REP*), Democratic (*DEM*), and (*REP-DEM*) differences (*DIF*) for the indicated regression equations. Panel B reports a summary of statistically significant industry performance over presidential cycles for Republicans (*REP*), Democratic (*DEM*), and (REP-DEM) differences (*DIF*) for the indicated time-periods estimated with Equation 3.3. The political dummy variable (RPD) takes the value of one if a Republican is president and zero otherwise. The table indicates industry outperformance (+) or underperformance (-) statistically significant at 10 percent or greater using Newey and West (1987) heteroskedasticity and autocorrelation corrected test-statistics.

The results, to this point, suggest the political affiliation of a president has no effect on industry returns, beyond the expectations of rational investors. Consequently, the study concludes no opportunity exists for timing industry investments with presidential cycles, beyond that already documented for the general market. Nominal industry returns are higher under Democrats. However, even then, observing industry returns relative to the market and additional risk factors, the presidential dummy variable loses explanatory power. The results provide evidence of a positive bias in industry returns for small-cap firms under Democratic administrations, as previous studies of major market indices document. The results do not support conventional wisdom, which holds particular industries perform better under a given political regime. For both Democratic and Republican administrations, investors are simply better off holding the market portfolio than specific industries or Treasury bills.

### 3.5 Industry Quadrennial Cycles

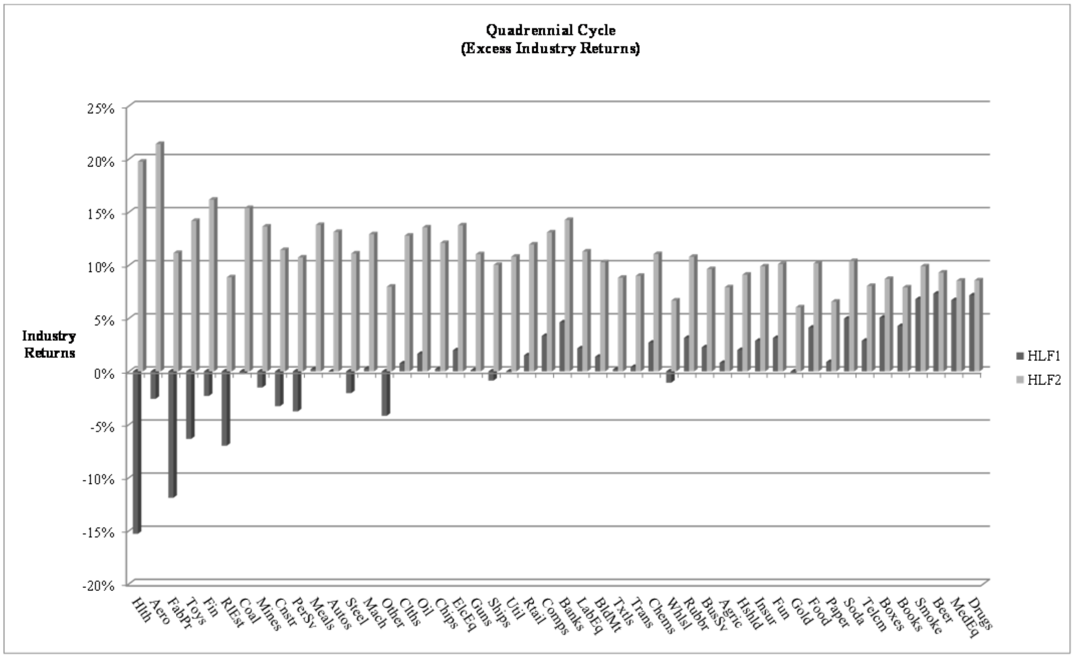
This section observes industry returns for evidence of quadrennial cycles. Systematic differences in industry returns between the first and second half of a four-year presidential term, irrespective of political affiliation, indicate quadrennial cycle. Prior studies find major U.S. stock market indices are typically higher during the second half of a presidential cycle.

$$R_t = \alpha_0 + \alpha_1 H2D_t + \varepsilon_t \qquad \text{(Eq. 3.2)}$$

Equation 3.2 tests for quadrennial cycle with a regression of excess industry returns (*R*) on a constant and the quadrennial cycle timing variable (*H2D*).

Table 3.2 reports the results from Equation 3.2 for quadrennial cycles. Twenty industries, or approximately 42 percent of the industries, have statistically significant return differences (DIF) between the first half (HLF1) and second half (HLF2) of a presidential term. Higher returns occur in the last two years of an administration, for all industries. The largest return differences between first half and second half are for healthcare (35.0%) and aircraft (24.0%). The pharmaceutical (1.4%) and medical equipment (1.8%) industries have the smallest differences. Overall, there is no evident pattern across industries, with higher second-half returns observed in the primary, manufacturing, consumer staples, and consumer durables industries, in addition to both high and low beta industries. Figure 3.3 illustrates industry returns sorted left to right from highest second-half outperformance to highest first-half outperformance.

**Figure 3.3 Industry quadrennial cycles**




Notes: Figure 3.3 illustrates excess industry returns over quadrennial cycles estimated with Equation 3.2. The quadrennial cycle timing variable (*H2D*) takes the value of one during the second half of a four-year U.S. presidential cycle and zero otherwise. The table sorts excess returns from left to right by largest difference in returns between the second half and first half of a four-year U.S. presidential cycle. The $\alpha_0$ intercept measures average first-half returns and ($\alpha_0 + \alpha_1$) measures average second-half industry returns.

Notably, quadrennial cycles are more evident for unadjusted returns in the sub-period 1966 to 2006, with statistically significant differences at level of 10 percent or greater in 43 of the 48 industries. Stronger differences in second-half returns, during the latter period, are similar to the results of studies, such as Allvine and O'Neil (1980) and Booth and Booth (2003), that conjecture a more active role by government and politicians managing the post-WWII economy. Higher returns during the second half of a presidential administration support the contention that politicians are able to manipulate the economy to further their prospect of gaining reelection.

As with presidential cycles, it is possible that the observed relative outperformance of second-half returns merely represents new market equilibrium rates of return. Risk and market volatility unquestionably increase with the uncertainty of an election and potential changes in the political agenda. Therefore, second-half returns may simply represent expected compensation for extra risk during the period prior to an election. Equation 3.5 controls for relative market movement in the quadrennial cycle model with the inclusion of a term for excess market returns. The model becomes the basic single-index with Jensen's alpha now split between first-half returns and second-half returns.

$$R_t = \alpha_0 + \alpha_1 H2D_t + \beta_1 (r_{mt} - rf_t) + \varepsilon_t \qquad \text{(Eq. 3.5)}$$

Table 3.6 reports Equation 3.5 results. Relative to the market, the outperformance of second-half industry returns largely diminishes. Differences in returns remain positive and statistically significant in only two industries and negative in four. Interestingly, with the inclusion of a term for general market movement, a majority of industries actually show negative second-half returns, although statistically insignificant. Even in the latter sub-period, differences in returns between the first and second halves remain statistically significant in only five industries. The results indicate that, while industry returns are higher in the latter half of a presidency, outperformance dissipates after correcting for the market. Additionally, outperformance is not persistent across sub-periods.

**Table 3.6 Industry quadrennial cycles with a market correction**

| | 1926:07 to 2006:06 | | | 1926:07 to 1966:06 | | | 1966:07 to 2006:06 | | |
|---|---|---|---|---|---|---|---|---|---|
| Industry | HLF1 | HLF2 | DIF | HLF1 | HLF2 | DIF | HLF1 | HLF2 | DIF |
| Agriculture | -0.3% | -2.2% | -1.9% | 1.7% | -5.3% | -7.0% | -2.1% | 1.0% | 3.1% |
| Food Products | 3.2% ** | 1.7% | -1.5% | 1.6% | 0.5% | -1.2% | 4.5% * | 3.4% | -1.2% |
| Beer & Liquor | 6.1% * | -1.5% | -7.6% * | 7.9% | -4.0% | -11.9% * | 3.2% | 2.4% | -0.8% |
| Tobacco Products | 6.0% ** | 2.7% | -3.3% | 3.1% | 1.5% | -1.6% | 9.3% ** | 3.6% | -5.8% |
| Recreation | -7.6% * | 0.4% | 8.0% | -7.1% | 1.7% | 8.8% | -8.5% ** | -0.5% | 8.0% |
| Entertainment | 1.5% | -5.2% * | -6.7% | 0.8% | -12.8% *** | -13.6% ** | 1.5% | 3.9% | 2.4% |
| Printing and Publishing | 3.0% | -3.7% | -6.7% | 4.8% | -6.0% | -10.9% | 1.0% | -1.0% | -2.0% |
| Consumer Goods | 1.0% | -0.4% | -1.4% | 0.4% | 1.1% | 0.8% | 1.7% | -1.8% | -3.5% |
| Apparel | -0.4% | 1.4% | 1.8% | 4.5% | -1.4% | -5.9% | -4.2% | 3.5% | 7.6% |
| Medical Equipment | 5.7% ** | -0.9% | -6.6% * | 8.4% ** | -2.7% | -11.1% ** | 3.4% | 0.6% | -2.8% |
| Pharmaceutical Products | 6.1% *** | -0.9% | -7.0% ** | 6.1% * | -0.3% | -6.4% | 5.9% ** | -1.3% | -7.2% * |
| Chemicals | 1.5% | -0.4% | -1.9% | 4.0% ** | -0.4% | -4.3% | -1.2% | -0.1% | 1.1% |
| Textiles | -1.1% | -3.7% | -2.5% | 0.0% | -5.7% * | -5.6% | -3.3% | -0.4% | 2.9% |
| Construction Materials | 0.1% | -2.2% | -2.3% | -0.7% | -5.0% *** | -4.3% * | 0.6% | 0.9% | 0.3% |
| Construction | -4.8% | -3.5% | 1.3% | -6.3% | -7.9% | -1.5% | -3.6% | 1.5% | 5.1% |
| Steel Works Etc | -3.5% | -3.2% | 0.3% | -1.5% | -4.1% | -2.5% | -5.9% | -1.7% | 4.1% |
| Machinery | -1.1% | -0.9% | 0.3% | -0.2% | -1.1% | -0.9% | -2.3% | -0.3% | 2.0% |
| Electrical Equipment | 0.5% | -0.7% | -1.2% | -2.5% | -1.5% | 1.0% | 2.9% | 0.8% | -2.1% |
| Automobiles and Trucks | -1.4% | -0.4% | 1.0% | -1.0% | 2.1% | 3.0% | -3.1% | -1.4% | 1.7% |
| Aircraft | -4.0% | 5.6% | 9.6% * | -4.9% | 8.4% | 13.3% | -4.4% | 4.2% | 8.7% |
| Shipbuilding, Railroad Equipment | -2.1% | -2.4% | -0.3% | -1.5% | -6.0% * | -4.4% | -3.6% | 2.3% | 5.8% |
| Non-Metallic and Industrial Metal Mining | -2.6% | 2.7% | 5.3% | 0.3% | 1.2% | 1.0% | -5.1% | 3.9% | 9.0% |
| Coal | -1.2% | 6.2% | 7.4% | -3.2% | 6.5% | 9.7% | 3.1% | 3.6% | 0.6% |
| Petroleum and Natural Gas | 0.7% | 3.6% * | 3.0% | 1.0% | 1.1% | 0.1% | -0.5% | 7.0% ** | 7.5% * |
| Utilities | -1.0% | 1.7% | 2.7% | -4.5% | 2.5% | 7.0% | 0.6% | 3.2% | 2.7% |
| Communication | 2.1% | 0.9% | -1.3% | 0.1% | 4.7% ** | 4.6% * | 5.0% * | -3.8% | -8.8% ** |
| Business Services | 1.2% | -1.0% | -2.2% | 4.3% | -2.7% | -7.0% | 1.1% | -2.4% | -3.5% |
| Computers | 2.0% | 0.5% | -1.5% | 7.6% ** | 3.9% | -3.8% | -2.4% | -3.6% | -1.3% |
| Electronic Equipment | -1.3% | -3.1% | -1.8% | 2.3% | -4.1% | -6.4% | -4.1% | -2.9% | 1.3% |
| Measuring and Control Equipment | 1.0% | -0.1% | -1.1% | 11.2% *** | -2.6% | -13.8% *** | -5.9% * | -0.3% | 5.6% |
| Shipping Containers | 3.9% * | -1.7% | -5.7% ** | 5.8% ** | -0.9% | -6.7% ** | 2.1% | -2.6% | -4.7% |
| Transportation | -0.9% | -3.4% * | -2.5% | -0.4% | -5.4% ** | -5.0% | -1.8% | -0.9% | 0.9% |
| Wholesale | -2.3% | -5.2% * | -2.9% | -3.0% | -11.8% ** | -8.8% | -1.8% | 1.9% | 3.6% |
| Retail | 0.4% | 1.0% | 0.6% | -1.5% | 2.0% | 3.5% | 2.9% | -0.6% | -3.5% |
| Restaurants, Hotels, Motels | -0.9% | 2.3% | 3.2% | 2.2% | -2.3% | -4.5% | -3.1% | 6.2% | 9.3% * |
| Banking | 3.4% | 2.3% | -1.1% | 4.3% | 1.1% | -3.2% | 2.2% | 3.9% | 1.7% |
| Insurance | 1.6% | -2.3% | -3.9% | -0.9% | -5.6% | -4.7% | 2.5% | 2.8% | 0.4% |
| Real Estate | -8.3% ** | -4.8% | 3.6% | -8.9% * | -9.3% | -0.4% | -9.0% ** | 1.3% | 10.3% * |
| Trading | -3.7% * | 1.6% | 5.3% ** | -8.6% *** | -0.5% | 8.0% ** | 0.2% | 5.0% ** | 4.8% |
| Other | -5.3% * | -3.6% | 1.7% | 1.1% | -3.9% | -5.0% | -10.5% *** | -4.2% | 6.4% |
| Personal Services | -4.8% | -1.7% | 3.1% | -4.9% | 0.5% | 5.4% | -4.5% | -4.1% | 0.4% |
| Rubber and Plastic Products | 1.1% | -0.9% | -2.1% | 1.8% | -1.0% | -2.9% | -0.3% | 0.0% | 0.3% |
| Candy & Soda | 3.8% | -0.3% | -4.1% | -0.9% | 2.2% | 3.1% | 6.9% * | -2.0% | -8.9% |
| Business Supplies | -0.3% | -7.1% * | -6.8% | -5.6% | -12.0% * | -6.4% | 1.2% | 2.3% | 1.1% |
| Healthcare | -11.5% | 3.1% | 14.6% | -18.9% | 4.2% | 23.1% | -11.1% | 1.8% | 13.0% |
| Fabricated Products | -8.4% ** | -2.8% | 5.6% | 0.7% | -2.8% | -3.5% | -9.1% ** | -3.1% | 6.0% |
| Defense | 3.1% | 0.2% | -2.9% | 15.3% * | -31.3% *** | -46.5% *** | 2.2% | 2.6% | 0.4% |
| Precious Metals | 2.3% | -2.5% | -4.9% | 7.2% | 27.3% | 20.1% | 2.1% | -3.9% | -6.0% |
| Significant at >10% | 11 | 5 | 6 | 9 | 9 | 9 | 10 | 2 | 5 |

Notes: Table 3.6 reports regression results estimated with Equation 3.5 for industry outperformance over quadrennial cycles corrected for general market movement. The model equates to a single-index model with the inclusion of a quadrennial cycle timing variable (*H2D*) that takes the value of one during the second half of a four-year U.S. presidential cycle and zero otherwise. The $\alpha_0$ intercept measures first half (*HLF1*) outperformance, $\alpha_1$ measures marginal second half outperformance (*HLF2*), and ($\alpha_0 + \alpha_1$) measures second half outperformance. The table reports results for the full period and two equal sub-periods. The table indicates statistical significance at 1%***, 5%**, and 10%* based on Newey and West (1987) heteroskedasticity and autocorrelation corrected test-statistics.

Lastly, Equation 3.6 includes the Fama and French (1993) size (*SMB*) and value (*HML*) factors, to control for any possible small-cap or value effects in quadrennial cycles. The model now becomes a modified three-factor model.

$$R_t = \alpha_0 + \alpha_1 H2D_t + \beta_1 (r_{mt} - rf_t) + \beta_2 SMB + \beta_3 HML + \varepsilon_t \qquad \text{(Eq. 3.6)}$$

**Table 3.7 Industry quadrennial cycles with a three-factor correction**

| | 1926:07 to 2006:06 | | | 1926:07 to 1966:06 | | | 1967:06 to 2006:06 | | |
|---|---|---|---|---|---|---|---|---|---|
| Industry | HLF1 | HLF2 | DIF | HLF1 | HLF2 | DIF | HLF1 | HLF2 | DIF |
| Agriculture | -0.5% | -2.9% | -2.4% | 1.7% | -5.3% | -7.0% | -2.6% | -3.1% | -0.4% |
| Food Products | 2.9% * | 1.9% | -1.0% | 1.8% | 0.6% | -1.2% | 2.9% | 2.1% | -0.8% |
| Beer & Liquor | 5.5% * | -2.3% | -7.8% * | 7.4% | -4.3% | -11.7% * | 1.9% | 1.1% | -0.8% |
| Tobacco Products | 5.5% * | 2.9% | -2.6% | 3.2% | 1.6% | -1.6% | 7.5% * | 2.4% | -5.1% |
| Recreation | -7.8% ** | -1.5% | 6.2% | -8.0% | 1.0% | 9.0% | -8.7% ** | -3.7% | 5.1% |
| Entertainment | 1.0% | -6.3% ** | -7.3% * | 0.4% | -13.1% *** | -13.5% ** | 1.6% | 1.2% | -0.3% |
| Printing and Publishing | 2.4% | -4.9% * | -7.3% * | 4.1% | -6.5% | -10.7% | 0.2% | -3.1% | -3.3% |
| Consumer Goods | 1.5% | -0.1% | -1.6% | 0.4% | 1.2% | 0.8% | 1.4% | -1.2% | -2.6% |
| Apparel | -0.9% | -0.1% | 0.8% | 3.7% | -2.0% | -5.7% | -5.8% * | -1.4% | 4.4% |
| Medical Equipment | 6.3% *** | -1.0% | -7.3% ** | 8.1% ** | -2.9% | -11.0% ** | 5.1% * | 3.0% | -2.1% |
| Pharmaceutical Products | 7.0% *** | 0.0% | -7.0% ** | 6.4% ** | -0.1% | -6.5% | 7.1% *** | 2.7% | -4.4% |
| Chemicals | 1.5% | 0.1% | -1.4% | 4.5% ** | 0.1% | -4.5% | -3.2% | -2.4% | 0.8% |
| Textiles | -2.6% | -5.9% *** | -3.3% | -0.9% | -6.3% ** | -5.4% | -5.6% * | -7.0% ** | -1.4% |
| Construction Materials | -0.3% | -2.9% * | -2.6% | -0.9% | -5.1% *** | -4.2% * | -1.1% | -2.9% | -1.7% |
| Construction | -6.2% * | -5.8% * | 0.4% | -7.5% | -8.8% ** | -1.3% | -4.6% | -2.6% | 1.9% |
| Steel Works Etc | -4.9% ** | -4.5% ** | 0.3% | -2.1% | -4.5% * | -2.4% | -6.8% * | -5.5% * | 1.3% |
| Machinery | -1.5% | -1.7% | -0.2% | -0.5% | -1.4% | -0.9% | -2.4% | -2.3% | 0.1% |
| Electrical Equipment | 0.5% | -0.5% | -1.0% | -2.2% | -1.3% | 1.0% | 2.9% | 1.1% | -1.8% |
| Automobiles and Trucks | -2.5% | -1.1% | 1.4% | -0.9% | 2.1% | 3.1% | -6.1% * | -6.3% ** | -0.2% |
| Aircraft | -5.2% | 4.2% | 9.4% * | -5.4% | 7.9% | 13.4% | -6.1% * | 0.5% | 6.6% |
| Shipbuilding, Railroad Equipment | -4.0% | -4.0% | 0.0% | -2.4% | -6.6% ** | -4.3% | -5.5% | -1.4% | 4.2% |
| Non-Metallic and Industrial Metal Mining | -3.2% | 1.6% | 4.8% | -0.1% | 1.0% | 1.0% | -6.7% | -0.8% | 5.9% |
| Coal | -1.7% | 5.0% | 6.8% | -3.9% | 5.8% | 9.8% | 1.8% | -0.2% | -2.0% |
| Petroleum and Natural Gas | -0.6% | 3.5% * | 4.1% | 1.0% | 1.1% | 0.0% | -2.5% | 5.6% * | 8.1% * |
| Utilities | -2.5% | 1.3% | 3.8% | -4.5% | 2.5% | 7.0% | -2.5% | -0.2% | 2.3% |
| Communication | 2.5% | 1.4% | -1.1% | 0.3% | 4.9% *** | 4.6% * | 4.3% | -3.5% | -7.8% * |
| Business Services | 2.8% | -1.2% | -4.0% | 3.9% | -3.0% | -6.9% | 3.9% * | -0.9% | -4.8% * |
| Computers | 4.2% * | 1.4% | -2.8% | 8.0% *** | 4.2% | -3.8% | 1.5% | 1.0% | -0.6% |
| Electronic Equipment | -0.3% | -3.7% | -3.4% | 1.8% | -4.4% | -6.3% | -1.2% | -1.0% | 0.2% |
| Measuring and Control Equipment | 3.5% | 0.7% | -2.9% | 11.8% *** | -2.1% | -13.9% *** | -3.4% | 0.6% | 4.0% |
| Shipping Containers | 4.1% ** | -1.5% | -5.6% ** | 6.0% *** | -0.8% | -6.7% ** | 1.3% | -3.0% | -4.3% |
| Transportation | -3.0% * | -4.9% *** | -1.9% | -1.3% | -6.1% ** | -4.8% | -3.5% | -4.2% * | -0.8% |
| Wholesale | -2.6% | -6.6% ** | -4.0% | -3.6% | -12.2% ** | -8.6% | -2.5% | -1.2% | 1.2% |
| Retail | 1.0% | 1.2% | 0.2% | -1.3% | 2.2% | 3.5% | 2.5% | -1.8% | -4.3% |
| Restaraunts, Hotels, Motels | -0.9% | 1.5% | 2.4% | 1.9% | -2.5% | -4.4% | -4.1% | 2.8% | 6.9% |
| Banking | 3.0% | 2.3% | -0.7% | 4.4% | 1.3% | -3.2% | -0.6% | 0.9% | 1.5% |
| Insurance | 0.6% | -2.3% | -2.9% | -0.6% | -5.4% | -4.8% | 0.1% | 0.5% | 0.4% |
| Real Estate | -9.7% *** | -7.3% ** | 2.4% | -9.7% ** | -9.9% * | -0.2% | -10.9% *** | -7.0% ** | 3.9% |
| Trading | -5.0% *** | 0.8% | 5.7% ** | -8.9% *** | -0.8% | 8.1% ** | -1.5% | 2.5% | 4.0% |
| Almost Nothing | -4.7% * | -4.2% | 0.4% | 0.8% | -4.1% | -4.8% | -10.8% *** | -6.4% | 4.4% |
| Personal Services | -5.1% | -3.7% | 1.4% | -6.3% | -0.4% | 5.9% | -5.0% | -7.6% * | -2.6% |
| Rubber and Plastic Products | -0.3% | -3.1% | -2.8% | 0.2% | -1.9% | -2.1% | -0.9% | -4.7% * | -3.7% |
| Candy & Soda | 2.5% | -1.4% | -3.9% | -0.9% | 2.7% | 3.7% | 5.2% | -3.5% | -8.7% |
| Business Supplies | -3.2% | -10.5% ** | -7.2% | -9.4% | -13.9% * | -4.5% | -0.6% | -0.3% | 0.2% |
| Healthcare | -12.6% * | -1.8% | 10.9% | -36.9% | 18.2% | 55.1% | -11.1% | -3.4% | 7.7% |
| Fabricated Products | -9.4% ** | -6.1% * | 3.3% | -10.6% | 1.3% | 11.8% | -9.4% ** | -6.7% * | 2.7% |
| Defense | 0.0% | -5.1% | -5.1% | -7.9% | -23.3% ** | -15.4% | -0.6% | -2.8% | -2.2% |
| Precious Metals | 0.8% | -6.3% | -7.1% | 10.9% | 21.6% | 10.7% | 1.2% | -8.4% | -9.6% |
| Significant at >10% | 16 | 12 | 8 | 8 | 12 | 8 | 13 | 9 | 3 |

Notes: Table 3.7 reports regression results estimated with Equation 3.6 for industry outperformance over quadrennial cycles with a correction for general market movement, size (*SMB*), and value (*HML*) factors. The model equates to the Fama-French three-factor model with the inclusion of a quadrennial cycle timing variable (*H2D*) that takes the value of one during the second-half of a four-year U.S. presidential cycle and zero otherwise. The $\alpha_0$ intercept measures first-half (*HLF1*) outperformance, $\alpha_1$ measures marginal second half outperformance (*HLF2*), and ($\alpha_0 + \alpha_1$) measures second-half outperformance. The table reports results for the full period and two equal sub-periods. The table indicates statistical significance at 1%***, 5%**, and 10%* based on Newey and West (1987) heteroskedasticity and autocorrelation corrected test-statistics.

Table 3.7 reports the results from Equation 3.6. While differences remain significant in eight industries for the entire period, they lack persistence across sub-periods.

Notably, in the most recent 40 years, only three portfolios show a statistically significant difference, with only one of these positive. The inclusion of size and value factors fails to support a finding of quadrennial cycles in industry returns.

To summarize, there is no evidence of quadrennial cycles in industry returns, after correcting for relative market movement and additional risk factors. The appearance of excess returns during the second half of a four-year presidential administration simply represents expected returns for bearing additional risk. Table 3.8 visually compares the statistical significance of first-half and second-half returns, across different models and for different sub-periods. It is clear from Panel A that what initially appears as a strong indication of quadrennial cycles from the basic model, results dissipate or become negative with a correction for additional risk factors. Additionally, returns are not persistent across sub-periods, as Panel B illustrates.

**Table 3.8 Quadrennial cycle summary for different models and sub-periods**

| | Panel A: | Agric | Food | Beer | Smoke | Toys | Fun | Books | Hshld | Clths | MedEq | Drugs | Chems | Txtls | BldMt | Cnstr | Steel | Mach | ElcEq | Autos | Aero | Ships | Mines | Coal | Oil | Util | Telcm | BusSv | Comps | Chips | LabEq | Boxes | Trans | Whlsl | Rtail | Meals | Banks | Insur | RlEst | Fin | Other | PerSv | Rubbr | Soda | Paper | Hlth | FabPr | Guns | Gold |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eq. 3.2 | HLF1 | | | | + | | | | | | + | + | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | - | - | | |
| | HLF2 | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | | + | + | + | + | | + | + | + | + | + | | + | + | + | |
| | DIF | | | | | + | | | | + | | | | | | + | + | + | + | + | + | | + | + | + | + | | | | | | | | | + | + | | | + | + | + | + | | | | + | + | | |
| Eq. 3.5 | HLF1 | | + | + | + | - | | | | | + | + | | | | | | | | | | | | | | | | | | | | + | | | | | | | - | - | - | | | | | | - | | |
| | HLF2 | | | | | | - | | | | | | | | | | | | | | | | | | + | | | | | | | | - | - | | | | | | | | | | | - | | | | |
| | Diff | | | - | | | | | | | - | - | | | | | | | | | + | | | | | | | | | | | - | | | | | | | | + | | | | | | | | | |
| Eq. 3.6 | HLF1 | | + | + | + | - | | | | | + | + | | | | - | - | | | | | | | | | | | | + | | | + | - | | | | | | - | - | - | | | | | - | - | | |
| | HLF2 | | | | | | - | - | | | | | | - | - | - | - | | | | | | | | + | | | | | | | | - | - | | | | | - | | | | | | - | | - | | |
| | DIF | | | - | | | - | - | | | - | - | | | | | | | | | + | | | | | | | | | | | - | | | | | | | | + | | | | | | | | | |

plus/minus denotes positive/negative significance at a level of 10% or greater

| | Panel B: | Agric | Food | Beer | Smoke | Toys | Fun | Books | Hshld | Clths | MedEq | Drugs | Chems | Txtls | BldMt | Cnstr | Steel | Mach | ElcEq | Autos | Aero | Ships | Mines | Coal | Oil | Util | Telcm | BusSv | Comps | Chips | LabEq | Boxes | Trans | Whlsl | Rtail | Meals | Banks | Insur | RlEst | Fin | Other | PerSv | Rubbr | Soda | Paper | Hlth | FabPr | Guns | Gold |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HLF1 | 1926-2006 | | + | + | + | - | | | | | + | + | | | | | | | | | | | | | | | | | | | | + | | | | | | | - | - | - | | | | | | - | | |
| | 1926-1966 | | | | | | | | | | + | + | + | | | | | | | | | | | | | | | | + | | + | + | | | | | | | - | - | | | | | | | | + | |
| | 1966-2006 | | + | | + | - | | | | | | + | | | | | | | | | | | | | | | + | | | | - | | | | | | | | - | | - | | | + | | | - | | |
| HLF2 | 1926-2006 | | | | | | - | | | | | | | | | | | | | | | | | | + | | | | | | | | - | - | | | | | | | | | | | - | | | | |
| | 1926-1966 | | | | | | - | | | | | | | - | - | | | | | | | - | | | | | + | | | | | | - | - | | | | | | | | | | | - | | | - | |
| | 1966-2006 | | | | | | | | | | | | | | | | | | | | | | | | + | | | | | | | | | | | | | | | + | | | | | | | | | |
| DIF | 1926-2006 | | | - | | | | | | | - | - | | | | | | | | | + | | | | | | | | | | | - | | | | | | | | + | | | | | | | | | |
| | 1926-1966 | | | - | | | - | | | | - | | | | - | | | | | | | | | | | | + | | | | - | - | | | | | | | | + | | | | | | | | - | |
| | 1966-2006 | | | | | | | | | | | - | | | | | | | | | | | | | + | | - | | | | | | | | | + | | | + | | | | | | | | | | |

plus/minus denotes positive/negative significance at a level of 10% or greater

Notes: Panel A of Table 3.8 reports a summary of statistically significant industry performance over quadrennial cycles for the first half (*HLF1*), second half (*HLF2*), or (*HLF2-HLF1*) difference (*DIF*) for the indicated regression equations. Panel B reports a summary of statistically significant industry performance over quadrennial cycles for the first half (*HLF1*), second half (*HLF2*), or (*HLF2-HLF1*) difference (*DIF*) estimated with Equation 3.5. The quadrennial cycle dummy variable (*H2D*) takes the value of one during the second half of a four-year U.S. presidential cycle and zero otherwise. The table indicates industry outperformance (+) or underperformance (-) statistically significant at 10 percent or greater using Newey and West (1987) heteroskedasticity and autocorrelation corrected test-statistics.

### 3.6 Event Study Results

This section examines whether expected differences in industry performance resulting from election outcomes support the finding that presidential politics have no systematic effect on realized industry returns. An event study of the 2004 presidential election provides a measure of differences in expected industry performance. Most other elections have highly probable outcomes well in advance of Election Day, making it difficult to pick a date when the market prices election resolution. The closely contested 2004 election provides a unique opportunity to measure the effect of election outcomes on expected differences in industry performance. If, for example, expected industry performance differs systematically due to the election of a Democratic versus a Republican president, industry prices should reflect that difference immediately with election resolution. Expected industry performance may differ, for example, due to the systematic effect of political agendas on industry cash flows. Alternatively, differences in expected returns may merely reflect unsubstantiated beliefs that certain industries perform better under Democratic or Republican presidents. Earlier results show that stock market returns are systematically higher under Democratic presidents. Consequently, market efficiency suggests that the general stock market should gain value following news of a Democratic victory and lose value following news of a Republican victory. Prior results also show that a president's political affiliation has no systematic bearing on differential industry performance. Market efficiency further suggests that election outcomes should have no effect on expected industry returns, despite the popular belief that political cycles drive industry performance.

Two of the closest presidential elections in the past century, based on popular vote, were the 2000 Bush-Gore election and the 2004 Bush-Kerry election.[52] Bush ultimately won the 2000 election by a 0.5% popular vote margin. However, his official election victory awaited a U.S. Supreme Court decision, which resolved the contested Florida vote count. The stock market could have potentially factored in a Bush victory on several occasions over the 36 days between the election and the 11 December 2000 Supreme Court decision. For instance, an uncertified Florida ballot count on 18

[52] http://www.mit.edu/~mi22295/elections.html

November gave the victory to Bush. On 26 November, the Florida Election Commissioner officially certified a Bush victory. In response, Bush immediately formed a transition team. Gallup Poll surveys, conducted after the election until 6 December, show Al Gore's public support steadily dropped from 52 to 39 percent.[53] Thus, pinpointing when stock prices reflect differences in expected returns in response to the 2000 election is difficult to determine.

The 2004 Bush-Kerry presidential campaign ranks as the next closest U.S. presidential election. Only a 2.4% difference in the popular vote determined a Republican victory. The 2004 Bush-Kerry presidential campaign was extremely close, from the campaign outset until voting closed on Election Day. According to Larry Sabato, director of the University of Virginia's Center for Politics, "Only a fool would have bet on [the 2004] election."[54] Uncharacteristically, neither Democratic nor Republican conventions generated an appreciable jump in candidate support. As the election drew near, polls showed the Democratic and Republican candidates virtually tied, as Table 3.9 details.[55] For instance, a Fox News poll two days prior to the election shows Kerry 3 percent ahead of Bush. Exit polls, conducted by the National Election Pool, continued to show Kerry 3 percent ahead in the popular vote on Election Day.[56] The election was so close that major news networks waited to proclaim a Bush victory until the morning after Election Day. Democratic candidate John Kerry conceded the race two hours before the stock market opened on the morning after the election.

[53] http://www.gallup.com/poll/2242/gores-image-slipping-election-contest-drags.aspx
[54] http://www.businessweek.com/magazine/content/04_26/b3889624.htm
[55] The data comes from Polling Reports at http://www.pollingreport.com/wh04two.htm
[56] http://www.ropercenter.uconn.edu/elections/presidential/presidential_election_2004.html

**Table 3.9 Poll results for the 2004 presidential election**

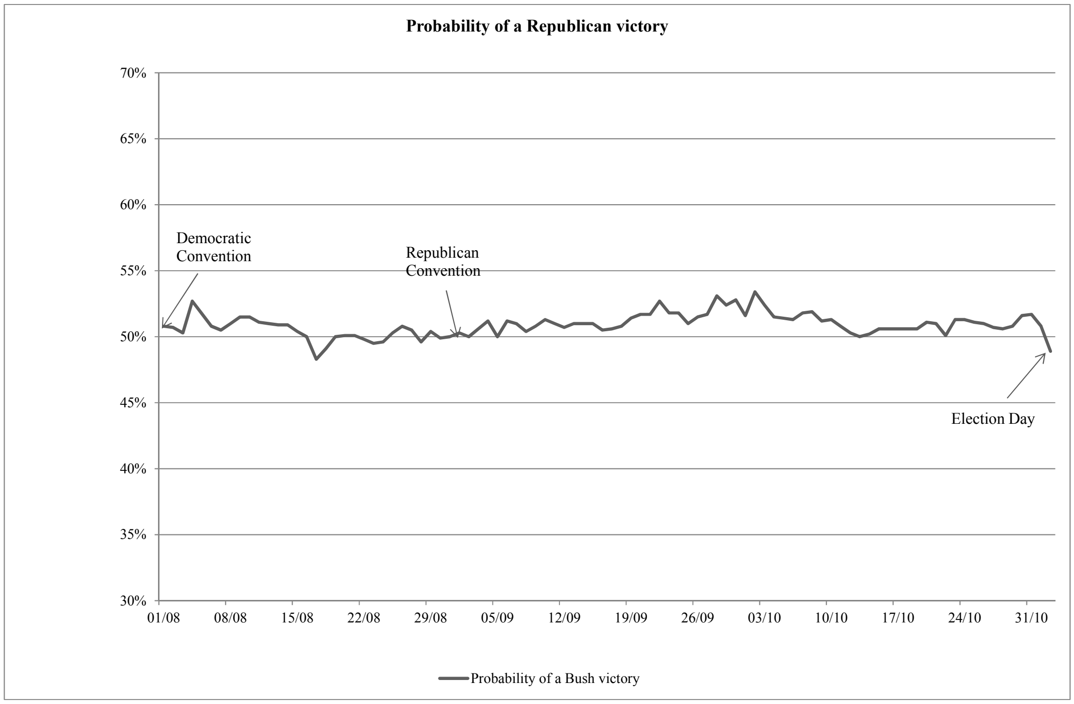
| Poll | Survey Date | Registered Voters Bush (%) | Registered Voters Kerry (%) | Margin Bush (%) | Margin Kerry (%) |
|---|---|---|---|---|---|
| FOX/Opinion Dynamics | 31/10 | 45 | 48 | | 3 |
| CNN/USA Today/Gallup | 31/10 | 47 | 48 | | 1 |
| FOX/Opinion Dynamics | 30/10 | 45 | 47 | | 2 |
| American Research Group | 30/10 | 48 | 49 | | 1 |
| FOX/Opinion Dynamics | 29/10 | 46 | 46 | | |
| Newsweek | 29/10 | 48 | 45 | 3 | |
| FOX/Opinion Dynamics | 28/10 | 47 | 47 | | |
| CNN/USA Today/Gallup | 24/10 | 49 | 48 | 1 | |
| Los Angeles Times | 24/10 | 47 | 48 | | 1 |
| Newsweek | 22/10 | 47 | 47 | | |
| CNN/USA Today/Gallup | 16/10 | 50 | 46 | 4 | |
| Newsweek | 15/10 | 48 | 47 | 1 | |
| Time | 15/10 | 46 | 46 | | |
| Scripps Center, Ohio U. | 13/10 | 45 | 50 | | 5 |
| ICR | 11/10 | 48 | 46 | 2 | |
| CNN/USA Today/Gallup | 10/10 | 48 | 48 | | |
| Time | 07/10 | 43 | 44 | | 1 |
| ICR | 05/10 | 50 | 46 | 4 | |
| American Research Group | 04/10 | 45 | 48 | | 3 |
| CNN/USA Today/Gallup | 03/10 | 49 | 48 | 1 | |
| Newsweek | 02/10 | 46 | 49 | | 3 |

Notes: Table 3.9 reports the results of polls over 30-days prior to the 2004 presidential election.[57]

As confirmation of the close election, Figure 3.4 compares the poll results with the Iowa Electronic Market (IEM) percentage of vote probabilities. Prediction markets, such as the IEM, take nominal bets that translate into electoral outcome probabilities.[58] Studies such as Berg, Nelson, and Rietz (2008) document that prediction markets accurately forecast election outcomes. Additionally, Snowberg, Wolfers, and Zitzewitz (2008) document the importance of political prediction markets in assisting researchers to pinpoint event dates. Figure 3.4 illustrates the percentage vote share for Republican candidate George Bush over a three-month period before the 2004 election. As with election polls, IEM probabilities depict a closely contested campaign, showing John Kerry ahead on Election Day. Both election poll statistics and IEM probabilities support the selection of the 2004 election for an event study.

[57] Source http://www.pollingreport.com/wh04two.htm
[58] For complete information on the Iowa Electronic Market see http://www.biz.uiowa.edu/iem/index.cfm.

**Figure 3.4 Election probabilities for the 2004 presidential election**




Notes: Figure 3.4 illustrates the Iowa Electronic Market probability of a Republican victory in the 2004 Bush-Kerry presidential election.[59] The period begins 1 August 2004 upon conclusion of the Democratic nominating conference and ends on Election Day 2 November 2004.

Distinct Bush-Kerry political agendas had clear implications for industry cash flows and profitability. Comparatively, centrist candidate positions made the political agendas of other recent elections indistinguishable (Hale (1995)). However, in 2004, Republicans strongly proposed tax-advantaged investments, domestic oil exploration, and expanded privatization of healthcare provision. Meanwhile, the Democrats promoted taxes on the wealthy, alternative energy, tighter emission controls, and affordable housing (Kim, (2004)). As such, the energy extraction, automotive, and investment industries particularly stood to benefit from a Republican victory. Conversely, a Democratic victory benefited industries such as alternative energy and construction. A combination of contrasting political agendas and a closely contested 2004 Bush-Kerry election provides a unique event study to measure the market's response to differences in Democratic and Republican policy agendas.

[59] See http://www.biz.uiowa.edu/iem/closed/Pres04_VS.html for complete details on political stock markets.

Previous event studies examine how broad-market indices respond to presidential elections, with mixed results. Niederhoffer, Gibbs, and Bullock (1970) observe Dow Jones Industrial Average (DJIA) changes over elections held from 1900 to 1968. The DJIA increases an average 1.12 percent for eight of nine Republican victories and it decreases an average -0.81 for four of five Democratic victories. Similarly, Riley and Luksetich (1980) find the DJIA increases following Republican victories for elections held from 1927 to 1998. Conversely, Santa-Clara and Valkanov (2003) observe no immediate change in excess returns, for either political party, following elections held from 1927 to 1998. Rather, Santa-Clara and Valkanov (2003) observe excess returns gradually build over four-year presidential terms, particularly for Democrats.

Other research documents the response of particular sectors to election news. Homaifar, Randolph, Helms, and Haddad (1988), covering six elections from 1964 to 1984, examine price changes to defense industry stocks. They conclude stock price sensitivity relates to candidate policy and not political affiliation. Similarly, Roberts (1990) evaluates the sensitivity of defense firm values to changes in 1980 Reagan-Carter election probabilities. Firm values have no systematic relationship with election outcomes, which Roberts (1990) attributes to indistinguishable candidate defense policies in 1980.

Herron, Lavin, Cram, and Silver (1999) examine Dow Jones indices returns for the 1992 election. They argue aggregate market indices fail to reveal priced political outcomes. A Democratic victory in 1992 affects only 20 percent of Dow Jones industry returns. Pollution control, aerospace, defense, pharmaceuticals, personal care, and financial services were the most affected industries. Interestingly, defense and pharmaceuticals are traditional Republican industries (Kim (2004)). Herron, Lavin, Cram, and Silver (1999) conclude the 1992 election results are candidate rather than party specific. Knight (2006) evaluates the relation of individual stock performance to changes in election probabilities. His sample includes 70 firms expected to benefit under either Bush or Gore 2000 presidencies. Knight identifies pharmaceutical, defense, energy, tobacco, and Microsoft competitors as “policy sensitive” stocks. Similar to Herron, Lavin, Cram, and Silver (1999), his study shows the market capitalizes candidate rather than party platforms.

The event-study analysis groups the Fama-French 48 industries into Democratic or Republican oriented portfolios based on three criteria.[60] These include past performance, political campaign contributions, and Wall Street analysts' projections. Each group provides different indicators of potential differences in expected industry performance. Table 3.10 provides details of portfolio constituent industries.

The best-performing Democratic and Republican portfolios comprise the top 16 of 48 industries that provide each party with the greatest relative performance differences (DIF), as Table 3.4 reports. These portfolios provide a measure of investor attention to realized industry performance over previous political cycles. If investors use election outcomes as a signal of expected industry returns, the results should indicate significant differences in excess returns for the best-performing Republican industries upon resolution of the 2004 election. The analysis includes a neutral portfolio that comprises the remaining 16 of 48 Fama-French industries.

Next, the analysis evaluates portfolios based on total industry campaign contributions, either to the political party or directly to the candidate. The 2004 election marks the first presidential election under the 2002 Bipartisan Campaign Reform Act. This legislation requires extensive reporting of all campaign contributions. Contribution data is available through the Center for Responsive Politics.[61] Campaign contributions provide a measure of industry investment in political outcomes. Presumably, industries anticipate returns in the form of improved profitability or cash flows from their campaign contributions. Investors could thus interpret campaign contributions as a signal of expected industry performance contingent on election results. The event study analysis includes the top 16 of 48 industries contributing to the Republican campaign in one portfolio and likewise for the Democrats.[62]

[60] Daily return data for the Fama-French 48 industries comes from the Kenneth French website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[61] http://www.opensecrets.org/
[62]Some industries appear to hedge their political bets with almost equivalent contributions to Republicans and Democrats.

**Table 3.10 Event study groupings for the 2004 presidential election**

| | Best Performing | | | Most Contributions | | Analaysts |
|---|---|---|---|---|---|---|
| Industry | Democrat | Republican | Neutral | Democrat | Republican | Republican |
| Agriculture | D | | | | | |
| Aircraft | | | N | | | |
| Apparel | | | N | | | |
| Automobiles and Trucks | | | N | | R | R |
| Banking | | | N | D | R | R |
| Beer & Liquor | | | N | | | |
| Business Services | D | | | D | R | |
| Business Supplies | D | | | | | |
| Candy & Soda | | R | | | | |
| Chemicals | | R | | | | R |
| Coal | D | | | | | R |
| Communication | | R | N | | | |
| Computers | D | | | D | R | |
| Construction | D | | | D | R | |
| Construction Materials | | R | | D | | |
| Consumer Goods | | | N | | | |
| Defense | | R | | D | R | |
| Electrical Equipment | | R | | | | |
| Electronic Equipment | D | | | | | |
| Entertainment | | | N | D | R | |
| Fabricated Products | D | | | D | R | |
| Food Products | | R | | | | |
| Healthcare | D | | | D | R | R |
| Insurance | | | N | D | R | R |
| Machinery | | | N | | | |
| Measuring and Control Equipment | D | | | | | |
| Medical Equipment | | | N | | | R |
| Non-Metallic and Metal Mining | | | N | | | R |
| Other | D | | | | | |
| Personal Services | D | | | | | |
| Petroleum and Natural Gas | D | | | | R | R |
| Pharmaceutical Products | | R | | D | R | R |
| Precious Metals | | | N | | | |
| Printing and Publishing | | R | | D | | R |
| Real Estate | D | | | D | R | |
| Recreation | | R | N | | | |
| Restaurants, Hotels, Motels | | R | | | | R |
| Retail | | R | | D | R | R |
| Rubber and Plastic Products | | | | | | |
| Shipbuilding, Railroad Equipment | D | | | | | |
| Shipping Containers | | R | | | | |
| Steel Works Etc | | R | | | | R |
| Textiles | | | N | | | |
| Tobacco Products | | R | | | | |
| Trading | | | | D | R | R |
| Transportation | | | N | | | |
| Utilities | | R | | D | R | R |
| Wholesale | D | | | | | |
| Total: | 16 | 16 | 16 | 16 | 16 | 16 |

Notes: Table 3.10 details groupings of Fama-French 48 industries used to form event study portfolios. The best-performing Democratic and Republican industries are the top 16 industries for each party with the greatest risk adjusted performance differences (*DIF*) from Table 3.4. The remaining 16 industries comprise a neutral portfolio. Industries grouped by contributions are the top 16 industries each for Democrats and Republicans receiving the highest political contributions. Lastly, the last column lists the 16 industries Wall Street analysts forecast to benefit most under a Republican presidency.

Lastly, the analysis evaluates a portfolio comprised of 16 industries that, according to a consensus of Wall Street analysts, would benefit from a Republican presidency.[63] Analysts base their projections on 2004 presidential campaign promises. The analysts' projections provide a signal of the Republican Party's intended economic policies, which could affect differences in expected industry performance.

The event study follows common methodology outlined in MacKinlay (1997) and Binder (1998). The event window includes 20 trading days on either side of 3 November 2004, the day following the election. In total, the event window covers 41 trading days starting 7 October 2004 and ending 3 December 2004. First, Equation 7 estimates parameters for a single-index model over 250 trading days prior to the event window. As the different strategy portfolios comprise industries held in equal weights, the appropriate benchmark to gauge excess performance is an equal-weighted index. Campbell and Wasley (1993) also recommend the use of an equal-weighted index in event studies that use the market model to measure abnormal returns.[64]

$$r_{pt} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it} \qquad \text{(Eq. 3.7)}$$

The market model (Equation 3.7) regresses the returns for each industry grouping ($r_i$) on a constant ($\alpha_i$) and an equal-weighted market index ($r_m$), estimated from 9 October 2003 to 6 October 2004. Next, Equation 3.8 calculates daily abnormal returns ($AR_i$) over the event window as the error terms from the estimated single-index model. Then, Equation 3.9 calculates equal-weighted average abnormal returns ($AAR_p$) from the $N$ industries included in each event study portfolio. Lastly, Equation 3.10 calculates cumulative average abnormal returns ($CAAR_p$) as aggregate average abnormal returns over different $t_1$ to $t_2$ windows.

$$AR_{it} = r_{it} - (\hat{\alpha}_i + \hat{\beta}_i r_{mt}) \qquad \text{(Eq. 3.8)}$$

$$AAR_{pt} = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \qquad \text{(Eq. 3.9)}$$

[63] Kim (2004).
[64] Results are comparable whether the performance benchmark uses an equal-weighted or value-weighted index.

$$CAAR(t_1, t_2)_p = \sum_{t=t_1}^{t_2} AAR_{pt} \qquad \text{(Eq. 3.10)}$$

Table 3.11 reports p-values for both Patell (1976) parametric test-statistics and Corrado (1989) non-parametric test-statistics for comparison. Event studies with common event days or cross-sectional dependence present a potential upward bias in test-statistics and increased Type I errors. However, Brown and Warner (1985) find no significant bias in abnormal returns adjusted with a common benchmark, even in the presence of cross-sectional dependence. Small sample size also potentially results in misspecified test-statistics for non-normal distributions. The Corrado (1989) non-parametric rank test makes no distributional assumptions and also provides well-specified test-statistics for small samples. Campbell and Wasley (1993) recommend the Corrado (1989) rank test for event studies with potentially non-normal distributions.

**Table 3.11 CAARs for industry groups**

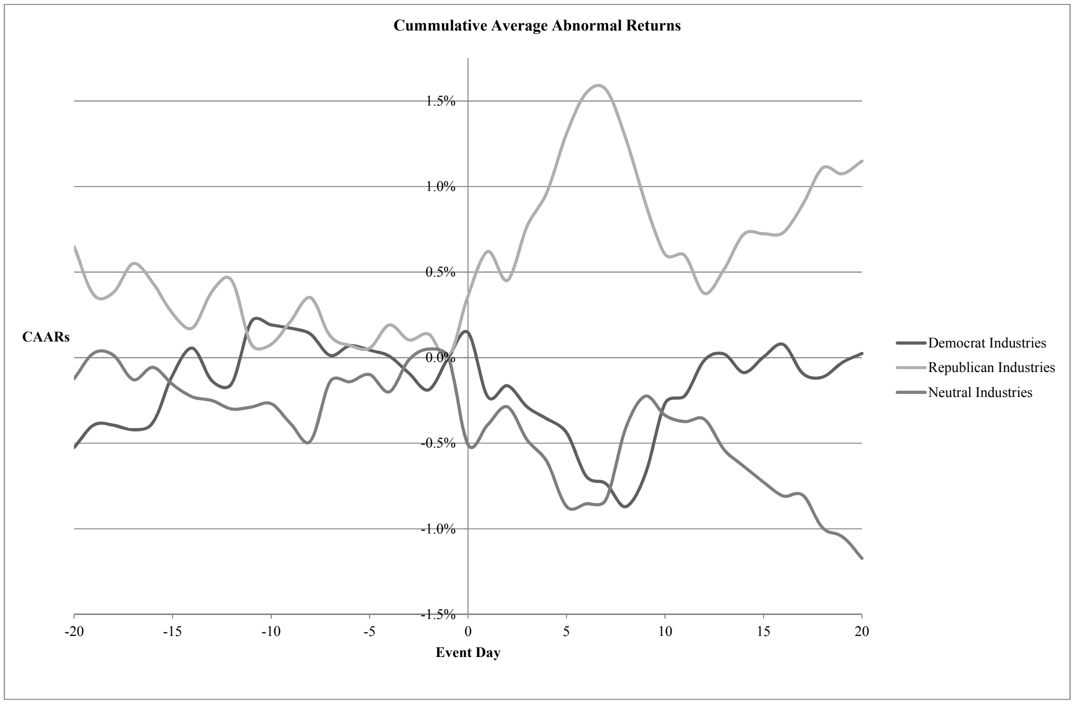
| | Event Window - 03 November 2004 Presidential election | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (-20,0) | (-10,0) | (-5,0) | (-2,0) | (-1,0) | (0,0) | (0,1) | (0,2) | (0,5) | (0,10) | (0,20) |
| **Cummulative Average Abnormal Returns (CAARS):** | | | | | | | | | | | |
| **Best Performing 16 Industries - Democrats** | | | | | | | | | | | |
| CAARs | 0.80% | -0.07% | 0.08% | 0.24% | 0.33% | 0.15% | -0.23% | -0.16% | -0.44% | -0.27% | 0.02% |
| Patell p-values | *0.17* | *0.95* | *0.31* | *0.57* | *0.32* | *0.78* | ***0.06*** | *0.31* | *0.21* | *0.35* | *0.83* |
| Rank test p-values | *0.22* | *0.95* | *0.20* | *0.47* | *0.26* | *0.63* | ***0.09*** | *0.18* | ***0.07*** | *0.27* | *0.96* |
| **Best Performing 16 Industries - Republicans** | | | | | | | | | | | |
| CAARs | -0.27% | 0.29% | 0.29% | 0.26% | 0.22% | 0.36% | 0.62% | 0.45% | 1.31% | 0.60% | 1.15% |
| Patell p-values | *0.69* | *0.95* | *0.74* | *0.67* | *0.71* | *0.21* | *0.16* | *0.50* | ***0.04*** | *0.96* | *0.53* |
| Rank test p-values | *0.44* | *0.85* | *0.56* | *0.50* | *0.67* | *0.24* | *0.21* | *0.43* | *0.63* | *0.12* | *0.62* |
| **Neutral 16 Industries** | | | | | | | | | | | |
| CAAR | -0.54% | -0.22% | -0.37% | -0.50% | -0.56% | -0.51% | -0.39% | -0.29% | -0.87% | -0.34% | -1.17% |
| Patell p-values | *0.38* | *0.27* | *0.19* | *0.83* | *0.73* | ***0.09*** | *0.47* | *0.94* | *0.24* | *0.70* | *0.90* |
| Rank test p-values | *0.24* | *0.45* | *0.19* | *0.96* | *0.82* | ***0.08*** | *0.24* | *0.61* | ***0.09*** | ***0.03*** | *0.14* |
| **Top 16 Industries by Contributions - Democrats** | | | | | | | | | | | |
| CAARs | 0.87% | 0.52% | 0.82% | 0.37% | 0.16% | 0.17% | 0.38% | 0.45% | 1.12% | 0.65% | 1.20% |
| Patell p-values | ***0.01*** | *0.13* | ***0.02*** | *0.30* | *0.79* | *0.74* | *0.53* | *0.47* | *0.24* | *0.83* | *0.43* |
| Rank test p-values | ***0.03*** | *0.29* | ***0.07*** | *0.27* | *0.77* | *0.92* | *0.89* | *0.80* | *0.49* | *0.18* | *0.76* |
| **Top 16 Industries by Contributions - Republicans** | | | | | | | | | | | |
| CAARs | 0.64% | 0.48% | 0.60% | 0.29% | 0.13% | 0.19% | 0.34% | 0.40% | 0.35% | -0.16% | 0.13% |
| Patell p-values | ***0.02*** | *0.13* | ***0.04*** | *0.47* | *0.91* | *0.77* | *0.70* | *0.56* | *0.44* | ***0.09*** | *0.50* |
| Rank test p-values | ***0.02*** | *0.16* | ***0.03*** | *0.35* | *0.82* | *0.95* | *0.91* | *0.99* | *0.14* | ***0.04*** | *0.37* |
| **Wall Street Analysts Top 16 Industries - Republicans** | | | | | | | | | | | |
| CAARs | -1.09% | -0.46% | -0.87% | -0.09% | 0.01% | 0.26% | 0.18% | 0.22% | 0.15% | -0.65% | -0.82% |
| Patell p-values | *0.86* | *0.95* | *0.58* | *0.87* | *0.96* | *0.31* | *0.65* | *0.40* | *0.24* | *0.27* | *0.54* |
| Rank test p-values | *0.54* | *0.90* | *0.94* | *0.85* | *0.97* | *0.55* | *0.75* | *0.59* | *0.72* | ***0.02*** | *0.18* |
| **Cummulative Market Returns:** | | | | | | | | | | | |
| CRSP Value Weight | 2.02% | 5.08% | 3.03% | 2.60% | 2.60% | 1.43% | 1.81% | 1.69% | 2.69% | 3.65% | 4.88% |
| CRSP Equal Weight | 1.90% | 4.13% | 2.19% | 1.82% | 1.79% | 0.77% | 1.24% | 1.13% | 2.96% | 4.64% | 7.84% |

Notes: Table 3.11 reports average daily CAARs and associated test-statistics for the indicated event windows and different Fama-French 48 industry groupings. The best-performing Democratic and Republican industries are the top 16 for each party with the greatest risk-adjusted return differences for the respective political parties from Table 3.4. The remaining 16 industries comprise a neutral portfolio. Industries grouped by contributions are the top 16 for Democrats and Republicans receiving the highest political contributions. The Wall Street analysts' portfolio comprises the 16 industries analysts expect to benefit most under a Republican presidency. Bold indicates statistically significant p-values at 10 percent or greater. Lastly, the bottom of the table reports cumulative CRSP market returns.

The event study analysis simply aims to measure how investor expectations for the outperformance of certain industries relate to election outcomes. Each event study portfolios comprise those industries with an expected common sensitivity to election cycles. Portfolio outperformance is the measure of returns in excess of expected returns predicted by the market model. In contrast, earlier analysis examines the marginal difference in realized industry performance conditional on whether a Democrat or Republican was president.

To begin, Figure 3.5 illustrates and Table 3.11 details cumulative abnormal returns around event day zero for the best-performing Democratic and Republican industries. Republican industries (0.36%) marginally outperform Democratic industries (0.15%) on the event day. Republican industry CAARs steadily increase and then peak five days after the election at 1.31 percent. Only Republican industries increase over the first five trading days. Prior to the election, Democratic industry performance reflects exit polls predicting a Republican defeat. However, after an initial increase, outperformance peaks on the event day with announcement of a Republican victory. Subsequently, Democratic industry performance steadily declines with a -0.44 percent five-day CAAR. Neutral industries respond negatively to the Republican victory with a -0.51 percent abnormal event day return. Similar to Democratic industries, neutral industries subsequently track downward with a -0.87 percent five-day CAAR. Visually, Republican industry CAARs reflect the greatest differences in expected returns following the Republican victory. As Table 3.11 also reports, portfolio abnormal performance is, for the most part, statistically indistinguishable from zero. Except in one instance, Republican industries have highly insignificant CAARs. In total, the three industry groupings have 10 percent statistically significant Patell or rank test p-values only 12 percent of the time. Put differently, statistically significant outperformance occurs only slightly more than expected by random chance. The results suggest that CAARs for Democratic, Republican, and neutral industries alike primarily reflect noise. While the market initially responds to election news, insignificant differences in expected returns support market efficiency, considering the absence of excess industry performance over past political cycles.

**Figure 3.5 CAARs based on past industry performance**

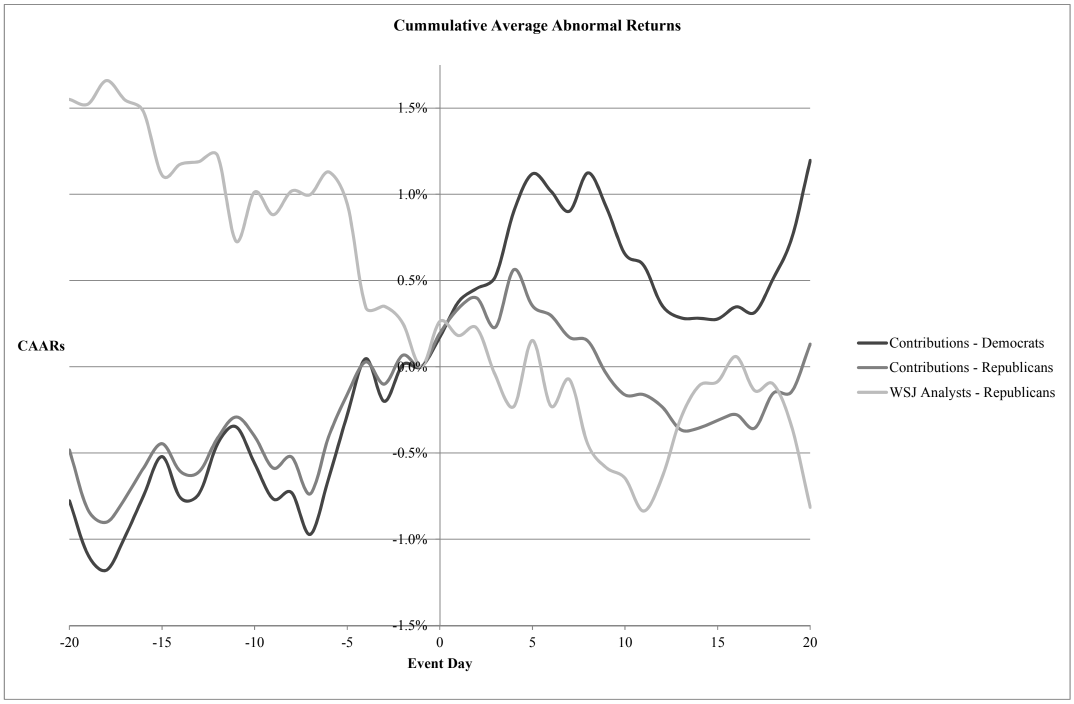



Notes: Figure 3.5 illustrates cumulative average abnormal returns (CAAR) over 41 trading days centered on the 2004 Bush-Kerry U.S. presidential election. The Democratic and Republican portfolios comprise of 16/48 Fama-French industries for each party that provide the greatest performance differences (*DIF*) reported in Table 3.4. Additionally, a neutral portfolio comprises the remaining 16/48 Fama-French industries. Table 3.10 details portfolio constituent industries.

The analysis also examines abnormal returns for industries grouped by political campaign contributions and analysts' recommendations. Industry contributions potentially indicate financial benefit and differences in expected performance. For instance, the oil and gas industries were top contributors to the 2004 Republican campaign. If presidential campaign promises translate into industry benefit, a Republican victory should increase expected returns for the oil and gas industries. Similarly, a Democratic victory should increase expected returns for top contributing Democratic industries. The top Republican contributing industries do generate significant 0.64 percent excess returns over 20 days prior to the election. However, the top Democratic contributing industries also provide significant 0.87 percent excess returns over the same period. Notably, most significant outperformance, for both the Democratic and Republican portfolios, occurs over five days prior to the election. The results perhaps indicate increased market uncertainty prior to the closely contested election, especially for industries with performance closely linked to the election outcome. For instance, Li and Born (2006) document that political uncertainty prior to elections drives market performance. Additionally, Figure 3.6 illustrates similar event day performance again for both the top contributing Democratic (0.17%) and Republican (0.19 %) industries. Over the post-election event window, Democratic industries (1.20%) actually outperform Republican industries (0.13%), although excess returns are statistically insignificant. In general, excess returns for industries grouped by political contribution lack statistical significance.

Lastly, the analysis documents the performance of industries Wall Street analysts pick to benefit from Republican victory, based on presidential campaign rhetoric. The oil extraction and investment industries feature prominently in analysts' recommendations. Interestingly, after a 0.26 percent event day gain, industries selected by Wall Street analysts have a statistically significant and negative 0.65 percent 10-day CAAR, generating the greatest underperformance of all other industry groups. With that exception, all remaining CAARs for the Wall Street analyst selected industries lack statistical significance. Perhaps as Li and Born (2006) conjecture, the market takes a "wait and see" attitude before translating campaign promises and election outcomes into differences in expected returns.

**Figure 3.6 CAARs based on analyst recommendations and contributions**

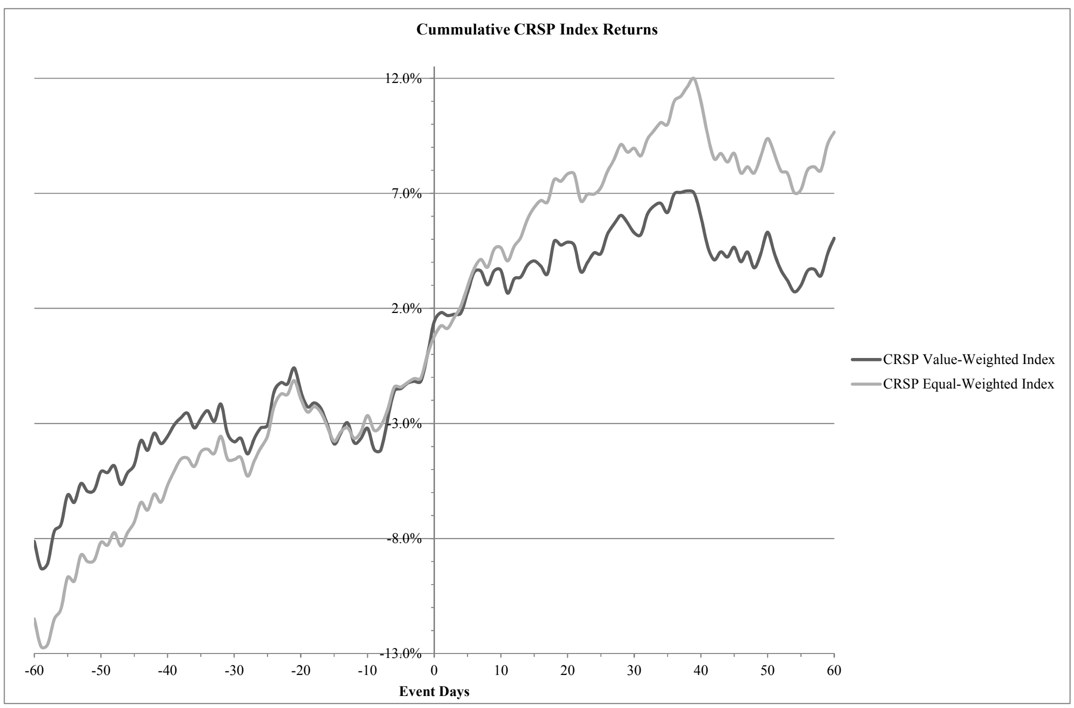



Notes: Figure 3.6 illustrates cumulative average abnormal returns (CAARs) over 41 trading days centered on the 2004 Bush-Kerry U.S. presidential election. The Democratic and Republican portfolios comprise the 16/48 Fama-French industries for each party with the highest total industry campaign contributions, to either the political party or the candidate. Lastly, the analyst portfolio comprises the 16/48 Fama-French industries Wall Street analysts forecast to benefit most under a Republican presidency. Table 3.10 details portfolio constituent industries.

Figure 3.7 illustrates Center for Research on Security Prices (CRSP) equal-weight and value-weight market cumulative returns. The analysis uses an expanded 120-trading-day window to view long-term market direction. The general market has an upward trend over the entire window. Market performance noticeably increases 10 days before and after the election. Cumulative returns 10 days after the election are 3.65 percent and 4.64 percent for the value-weighted and equal-weighted CRSP market indices. Similarly, Snowberg, Wolfers, and Zitzewitz (2007) document 2 to 3 percent market gains following election of a Republican president. Riley and Luksetich (1980) also document that the market prefers Republicans, at least in the short term. Generally, the 2004 presidential election has little noticeable effect on expected market performance. Given historical performance under Republicans, expected market returns should decline in response to a Republican victory. Market performance does decline but not until 40 trading days after the election. However, a steadily upward trending market prior to the election creates difficulty disentangling political effects from unrelated long-term market developments.

Market reaction to the 2004 election suggests investors do not price a president's political affiliation or election outcomes into industry returns. Industries that previously performed well under Republicans initially outperform other industries – but only insignificantly so. Industry political campaign contributions and Wall Street analysts' projections also provide no additional insight into differences in expected returns surrounding presidential elections. Statistically insignificant excess returns, for all industries, suggest presidential election outcomes provide only a noisy signal of future industry performance. Analyzing only one presidential election limits the inferences drawn. However, the closely contested and politically divergent 2004 election offers a unique opportunity for an event study. If political cycles drive expected industry performance, the 2004 election should provide evidence. If not, other elections, with prior outcome certainty and convergent political agendas, would likely produce weaker results.

**Figure 3.7 Cumulative CRSP index returns for the 2004 presidential election**




Notes: Figure 3.7 illustrates cumulative value-weight and equal-weight CRSP market index returns over 121 trading days centered on the 2004 Bush-Kerry U.S. presidential election.

### 3.7 Conclusion

This study investigates industry returns for evidence of political cycles. Political industry cycles comprise both unexpected and expected elements (Santa-Clara and Valkanov (2003)). Unexpected industry returns occur over time, when Democratic or Republican policies positively or negatively surprise investors. Alternatively, unexpected returns can result from investor inattention to previous political cycles. Differences in expected industry performance reflect the market's immediate response to the election of a Democratic or Republican president. Political risk premiums or changes in expected industry cash flows can cause differences in expected returns. The literature documents two political stock market cycles: presidential cycle and quadrennial cycle. A president's political affiliation determines presidential cycles. The year of a four-year presidential term determines quadrennial cycles.

As a first step, the study seeks to replicate the findings of prior studies documenting political cycles in the general market. Similar to Santa-Clara and Valkanov (2003), results confirm that the stock market performs best under Democratic presidencies. Over the sample of 21 presidencies from 1926 to 2006, stock returns are 8.6 percent higher under Democratic relative to Republican administrations. Santa-Clara and Valkanov (2003) also document higher market returns in the latter half of any presidential term. Similarly, results show that industry returns are 10 percent higher in the second half of all presidential terms. The observation of political stock market cycles violates market efficiency, potentially explained by industry analysis.

The principal focus of the study is an examination of industry returns for evidence of political cycles. Industry cash flows provide a mechanism for political cycles to directly impact on stock prices. In turn, dominant industries, with cash flows sensitive to political agendas, potentially drive market-wide political cycles. Similar to the market, unadjusted industry returns are higher under Democrats and the last two years of any presidency. However, after a correction for common risk factors with a Fama-French three-factor model, industry performance exhibits no evidence of systematic or persistent political cycles.

Market reaction to the 2004 election also reflects the absence of differences in expected industry performance in response to election outcomes. The event study analysis groups industries by political orientation based on past performance, campaign contributions, and analysts' recommendations. Regardless of the industry grouping, the results document no evidence of statistically significant abnormal returns surrounding the closely contested and politically divergent 2004 presidential election. Industries that previously performed well under Republicans do exhibit the greatest response to the election result, although insignificantly so. While the market responds to election resolution, lack of statistically significant excess returns suggests that investors take election outcomes as a noisy signal of expected industry performance.

Overall, the results question the popular belief that political cycles drive industry performance and provide evidence that political cycles are solely a market-wide phenomenon. Macroeconomic determinants may resolve the puzzling feature in the data of political stock market cycles. Possibly, investors formulate expectations for general stock market performance based on how a president's political affiliation or opportunistic motivation influences macroeconomic determinants. Alternatively, as Santa-Clara and Valkanov (2003) suggest, asset returns may determine political outcomes, rather than the opposite.

# Chapter 4 Sector Rotation across the Business Cycle

## 4.1 Introduction

Sector rotation refers to a common investment strategy that targets investments in particular economic sectors at different stages of the business cycle. Bodie, Kane, and Marcus (2009) suggest the "way that many [financial] analysts think about the relationship between industry analysis and the business cycle is the notion of sector rotation." Similarly, Lofthouse (2001) states that financial analysts "think in terms of stylized economic cycles, with different sectors performing at different stages of the cycle." Fabozzi (2007, pg. 581) acknowledges, "Sector rotation strategies have long played a key role in equity portfolio management." Validating its importance, the Chartered Financial Analyst (CFA) curriculum includes sector rotation in the "Core Body of Knowledge" essential for investment professionals.[65] The number of websites dedicated to the topic lends further support to the popularity of sector rotation. For instance, an Internet search of "sector rotation" returns about 415,000 hits on Google.[66] Although it is difficult to ascertain the exact number of sector rotation investors, the recent growth in sector and industry financial instruments suggests the prominence of sector rotation with finance practitioners.[67] In 2009, sector exchange-traded funds (ETFs) were the fastest growing segment of equity ETFs, with net inflows of U.S. $14 billion and net asset value of U.S. $82 billion.[68] Indicating the popularity of sector and industry funds, the Fidelity Select Sector Group offers a selection of 40 funds[69] and iShares offers 60 different sector/industry ETFs.[70]

Popular belief holds that certain sectors provide systematic business-cycle performance and that sector rotation generates excess market returns. According to Fidelity, technology stocks outperform the market following a business-cycle trough.[71] Just after a peak, investors are better off putting their money in utilities. Other financial

[65] CFA Institute (2009)
[66] Google search conducted on 08 January 2011
[67] Popular funds include the Rydex/SGI All-Cap Opportunity H (RYSRX), Rydex/SGI All-Cap Opportunity (RYAMX), Claymore/Zacks Sector Rotation (XRO), and PowerShares Value Line Industry Rotation (PYH).
[68] Investment Company Institute (2010)
[69] http://personal.fidelity.com/products/funds/content/sector/products.shtml
[70] http://us.ishares.com/portfolio_strategies/investment_strategies/sector_strategies.htm
[71] http://personal.fidelity.com/products/funds/content/sector/cycle.shtml

websites share Fidelity's view on sector performance. Standard & Poor's Guide to Sector Investing recommends technology after a recession.[72] With the onset of an economic slowdown, Goldman Sachs[73] and CNN Money[74] advise investors to target utilities. Even though, as some suggest, "if you are in the right sector at the right time, you can make a lot of money very fast," translating popular beliefs into a profitable sector rotation strategy presents a challenge.[75] Sector rotation additionally requires correctly timing contemporaneous stages of the business cycle. Difficulty forecasting business-cycle stages might explain the lack of academic research on whether systematic sector performance provides an opportunity for profitable sector rotation. This study addresses that void in the literature.

This study tests the two fundamental assumptions of sector rotation. Do certain sectors provide systematic performance across business cycles? Does sector rotation generate excess market performance? Bodie, Kane, and Marcus (2009) comment that "sector rotation, like any other form of market timing, will be successful only if one anticipates the next stage of the business cycle better than other investors." This study overcomes the obstacle of correctly timing business cycles with a simple and intuitive approach. That approach gives sector rotation investors the benefit of the doubt, by assuming investors can perfectly time business cycle turning points. If the business cycle drives sector returns, then an investor who perfectly times business cycle stages and rotates sectors following popular belief on sector performance should generate excess returns. The base-case analysis begins with the assumption of a sector rotation strategy that follows conventional guidance on sector performance, following a popular sector rotation variant prescribed by investment analysts and practitioner guides. There are, however, many potential variants of sector rotation. Consequently, the analysis relaxes any assumption of a specific sector rotation model – testing the performance of *all* sectors across *all* business-cycle stages. Lastly, the study concludes with the analysis of an alternative sector rotation strategy.

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[72] Stovall (1996).
[73]http://www.reuters.com/article/2008/01/09/us-usa-economy-goldman-idUSN0956579820080109
[74] Money (2006) http://money.cnn.com/2006/08/08/markets/fed_pause_stocks.moneymag/index.htm
[75] Money (2006) http://money.cnn.com/2006/08/08/markets/fed_pause_stocks.moneymag/index.htm

Investors can choose to implement sector rotation at sector, industry, or firm level. The choice depends on how precisely an investor wants to target expected sector performance and the desired level of diversification. Sectors describe broad economic segments. Targeting sectors provides broad exposure with maximum diversification benefit. A common approach to sector rotation is industry-level implementation. Industries are sub-units of sectors. For instance, the Global Industrial Classification Scheme (GICS) details 10 sectors, 24 major industry groups, and 67 industries. Industries allow a more targeted approach to sector exposure, while still maintaining the benefit of diversification. For instance, the healthcare sector includes pharmaceutical, healthcare provider, and medical equipment sub-sectors or industries. A sector rotation investor might overweight pharmaceuticals relative to other healthcare sub-sectors, based on a specific view of expected industry performance. Lastly, stock-level implementation provides the most targeted approach, but lacks any diversification benefit. Industry-level analysis provides a detailed view of sub-sector groups that contribute to sector performance. Moreover, as evident by Fidelity Select, iShare offerings, and practitioner guides,[76] industry-level implementation represents a common approach for sector rotation investors. The base-case analysis focuses on the Fama and French 49 industry portfolios. Expanded robustness analysis further considers alternative sector and industry groupings.

The base-case analysis documents sector rotation outperformance – but only marginally so. The analysis investigates industry performance over 10 National Bureau of Economic Research (NBER) dated business cycles from 1948 to 2007. The NBER defines only broad phases of economic expansion and recession. As common practice, the analysis first divides broad NBER phases into additional sub-periods. The analysis then maps industries to business-cycle stages where popular belief anticipates optimal performance will occur. With few exceptions, industries expected to perform well in various stages show no systematic performance. The analysis next combines industries across stages to analyze whether conventional sector rotation generates outperformance. Investors, guided by popular belief on sector performance and with perfect foresight in timing business-cycle stages, achieve a risk-adjusted 2.3 percent annual return, before

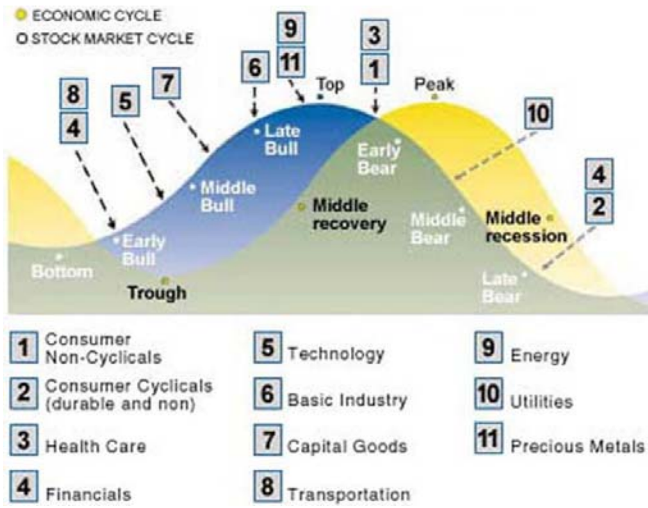
[76] See, for example, industry-level analysis in "Standard & Poor's Guide to Sector Investing," Stovall (1996).

any transaction costs. To put that performance in perspective, investors who perfectly time business cycles can achieve higher returns simply by exiting equities when the economy enters a recession.[77] With transaction costs, sector rotation performance quickly diminishes. The base-case analysis shows that if sector rotation investors earn excess returns, strategy performance has little to do with the popularly perceived driver – systematic sector performance across business cycles.

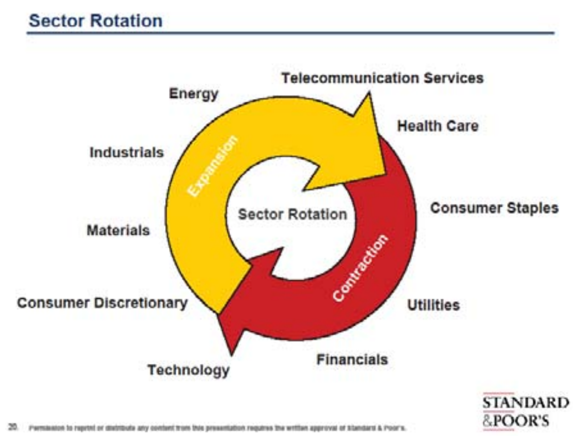
The results are robust to a variety of tests and specifications. The analysis investigates whether the results differ when investors anticipate business-cycle stages early or late. Implementing sector rotation two months in advance drops performance from 2.3 percent to 1 percent. Outperformance drops to 1.8 percent when investors delay sector rotation by two months. Alternatively, the analysis examines business-cycle stages delineated by the Chicago Federal Reserve National Activity Index (CFNAI). The analysis also uses business-cycle proxies found in the literature to forecast industry performance. Whether the analysis investigates CFNAI stages or business-cycle proxies, the results hold. When considering alternative sector and industry groupings, the results remain unaffected. The main results are also robust to various performance measures such as the Sharpe ratio, Jensen's alpha, and the recently introduced manipulation-proof performance measure (MPPM).[78] The analysis further investigates whether the results depend on the risk-adjustment, as Chordia and Shivakumar (2002) and Avramov and Chordia (2006) document time-variant risk premiums conditional on business-cycle fluctuations. However, the results remain the same whether measured by a single-index, Fama and French three-factor, or Carhart four-factor model.

[77] For instance, a simple market timing strategy that invests continuously in the market except during early recession generates 2.5 percent outperformance, compared with 2.3 percent for sector rotation.
[78] The MPPM controls for potentially biased performance measures due to non-iid returns. See Goetzmann, Ingersoll, Spiegel, and Welch (2007) for a complete discussion.

**Figure 4.1 Popular guidance on sector rotation**




http://personal.fidelity.com/products/funds/content/sector/cycle.shtml




http://www2.standardandpoors.com/spf/pdf/index/Global_Sector_Investing.pdf

Notes: Figure 4.1 illustrates alternative sector rotation strategies.

Lastly, the study generalizes the base-case analysis to allow for all variations of sector rotation. The base-case analysis follows a commonly accepted version of sector rotation, as defined by Stovall (1996) in Table 4.1 and illustrated by Standard & Poor's in Figure 4.1. However, there are other potential variants of sector rotation. The results are thus subject to the criticism of being limited to a specific sector rotation model, among any number of other potential sector rotation models. To counter such criticism, the analysis tests for systematic performance of *any* sector across *any* business-cycle stage. Measuring statistically significant outperformance, the generalized results align with a hypothesis of neither systematic nor persistent differences in sector returns across business-cycle stages. The significance levels observed are only marginally different from those expected to occur randomly, without any systematic outperformance. The result suggests that no sector rotation variant provides systematic outperformance, questioning the popular belief that timing sector investments with business cycles generates excess market performance.

**Table 4.1 Business cycle stages of expected industry performance**

| Period of Expansion | | | Period of Recession | |
|---|---|---|---|---|
| Early Expansion - Stage I | Middle Expansion - Stage II | Late Expansion - Stage III | Early Recession - Stage IV | Late Recession - Stage V |
| **Technology:** | **Basic Materials:** | **Consumer Staples:** | **Utilities:** | **Consumer Cyclical:** |
| Computer Software | Precious Metals | Agriculture | Gas & Electrical Utilities | Apparel |
| Measuring & Control Equip. | Chemicals | Beer & Liquor | Telecom | Automobiles & Trucks |
| Computers | Steel Works Etc | Candy & Soda | | Business Supplies |
| Electronic Equipment | Non-Metallic & Metal Mining | Food Products | | Construction |
| **Transportation:** | **Capital Goods:** | Healthcare | | Construction Materials |
| General Transportation | Fabricated Products | Medical Equipment | | Consumer Goods |
| Shipping Containers | Defense | Pharmaceutical Products | | Entertainment |
| | Machinery | Tobacco Products | | Printing & Publishing |
| | Ships & Railroad Equip. | **Energy:** | | Recreation |
| | Aircraft | Coal | | Restaurants, Hotels, Motels |
| | Electrical Equipment | Petroleum & Natural Gas | | Retail |
| | **Services:** | | | Rubber & Plastic Products |
| | Business Services | | | Textiles |
| | Personal Services | | | Wholesale |
| | | | | **Financial:** |
| | | | | Banking |
| | | | | Insurance |
| | | | | Real Estate |
| | | | | Trading |

Notes: Table 4.1 reports the business cycle stage of anticipated sector/industry outperformance following the Stovall (1996) classification and the investment websites illustrated in Figure 4.1. The table divides the periods of expansion into three equal stages (early/middle/late) and periods of recession into two equal stages (early/late). The Fama and French 49 industry portfolios (excluding "other") map to a corresponding sector for the base-case analysis.

This study contributes to the literature as the first to question the underlying assumptions of sector rotation: systematic sector performance and the opportunity for investors to profitably time sector rotation with the business cycle. Recent papers, such as Elton, Gruber, and Blake (2009) and Avramov and Wermers (2006), suggest the importance that sector rotation plays in mutual fund performance. Apart from a return predictability perspective, this study provides additional insights. Sector rotation generates order flows, which transmit information about asset fundamentals. For instance, Beber, Brandt, and Kavajecz (2010) provide evidence that sector-order flows forecast macroeconomic conditions. The evidence suggests that sector-order flows, however, do not translate into systematic sector performance. Evidence in Avramov and Wermers (2006) finds that switching industry investments across business cycles drives equity fund performance. Jiang, Yao, and Yu (2007), similarly, conclude that industry rotation underlies mutual fund timing strategies, where fund managers switch between cyclical and non-cyclical stocks. A natural question to ask is whether mutual funds follow conventional sector rotation or alternative timing strategies. The results suggest that mutual funds profit from the latter. This study contributes to a renewed interest in the literature on rotation strategies and industry allocation, providing additional insight into these questions, among others.

### 4.2 Literature Review and Hypotheses Development

One can dismiss, within the framework of rational expectations and the efficient market hypothesis, the idea that investors systematically profit from sector rotation. Sector prices should instantaneously reflect all available information and fundamental value – irrespective of business-cycle stages. Yet, the prominence of sector rotation in practice suggests that investors profit from timing systematic sector performance with the business cycle.

The apparent ability to profit from sector rotation might be consistent with the Hong and Stein (1999) gradual information diffusion hypothesis. Gradual information diffusion, as Hong and Stein (1999) describe, involves two groups of traders (news watchers and arbitrageurs) and the lead-lag relation of their responses to economic news. News watchers have a limited ability to process news and consequently revise asset prices with a delay. Arbitrageurs, in contrast, fully incorporate news in their price adjustments and devise simple trading strategies that generate excess returns. Analogously, one can view sector rotation investors as arbitrage traders who respond to economic news by profitably timing sector rotation.

Hong, Torous, and Valkanov (2007) empirically test the gradual information diffusion hypothesis with U.S. industries. They observe an informational delay between general stock market returns and the returns of industries with close economic links. Their study covers the period 1946–2002 with Fama and French industry data. Returns for industries with strong economic links (e.g. metals, services, and petroleum) lead the general market by up to two months. Hong, Torous, and Valkanov (2007) conjecture that economic news affects industry fundamentals differently and that the informational content in the performance of certain industries diffuses slowly across asset markets.

Extending Hong, Torous, and Valkanov (2007), a study by Menzly and Ozbas (2010) provides evidence of industry return continuation, which they attribute to the sequential diffusion of information across related industries. Menzly and Ozbas (2010) observe that certain industries transmit price-sensitive information with a delay to related upstream and downstream firms. Parallels exist between the findings of Menzly and Ozbas (2010) and popularly anticipated industry performance across business cycles. For instance, sector rotation investors anticipate early expansion performance in basic materials that leads to middle expansion performance in manufacturing. Menzly and Ozbas (2010) observe that investors who trade on the knowledge of industry return momentum earn 8.7 percent annual outperformance. Similarly, this study examines whether sequential sector performance across the business cycle provides an opportunity for profitable sector rotation.

Related literature documents differences in the informational content of economic news, dependent on business-cycle conditions. McQueen and Roley (1993), using data from 1977 to 1988, show differences in the effect of economic news on Standard & Poor’s 500 performance. McQueen and Roley (1993) find that the S&P 500 decreases in value with news of economic growth when the economy is strong and increases in value when the economy is weak. Boyd, Hu, and Jagannathan (2005) examine the effect of unemployment news on returns to the S&P 500 from 1957 to 2000. Boyd, Hu, and Jagannathan (2005) find that the impact of unemployment news on equity returns depends on whether the economy is in a period of expansion or recession. The empirical evidence thus shows that the effect of economic news on expected sector performance depends not only on the sector but also on current business-cycle conditions.

While earlier research typically examines asset performance across broad phases of economic expansion and contraction, DeStefano (2004) and Guidolin and Timmermann (2008), among others, observe finer business-cycle partitions. Guidolin and Timmermann (2008) delineate four different stages of the economy characterized by market volatility. Using monthly U.S. stock market data from 1927 to 2005, Guidolin and Timmermann (2008) find that economic stages provide information for rebalancing portfolios formed on firm capitalization and value dimensions.

Empirical research provides evidence that fund managers time their sector investments with business cycles and that their order flows coincide with conventional sector rotation. Lynch, Wachter, and Boudry (2004) also note that fund manager performance varies over business cycles. Avramov and Wermers (2006) show that predictable variation in fund performance relates to a manager's skill in timing industry rotation with NBER business-cycle turning points. Jiang, Yao, and Yu (2007) also observe that fund managers adjust industry allocations based on common business cycle proxies. In a related study, Beber, Brandt, and Kavajecz (2010) conclude that active order flows, defined as flows in excess of market capitalization, directly link to economic news. Notably, for the motivation of this study, Beber, Brandt, and Kavajecz (2010) observe that aggregate sector rebalancing emulates a conventional sector rotation strategy, one that exploits the relative outperformance of certain sectors at different business-cycle stages. Moreover, and of further interest for this study, Beber, Brandt, and Kavajecz (2010) find institutional order flows into certain sectors predict economic direction. For instance, order flows into the basic materials sector predict economic expansion while order flows into the telecommunication, consumer discretionary, and financial sectors predict economic contraction. Such investment flows also coincide with popular belief on the sequence of sector performance.

One can view the systematic recurrence of sector performance, such as the financial sector in early contraction, as a cyclical variant of price continuation consistent with gradual information diffusion. If so, under-reaction to economic news might possibly explain short-term and medium-term price continuation in sector returns, resulting in long-term overreaction and subsequent price reversal. Perhaps not coincidentally, and of interest to the basic premise of sector rotation, the frequency of price continuation and price reversal observed in empirical studies roughly corresponds with business-cycle stages and complete business cycles.

Interestingly, the literature documents that industry performance largely explains price momentum. In an influential study, Moskowitz and Grinblatt (1999) examine industry return momentum from 1963 to 1995, concluding that industry affiliation drives stock momentum. Moskowitz and Grinblatt (1999) attribute return momentum to cross-industry gradual information diffusion. Moskowitz and Grinblatt (1999) speculate that investors herd in popular industries, similar in spirit to conventional sector rotation investors. O'Neal (2000) establishes the profitability of industry momentum strategies using Fidelity Sector Select Funds from 1989 to 1999. Forerunning later research by Beber, Brandt, and Kavajecz (2010), O'Neal (2000) also finds that industry return continuation coincides with business cycles. Bacmann, Dubois, and Isakov (2001), likewise, confirm a link between industry return continuation and business cycles.

An empirical examination of cyclical sector performance is topical for both financial researchers and investors. According to Hong and Stein (1999), informed arbitrage traders can generate excess returns with simple trading strategies based on the release of economic news. Sector- and industry-level investing also constitutes a dynamic growth segment in financial markets. Cavaglia, Brightman, and Aked (2000) and Conover, Jensen, Johnson, and Mercer (2008) document the increased importance of industry-level versus country-level investing. Kacperczyk, Sialm, and Zheng (2005), in a study of U.S. mutual funds from 1984 to 1999, find that active managers with concentrated industry positions generate the greatest outperformance. From a practitioner's perspective, the widespread availability of sector funds and ETFs makes sector allocation strategies more feasible than ever. Nonetheless, there is an apparent absence of empirical research on sector performance over business cycles.

Related literature does describe the performance of alternative business-cycle timing strategies. For instance, Siegel (1991) illustrates the potential of profitably timing allocations between equities and cash. Over an extended 1802–1990 sample, Siegel (1991) documents 12 percent annual market outperformance switching between equity and cash at NBER business-cycle turning points. Brocato and Steed (1998) similarly observe market outperformance rebalancing portfolios at NBER turning points. Further, Levis and Liodakis (1999) and Ahmed, Lockwood, and Nanda (2002) report outperformance to rotation strategies based on firm characteristics (such as earnings, value, and capitalization) conditioned by well-known business-cycle variables. Research by Conover, Jensen, Johnson, and Mercer (2008) show 3.4 percent annual outperformance to a strategy that times investments in cyclical and non-cyclical stocks with Federal Reserve monetary policy. While closely related, this study fundamentally differs from previous research, by thoroughly analyzing sector and industry performance across different measures of business-cycle stages. Additionally, as Fama and French (1997) and Lochstoer (2009) identify time-variant industry-risk premiums related to business cycles, this study also evaluates industry performance using different risk correction measures.

Based on the results, sector performance across business cycles is inconsistent with the gradual information diffusion hypothesis. Economic news appears to transmit immediately, rather than gradually, across sectors. Hou (2007) provides an explanation of why gradual information diffusion might not apply to sector performance. Examining U.S. stock market returns over 1963–2001, Hou (2007) describes slow information diffusion as primarily a within-industry effect, rather than a cross-industry effect. Hou (2007) finds information transmits sluggishly from industry leaders to industry followers. The results provide no evidence of systematic sector performance across business-cycle stages. As such, the results suggest that sector rotation investors have no opportunity to realize excess returns trading on systematic sector performance or gradual information diffusion. Unsystematic sector performance suggests markets are fully rational, rather than boundedly rational as gradual information diffusion prescribes.

The above discussion leads to a formal statement of this study's null and alternative hypotheses.

**$H_0$**: Industry returns are unrelated to the stage of a business cycle stage.
**$H_1$**: There is a systematic relationship between industry performance and stages of the business cycle.
**$H_2$**: Rotating sector investments with business cycle stages generates systematic excess returns.

Answering these hypotheses tests the fundamental assumption of sector rotation investors that timing industry allocations with the business cycle is a profitable investment strategy.

### 4.3 Business Cycles

#### 4.3.1 NBER business cycle dates

The base-case analysis covers 10 business cycles from January 1948 to December 2007. Two considerations determine the starting point of the sample. First, the starting point eliminates the possibility of business-cycle distortions caused by the Great Depression or World War II.[79] For instance, although the U.S. economy was officially in a recession during 1945, industries still operated at full wartime production. Secondly, studies such as Stock and Watson (2002) suggest business-cycle durations changed after World War II. Fama (1975) accredits the change to adoption of the 1951 Federal Reserve Accord. The Accord allows the Federal Reserve Bank to moderate business cycles through interest rate adjustments.

The official U.S. Government agency responsible for dating business cycles is the NBER. While academics and practitioners widely accept NBER cycle reference dates, other business-cycle measures are also available.[80] The NBER dates cycle peaks and cycle troughs that broadly define phases of economic expansion and economic recession. Panel A of Table 4.2 reports business cycle durations from business cycle peak to business cycle peak. The sample covers the 10 business cycles enumerated in the far left column of Panel A. Each business cycle spans the first month following a peak to the subsequent peak. Business cycles average 70 months over the sample. Earlier business cycle durations are much shorter than recent cycles, particularly during phases of economic expansion.[81]

[79] See, for example, Investment Company Institute (2009) and Chatterjee (1999).
[80] For a survey of business cycle dating methodologies, see Cover and Pecorino (2005).
[81] Moore (1974) provides a detailed discussion of post-1948 differences in business cycle dynamics.

**Table 4.2 NBER reference business cycle dates and stage partitions**

| Panel A: | NBER business cycle dates from Jan 1948 - Dec 2007 | | | |
|---|---|---|---|---|
| Business Cycle | Peak Date | Trough Date | Peak Date | Total Months |
| 1 | 11/48 | 10/49 | 07/53 | 56 |
| 2 | 07/53 | 05/54 | 08/57 | 49 |
| 3 | 08/57 | 04/58 | 04/60 | 32 |
| 4 | 04/60 | 02/61 | 12/69 | 116 |
| 5 | 12/69 | 11/70 | 11/73 | 47 |
| 6 | 11/73 | 03/75 | 01/80 | 74 |
| 7 | 01/80 | 07/80 | 07/81 | 18 |
| 8 | 07/81 | 11/82 | 07/90 | 108 |
| 9 | 07/90 | 03/91 | 03/01 | 128 |
| 10 | 03/01 | 11/01 | 12/07 | 81 |

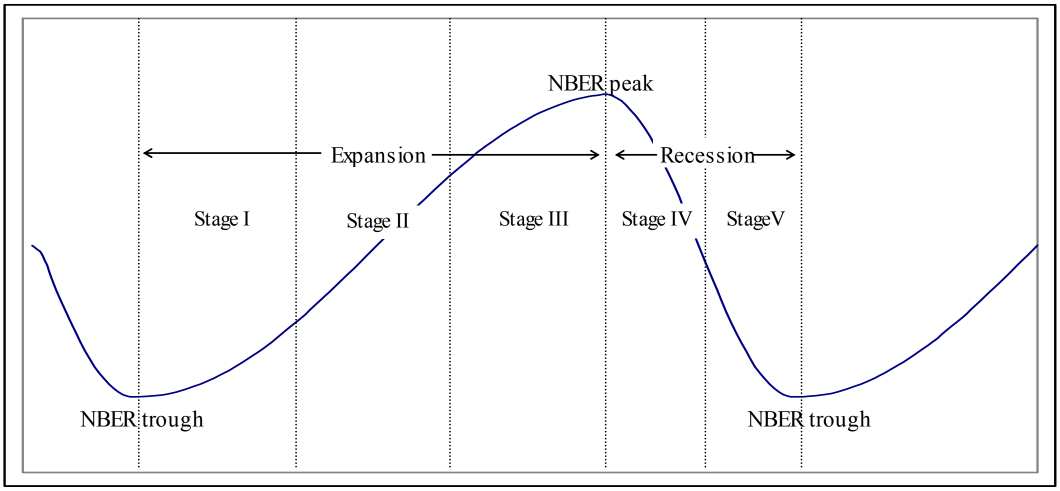
| Panel B: | Number of months in NBER delineated business cycle stages | | | | | | |
|---|---|---|---|---|---|---|---|
| Business | Periods of Recession | | | Periods of Expansion | | | |
| Cycle | Early Stage Months | Late Stage Months | Total Months | Early Stage Months | Middle Stage Months | Late Stage Months | Total Months |
| 1 | 6 | 5 | 11 | 15 | 15 | 15 | 45 |
| 2 | 5 | 5 | 10 | 13 | 13 | 13 | 39 |
| 3 | 4 | 4 | 8 | 8 | 8 | 8 | 24 |
| 4 | 5 | 5 | 10 | 35 | 35 | 36 | 106 |
| 5 | 6 | 5 | 11 | 12 | 12 | 12 | 36 |
| 6 | 8 | 8 | 16 | 19 | 19 | 20 | 58 |
| 7 | 3 | 3 | 6 | 4 | 4 | 4 | 12 |
| 8 | 8 | 8 | 16 | 30 | 31 | 31 | 92 |
| 9 | 4 | 4 | 8 | 40 | 40 | 40 | 120 |
| 10 | 4 | 4 | 8 | 25 | 25 | 23 | 73 |
| **stage average:** | 5 | 5 | 10 | 20 | 20 | 20 | 60 |

Notes: Panel A of Table 4.2 reports NBER published business cycle peak and trough reference dates. Periods of recession run from the first month following a cycle peak to the subsequent trough, and periods of expansion run from the first month following a cycle trough to the subsequent peak. The sample covers 10 business cycles from 1948 to 2007, enumerated in the first column. The last column reports the total months in a business cycle from one month after a peak to the next peak. The last recorded NBER business cycle date is the economic peak dated December 2007. Panel B of Table 4.2 reports the duration in months for stages of expansion and recession that correspond with the business cycles reported in Panel A. The analysis partitions NBER defined periods of expansion into three equal stages (early, middle, and late) and NBER defined periods of recession into two equal stages (early and late). The bottom of Panel B reports the average duration of each business cycle stage.

### 4.3.2 Business cycle stages

While the NBER defines broad economic phases, researchers and investment practitioners commonly divide expansions and recessions into more discrete stages. Investment professionals and practitioner guides, such as Stovall (1996), commonly divide expansions into three equal stages (early/middle/late) and recessions into two equal stages (early/late). Three stages of expansion allow for the longer duration of expansions relative to recessions. Other research, such as DeStefano (2004), divides both expansions and recessions into two equal stages. The base-case analysis evaluates sector/industry performance across five business cycle stages. Subsequent analysis further evaluates performance across two-stage and four-stage business cycle partitions in subsequent robustness checks.

**Figure 4.2 Stylized business cycles with stage partitions**




| Stages of Expansion | |
|---|---|
| Early Expansion (Stage I) | 202 months |
| Middle Expansion (Stage II) | 201 months |
| Late Expansion (Stage III) | 213 months |

| Stages of Recession | |
|---|---|
| Early Recession (Stage IV) | 53 months |
| Late Recession (Stage V) | 51 months |

Notes: Figure 4.2 illustrates a stylized business cycle. The official government agency responsible for dating U.S. business cycles is the National Bureau of Economic Research (NBER). The NBER publishes dates for business cycle peaks and troughs. Phases of expansion run from the month following a trough to the next peak and phases of recession run from the month following a peak to the next trough. Similar to Stovall (1996) and common practice, the analysis divides expansions into three equal stages (early/middle/late) and recessions into two stages (early/late).

The analysis measures expansions from the first month following a cycle trough to the subsequent cycle peak and recessions from the first month following a cycle peak to the subsequent cycle trough. The analysis also delineates three equal stages of expansion and two equal stages of recession. The five business cycle stages are early expansion (Stage I), middle expansion (Stage II), late expansion (Stage III), early recession (Stage IV), and late recession (Stage V). Panel B of Table 4.2 reports the duration of expansions, recessions, and stages over 10 business cycles occurring from 1948 to 2007. Recessions average approximately 10 months and expansions approximately five years.

### 4.3.3 Evaluation of business cycles proxies

The analysis first investigates whether the five NBER delineated stages are consistent with well-known business cycle proxies. The common business cycle proxies (BCP) in the literature are term-spread, default-spread, dividend yield, unemployment, and industrial production. Studies by Keim and Stambaugh (1986), Chen, Roll, and Ross (1986), Fama and French (1989), Schwert (1990), Campbell (1987), Chen (1991), Jensen, Mercer, and Johnson (1996), and Petkova (2006), among others, document the relation between these proxies and business-cycle conditions.

Panel A of Table 4.3 provides a summary of expected business cycle proxy changes over the five NBER delineated stages. For instance, term-spread, default-spread, and dividend yield are smallest near economic peaks and largest near economic troughs (Fama and French (1989)).[82] The expectation is that these variables will decrease across early, middle, and late stages of expansion. Conversely, these same variables should increase across stages of early and late recession. Other studies, such as Balvers, Cosimano, and McDonald (1990) and Chen (1991), document a close link between business cycles and both unemployment rates and industrial production. Stock and Watson (1998) and Hamilton and Lin (1996) show, for example, that industrial production peaks and unemployment rates bottom out as the economy enters recession. Industrial production should increase across successive stages of expansion and decrease across successive stages of recession. Conversely, unemployment rates should decrease across early, middle, and late expansion, then increase across early and late recession.

[82] The term-spread, default-spread, and dividend yield data come from http://www.globalfinancialdata.com

**Table 4.3 Business cycle proxies across business cycle stages**

| Panel A: | Change Early Expansion | Change Middle Expansion | Change Late Expansion | Change Early Recession | Change Late Recession |
|---|---|---|---|---|---|
| Term-spread | negative | negative | negative | positive | positive |
| Default-spread | negative | negative | negative | positive | positive |
| Dividend yield | negative | negative | negative | positive | positive |
| Unemployment | negative | negative | negative | positive | positive |
| Industrial production | positive | positive | positive | negative | negative |

| Panel B: | Stage I | | | Stage II | | | Stage III | | | Stage IV | | | Stage V | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Early Expansion | | | Middle Expansion | | | Late Expansion | | | Early Recession | | | Late Recession | | |
| Factor | Mean | Change | p-value | Mean | Change | p-value | Mean | Change | p-value | Mean | Change | p-value | Mean | Change | p-value |
| Term-spread | 0.020 | 0.005 | 0.00 | 0.013 | -0.008 | 0.00 | 0.003 | -0.010 | 0.00 | 0.006 | 0.003 | 0.05 | 0.015 | 0.009 | 0.00 |
| Default-spread | 0.010 | -0.003 | 0.00 | 0.008 | -0.002 | 0.00 | 0.008 | 0.000 | 0.22 | 0.010 | 0.002 | 0.00 | 0.013 | 0.003 | 0.01 |
| Dividend yield | 0.035 | -0.010 | 0.00 | 0.032 | -0.003 | 0.01 | 0.032 | 0.000 | 0.96 | 0.044 | 0.012 | 0.00 | 0.045 | 0.001 | 0.77 |
| Unemployment | 6.616 | -0.497 | 0.04 | 5.329 | -1.287 | 0.00 | 4.501 | -0.828 | 0.00 | 5.670 | 1.168 | 0.00 | 7.114 | 1.444 | 0.00 |
| Industrial production | 3.992 | 10.472 | 0.00 | 6.020 | 2.028 | 0.00 | 4.233 | -1.787 | 0.00 | -1.375 | -5.608 | 0.00 | -6.480 | -5.105 | 0.00 |

Notes: Panel A of Table 4.3 lists the expected change in business cycle proxies from one business cycle stage to the next. Panel B of Table 4.3 reports business cycle proxy means by business cycle stage and changes in means from the preceding stage estimated with Equation 4.1, where business cycle dummy variables ($D_s$) take the value of one or zero depending on the current business cycle stage. The analysis then calculates the difference in proxy means between successive business cycle stages. As an example, Panel B reports an average 0.5% difference in term-spread between the stages of early expansion and late recession ($\gamma_1$-$\gamma_5$). Lastly, the analysis performs a simple difference in means test, to verify the statistical significance of the difference in means between the current and preceding stage. The table reports p-values under a null hypothesis of no difference in proxies across successive business cycle stages, formally stated as Ho: $\gamma_s=\gamma_{s-1}$.

$$BCP_t = \sum_{s=1}^{5} \gamma_s D_{s,t} + \varepsilon_t \qquad \text{(Eq. 4.1)}$$

Panel B of Table 4.3 reports proxy averages by business-cycle stage estimated with Equation 4.1, where $D_s$ is a dummy variable that takes the value of one or zero dependent on the current business cycle stage. Next, the table reports changes in business-cycle proxy values ($\gamma_s$-$\gamma_{s-1}$) between successive business-cycle stages. As an example, there is an average 0.5% difference in term-spread between early expansion and late recession. Panel B establishes that changes in the selected business-cycle variables track NBER delineated business-cycle stages and show the expected sign as reported in Panel A. For instance, the results should indicate a significantly negative term-spread difference between early expansion and late recession. The analysis tests for statistical significance using a simple difference in means test. Panel B reports p-values under the null hypothesis of no difference in business-cycle proxies across successive stages, formally stated as $H_o$: $\gamma_s = \gamma_{s-1}$. Failure to reject the null would indicate no statistically significant difference in the business-cycle proxy across successive stages and would invalidate the stage delineations.

The results document that changes in the business-cycle proxies across successive business-cycle stages, with few exceptions, have the expected sign and are highly significant. For instance, changes in unemployment rates from one business-cycle stage to the next are all significantly negative across stages of expansion and significantly positive across stages of contraction. Similarly, changes in default-spread are negative, as expected, during early and middle expansion, and positive during early and late recession. The change in dividend yield is insignificant in both late expansion and late recession, indicating that dividend yield provides a weak signal of business-cycle turning points. The change in industrial production growth is also as expected, except during late expansion. Overall, the results reported in Table 4.3 confirm that the NBER delineated stages are consistent with well-known business-cycle proxies and thus encapsulate progressive stages of business-cycle dynamics.

### 4.4 Industry Performance across Business Cycles

#### 4.4.1 Data description

For the base-case scenario, monthly market, industry, and Treasury bill return data come from the Kenneth French website. Market returns represent the total value weighted returns for all NYSE, AMEX, and NASDAQ listed stocks. The analysis initially uses the Fama and French 49 industry portfolios. Fama and French map firms to industry groupings based on their standard industrial classification (SIC).[83] Firms mapped to the "other" industry come from a variety of sectors and industries. As such, the "other" industry holds no relevance in a sector rotation strategy. Consequently, the analysis omits the "other" industry, leaving 48 of the original Fama and French 49 industries.[84] The one-month Treasury bill serves as a proxy for the risk-free interest rate. The analysis reports all results as continuously compounded annualized returns.

[83] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for further detail on the data and the formation of industry portfolios.

[84] The "other" industry group represents approximately 3.5 percent of total firms listed on NYSE, AMEX, and NASDAQ.

### 4.4.2 Popular guidance on industry performance

Table 4.1 shows the particular stage of the business cycle where popular belief anticipates industries will perform best. The base case follows the popular Stovall (1996) practitioner guide to sector investing. Stovall (1996) divides all equities into 10 basic sectors. He then maps sectors and sub-sector industry groups to one of five business cycle stages.[85] For example, Stovall suggests that the technology and transportation sectors provide early expansion performance, basic materials and capital goods provide middle expansion performance, and so forth. As Table 4.1 illustrates, there are four technology sub-sector industries and two transportation sub-sector industries. Conventional guidance suggests each industry in those sectors provides early recession performance. Performance then shifts from sector to sector across business-cycle stages. The base-case analysis maps each of the 48 industry portfolios to a corresponding sector, then maps each sector to the business-cycle stage of anticipated sector performance, following the Stovall (1996) classification.

### 4.4.3 Nominal industry performance

Table 4.4 provides industry descriptive industry statistics and nominal performance for the business-cycle stage popular belief anticipates outperformance will occur.[86] The table reports the average number of firms, number of observations, mean returns, standard deviation of returns, and single-index betas by the indicated stage. For comparison, Table 4.4 reports mean returns, standard deviation of returns, and single-index betas for the full sample 1948–2007. The table also reports industry averages and market statistics beneath each business-cycle stage.

The second column of Table 4.4 reports the average number of firms in an industry. Implementing sector rotation at industry level allows for more precise targeting of performance. The wide variety of available industry funds and ETFs reflects the popularity of industry-level investing. The increased precision targeting industry versus

[85] Lofthouse (2001) traces a similar approach of mapping sectors to stylized stages of economic cycles back to Markese (1986). There are also different variants of mapping sector performance to business-cycle stages. Salsman (1997) uses dividend yield, short-term interest rates, and precious metal prices to map sector performance. The present study concludes with the total relaxation of any assumed sector rotation model.
[86] Full results for all Fama and French 49 industries across all business cycle stages are available upon request.

sector performance, however, comes at the cost of reduced diversification benefits. The defense, tobacco, and coal industries, for instance, comprise on average fewer than 10 firms. As such, investments in those industries are subject to a high level of firm-specific risk. It is unlikely, however, that sector rotation investors would invest in only one industry during a particular business-cycle stage. For example, there are 12 industries, including defense, expected to provide middle expansion performance. Overall, conventional sector rotation investors would thus hold a well-diversified middle expansion portfolio.[87]

The base-case analysis initially measures nominal industry performance to determine whether significant differences occur over business cycles. The analysis then observes whether industry performance coincides with popular belief. Computer software, for instance, should provide early expansion performance and basic materials should provide middle expansion performance. Equation 4.2 estimates nominal industry performance for business-cycle stages.

$$r_{it} = \sum_{s=1}^{5} \mu_{is} D_{st} + \varepsilon_{it} \qquad \text{(Eq. 4.2)}$$

The equation runs a regression of nominal industry returns ($r_i$) on a dummy variable ($D_s$) that indicates one of five different business-cycle stages. As an example, $D_1$ takes the value of one during months of early expansion and zero in all other months. Dummy variables $D_1$, $D_2$, and $D_3$ correspond with the three stages of economic expansion (early/middle/late). Dummy variables $D_4$ and $D_5$ correspond with the two stages of economic recession (early/late). Thus, the $\mu_{is}$ regression coefficients measures average nominal industry returns for each of five business-cycle stages. For comparison, the last three columns in Table 4.4 report industry statistics over the full sample period. Table 4.4 also reports p-values from a Wald test under the null hypothesis that industry returns are not significantly different across business-cycle stages. However, in most cases, the p-values reject the null, indicating that industry performance varies across business-cycle stages. Sector rotation investors would find this initial result encouraging. Failure

[87] For an overview of tradeoffs in implementing sector rotation strategies at sector, industries, and firm levels, see http://us.ishares.com/portfolio_strategies/investment_strategies/sector_strategies.htm

to reject the null hypothesis of equal returns would question the basic premise of sector rotation from the start.

Table 4.4 also reports average market returns beneath each business-cycle stage. The analysis compares industry and market returns to provide a simple relative return metric. As an example, Table 4.4 reports transportation industry returns of 25 percent, compared with 17 percent market returns for early expansion. The transportation industry thus provides market outperformance, where conventional wisdom expects. However, the realization of expected outperformance does not always occur. Out of the 48 industries, 34 have nominal returns higher than market returns, in the stage of expected outperformance. Thus, 70 percent of industries offer the expected higher nominal performance. Market outperformance, however, comes at a price. All but one industry (food products) has higher return volatility than the market. Observing average industry performance for two stages reveals surprising results. The 14 percent average return for industries expected to perform well in early expansion actually underperforms the market by 3 percent. Similarly, average returns for industries expected to perform well in middle expansion earn 1 percent less than the market.

**Table 4.4 Industry summary statistics by business-cycle stages**

| | Business Cycle Stage | | | | | | Full Sample 1948:01-2007:12 | | |
|---|---|---|---|---|---|---|---|---|---|
| Sectors/Industries | no. firms | no. obs. | mean | std.dev. | beta | Wald p-value | mean | std.dev. | beta |
| **Early Expansion - Stage I:** | | | | | | | | | |
| Computers | 90 | 201 | 0.13 | 0.22 | 1.38 | 0.00 | 0.13 | 0.24 | 1.24 |
| Computer Software | 175 | 130 | 0.00 | 0.34 | 1.71 | 0.15 | 0.02 | 0.42 | 1.79 |
| Electronic Equipment | 157 | 201 | 0.17 | 0.25 | 1.50 | 0.00 | 0.11 | 0.26 | 1.44 |
| Measuring & Control | 70 | 201 | 0.10 | 0.22 | 1.36 | 0.00 | 0.12 | 0.24 | 1.32 |
| Shipping Containers | 26 | 201 | 0.18 | 0.17 | 0.96 | 0.00 | 0.12 | 0.18 | 0.98 |
| Transportation | 93 | 201 | 0.25 | 0.17 | 1.02 | 0.00 | 0.10 | 0.19 | 1.09 |
| **Industry Averages** | | | 0.14 | 0.23 | 1.32 | 0.03 | 0.10 | 0.25 | 1.31 |
| **Market** | | 201 | 0.17 | 0.13 | 1.00 | 0.00 | 0.12 | 0.14 | 1.00 |
| **Middle Expansion - Stage II:** | | | | | | | | | |
| Chemicals | 79 | 202 | 0.12 | 0.17 | 1.12 | 0.00 | 0.11 | 0.17 | 1.01 |
| Steel Works | 78 | 202 | 0.13 | 0.22 | 1.23 | 0.00 | 0.10 | 0.23 | 1.25 |
| Precious Metals | 20 | 166 | 0.08 | 0.32 | 0.76 | 0.58 | 0.08 | 0.35 | 0.71 |
| Mining | 24 | 202 | 0.12 | 0.23 | 1.19 | 0.00 | 0.12 | 0.21 | 1.01 |
| Fabricated Products | 20 | 166 | 0.12 | 0.20 | 1.00 | 0.01 | 0.05 | 0.24 | 1.10 |
| Machinery | 149 | 202 | 0.17 | 0.18 | 1.22 | 0.00 | 0.11 | 0.19 | 1.17 |
| Electrical Equipment | 68 | 202 | 0.19 | 0.19 | 1.26 | 0.00 | 0.14 | 0.20 | 1.19 |
| Aircraft | 25 | 202 | 0.19 | 0.21 | 1.15 | 0.00 | 0.14 | 0.23 | 1.12 |
| Shipbuilding & Railroad | 11 | 202 | 0.08 | 0.19 | 1.15 | 0.01 | 0.10 | 0.21 | 1.00 |
| Defense | 7 | 166 | 0.15 | 0.21 | 1.07 | 0.02 | 0.12 | 0.23 | 0.83 |
| Personal Services | 38 | 202 | 0.12 | 0.22 | 1.17 | 0.00 | 0.09 | 0.23 | 1.08 |
| Business Services | 166 | 202 | 0.13 | 0.16 | 1.04 | 0.00 | 0.10 | 0.18 | 1.09 |
| **Industry Averages** | | | 0.13 | 0.21 | 1.11 | 0.05 | 0.10 | 0.22 | 1.05 |
| **Market** | | 202 | 0.14 | 0.13 | 1.00 | 0.00 | 0.12 | 0.14 | 1.00 |

***Continued:***

| Sectors/Industries | no. firms | no. obs. | Business Cycle Stage mean | std.dev. | beta | Wald p-value | Full Sample 1948:01-2007:12 mean | std.dev. | beta |
|---|---|---|---|---|---|---|---|---|---|
| **Late Expansion - Stage III:** | | | | | | | | | |
| Agriculture | 11 | 213 | 0.11 | 0.22 | 0.81 | 0.00 | 0.10 | 0.21 | 0.90 |
| Food Products | 80 | 213 | 0.07 | 0.15 | 0.61 | 0.00 | 0.13 | 0.14 | 0.71 |
| Candy & Soda | 12 | 166 | 0.05 | 0.24 | 0.74 | 0.01 | 0.12 | 0.22 | 0.84 |
| Beer & Liquor | 15 | 213 | 0.10 | 0.19 | 0.81 | 0.00 | 0.13 | 0.18 | 0.82 |
| Tobacco Products | 9 | 213 | 0.15 | 0.20 | 0.40 | 0.04 | 0.15 | 0.20 | 0.64 |
| Healthcare | 74 | 136 | 0.09 | 0.33 | 1.16 | 0.02 | 0.09 | 0.31 | 1.17 |
| Medical Equipment | 87 | 213 | 0.12 | 0.17 | 0.86 | 0.01 | 0.14 | 0.19 | 0.93 |
| Pharmaceutical | 130 | 213 | 0.10 | 0.16 | 0.70 | 0.01 | 0.13 | 0.17 | 0.86 |
| Coal | 8 | 213 | 0.21 | 0.33 | 1.02 | 0.00 | 0.14 | 0.29 | 1.08 |
| Petroleum & Natural Gas | 136 | 213 | 0.11 | 0.18 | 0.74 | 0.00 | 0.14 | 0.18 | 0.83 |
| **Industry Averages** | | | 0.11 | 0.22 | 0.79 | 0.01 | 0.13 | 0.21 | 0.88 |
| **Market** | | 213 | 0.07 | 0.15 | 1.00 | 0.00 | 0.12 | 0.14 | 1.00 |
| | | | | | | | | | |
| **Early Recession - Stage IV:** | | | | | | | | | |
| Utilities | 137 | 53 | 0.00 | 0.16 | 0.76 | 0.05 | 0.11 | 0.13 | 0.55 |
| Communication | 43 | 53 | -0.04 | 0.14 | 0.63 | 0.07 | 0.10 | 0.14 | 0.70 |
| **Industry Averages** | | | -0.02 | 0.15 | 0.70 | 0.06 | 0.11 | 0.14 | 0.62 |
| **Market** | | 53 | -0.16 | 0.16 | 1.00 | 0.00 | 0.12 | 0.14 | 1.00 |
| | | | | | | | | | |
| **Late Recession - Stage V:** | | | | | | | | | |
| Recreation | 32 | 51 | 0.64 | 0.31 | 1.22 | 0.00 | 0.09 | 0.25 | 1.18 |
| Entertainment | 33 | 51 | 0.50 | 0.31 | 1.28 | 0.10 | 0.14 | 0.24 | 1.27 |
| Printing & Publishing | 32 | 51 | 0.62 | 0.23 | 1.03 | 0.00 | 0.12 | 0.20 | 1.05 |
| Consumer Goods | 82 | 51 | 0.49 | 0.21 | 1.01 | 0.00 | 0.12 | 0.16 | 0.87 |
| Apparel | 57 | 51 | 0.63 | 0.27 | 1.09 | 0.00 | 0.10 | 0.20 | 1.05 |
| Rubber & Plastic | 29 | 51 | 0.42 | 0.22 | 0.90 | 0.00 | 0.12 | 0.20 | 1.05 |
| Textiles | 46 | 51 | 0.47 | 0.25 | 1.09 | 0.00 | 0.10 | 0.20 | 1.00 |
| Construction Materials | 125 | 51 | 0.51 | 0.23 | 1.17 | 0.00 | 0.11 | 0.18 | 1.10 |
| Construction | 32 | 51 | 0.63 | 0.33 | 1.51 | 0.00 | 0.12 | 0.24 | 1.29 |
| Automobiles & Trucks | 65 | 51 | 0.38 | 0.25 | 1.06 | 0.00 | 0.11 | 0.20 | 1.05 |
| Business Supplies | 32 | 51 | 0.44 | 0.24 | 1.19 | 0.00 | 0.11 | 0.20 | 1.03 |
| Wholesale | 96 | 51 | 0.43 | 0.23 | 1.06 | 0.00 | 0.11 | 0.19 | 1.07 |
| Retail | 172 | 51 | 0.55 | 0.24 | 1.11 | 0.00 | 0.12 | 0.18 | 0.98 |
| Restaurants & Hotels | 48 | 51 | 0.52 | 0.28 | 1.27 | 0.00 | 0.12 | 0.21 | 1.08 |
| Banking | 151 | 51 | 0.48 | 0.23 | 1.14 | 0.02 | 0.12 | 0.18 | 0.96 |
| Insurance | 77 | 51 | 0.44 | 0.20 | 0.86 | 0.01 | 0.12 | 0.19 | 0.89 |
| Real Estate | 32 | 51 | 0.56 | 0.31 | 1.21 | 0.00 | 0.07 | 0.24 | 1.10 |
| Trading | 186 | 51 | 0.53 | 0.23 | 1.16 | 0.00 | 0.14 | 0.20 | 1.21 |
| **Industry Averages** | | | 0.51 | 0.25 | 1.13 | 0.01 | 0.11 | 0.20 | 1.07 |
| **Market** | | 51 | 0.40 | 0.18 | 1.00 | 0.00 | 0.12 | 0.14 | 1.00 |

Notes: Table 4.4 reports industry summary statistics for the business cycle stage popular belief anticipates outperformance will occur, as listed in Table 4.1. The table reports nominal mean returns and standard deviations (std.dev.) as annualized rates. Equation 4.2 estimates nominal mean industry returns for each business-cycle stage, with a regression of industry returns ($r_i$) on the business-cycle stage dummy variables ($D_s$). The stage dummy variables take a value of one or zero at time t depending on the current business-cycle stage. The reported industry betas are from a single-index model. The table also reports Wald p-values under a null hypothesis of equal industry returns across all five business-cycle stages. For comparative purposes, Table 4.4 provides industry summary statistics for the full sample 1948–2007. The table reports equally weighted industry averages and market returns beneath each business-cycle stage. Column 1 reports the average number of firms (no. firms) included in an industry. Column 2 reports the number of industry return observations (no. obs.) included in a business-cycle stage.

Based on the base-case results, popular belief holds true in the remaining three stages. Industries on average outperform the market, as expected, in late expansion, early recession, and late recession. Nominal sector performance coincides only partially with popular expectations. Moreover, industry standard deviations and betas indicate that risk-adjusted performance will coincide even less with popular expectations. For instance, in early and middle expansion, average industry underperformance coincides with average standard deviations higher than the market and above average industry betas. For the remaining three stages, the results are inconsistent, with mostly lower industry betas but higher industry standard deviations.

The nominal industry performance results are not encouraging for sector rotation investors. Historically, alternative industries do provide performance during early and middle expansion, but popular sector rotation strategy does not include those industries.[88] The next section investigates whether industries provide systematic risk-adjusted business-cycle performance.

### 4.4.4 Risk-adjusted industry performance measures

Table 4.5 reports industry excess market returns, Jensen's alphas, Fama and French (1992) three-factor alphas, and Carhart (1997) four-factor alphas by business-cycle stage.[89] The table reports performance alphas estimated with Equations 4.3 to 4.6 reported as annualized rates. Emboldened alpha estimations indicate statistical significance at 10 percent calculated with White (1980) heteroskedasticity consistent t-statistics. Columns 3, 5, 7, and 9 of Table 4.5 report results from a Wald test of equal industry performance across business-cycle stages. Formally stated, Wald p-values estimates are under the null hypothesis $H_0$: $\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5$, which Table 4.5 reports separately for each industry and performance measure.

Equation 4.3 estimates excess market industry performance ($\alpha^m$), with a regression of excess market industry returns ($r_i$-$r_m$) on the five business-cycle dummy variables ($D_s$). The regression coefficient $\alpha_{is}^m$ measures market outperformance for industry *i* during business cycle stage *s*. The results show that 10 of 48 industries, approximately one in five, generate statistically significant excess market performance when expected. More than half of the significant excess market performance occurs in early and late

[88] The concluding analysis relaxes the assumption of any sector rotation model, by examining the performance of all industries across all stages of the business cycle.
[89] For brevity, the study focuses on the business-cycle stage of expected industry outperformance and provides complete results on request.

recession. Notably, excess market performance comes before any adjustment for systematic exposure to known sources of risk, which the following analysis takes into account next.

$$r_{it} - r_{mt} = \sum_{s=1}^{5} \alpha_{is}^{m} D_{st} + \varepsilon_{it} \qquad \text{(Eq. 4.3)}$$

**Table 4.5 Industry performance measures by business-cycle stages**

| | Excess Market | | Jensen's alpha | | Fama-French alpha | | Carhart alpha | |
|---|---|---|---|---|---|---|---|---|
| **Industries** | $\alpha^{m}$ | **Wald p-value** | $\alpha^{J}$ | **Wald p-value** | $\alpha^{F}$ | **Wald p-value** | $\alpha^{C}$ | **Wald p-value** |
| **Early Expansion - Stage I:** | | | | | | | | |
| Computers | -0.03 | 0.48 | **-0.08** | 0.32 | -0.05 | 0.92 | -0.01 | 0.90 |
| Computer Software | -0.12 | 0.55 | **-0.17** | 0.88 | **-0.18** | 0.85 | **-0.19** | 0.83 |
| Electronic Equip. | 0.00 | 0.29 | -0.06 | 0.94 | -0.04 | 0.94 | -0.01 | 0.90 |
| Measuring & Control | **-0.06** | 0.06 | **-0.10** | 0.05 | **-0.07** | 0.22 | **-0.06** | 0.22 |
| Shipping Containers | 0.01 | 0.10 | 0.01 | 0.12 | -0.01 | 0.15 | -0.01 | 0.15 |
| Transportation | **0.07** | 0.00 | **0.07** | 0.00 | 0.03 | 0.08 | 0.02 | 0.10 |
| **Industry Average:** | -0.02 | | -0.05 | | -0.05 | | -0.04 | |
| **Middle Expansion - Stage II:** | | | | | | | | |
| Chemicals | -0.02 | 0.05 | -0.03 | 0.04 | -0.03 | 0.16 | -0.02 | 0.13 |
| Steel Works | -0.01 | 0.53 | -0.03 | 0.60 | **-0.06** | 0.32 | -0.05 | 0.25 |
| Precious Metals | -0.05 | 0.97 | -0.03 | 0.97 | -0.07 | 0.97 | -0.07 | 0.96 |
| Mining | -0.01 | 0.05 | -0.03 | 0.05 | **-0.06** | 0.01 | **-0.06** | 0.01 |
| Fabricated Products | -0.01 | 0.16 | -0.01 | 0.24 | -0.04 | 0.16 | -0.03 | 0.16 |
| Machinery | 0.03 | 0.02 | 0.01 | 0.19 | 0.00 | 0.26 | 0.00 | 0.22 |
| Electrical Equip. | **0.05** | 0.36 | 0.02 | 0.33 | 0.02 | 0.39 | 0.01 | 0.41 |
| Aircraft | 0.05 | 0.66 | 0.03 | 0.84 | 0.01 | 0.96 | 0.00 | 0.96 |
| Shipbuilding/Railroad | **-0.05** | 0.62 | **-0.07** | 0.62 | **-0.08** | 0.58 | **-0.08** | 0.59 |
| Defense | 0.01 | 0.67 | 0.01 | 0.48 | -0.02 | 0.52 | -0.03 | 0.48 |
| Personal Services | -0.02 | 0.17 | -0.03 | 0.29 | -0.04 | 0.48 | -0.03 | 0.50 |
| Business Services | 0.00 | 0.09 | -0.01 | 0.13 | -0.01 | 0.16 | -0.01 | 0.17 |
| **Industry Average:** | 0.00 | | -0.01 | | -0.03 | | -0.03 | |
| **Late Expansion - Stage III:** | | | | | | | | |
| Agriculture | 0.04 | 0.24 | 0.04 | 0.20 | 0.04 | 0.15 | 0.04 | 0.14 |
| Food Products | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 |
| Candy & Soda | -0.03 | 0.32 | -0.03 | 0.20 | -0.04 | 0.18 | -0.03 | 0.18 |
| Beer & Liquor | 0.03 | 0.37 | 0.03 | 0.65 | 0.03 | 0.37 | 0.04 | 0.37 |
| Tobacco Products | 0.08 | 0.01 | **0.09** | 0.09 | **0.08** | 0.05 | **0.10** | 0.05 |
| Healthcare | 0.01 | 0.23 | 0.01 | 0.30 | 0.01 | 0.24 | 0.02 | 0.24 |
| Medical Equipment | **0.05** | 0.04 | **0.05** | 0.05 | **0.05** | 0.10 | 0.03 | 0.09 |
| Pharmaceutical | 0.03 | 0.00 | 0.04 | 0.01 | 0.04 | 0.04 | 0.01 | 0.04 |
| Coal | **0.14** | 0.06 | **0.14** | 0.09 | **0.13** | 0.07 | 0.06 | 0.06 |
| Petroleum & Natural Gas | 0.05 | 0.50 | 0.05 | 0.42 | 0.04 | 0.36 | 0.03 | 0.35 |
| **Industry Average:** | 0.04 | | 0.04 | | 0.04 | | 0.03 | |
| **Early Recession - Stage IV:** | | | | | | | | |
| Gas & Electric | **0.20** | 0.01 | **0.13** | 0.74 | **0.12** | 0.49 | **0.12** | 0.50 |
| Communication | **0.15** | 0.02 | 0.05 | 0.65 | 0.04 | 0.74 | 0.04 | 0.64 |
| **Industry Average:** | 0.17 | | 0.09 | | 0.08 | | 0.08 | |

***Continued:***

| Industries | Excess Market $\alpha^m$ | Wald p-value | Jensen's alpha $\alpha^J$ | Wald p-value | Fama-French alpha $\alpha^F$ | Wald p-value | Carhart alpha $\alpha^C$ | Wald p-value |
|---|---|---|---|---|---|---|---|---|
| **Late Recession - Stage V:** | | | | | | | | |
| Recreation | 0.18 | 0.47 | 0.10 | 0.66 | 0.06 | 0.56 | 0.00 | 0.59 |
| Entertainment | 0.07 | 0.76 | -0.01 | 0.18 | -0.05 | 0.06 | -0.04 | 0.05 |
| Printing & Publishing | **0.16** | 0.06 | **0.15** | 0.07 | **0.12** | 0.07 | 0.08 | 0.07 |
| Consumer Goods | 0.07 | 0.37 | 0.06 | 0.28 | 0.07 | 0.24 | 0.00 | 0.22 |
| Apparel | **0.17** | 0.27 | 0.14 | 0.34 | 0.07 | 0.27 | 0.08 | 0.39 |
| Rubber & Plastic | 0.01 | 0.45 | 0.04 | 0.56 | 0.01 | 0.47 | -0.03 | 0.47 |
| Textiles | 0.05 | 0.34 | 0.03 | 0.34 | -0.02 | 0.81 | 0.01 | 0.89 |
| Construction Materials | 0.08 | 0.09 | 0.03 | 0.33 | 0.00 | 0.29 | -0.03 | 0.31 |
| Construction | 0.17 | 0.00 | 0.01 | 0.03 | -0.01 | 0.01 | 0.03 | 0.01 |
| Automobiles & Trucks | -0.01 | 0.07 | -0.03 | 0.08 | -0.07 | 0.39 | -0.05 | 0.34 |
| Business Supplies | 0.03 | 0.22 | -0.03 | 0.26 | -0.04 | 0.65 | -0.04 | 0.68 |
| Wholesale | 0.02 | 0.56 | 0.00 | 0.75 | -0.01 | 0.72 | -0.07 | 0.72 |
| Retail | **0.11** | 0.10 | 0.08 | 0.10 | 0.04 | 0.09 | 0.01 | 0.10 |
| Restaurants & Hotels | 0.09 | 0.37 | 0.01 | 0.57 | -0.02 | 0.60 | -0.04 | 0.66 |
| Banking | 0.06 | 0.43 | 0.01 | 0.48 | 0.00 | 0.34 | -0.05 | 0.38 |
| Insurance | 0.03 | 0.92 | 0.07 | 0.92 | 0.09 | 0.82 | 0.04 | 0.84 |
| Real Estate | 0.11 | 0.08 | 0.05 | 0.14 | -0.03 | 0.10 | -0.12 | 0.11 |
| Trading | **0.10** | 0.02 | 0.05 | 0.60 | 0.03 | 0.77 | 0.05 | 0.82 |
| **Industry Average:** | 0.08 | | 0.04 | | 0.01 | | -0.01 | |

Notes: Table 4.5 reports industry excess market returns ($\alpha^m$), Jensen's alphas ($\alpha^J$), Fama and French (1992) three-factor alphas ($\alpha^F$), and Carhart (1997) four-factor alphas ($\alpha^C$) for the business-cycle stages of expected outperformance listed in Table 4.1. Equations 4.3–4.6 estimate excess market returns, Jensen's alphas, Fama and French alphas, and Carhart alphas by business-cycle stage. The table reports annualized alpha returns. Emboldened alpha performance indicates 10 percent statistical significance estimated with White (1980) heteroskedasticity consistent t-statistics. Columns 3, 5, 7, & 9 of Table 4.5 report Wald test p-values under a null hypothesis of constant industry performance across all five business-cycle stages. Wald p-values are under the null hypothesis $H_o$: $\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5$. Table 4.5 also reports equally weighted industry averages beneath each business-cycle stage.

Equation 4.4 estimates a Jensen's alphas ($\alpha^J$) attributable to each business-cycle stage with a modified single-index model.

$$r_{it} - rf_t = \sum_{s=1}^{5} \alpha_{is}^J D_{st} + \sum_{s=1}^{5} \beta_{m,is}(r_{mt} - rf_t)D_{st} + \varepsilon_{it} \qquad \text{(Eq. 4.4)}$$

Equation 4.4 runs a regression of industry returns in excess of the one-month Treasury bill ($r_i$-$rf$) on one of five business-cycle timing variables ($D_s$) and the conditional market risk premium ($r_m$-$rf$). The Fama and French market index represents the market proxy.

To ensure the results do not depend on exposure to other well-known risk factors, the analysis also estimates Fama and French three-factor alphas and Carhart four-factor alphas. The Fama and French alphas ($\alpha^F$), estimated with Equation 4.5, control for size and value risk factors in addition to market risk. Lastly, the Carhart four-factor alphas

($\alpha^C$), estimated with Equation 4.6, add a momentum factor to the Fama and French three-factor model.

$$r_{it} - rf_t = \sum_{s=1}^{5} \alpha_{is}^F D_{st} + \sum_{s=1}^{5} \left[ \beta_{is}^m (r_{mt} - rf_t) + \beta_{is}^s SMB_t + \beta_{is}^v HML_t \right] D_{st} + \varepsilon_{it} \qquad \text{(Eq. 4.5)}$$

$$r_{it} - rf_t = \sum_{s=1}^{5} \alpha_{is}^C D_{st} + \sum_{s=1}^{5} \left[ \beta_{is}^m (r_{mt} - rf_t) + \beta_{is}^s SMB_t + \beta_{is}^v HML_t + \beta_{is}^c MOM_t \right] D_{st} + \varepsilon_{it} \qquad \text{(Eq. 4.6)}$$

Regardless of the risk-adjusted alpha performance measure, there is scant evidence of statistically significant industry outperformance where popular belief would suggest. The performance results strengthen the earlier findings reported for nominal returns. Based on Jensen's alphas, there are six industries with significant outperformance. Based on the Fama and French three-factor model, there are only five industries with significant outperformance, and using the Carhart four-factor model only two. At a 10 percent significance level, that is what one would roughly expect to observe randomly, in the absence of true systematic industry outperformance.[90]

An additional step tests for systematic differences in industry performance across all five business-cycle stages with Wald tests. Table 4.5 reports Wald test p-values under a null hypothesis of constant measures of industry performance across the business cycle. If industry outperformance varies across business-cycle stages, one should reject the null hypothesis of constant performance. However, the results fail to reject the null hypothesis of constant excess market returns for 29 of the 48 industries at a 10 percent significance level. Similarly, Wald tests of Jensen's, Fama-French, and Carhart performance alphas indicate acceptance of the null hypothesis of constant industry performance roughly 75 percent of the time at 10 percent significance. The Wald tests results of constant industry performance differ substantially from Wald tests of constant nominal returns. The results show that general market movement and exposure to systematic risk factors largely explain differences in industry return performance across business cycles.

[90] If anything, it seems that the utilities and communications industries perform as popular belief anticipates, showing early recession performance.

### 4.5 Sector Rotation Performance

Can conventional sector rotation still be profitable, despite limited evidence of systematic industry performance? This section focuses on strategy implementation, observing the performance of sector rotation across the last 10 business cycles. The base-case sector rotation strategy assumes investors perfectly time NBER business-cycle stages and rotate the Fama and French 49 industries following the conventional sector rotation depicted in Table 4.1. The strategy invests equally in all industries held at each stage. Table 4.6 reports the performance of a conventional sector rotation strategy and compares the results with a simple market investment. The table reports annualized strategy returns and Jensen's alphas, with corresponding White (1980) heteroskedasticity consistent t-statistics. Table 4.6 also provides strategy Sharpe ratios, along with single-index betas and standard deviations.

Annualized sector rotation outperformance, based on perfectly timing business cycles and a conventional sector rotation model, amounts to 2.3 percent.[91] At first glance, the outperformance appears economically large. However, in perspective, the 2.3 percent represents the maximum outperformance. Only investors who followed popular market wisdom over the past 60 years, ignored transactions costs, and perfectly timed the last 10 NBER business cycles, would have realized 2.3 percent outperformance. Siegel (1991) suggests a simpler market-timing strategy, showing that shifting between equities and cash at business-cycle turning points generates significant outperformance. However, Siegel (1991) also recognizes the difficulty in correctly timing business cycles. To provide perspective on sector rotation outperformance, the results also report the performance of the simpler market-timing strategy suggested by Siegel (1991). Here, the analysis assumes a theoretical investor who correctly times NBER recessions and expansions. Such an investor, shifting from equities to cash early recession and back to equities late recession, would have realized 2.5 percent outperformance. That same investor would have also held a more diversified market portfolio, subject to less industry-specific risk. The next section considers what happens under more realistic assumptions, with the introduction of transaction costs.

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[91] Since the analysis estimates Jensen's alphas with a constant beta over the full sample period, outperformance does not equal the weighted average of industry outperformance by business-cycle stage reported in Table 4.4.

**Table 4.6 Performance comparison of alternative investment strategies**

| Strategy | mean | std.dev. | beta | Sharpe ratio | Jensen's alpha | t-statistic |
|---|---|---|---|---|---|---|
| Market | 11.6% | 14.5% | 1.00 | 0.13 | | |
| ***0% round-trip transaction costs:*** | | | | | | |
| Base case sector rotation | 14.2% | 16.8% | 1.00 | 0.15 | 2.3% | 1.94 |
| Market-timing | 13.6% | 13.6% | 0.89 | 0.17 | 2.5% | 3.57 |
| ***Alternative sector/industry groups*** | | | | | | |
| 10 Sectors | 13.2% | 17.3% | 1.04 | 0.13 | 1.1% | 0.94 |
| 13 Standard & Poor's sector indices | 12.1% | 17.8% | 0.86 | 0.11 | 1.4% | 0.77 |
| 23 Industry groups | 13.9% | 16.9% | 1.00 | 0.15 | 2.1% | 1.76 |
| ***Alternative business cycle stages*** | | | | | | |
| 2 NBER stages | 11.9% | 15.9% | 1.04 | 0.12 | 0.0% | -0.02 |
| 4 NBER stages | 13.5% | 16.6% | 1.02 | 0.14 | 1.6% | 1.55 |
| 5 CFNAI stages | 6.2% | 15.4% | 0.82 | 0.03 | -3.8% | -2.99 |
| ***0.5% round-trip transaction costs:*** | | | | | | |
| Base case sector rotation | 13.7% | 16.8% | 1.00 | 0.14 | 1.9% | 1.59 |
| Market-timing | 13.4% | 13.7% | 0.89 | 0.17 | 2.3% | 3.32 |
| ***Alternative sector/industry groups*** | | | | | | |
| 10 Sectors | 12.7% | 17.3% | 1.04 | 0.12 | 0.7% | 0.59 |
| 13 Standard & Poor's sector indices | 11.7% | 17.8% | 0.86 | 0.10 | 0.9% | 0.53 |
| 23 Industry groups | 13.5% | 16.9% | 1.00 | 0.14 | 1.7% | 1.42 |
| ***Alternative business cycle stages*** | | | | | | |
| 2 NBER stages | 11.7% | 15.9% | 1.04 | 0.12 | -0.2% | -0.27 |
| 4 NBER stages | 13.2% | 16.7% | 1.02 | 0.14 | 1.2% | 1.22 |
| 5 CFNAI stages | 3.7% | 15.3% | 0.83 | -0.02 | -6.1% | -4.84 |
| ***1.0% round-trip transaction costs:*** | | | | | | |
| Base case sector rotation | 13.2% | 16.8% | 1.00 | 0.14 | 1.5% | 1.24 |
| Market-timing | 13.2% | 13.7% | 0.89 | 0.16 | 2.1% | 3.06 |
| ***Alternative sector/industry groups*** | | | | | | |
| 10 Sectors | 12.2% | 17.3% | 1.04 | 0.12 | 0.3% | 0.24 |
| 13 Standard & Poor's sector indices | 11.2% | 17.8% | 0.86 | 0.10 | 0.5% | 0.30 |
| 23 Industry groups | 13.0% | 16.9% | 1.00 | 0.13 | 1.3% | 1.06 |
| ***Alternative business cycle stages*** | | | | | | |
| 2 NBER stages | 11.5% | 15.9% | 1.04 | 0.11 | -0.3% | -0.52 |
| 4 NBER stages | 12.8% | 16.7% | 1.03 | 0.13 | 0.9% | 0.88 |
| 5 CFNAI stages | 1.2% | 15.4% | 0.83 | -0.06 | -8.4% | -6.63 |
| ***1.5% round-trip transaction costs:*** | | | | | | |
| Base case sector rotation | 12.8% | 16.8% | 1.00 | 0.13 | 1.1% | 0.89 |
| Market-timing | 13.0% | 13.7% | 0.90 | 0.16 | 1.9% | 2.78 |
| ***Alternative sector/industry groups*** | | | | | | |
| 10 Sectors | 11.8% | 17.3% | 1.04 | 0.11 | -0.1% | -0.12 |
| 13 Standard & Poor's sector indices | 10.8% | 17.8% | 0.86 | 0.09 | 0.1% | 0.06 |
| 23 Industry groups | 12.5% | 16.9% | 1.00 | 0.12 | 0.8% | 0.71 |
| ***Alternative business cycle stages*** | | | | | | |
| 2 NBER stages | 11.3% | 15.9% | 1.04 | 0.11 | -0.5% | -0.77 |
| 4 NBER stages | 12.4% | 16.7% | 1.03 | 0.12 | 0.5% | 0.54 |
| 5 CFNAI stages | -1.2% | 15.5% | 0.83 | -0.11 | -10.6% | -8.32 |

Notes: Table 4.6 reports mean returns, standard deviations, single-index betas, Sharpe ratios, and Jensen's alphas for the base-case sector rotation and market-timing strategies with different transaction costs. The table reports mean returns, standard deviations, and Jensen's alphas as annualized rates and White (1980) heteroskedasticity consistent Jensen's alpha t-statistics. The shaded strategy performance results reported in Table 4.6 are for alternative sector/industry groupings and business cycle stages that sections 4.6.1 and 4.6.2 discuss later as robustness tests.

Transaction costs, both explicit and implicit, are difficult to estimate precisely. Estimated transaction costs include commissions, bid-ask spread, and market impact. Actual costs depend on the stock, where it trades, and when it trades.[92] Estimates vary considerably and change over the sample.[93] As an allowance, Table 4.7 reports performance with round-trip transaction costs that range between 0.5 and 1.5 percent. Sector rotation has 50 round-trip transactions and the market-timing strategy has 20 round-trip transactions from 1948 to 2007. With the inclusion of transaction costs, the base-case sector rotation outperformance decreases to between 1.1 to 1.9 percent and becomes statistically indistinguishable from zero. The alternative market-timing strategy increases in relative outperformance, owing to fewer transactions.

Thus far, the results indicate only marginal sector rotation outperformance for sector rotation implemented in accordance with popular wisdom, even if one assumes investors can correctly time business cycles. Results for industries expected to perform well in early expansion and middle expansion are particularly disappointing. Still, it would be premature to conclude that sector rotation does not work. Investors may use different industry or sector classifications, different business-cycle indicators, or different business-cycle stages. Alternatively, investors may time business cycles in advance or with a delay, which could generate outperformance.

Robustness tests of the base-case scenario consider alternative data sets, performance measures, and sample periods. The robustness tests also investigate whether the results improve if investors anticipate changes in business-cycle turning points earlier or later. In addition to NBER business cycles, the analysis tests business-cycle stages constructed from the CFNAI and a forecast model based on well-known business-cycle proxies. Another test separates the sample into two sub-periods and business-cycle stages in halves. The analysis concludes with the total relaxation of any specific sector rotation model, testing for the systematic performance of any sector across any business-cycle stage.

[92] See for example Goyenko, Holden, and Trzcinka (2009) and Hasbrouck (2009).
[93] Estimates of total trading costs vary greatly depending on the study. For instance, Lesmond, Schill, and Zhou (2004) estimate round-trip transaction costs of 1 to 2 percent for most large-cap trades while Keim and Madhavan (1998) estimate total round-trip transaction costs as low as 0.2 percent.

### 4.6 Robustness Checks

#### 4.6.1 Alternative sector/industry groups and data sets

There are alternative sector and industry classifications available to sector rotation investors. As such, the base-case analysis might merely reflect a particular industry grouping. Additionally, the performance of the narrowly defined Fama and French 49 industry portfolios might unduly reflect idiosyncratic performance. Consequently, one can argue that the results merely measure firm specific developments unrelated to the business cycle. To accommodate both possibilities, the following analysis investigates the performance of three alternative sector and industry groups.

The analysis first maps the Fama and French 49 industry portfolios to two alternative portfolio groupings. There are alternative sector and industry groupings readily available on the Kenneth French website. However, the Fama and French classifications vary considerably in how they map firms to the "other" industry group. For instance, "other" represents an average 27 percent of all NYSE, AMEX, and NASDAQ listed firms in the Fama and French 17 industry portfolios from 1948 to 2007. Moreover, those firms come from a variety of sectors. In contrast, "other" in the Fama and French 49 industry group represents 3.5 percent of the total. As such, the omission of such a large percent of the market, and important sectors, renders the performance of alternative Fama and French portfolios incomparable.

As an alternative, the analysis maps the original Fama and French 49 industries to 10 sector portfolios and 23 major industry portfolios, as listed in Table 4.7. The 10 sector portfolios are constructed following the Kacperczyk, Sialm, and Zheng (2005) mapping of the Fama and French 48 portfolios. The additional computer software industry included in the Fama and French 49 industry portfolios goes into the business equipment and services sector. Additionally, the analysis maps the Fama and French 49 industries to one of 23 GICS major industry groups. The Global Industry Classification Standard (GICS), first introduced in 1999, provides a widely accepted alternative to SIC classifications.[94] Bhojraj, Lee, and Oler (2003) report GICS classifications are superior

[94] For details, see http://www2.standardandpoors.com/spf/pdf/index/GICS_methodology.pdf

to alternative classification schemes. Results obtained from the alternative 10 sector and 23 major industry portfolios compares directly with the base-case analysis using the Fama and French 49 industries.

**Table 4.7 Alternative sector and industry mappings**

| 49 Fama-French Industries | | 23 GICS Major Industry Groups | | 10 Sectors | |
|---|---|---|---|---|---|
| **Code** | **Industry Description** | **Code** | **Industry Group Description** | **Code** | **Sector Description** |
| 01 | Agriculture | 3020 | Consumer Staples | 01 | Consumer Non-Durable |
| 24 | Aircraft | 2010 | Industrials | 04 | Manufacturing |
| 10 | Apparel | 2520 | Consumer Discretionary | 01 | Consumer Non-Durable |
| 23 | Automobiles & Trucks | 2510 | Consumer Discretionary | 02 | Consumer Durable |
| 45 | Banking | 4010 | Financials | 10 | Finance |
| 04 | Beer & Liquor | 3020 | Consumer Staples | 01 | Consumer Non-Durable |
| 34 | Business Services | 2020 | Industrials | 08 | Business Equipment & Services |
| 39 | Business Supplies | 2020 | Industrials | 04 | Manufacturing |
| 03 | Candy & Soda | 3020 | Consumer Staples | 01 | Consumer Non-Durable |
| 14 | Chemicals | 1510 | Materials | 04 | Manufacturing |
| 29 | Coal | 1010 | Energy | 05 | Energy |
| 32 | Communication | 5010 | Telecommunication Services | 07 | Telecom |
| 36 | Computer Software | 4510 | Information Technology | 08 | Business Equipment & Services |
| 35 | Computers | 4520 | Information Technology | 08 | Business Equipment & Services |
| 18 | Construction | 2550 | Consumer Discretionary | 04 | Manufacturing |
| 17 | Construction Materials | 1510 | Materials | 04 | Manufacturing |
| 09 | Consumer Goods | 2530 | Consumer Discretionary | 02 | Consumer Durable |
| 26 | Defense | 2010 | Industrials | 04 | Manufacturing |
| 22 | Electrical Equipment | 2010 | Industrials | 04 | Manufacturing |
| 37 | Electronic Equipment | 4530 | Information Technology | 08 | Business Equipment & Services |
| 07 | Entertainment | 2540 | Consumer Discretionary | 01 | Consumer Non-Durable |
| 20 | Fabricated Products | 2010 | Industrials | 04 | Manufacturing |
| 02 | Food Products | 3010 | Consumer Staples | 01 | Consumer Non-Durable |
| 11 | Healthcare | 3510 | Healthcare | 03 | Healthcare |
| 46 | Insurance | 4030 | Financials | 10 | Finance |
| 21 | Machinery | 2010 | Industrials | 04 | Manufacturing |
| 38 | Measuring & Control | 4520 | Information Technology | 08 | Business Equipment & Services |
| 12 | Medical Equipment | 3510 | Healthcare | 03 | Healthcare |
| 28 | Mining | 1510 | Materials | 05 | Energy |
| 33 | Personal Services | 2530 | Consumer Discretionary | 01 | Consumer Non-Durable |
| 30 | Petroleum & Natural Gas | 1010 | Energy | 05 | Energy |
| 13 | Pharmaceutical | 3520 | Healthcare | 03 | Healthcare |
| 27 | Precious Metals | 1510 | Materials | 05 | Energy |
| 08 | Printing & Publishing | 2540 | Consumer Discretionary | 01 | Consumer Non-Durable |
| 47 | Real Estate | 4040 | Financials | 10 | Finance |
| 06 | Recreation | 2520 | Consumer Discretionary | 02 | Consumer Durable |
| 44 | Restaurants & Hotels | 2530 | Consumer Discretionary | 09 | Wholesale & Retail |
| 43 | Retail | 2550 | Consumer Discretionary | 09 | Wholesale & Retail |
| 15 | Rubber & Plastic | 2550 | Consumer Discretionary | 04 | Manufacturing |
| 25 | Shipbuilding & Railroad | 2010 | Industrials | 04 | Manufacturing |
| 40 | Shipping Containers | 2030 | Industrials | 04 | Manufacturing |
| 19 | Steel Works | 1510 | Materials | 04 | Manufacturing |
| 16 | Textiles | 2520 | Consumer Discretionary | 01 | Consumer Non-Durable |
| 05 | Tobacco Products | 3020 | Consumer Staples | 01 | Consumer Non-Durable |
| 48 | Trading | 4020 | Financials | 10 | Finance |
| 41 | Transportation | 2030 | Industrials | 04 | Manufacturing |
| 31 | Utilities | 5510 | Utilities | 06 | Utilites |
| 42 | Wholesale | 2550 | Consumer Discretionary | 09 | Wholesale & Retail |

Notes: Table 4.7 provides a mapping of the Fama and French 49 industry portfolios to 23 Global industrial Classification Standard (GICS) industry groups and 10 sector classifications.

Lastly, the analysis evaluates 13 Standard & Poor's sector indices. The Standard & Poor's indices provide sector benchmarks, well known by financial practitioners. Sector indices are constructed from Standard & Poor's 500 constituent stocks based on their SIC or, if available, GICS sector classification.[95] As such, the Standard & Poor's indices comprise large capitalized firms, while the Fama and French portfolios comprise the entire market. For comparison with the base case analysis, the analysis only includes the 13 Standard & Poor's sector indices with data available from 1948 to 2007. The Standard & Poor's index data comes from Global Financial Data.[96]

Table 4.8 compares the summary statistics and performance measures for the 10 sector portfolios (10FF), 13 Standard & Poor's sector indices (13SP), and 23 GICS major industry groups (23FF). The analysis evaluates the alternative sector and industry portfolios by the business-cycle stage popular belief anticipates outperformance will occur. Table 4.8 reports mean returns, standard deviations, and single-index betas by business-cycle stage and for the full sample. Additionally, Table 4.8 also reports excess market performance, Jensen's alphas, Fama and French alphas, and Carhart alphas. Bold indicates statistically significant performance at 10 percent using White (1980) heteroskedasticity consistent t-statistics. The table reports returns and performance measures as annual rates. The results reported in Table 4.8 directly compare with the base-case results reported in Table 4.4 and Table 4.5.

Nominal returns and alpha performance for the alternative portfolio largely compare with the earlier analysis. Generally, nominal returns are slightly lower, compared with the Fama and French 49 industries. At the same time, less return volatility and market risk indicate the more aggregated sector and major industry group portfolios provide diversification benefits. The Standard & Poor's sector indices, in particular, have the least return and beta risk, but also offer the least performance, perhaps reflecting its large-cap composition. Similar to the earlier results, the alternative portfolios also underperform the market in early and middle expansion. The one exception is the average early expansion performance of the Standard & Poor's indices. Significant

[95] Complete details on the construction of Standard & Poor's sector indices are available at http://www.seemore-indices.com/assets/files/sectors/pdf/Factsheet_SP_Sector_Indices.pdf
[96] https://www.globalfinancialdata.com

excess market performance also largely compares with the Fama and French industries. The 23 major industry portfolios provide significant excess market returns about 30 percent of the time where performance is expected, compared with 20 percent of the time for the 10 sector portfolios. The alternative portfolios provide substantially less significant Jensen's, Fama-French, and Carhart alpha outperformance. For instance, only one Standard & Poor's index, railroads in early expansion, generates significant Jensen's alpha outperformance. Table 4.6 provides strategy performance measures for sector rotation implemented with the alternative sector and major group industry portfolios. The 23 major industry group portfolios provide the highest Jensen's alpha performance, at 2.1 percent, before transaction costs. This performance compares unfavorably with the base-case sector rotation performance of 2.3 percent and 2.5 percent for the market-timing strategy. Strategy performance for the 10 sector portfolios and 13 Standard & Poor's indices is even less, and statistically insignificant. The analysis of alternative sector and industry groups shows that the base-case results are not specific to a particular industrial classification or data set.

**Table 4.8 Summary statistics for alternative sector and industry groups**

| | | Business Cycle Stages | | | | | | | Sample 1948-2007 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Performance Measures | | | | | | |
| | Sectors/Industries | mean | std.dev. | beta | $\alpha^m$ | $\alpha^J$ | $\alpha^F$ | $\alpha^C$ | mean | std.dev. | beta |
| **Early Expansion Sectors/Industries- Stage I:** | | | | | | | | | | | |
| 10 FF Sectors | Business Equipment & Services | 0.11 | 0.20 | 1.38 | **-0.05** | **-0.09** | **-0.07** | **-0.05** | 0.11 | 0.22 | 1.35 |
| 13 SP Indices | Computer Technology | 0.11 | 0.23 | 1.21 | -0.05 | **-0.08** | -0.05 | 0.00 | 0.14 | 0.23 | 1.06 |
| | Railroads | 0.25 | 0.19 | 1.05 | **0.07** | **0.06** | 0.03 | 0.01 | 0.10 | 0.20 | 0.97 |
| | **Average:** | 0.18 | 0.21 | 1.13 | 0.01 | -0.01 | -0.01 | 0.00 | 0.12 | 0.22 | 1.01 |
| 23 FF Groups | Transportation | 0.21 | 0.15 | 0.99 | **0.04** | **0.04** | 0.01 | 0.00 | 0.11 | 0.17 | 1.04 |
| | Software & Services | 0.00 | 0.34 | 1.71 | -0.12 | **-0.17** | **-0.18** | **-0.19** | 0.02 | 0.42 | 1.79 |
| | Technology Hardware & Equipment | 0.11 | 0.20 | 1.37 | **-0.05** | **-0.09** | **-0.06** | **-0.04** | 0.13 | 0.22 | 1.28 |
| | Semiconductors & Equipment | 0.17 | 0.25 | 1.50 | 0.00 | -0.06 | -0.04 | -0.01 | 0.11 | 0.26 | 1.44 |
| | **Average:** | 0.12 | 0.24 | 1.39 | -0.03 | -0.07 | -0.07 | -0.06 | 0.09 | 0.27 | 1.39 |
| **Middle Expansion Sectors/Industries - Stage II:** | | | | | | | | | | | |
| 10 FF Sectors | Manufacturing | 0.15 | 0.16 | 1.13 | 0.01 | 0.00 | -0.02 | -0.02 | 0.11 | 0.17 | 1.09 |
| 13 SP Indices | Chemicals | 0.11 | 0.18 | 1.08 | -0.02 | -0.03 | -0.04 | -0.02 | 0.09 | 0.18 | 0.91 |
| | Precious Metals | 0.10 | 0.31 | 0.64 | -0.03 | 0.00 | -0.02 | -0.02 | 0.12 | 0.33 | 0.50 |
| | Metal and Mining | 0.14 | 0.31 | 1.07 | 0.00 | -0.01 | -0.04 | -0.03 | 0.13 | 0.28 | 1.05 |
| | Capital Goods | 0.13 | 0.16 | 1.06 | -0.01 | -0.02 | -0.02 | -0.01 | 0.10 | 0.17 | 0.97 |
| | **Average:** | 0.12 | 0.24 | 0.96 | -0.02 | -0.01 | -0.03 | -0.02 | 0.11 | 0.24 | 0.86 |
| 23 FF Groups | Materials | 0.12 | 0.18 | 1.09 | -0.01 | -0.02 | **-0.04** | -0.04 | 0.11 | 0.18 | 1.03 |
| | Capital Goods | 0.15 | 0.17 | 1.15 | 0.01 | 0.00 | -0.02 | -0.02 | 0.11 | 0.18 | 1.08 |
| | Commercial Services & Supplies | 0.12 | 0.16 | 1.06 | -0.02 | -0.02 | -0.02 | -0.02 | 0.11 | 0.17 | 1.06 |
| | Consumer Services | 0.15 | 0.16 | 1.04 | 0.01 | 0.00 | 0.00 | 0.01 | 0.11 | 0.18 | 1.01 |
| | **Average:** | 0.13 | 0.17 | 1.09 | 0.00 | -0.01 | -0.02 | -0.02 | 0.11 | 0.18 | 1.04 |

***Continued:***

| | Sectors/Industries | Business Cycle Stages: mean | std.dev. | beta | Performance Measures: $\alpha^m$ | $\alpha^J$ | $\alpha^F$ | $\alpha^C$ | Sample 1948-2007: mean | std.dev. | beta |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Late Expansion Sectors/Industries - Stage III:** | | | | | | | | | | | |
| 10 FF Sectors | Consumer Non-Durable | 0.06 | 0.16 | 0.88 | -0.01 | 0.00 | -0.01 | 0.01 | 0.12 | 0.15 | 0.94 |
| | Healthcare | 0.10 | 0.18 | 0.89 | 0.03 | 0.03 | 0.03 | 0.02 | 0.13 | 0.18 | 0.98 |
| | Energy | 0.13 | 0.19 | 0.82 | 0.06 | **0.06** | 0.05 | 0.03 | 0.12 | 0.19 | 0.92 |
| | **Average:** | 0.10 | 0.17 | 0.86 | 0.03 | 0.03 | 0.03 | 0.02 | 0.12 | 0.18 | 0.95 |
| 13 SP Indices | Health | 0.12 | 0.17 | 0.54 | 0.05 | 0.06 | 0.05 | 0.04 | 0.13 | 0.20 | 0.71 |
| | Oil & Natural Gas | 0.08 | 0.17 | 0.63 | 0.01 | 0.02 | 0.01 | 0.00 | 0.11 | 0.17 | 0.74 |
| | Consumer Staples | 0.05 | 0.14 | 0.62 | -0.02 | -0.01 | -0.02 | -0.01 | 0.10 | 0.15 | 0.76 |
| | **Average:** | 0.08 | 0.16 | 0.60 | 0.02 | 0.02 | 0.02 | 0.01 | 0.11 | 0.17 | 0.74 |
| 23 FF Groups | Energy | 0.16 | 0.22 | 0.88 | **0.09** | **0.09** | **0.08** | 0.04 | 0.14 | 0.21 | 0.96 |
| | Food & Staples Retailing | 0.07 | 0.15 | 0.61 | 0.00 | 0.01 | 0.00 | 0.01 | 0.13 | 0.14 | 0.71 |
| | Food, Beverages, & Tobacco | 0.10 | 0.15 | 0.68 | 0.03 | 0.04 | 0.03 | 0.04 | 0.12 | 0.15 | 0.80 |
| | Healthcare | 0.11 | 0.21 | 0.99 | 0.04 | 0.04 | 0.04 | 0.03 | 0.13 | 0.21 | 1.04 |
| | Pharmaceuticals | 0.10 | 0.16 | 0.70 | 0.03 | 0.04 | 0.04 | 0.01 | 0.14 | 0.17 | 0.86 |
| | **Average:** | 0.11 | 0.18 | 0.78 | 0.04 | 0.04 | 0.04 | 0.03 | 0.13 | 0.18 | 0.87 |
| **Early Recession Sectors/Industries - Stage IV:** | | | | | | | | | | | |
| 10 FF Sectors | Telecom | -0.04 | 0.14 | 0.63 | **0.15** | 0.05 | 0.04 | 0.04 | 0.10 | 0.14 | 0.70 |
| | Utilities | 0.00 | 0.16 | 0.76 | **0.20** | **0.13** | **0.12** | **0.12** | 0.11 | 0.13 | 0.55 |
| | **Average:** | -0.02 | 0.15 | 0.70 | 0.17 | 0.09 | 0.08 | 0.08 | 0.11 | 0.14 | 0.62 |
| 13 SP Indices | Telecommunications | -0.02 | 0.15 | 0.49 | 0.10 | 0.00 | -0.02 | -0.02 | 0.06 | 0.16 | 0.60 |
| | Gas & Electric Utitlities | -0.03 | 0.17 | 0.67 | **0.12** | 0.07 | 0.05 | 0.06 | 0.06 | 0.14 | 0.57 |
| | **Average:** | -0.02 | 0.16 | 0.58 | 0.11 | 0.03 | 0.01 | 0.02 | 0.06 | 0.15 | 0.58 |
| 23 FF Groups | Telecommunication Services | -0.04 | 0.14 | 0.63 | **0.15** | 0.05 | 0.04 | 0.04 | 0.10 | 0.14 | 0.70 |
| | Utilities | 0.00 | 0.16 | 0.76 | **0.20** | **0.13** | **0.12** | **0.12** | 0.11 | 0.13 | 0.55 |
| | **Average:** | -0.02 | 0.15 | 0.70 | 0.17 | 0.09 | 0.08 | 0.08 | 0.11 | 0.14 | 0.62 |
| **Late Recession Sectors/Industries - Stage V:** | | | | | | | | | | | |
| 10 FF Sectors | Consumer Durable | 0.50 | 0.22 | 1.10 | 0.07 | 0.04 | 0.02 | -0.01 | 0.11 | 0.18 | 1.03 |
| | Wholesale & Retail | 0.50 | 0.23 | 1.15 | 0.07 | 0.03 | 0.00 | -0.03 | 0.12 | 0.17 | 1.04 |
| | Finance | 0.50 | 0.22 | 1.09 | 0.07 | 0.05 | 0.02 | -0.02 | 0.11 | 0.17 | 1.04 |
| | **Average:** | 0.50 | 0.22 | 1.11 | 0.07 | 0.04 | 0.01 | -0.02 | 0.11 | 0.17 | 1.04 |
| 13 SP Indices | Consumer Durables | 0.37 | 0.19 | 0.89 | -0.02 | 0.01 | -0.01 | 0.00 | 0.09 | 0.16 | 0.90 |
| | Banking | 0.29 | 0.24 | 0.94 | -0.08 | -0.06 | -0.09 | -0.13 | 0.07 | 0.19 | 0.83 |
| | **Average:** | 0.33 | 0.22 | 0.92 | -0.05 | -0.03 | -0.05 | -0.06 | 0.08 | 0.17 | 0.87 |
| 23 FF Groups | Automobiles & Components | 0.38 | 0.25 | 1.06 | -0.01 | -0.03 | -0.07 | -0.05 | 0.11 | 0.20 | 1.05 |
| | Consumer Non-Durables & Apparel | 0.58 | 0.25 | 1.13 | **0.13** | 0.09 | 0.04 | 0.03 | 0.10 | 0.19 | 1.08 |
| | Media | 0.56 | 0.25 | 1.15 | **0.12** | 0.07 | 0.03 | 0.02 | 0.13 | 0.20 | 1.16 |
| | Retailing | 0.50 | 0.23 | 1.15 | 0.08 | 0.03 | 0.01 | -0.01 | 0.12 | 0.18 | 1.10 |
| | Banks | 0.48 | 0.23 | 1.14 | 0.06 | 0.01 | 0.00 | -0.05 | 0.12 | 0.18 | 0.96 |
| | Diversified Financials | 0.53 | 0.23 | 1.16 | **0.10** | 0.05 | 0.03 | 0.05 | 0.14 | 0.20 | 1.21 |
| | Insurance | 0.44 | 0.20 | 0.86 | 0.03 | 0.07 | 0.09 | 0.04 | 0.12 | 0.19 | 0.89 |
| | Real Estate | 0.56 | 0.31 | 1.21 | 0.11 | 0.05 | -0.03 | -0.12 | 0.07 | 0.24 | 1.10 |
| | **Average:** | 0.50 | 0.24 | 1.11 | 0.08 | 0.04 | 0.01 | -0.01 | 0.11 | 0.20 | 1.07 |

Notes: Table 4.8 reports mean returns, standard deviations, market betas, excess market alphas, Jensen's alphas, Fama and French alphas, and Carhart alphas for the business-cycle stage popular belief anticipates outperformance will occur. Equation 4.2 estimates mean returns and Equations 4.3 to 4.6 estimate the respective performance alphas. Table 4.8 also reports mean returns, standard deviations, and market betas for the full 1948–2007 sample period. The table reports mean returns, standard deviations, and performance alphas as annual rates and indicate 10 percent statistical significance using White (1980) heteroskedasticity consistent t-statistics in bold.

### 4.6.2 Alternative business-cycle stage delineation

Arguably, business-cycle stage delineations are arbitrary. Although the five-stage analysis follows a common approach, one can potentially construct any number of business-cycle partitions. As a result, the base-case results face the criticism that they are specific to a particular delineation of business-cycle stages. The NBER officially dates U.S. business-cycle peaks and troughs, delineating one stage of expansion and one stage of recession. DeStefano (2004) further separates the NBER stages of expansion and contraction into two equal halves each, four stages in all. The following analysis considers both NBER two-stage and DeStefano (2004) four-stage partitions, to verify that the results are robust to alternative business-cycle stage specifications. The two-stage analysis uses NBER cycle dates to delineate one stage of expansion and one stage of recession. Expansions last an average 616 months and recessions last an average 104 months. The two-stage analysis maps early, middle, and late expansion industries into one stage of expansion, and early and late recession industries into one stage of recession. The four-stage analysis further divides expansions and recessions in equal halves. Early and late expansion stages last on average 302 and 314 months. Early and late recession stages last on average 53 and 51 months, identical to the five-stage analysis. The four-stage analysis maps middle expansion industries into the late expansion stage, with the remaining industries mapped as previous.

Table 4.9 and Table 4.10 provide summary statistics and performance measures for the Fama and French 49 industries across NBER business cycles delineated by two and four stages. Similar to the previous analysis, the table reports mean returns, standard deviations, and single-index betas by business cycle stage and for the full sample. The table also reports Jensen's, Fama-French, and Carhart alpha performance measures for the stage of anticipated outperformance, where bold indicates statistical significance at 10 percent using White (1980) heteroskedasticity consistent t-statistics. The table reports returns and performance measures as annual rates.

Systematic industry performance does not improve using either the two-stage or the four-stage partitions. Nominal industry performance across one stage of expansion now equals the market, although with greater return volatility, as Table 4.9 reports. The occurrence of systematic excess market returns, and alpha performance, is less with two than five stages. Only two industries in expansions and three in recessions provide systematic excess market returns. Moreover, only four industries now provide Jensen's alpha outperformance over both stages of expansion and recession, and even less for Fama and French and Carhart alphas. Combining early and late stages of recession substantially reduces average excess market performance. Previously, the results documented 8 percent average excess market performance in late recession, which now drops to an average 2 percent for a single stage of recession. Simply holding utilities and telecommunications industries in the early stage of recession proves the superior strategy, as popular belief would suggest. Delineating business cycles by four stages, reported in Table 4.10, similarly provides no additional insight into systematic industry performance. The performance of technology industries improves somewhat with a longer stage of early expansion. Nonetheless, nominal industry returns underperform the market by 2 percent. Additionally, the four technology industries continue to generate significant Jensen's alpha underperformance. The combined middle and late expansion nominal industry returns now outperform the market – but only marginally so. Statistically significant excess market and alpha performance measures also show only slight improvement over the base-case analysis. Even then, only four of 22 industries exhibit systematic excess market performance, compared with three industries over middle and late expansion stages previously reported.

Table 4.6 reports strategy performance measures for sector rotation implementation for two-stage and four-stage NBER business cycle delineations. Rotating sectors at expansion and recession turning points generate the least performance. And, while the DeStefano (2004) four-stage approach realizes a 1.6 percent Jensen's alpha, outperformance is statistically indistinguishable from zero. Both alternative strategies thus generate inferior performance, in comparison with the base-case sector rotation. Overall, alternative specifications of business-cycle stage partitions provide no improvement on the base case and the previous results continue to hold.

**Table 4.9 Two-stage industry summary statistics and performance**

| | Business Cycle Stages | | | | | | | Full Sample 1948-2007 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Performance Measures | | | | | | |
| Sectors/Industries | mean | std.dev. | beta | $\alpha^m$ | $\alpha^J$ | $\alpha^F$ | $\alpha^C$ | mean | std.dev. | beta |
| **Expansion - Stage I:** | | | | | | | | | | |
| Computers | 0.13 | 0.23 | 1.24 | 0.01 | -0.01 | 0.03 | **0.04** | 0.13 | 0.24 | 1.24 |
| Computer Software | 0.04 | 0.38 | 1.77 | -0.07 | **-0.11** | **-0.08** | -0.08 | 0.02 | 0.42 | 1.79 |
| Electronic Equipment | 0.12 | 0.25 | 1.46 | 0.00 | -0.03 | 0.00 | 0.02 | 0.11 | 0.26 | 1.44 |
| Measuring & Control | 0.13 | 0.22 | 1.31 | 0.00 | -0.02 | 0.01 | 0.01 | 0.12 | 0.24 | 1.32 |
| Shipping Containers | 0.12 | 0.18 | 0.98 | 0.00 | 0.00 | -0.01 | 0.00 | 0.12 | 0.18 | 0.98 |
| Transportation | 0.12 | 0.18 | 1.05 | 0.00 | -0.01 | **-0.04** | **-0.03** | 0.10 | 0.19 | 1.09 |
| Chemicals | 0.11 | 0.17 | 1.02 | -0.01 | -0.01 | **-0.03** | -0.02 | 0.11 | 0.17 | 1.01 |
| Steel Works | 0.12 | 0.22 | 1.29 | -0.01 | -0.03 | **-0.05** | **-0.03** | 0.10 | 0.23 | 1.25 |
| Precious Metals | 0.07 | 0.33 | 0.59 | -0.04 | -0.02 | -0.04 | -0.06 | 0.08 | 0.35 | 0.71 |
| Mining | 0.15 | 0.21 | 0.99 | 0.02 | 0.02 | 0.00 | 0.00 | 0.12 | 0.21 | 1.01 |
| Fabricated Products | 0.08 | 0.22 | 1.04 | -0.03 | -0.03 | **-0.06** | **-0.05** | 0.05 | 0.24 | 1.10 |
| Machinery | 0.13 | 0.18 | 1.15 | 0.01 | 0.00 | -0.02 | 0.00 | 0.11 | 0.19 | 1.17 |
| Electrical Equipment | 0.16 | 0.19 | 1.20 | **0.03** | 0.02 | 0.02 | 0.02 | 0.14 | 0.20 | 1.19 |
| Aircraft | 0.15 | 0.22 | 1.09 | 0.03 | 0.02 | -0.01 | 0.00 | 0.14 | 0.23 | 1.12 |
| Shipbuilding & Railroad | 0.11 | 0.20 | 0.99 | -0.01 | -0.01 | **-0.04** | **-0.05** | 0.10 | 0.21 | 1.00 |
| Defense | 0.12 | 0.22 | 0.81 | 0.00 | 0.01 | -0.03 | -0.04 | 0.12 | 0.23 | 0.83 |
| Personal Services | 0.09 | 0.22 | 1.06 | -0.03 | -0.03 | **-0.04** | **-0.04** | 0.09 | 0.23 | 1.08 |
| Business Services | 0.11 | 0.17 | 1.07 | -0.01 | -0.02 | -0.02 | -0.01 | 0.10 | 0.18 | 1.09 |
| Agriculture | 0.12 | 0.21 | 0.87 | 0.00 | 0.01 | 0.00 | -0.01 | 0.10 | 0.21 | 0.90 |
| Food Products | 0.11 | 0.14 | 0.70 | -0.01 | 0.01 | 0.00 | 0.00 | 0.13 | 0.14 | 0.71 |
| Candy & Soda | 0.13 | 0.21 | 0.80 | 0.01 | 0.02 | 0.01 | 0.01 | 0.12 | 0.22 | 0.84 |
| Beer & Liquor | 0.12 | 0.17 | 0.82 | 0.00 | 0.01 | 0.00 | 0.00 | 0.13 | 0.18 | 0.82 |
| Tobacco Products | 0.13 | 0.20 | 0.68 | 0.01 | 0.03 | 0.01 | 0.03 | 0.15 | 0.20 | 0.64 |
| Healthcare | 0.10 | 0.27 | 1.11 | -0.01 | -0.02 | -0.04 | -0.05 | 0.09 | 0.31 | 1.17 |
| Medical Equipment | 0.13 | 0.18 | 0.93 | 0.00 | 0.01 | 0.02 | 0.01 | 0.14 | 0.19 | 0.93 |
| Pharmaceuticals | 0.13 | 0.17 | 0.88 | 0.01 | 0.02 | **0.03** | 0.03 | 0.13 | 0.17 | 0.86 |
| Coal | 0.16 | 0.28 | 1.06 | 0.04 | 0.03 | 0.00 | -0.02 | 0.14 | 0.29 | 1.08 |
| Petroleum & Natural Gas | 0.16 | 0.17 | 0.80 | **0.03** | **0.05** | 0.02 | 0.01 | 0.14 | 0.18 | 0.83 |
| **Industry Average** | 0.12 | 0.21 | 1.03 | 0.00 | 0.00 | -0.01 | -0.01 | 0.11 | 0.23 | 1.04 |
| **Market** | 0.12 | 0.14 | 1.00 | | | | | 0.12 | 0.14 | 1 |
| **Recession - Stage II:** | | | | | | | | | | |
| Utilities | 0.15 | 0.16 | 0.67 | 0.06 | **0.07** | 0.06 | 0.05 | 0.11 | 0.13 | 0.55 |
| Communication | 0.10 | 0.15 | 0.60 | 0.02 | 0.03 | 0.02 | 0.01 | 0.10 | 0.14 | 0.70 |
| Recreation | 0.13 | 0.30 | 1.21 | 0.05 | 0.05 | 0.06 | 0.05 | 0.09 | 0.25 | 1.18 |
| Entertainment | 0.17 | 0.30 | 1.27 | 0.08 | 0.08 | 0.08 | 0.10 | 0.14 | 0.24 | 1.27 |
| Printing & Publishing | 0.14 | 0.25 | 1.13 | 0.05 | 0.05 | 0.05 | 0.04 | 0.12 | 0.20 | 1.05 |
| Consumer Goods | 0.16 | 0.21 | 0.93 | **0.07** | **0.08** | **0.08** | **0.07** | 0.12 | 0.16 | 0.87 |
| Apparel | 0.13 | 0.26 | 1.07 | 0.05 | 0.05 | 0.04 | 0.07 | 0.10 | 0.20 | 1.05 |
| Rubber & Plastic | 0.05 | 0.23 | 0.99 | -0.03 | -0.03 | -0.03 | -0.03 | 0.12 | 0.20 | 1.05 |
| Textiles | 0.08 | 0.25 | 1.03 | 0.00 | 0.00 | -0.01 | 0.00 | 0.10 | 0.20 | 1.00 |
| Construction Materials | 0.09 | 0.23 | 1.15 | 0.01 | 0.01 | 0.00 | 0.00 | 0.11 | 0.18 | 1.10 |
| Construction | 0.03 | 0.31 | 1.45 | -0.04 | -0.05 | -0.05 | -0.03 | 0.12 | 0.24 | 1.29 |
| Automobiles & Trucks | 0.04 | 0.24 | 0.97 | -0.03 | -0.03 | -0.06 | -0.03 | 0.11 | 0.20 | 1.05 |
| Business Supplies | 0.07 | 0.24 | 1.10 | 0.00 | -0.01 | -0.03 | -0.03 | 0.11 | 0.20 | 1.03 |
| Wholesale | 0.04 | 0.23 | 1.05 | -0.03 | -0.03 | -0.03 | -0.03 | 0.11 | 0.19 | 1.07 |
| Retail | 0.17 | 0.22 | 1.03 | **0.09** | **0.09** | **0.08** | **0.09** | 0.12 | 0.18 | 0.98 |
| Restaurants & Hotels | 0.07 | 0.28 | 1.25 | -0.01 | -0.02 | -0.01 | -0.02 | 0.12 | 0.21 | 1.08 |
| Banking | 0.17 | 0.23 | 1.06 | **0.09** | **0.08** | 0.08 | 0.08 | 0.12 | 0.18 | 0.96 |
| Insurance | 0.12 | 0.23 | 0.96 | 0.04 | 0.04 | 0.05 | 0.03 | 0.12 | 0.19 | 0.89 |
| Real Estate | -0.01 | 0.32 | 1.36 | -0.08 | -0.09 | **-0.10** | **-0.12** | 0.07 | 0.24 | 1.10 |
| Trading | 0.08 | 0.24 | 1.22 | 0.00 | -0.01 | -0.01 | -0.01 | 0.14 | 0.20 | 1.21 |
| **Industry Average** | 0.10 | 0.24 | 1.08 | 0.02 | 0.02 | 0.01 | 0.01 | 0.11 | 0.20 | 1.02 |
| **Market** | 0.08 | 0.19 | 1.00 | | | | | 0.12 | 0.14 | 1 |

Notes: Table 4.9 reports mean returns, standard deviations, single-index betas, excess market returns ($\alpha^m$), Jensen's alphas ($\alpha^J$), Fama and French alphas ($\alpha^F$), and Carhart alphas ($\alpha^c$) over NBER delineated stages of expansion and recession. The analysis maps previous early, middle, and late expansion industries, listed in Table 4.1, into the stage of expansion. Likewise, the analysis maps early and late expansion industries into the stage of recession. Table 4.9 also reports mean returns, standard deviations, and single-index betas for the full sample 1948–2007. Equation 4.2 estimates mean returns and Equations 4.3 to 4.6 to estimate performance alphas. The table reports mean returns, standard deviations, and performance alphas as annual rates. Bold indicates performance alphas statistically significant at 10 percent using White (1980) heteroskedasticity consistent t-statistics.

**Table 4.10 Four-stage industry summary statistics and performance**

| | Business Cycle Stages | | | | | | | Full Sample 1948-2007 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Performance Measures | | | | | | |
| Sectors/Industries | mean | std.dev. | beta | $\alpha^m$ | $\alpha^J$ | $\alpha^F$ | $\alpha^C$ | mean | std.dev. | beta |
| **Early Expansion - Stage I:** | | | | | | | | | | |
| Computers | 0.14 | 0.21 | 1.29 | -0.02 | **-0.05** | -0.03 | 0.00 | 0.13 | 0.24 | 1.24 |
| Computer Software | 0.06 | 0.31 | 1.57 | -0.07 | **-0.12** | **-0.13** | **-0.13** | 0.02 | 0.42 | 1.79 |
| Electronic Equipment | 0.16 | 0.23 | 1.41 | -0.01 | **-0.05** | -0.03 | -0.01 | 0.11 | 0.26 | 1.44 |
| Measuring & Control | 0.13 | 0.21 | 1.34 | -0.03 | **-0.07** | **-0.05** | **-0.04** | 0.12 | 0.24 | 1.32 |
| Shipping Containers | 0.17 | 0.16 | 0.96 | 0.01 | 0.01 | 0.00 | 0.00 | 0.12 | 0.18 | 0.98 |
| Transportation | 0.22 | 0.16 | 1.01 | **0.04** | **0.04** | 0.01 | 0.00 | 0.10 | 0.19 | 1.09 |
| **Industry Average** | 0.15 | 0.21 | 1.26 | -0.01 | -0.04 | -0.04 | -0.03 | 0.10 | 0.25 | 1.31 |
| **Market** | 0.17 | 0.12 | 1.00 | | | | | 0.12 | 0.14 | 1.00 |
| **Late Expansion - Stage II:** | | | | | | | | | | |
| Chemicals | 0.04 | 0.18 | 0.98 | **-0.04** | **-0.04** | **-0.05** | **-0.05** | 0.11 | 0.17 | 1.01 |
| Steel Works | 0.09 | 0.24 | 1.30 | 0.01 | 0.00 | 0.00 | 0.00 | 0.10 | 0.23 | 1.25 |
| Precious Metals | 0.07 | 0.35 | 0.66 | -0.03 | -0.02 | -0.03 | -0.06 | 0.08 | 0.35 | 0.71 |
| Mining | 0.15 | 0.22 | 0.99 | **0.06** | **0.06** | 0.05 | 0.04 | 0.12 | 0.21 | 1.01 |
| Fabricated Products | 0.06 | 0.23 | 0.99 | -0.03 | -0.03 | -0.04 | -0.02 | 0.05 | 0.24 | 1.10 |
| Machinery | 0.09 | 0.20 | 1.14 | 0.01 | 0.00 | 0.00 | 0.02 | 0.11 | 0.19 | 1.17 |
| Electrical Equipment | 0.13 | 0.21 | 1.23 | **0.04** | 0.04 | **0.04** | 0.03 | 0.14 | 0.20 | 1.19 |
| Aircraft | 0.06 | 0.24 | 1.09 | -0.02 | -0.02 | -0.03 | -0.03 | 0.14 | 0.23 | 1.12 |
| Shipbuilding & Railroad | 0.07 | 0.21 | 0.96 | -0.01 | -0.01 | -0.03 | -0.03 | 0.10 | 0.21 | 1.00 |
| Defense | 0.06 | 0.24 | 0.83 | -0.03 | -0.03 | -0.05 | -0.04 | 0.12 | 0.23 | 0.83 |
| Personal Services | 0.04 | 0.25 | 1.17 | -0.04 | -0.05 | **-0.05** | -0.03 | 0.09 | 0.23 | 1.08 |
| Business Services | 0.07 | 0.19 | 1.07 | -0.01 | -0.01 | -0.01 | 0.00 | 0.10 | 0.18 | 1.09 |
| Agriculture | 0.10 | 0.22 | 0.86 | 0.02 | 0.02 | 0.01 | 0.01 | 0.10 | 0.21 | 0.90 |
| Food Products | 0.08 | 0.15 | 0.68 | -0.01 | 0.00 | -0.01 | 0.00 | 0.13 | 0.14 | 0.71 |
| Candy & Soda | 0.11 | 0.23 | 0.79 | 0.01 | 0.02 | 0.00 | 0.02 | 0.12 | 0.22 | 0.84 |
| Beer & Liquor | 0.11 | 0.19 | 0.84 | 0.02 | 0.03 | 0.02 | 0.03 | 0.13 | 0.18 | 0.82 |
| Tobacco Products | 0.14 | 0.20 | 0.55 | 0.05 | **0.06** | 0.05 | **0.06** | 0.15 | 0.20 | 0.64 |
| Healthcare | 0.08 | 0.31 | 1.14 | -0.02 | -0.02 | -0.04 | -0.03 | 0.09 | 0.31 | 1.17 |
| Medical Equipment | 0.11 | 0.19 | 0.90 | 0.03 | 0.03 | 0.03 | 0.01 | 0.14 | 0.19 | 0.93 |
| Pharmaceutical | 0.12 | 0.17 | 0.79 | 0.04 | **0.04** | **0.04** | 0.02 | 0.13 | 0.17 | 0.86 |
| Coal | 0.20 | 0.31 | 1.05 | **0.11** | **0.11** | **0.09** | 0.03 | 0.14 | 0.29 | 1.08 |
| Petroleum & Natural Gas | 0.14 | 0.18 | 0.81 | **0.05** | **0.06** | 0.04 | 0.03 | 0.14 | 0.18 | 0.83 |
| **Industry Averages** | 0.10 | 0.22 | 0.95 | 0.01 | 0.01 | 0.00 | 0.00 | 0.11 | 0.22 | 0.97 |
| **Market** | 0.08 | 0.15 | 1.00 | | | | | 0.12 | 0.14 | 1.00 |
| **Early Recession - Stage IV:** | | | | | | | | | | |
| Utilities | 0.00 | 0.16 | 0.76 | **0.20** | **0.13** | **0.12** | **0.12** | 0.11 | 0.13 | 0.55 |
| Communication | -0.04 | 0.14 | 0.63 | **0.15** | 0.05 | 0.04 | 0.04 | 0.10 | 0.14 | 0.70 |
| **Industry Averages** | -0.02 | 0.15 | 0.70 | 0.17 | 0.09 | 0.08 | 0.08 | 0.11 | 0.14 | 0.62 |
| **Market** | -0.16 | 0.16 | 1.00 | | | | | 0.12 | 0.14 | 1.00 |

*Continued:*

| | Business Cycle Stages | | | | | | | Full Sample 1948-2007 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Performance Measures | | | | | | |
| **Sectors/Industries** | **mean** | **std.dev.** | **beta** | $\alpha^m$ | $\alpha^J$ | $\alpha^F$ | $\alpha^C$ | **mean** | **std.dev.** | **beta** |
| **Late Recession - Stage V:** | | | | | | | | | | |
| Recreation | 0.64 | 0.31 | 1.22 | 0.18 | 0.10 | 0.06 | 0.00 | 0.09 | 0.25 | 1.18 |
| Entertainment | 0.50 | 0.31 | 1.28 | 0.07 | -0.01 | -0.05 | -0.04 | 0.14 | 0.24 | 1.27 |
| Printing & Publishing | 0.62 | 0.23 | 1.03 | **0.16** | **0.15** | **0.12** | 0.08 | 0.12 | 0.20 | 1.05 |
| Consumer Goods | 0.49 | 0.21 | 1.01 | 0.07 | 0.06 | 0.07 | 0.00 | 0.12 | 0.16 | 0.87 |
| Apparel | 0.63 | 0.27 | 1.09 | **0.17** | 0.14 | 0.07 | 0.08 | 0.10 | 0.20 | 1.05 |
| Rubber & Plastic | 0.42 | 0.22 | 0.90 | 0.01 | 0.04 | 0.01 | -0.03 | 0.12 | 0.20 | 1.05 |
| Textiles | 0.47 | 0.25 | 1.09 | 0.05 | 0.03 | -0.02 | 0.01 | 0.10 | 0.20 | 1.00 |
| Construction Materials | 0.51 | 0.23 | 1.17 | 0.08 | 0.03 | 0.00 | -0.03 | 0.11 | 0.18 | 1.10 |
| Construction | 0.63 | 0.33 | 1.51 | 0.17 | 0.01 | -0.01 | 0.03 | 0.12 | 0.24 | 1.29 |
| Automobiles & Trucks | 0.38 | 0.25 | 1.06 | -0.01 | -0.03 | -0.07 | -0.05 | 0.11 | 0.20 | 1.05 |
| Business Supplies | 0.44 | 0.24 | 1.19 | 0.03 | -0.03 | -0.04 | -0.04 | 0.11 | 0.20 | 1.03 |
| Wholesale | 0.43 | 0.23 | 1.06 | 0.02 | 0.00 | -0.01 | -0.07 | 0.11 | 0.19 | 1.07 |
| Retail | 0.55 | 0.24 | 1.11 | **0.11** | 0.08 | 0.04 | 0.01 | 0.12 | 0.18 | 0.98 |
| Restaurants & Hotels | 0.52 | 0.28 | 1.27 | 0.09 | 0.01 | -0.02 | -0.04 | 0.12 | 0.21 | 1.08 |
| Banking | 0.48 | 0.23 | 1.14 | 0.06 | 0.01 | 0.00 | -0.05 | 0.12 | 0.18 | 0.96 |
| Insurance | 0.44 | 0.20 | 0.86 | 0.03 | 0.07 | 0.09 | 0.04 | 0.12 | 0.19 | 0.89 |
| Real Estate | 0.56 | 0.31 | 1.21 | 0.11 | 0.05 | -0.03 | -0.12 | 0.07 | 0.24 | 1.10 |
| Trading | 0.53 | 0.23 | 1.16 | **0.10** | 0.05 | 0.03 | 0.05 | 0.14 | 0.20 | 1.21 |
| **Industry Averages** | 0.51 | 0.25 | 1.13 | 0.08 | 0.04 | 0.01 | -0.01 | 0.11 | 0.20 | 1.07 |
| **Market** | 0.40 | 0.18 | 1.00 | | | | | 0.12 | 0.14 | 1.00 |

Notes: Table 4.10 reports mean returns, standard deviations, single-index betas, excess market returns ($\alpha^m$), Jensen's alphas ($\alpha^J$), Fama and French alphas ($\alpha^F$), and Carhart alphas ($\alpha^c$) over four business-cycle stages. Following DeStefano (2004), the analysis divides NBER expansions and recessions into two equal stages each. The analysis maps previous middle expansion industries, listed in Table 4.1, into the late expansion stage. Table 4.10 also reports mean returns, standard deviations, and single-index betas for the full sample 1948–2007. Equation 4.2 estimates mean returns and Equations 4.3 to 4.6 estimate performance alphas. The table reports mean returns, standard deviations, and performance alphas as annual rates. Bold indicates performance alphas statistically significant at 10 percent using White (1980) heteroskedasticity consistent t-statistics.

### 4.6.3 Different ways to measure the business cycle

This section considers the Chicago Federal Reserve National Activity Index (CFNAI) and Conference Board Leading Indicator as alternatives to NBER cycle dates. As results for these two indicators are similar, the analysis focuses on the CFNAI.[97] In contrast to static NBER defined phases of expansion or recession, the CFNAI provides a continuous measure of business cycle conditions. The CFNAI incorporates 85 economic variables that cover four broad categories: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. CFNAI construction follows the methodology of Stock and Watson (1989), who create an index based on the first principal components of a large number of

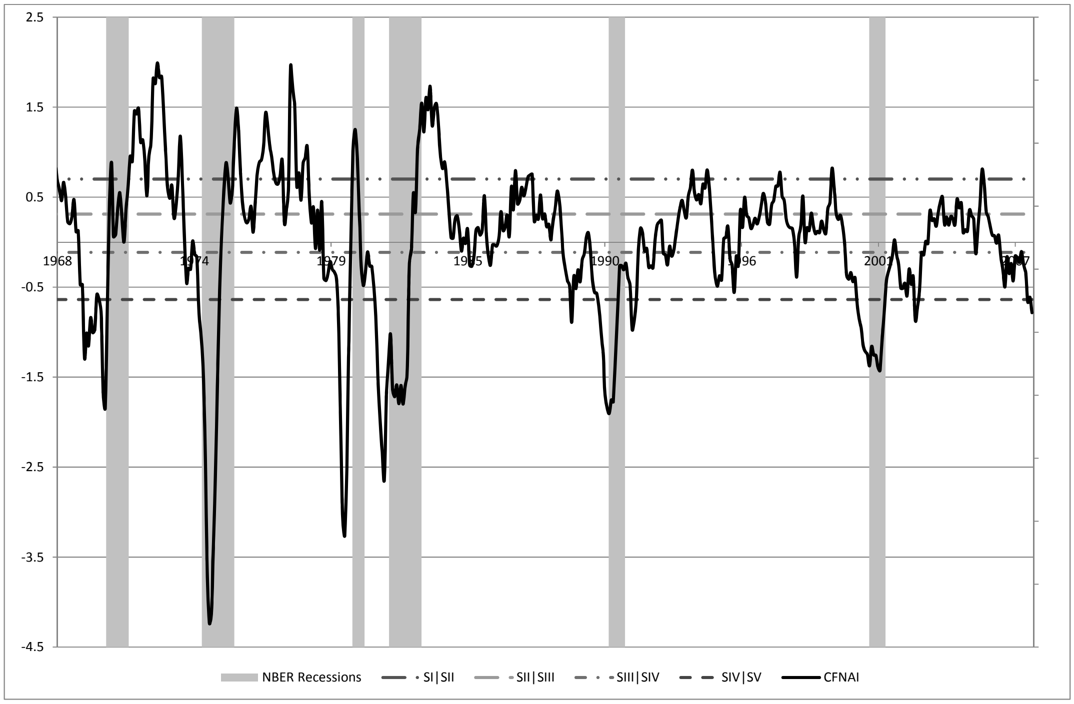
[97] The CFNAI and detrended Conference Board leading indicator have a 78 percent correlation coefficient. Both indices thus reveal similar business cycle information,. The study focuses on the CFNAI because it is freely available to the public and released monthly by the Chicago Federal Reserve Bank.

variables that track economic activity. By construction, the CFNAI has a zero mean and unit standard deviation. Positive (negative) CFNAI values indicate above (below) trend economic activity. Publication of the CFNAI began in 2001 with data available from 1967.[98] Figure 4.3 overlays the CFNAI on NBER delineated phases of economic expansion and contraction (shaded area). The CFNAI closely tracks NBER cycle dates, with some variation. The variation may better reflect investor uncertainty when attempting to pinpoint real-time changes in business-cycle stages.

The analysis considers three different approaches to measure industry performance related to CFNAI business cycles. Initially, the analysis partitions CFNAI business cycles into five equal stages. CFNAI values of 0.702, 0.312, -.0113, and -.637 delineate stages of early expansion through late recession. The first approach tests for industry outperformance using dummy variables and regressions equivalent to NBER cycles. The second approach partitions five CFNAI stages following the Chicago Federal Reserve website. The Chicago Federal Reserve defines values above 0.20 as late expansion and values below -0.70 as recession. The analysis subdivides Chicago Federal Reserve ranges of expansion and recession into additional stages deemed representative of business conditions: early and middle expansion split the 0.0 to 0.20 range and early recession ranges from 0.0 to -0.70. The third approach delineates four business-cycle stages based on CFNAI levels and changes. Figure 4.3 indicates that positive CFNAI levels and positive changes characterize early expansion; positive CFNAI levels and negative changes characterize late expansion; negative CFNAI levels and negative changes characterize early expansion; and lastly negative CFNAI levels and positive changes characterize late recession. The analysis then runs a regression for each industry over the full sample 1968–2007 to test for industry outperformance based on CFNAI levels and changes.

[98] More information is available at http://www.chicagofed.org/economic_research_and_data/cfnai.cfm

**Figure 4.3 CFNAI delineated business-cycle stages**




Notes: Figure 4.3 illustrates the CFNAI economic indicator over the period 1968–2007. Shaded areas indicate NBER defined periods of economic contraction. The analysis partitions the range of CFNAI values over 1968–2007 into five equal periods of economic activity. The five periods correspond to early expansion (SI), middle expansion (SII), late expansion (SIII), early recession (SIV), and late recession (SV). Business-cycle stage delineations are at CFNAI values of 0.702, 0.312, -.0113, and -.637 for boundaries SI|SII, SII|SIII, SIII|SIV, and SIV|SV respectively.

Table 4.11 reports industry performance measures for five CFNAI delineated business-cycle stages. The table presents results by the stage of expected performance to allow direct comparison with performance results presented for NBER business-cycle stages in Table 4.5.[99] There is even less systematic industry performance over CFNAI stages than NBER stages. No industry provides systematic excess market performance. Only two industries (petroleum and retail) provide the expected systematic outperformance, based on any of the Jensen's, Fama-French, and Carhart performance measures. Meanwhile, seven industries have systematically negative performance alphas. .Columns 3, 5, 7, and 9 of Table 4.11 reports p-values from a Wald test of equal industry performance across business-cycle stages. Wald p-values estimates are under the null hypothesis $H_0$: $\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5$, reported separately for each industry and performance measure. For instance, the p-values reject the null of constant market

[99] For brevity, the study reports results by the business-cycle stage of expected performance. Complete results are available upon request.

outperformance for only seven of the 48 industries at 10 percent statistical significance. Table 4.6 compares CFNAI sector rotation performance with alternative sector/industry groupings and business-cycle partitions. The CFNAI sector rotation strategy generates a statistically significant and *negative* 3.8 percent Jensen's alpha – before transaction costs. The CFNAI stage results using equal partitions, thus, provide no more insights into industry performance or rotation strategies. In unreported results, stage partitions based on CFNAI cutoffs also provide no improvement over the base-case analysis.

**Table 4.11 Industry performance over CFNAI business-cycle stages**

| | Excess Market | | Jensen's alpha | | Fama-French alpha | | Carhart alpha | |
|---|---|---|---|---|---|---|---|---|
| | | Wald | | Wald | | Wald | | Wald |
| **Industries** | $\alpha^{m}$ | p-value | $\alpha^{J}$ | p-value | $\alpha^{F}$ | p-value | $\alpha^{C}$ | p-value |
| **Early Expansion - Stage I:** | | | | | | | | |
| Computers | 0.04 | 0.33 | 0.04 | 0.24 | 0.06 | 0.19 | 0.02 | 0.18 |
| Computer Software | -0.13 | 0.56 | -0.14 | 0.24 | -0.13 | 0.30 | **-0.17** | 0.46 |
| Electronic Equip. | -0.01 | 0.97 | -0.02 | 0.77 | -0.01 | 0.83 | 0.01 | 0.93 |
| Measuring & Control | 0.02 | 0.90 | 0.01 | 0.76 | 0.03 | 0.55 | 0.01 | 0.52 |
| Shipping Containers | 0.00 | 0.88 | 0.00 | 0.89 | -0.01 | 0.87 | 0.02 | 0.88 |
| Transportation | -0.01 | 0.11 | -0.02 | 0.09 | -0.02 | 0.12 | -0.01 | 0.17 |
| **Industry Average:** | -0.02 | | -0.02 | | -0.01 | | -0.02 | |
| **Middle Expansion - Stage II:** | | | | | | | | |
| Chemicals | 0.01 | 0.66 | 0.01 | 0.66 | 0.01 | 0.61 | 0.01 | 0.65 |
| Steel Works | 0.02 | 0.10 | 0.02 | 0.09 | -0.02 | 0.18 | -0.02 | 0.18 |
| Precious Metals | -0.11 | 0.12 | -0.11 | 0.12 | -0.15 | 0.17 | **-0.15** | 0.16 |
| Mining | 0.01 | 0.28 | 0.01 | 0.28 | -0.04 | 0.44 | -0.04 | 0.44 |
| Fabricated Products | -0.07 | 0.41 | -0.07 | 0.41 | **-0.10** | 0.58 | **-0.10** | 0.55 |
| Machinery | 0.02 | 0.31 | 0.02 | 0.25 | 0.00 | 0.37 | 0.00 | 0.40 |
| Electrical Equip. | 0.01 | 0.94 | 0.01 | 0.96 | 0.00 | 0.94 | 0.00 | 0.94 |
| Aircraft | -0.03 | 0.09 | -0.03 | 0.11 | -0.05 | 0.15 | -0.05 | 0.12 |
| Shipbuilding/Railroad | -0.02 | 0.98 | -0.02 | 0.98 | -0.05 | 0.98 | -0.05 | 0.99 |
| Defense | 0.05 | 0.84 | 0.05 | 0.84 | 0.01 | 0.81 | 0.01 | 0.80 |
| Personal Services | -0.05 | 0.54 | -0.05 | 0.53 | -0.06 | 0.48 | -0.06 | 0.48 |
| Business Services | -0.01 | 0.42 | -0.01 | 0.23 | -0.01 | 0.34 | -0.01 | 0.38 |
| **Industry Average:** | -0.01 | | -0.01 | | -0.04 | | -0.04 | |
| **Late Expansion - Stage III:** | | | | | | | | |
| Agriculture | -0.04 | 0.50 | -0.02 | 0.50 | -0.03 | 0.72 | 0.00 | 0.63 |
| Food Products | -0.02 | 0.45 | 0.01 | 0.43 | 0.00 | 0.36 | 0.00 | 0.35 |
| Candy & Soda | 0.04 | 0.44 | 0.05 | 0.40 | 0.04 | 0.47 | 0.05 | 0.49 |
| Beer & Liquor | 0.02 | 0.56 | 0.05 | 0.47 | 0.05 | 0.48 | 0.06 | 0.49 |
| Tobacco Products | -0.01 | 0.05 | 0.00 | 0.03 | -0.04 | 0.02 | 0.01 | 0.02 |
| Healthcare | -0.01 | 0.73 | -0.01 | 0.70 | 0.01 | 0.56 | 0.05 | 0.52 |
| Medical Equipment | -0.03 | 0.14 | -0.02 | 0.15 | 0.00 | 0.12 | 0.05 | 0.09 |
| Pharmaceutical | 0.02 | 0.19 | 0.03 | 0.22 | 0.06 | 0.27 | 0.05 | 0.23 |
| Coal | 0.06 | 0.82 | 0.03 | 0.84 | 0.03 | 0.83 | -0.06 | 0.85 |
| Petroleum & Natural Gas | 0.07 | 0.74 | **0.11** | 0.55 | 0.03 | 0.62 | 0.06 | 0.65 |
| **average:** | 0.01 | | 0.02 | | 0.01 | | 0.03 | |
| **Early Recession - Stage IV:** | | | | | | | | |
| Gas & Electric | 0.00 | 0.94 | 0.03 | 0.67 | -0.03 | 0.74 | -0.02 | 0.75 |
| Communication | -0.07 | 0.11 | **-0.08** | **0.07** | -0.08 | 0.10 | -0.06 | **0.06** |
| **average:** | -0.03 | | -0.03 | | -0.05 | | -0.04 | |

***Continued:***

| Industries | Excess Market $\alpha^m$ | Excess Market Wald p-value | Jensen's alpha $\alpha^J$ | Jensen's alpha Wald p-value | Fama-French alpha $\alpha^F$ | Fama-French alpha Wald p-value | Carhart alpha $\alpha^C$ | Carhart alpha Wald p-value |
|---|---|---|---|---|---|---|---|---|
| **Late Recession - Stage V:** | | | | | | | | |
| Recreation | 0.07 | 0.09 | 0.07 | 0.05 | 0.06 | 0.03 | 0.06 | 0.05 |
| Entertainment | 0.05 | 0.00 | 0.04 | 0.00 | 0.05 | 0.00 | 0.08 | 0.00 |
| Printing & Publishing | -0.03 | 0.22 | -0.03 | 0.21 | -0.04 | 0.27 | -0.05 | 0.26 |
| Consumer Goods | 0.06 | 0.55 | 0.06 | 0.57 | 0.05 | 0.62 | 0.04 | 0.61 |
| Apparel | 0.07 | 0.02 | 0.07 | 0.02 | 0.05 | 0.02 | 0.07 | 0.03 |
| Rubber & Plastic | -0.01 | 0.84 | -0.01 | 0.82 | -0.01 | 0.98 | -0.03 | 0.98 |
| Textiles | 0.01 | 0.58 | 0.01 | 0.59 | 0.00 | 0.63 | 0.01 | 0.72 |
| Construction Materials | 0.05 | 0.16 | 0.05 | 0.14 | 0.03 | 0.06 | 0.02 | 0.06 |
| Construction | 0.00 | 0.76 | 0.00 | 0.65 | -0.01 | 0.75 | -0.01 | 0.74 |
| Automobiles & Trucks | -0.04 | 0.17 | -0.04 | 0.17 | -0.07 | 0.25 | -0.03 | 0.46 |
| Business Supplies | 0.01 | 0.83 | 0.01 | 0.80 | -0.02 | 0.78 | -0.02 | 0.72 |
| Wholesale | -0.02 | 0.15 | -0.02 | 0.13 | -0.02 | 0.30 | -0.04 | 0.22 |
| Retail | 0.07 | 0.02 | 0.06 | 0.02 | 0.06 | 0.02 | **0.07** | 0.04 |
| Restaurants & Hotels | 0.05 | 0.23 | 0.04 | 0.17 | 0.03 | 0.20 | 0.02 | 0.24 |
| Banking | 0.02 | 0.39 | 0.02 | 0.39 | 0.00 | 0.23 | 0.01 | 0.26 |
| Insurance | 0.01 | 0.79 | 0.02 | 0.73 | 0.01 | 0.86 | -0.01 | 0.87 |
| Real Estate | -0.07 | 0.15 | -0.08 | 0.12 | **-0.10** | 0.18 | **-0.11** | 0.19 |
| Trading | 0.00 | 0.93 | 0.00 | 0.91 | 0.00 | 0.90 | 0.01 | 0.86 |
| **average:** | 0.02 | | 0.02 | | 0.00 | | 0.00 | |

Notes: Table 4.11 reports industry excess market returns ($\alpha^m$), Jensen's alphas ($\alpha^J$), Fama and French (1992) three-factor alphas ($\alpha^F$), and Carhart (1997) four-factor alphas ($\alpha^C$) for the business cycle stages listed in Table 4.1. Equations 4.3–4.6 estimate excess market returns, Jensen's alphas, Fama and French alphas, and Carhart alphas. CFNAI data availability limits the sample to the period 1968–2007. The business-cycle dummy variable ($D_s$) now takes the value of one or zero at time *t* for one of five CFNAI delineated business-cycle stages. The table reports annualized alpha returns. Emboldened alpha performance indicates statistical significance of 10 percent or greater estimated with White (1980) heteroskedasticity consistent t-statistics. Columns 3, 5, 7, & 9 of Table 4.11 report Wald test p-values under a null hypothesis of constant industry performance across all business-cycle stages, formally stated $H_o$: $\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5$. Table 4.11 also reports equally weighted averages beneath each business-cycle stage.

Table 4.12 provides a measure of industry sensitivity to CFNAI business-cycle conditions. Equation 4.7 runs a regression of excess industry returns on a constant, CFNAI levels, CFNAI changes, and excess market returns. The regression results cover the full 1968–2007 period of CFNAI data availability. For ease of comparison with earlier results, the table orders industries by the business-cycle stage popular belief anticipates outperformance will occur. Essentially, the CFNAI coefficients measure the sensitivity of industry Jensen's alpha performance attributable to levels and changes in business-cycle activity. The analysis tests whether industry sensitivity to CFNAI levels and changes occurs jointly, with the correct signs and during the correct business-cycle stage. As an example, the computer industry should experience early expansion outperformance. Additionally, the CFNAI, by construction, has positive levels and positive changes in early expansion. Therefore, the results should indicate significantly positive CFNAI level and change coefficients for the computer industry in early expansion. Table 4.12 reports block bootstrap p-values from 10,000 replications of

Equation 4.7 for the joint probability of CFNAI coefficient signs. Shaded areas represent the expected sign of CFNAI level and change coefficients. The analysis moves middle expansion industries to the late expansion stage, as combinations of CFNAI levels and CFNAI changes has only four possible stages. Overall, CFNAI level and CFNAI change coefficients are significant at 10 percent about 25 and 33 percent of the time. Thus industries, to some degree, do exhibit sensitivity to CFNAI business-cycle conditions. However, only four industries (recreation, printing & publishing, apparel, and textiles), all in late recession, jointly exhibit the expected and statistically significant CFNAI coefficient signs. Those same industries have high joint probabilities (97 to 100 percent) of having both a negative CFNAI level and CFNAI change coefficients, as the last column of Table 4.12 reports. Otherwise, CFNAI business-cycle activity does not drive industry outperformance in the way that popular belief suggests.

**Table 4.12 Industry performance sensitivity to CFNAI business cycles**

| | | | | | | Joint probability of regression coefficient signs | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | CFNAI $\geq$ 0 and $\Delta$CFNAI $\geq$ 0 | CFNAI $\geq$ 0 and $\Delta$CFNAI < 0 | CFNAI < 0 and $\Delta$CFNAI < 0 | CFNAI < 0 and $\Delta$CFNAI $\geq$ 0 |
| **Stage** | **Industry** | **constant** | **CFNAI** | **$\Delta$CFNAI** | **(Mkt-Tbl)** | | | | |
| **Early Expansion** | Computers | -0.003 | 0.004 | 0.003 | **1.25** | 0.61 | 0.32 | 0.02 | 0.06 |
| | Computer Software | **-0.009** | -0.007 | **0.035** | **1.77** | 0.11 | 0.00 | 0.01 | 0.87 |
| | Electronic Equipment | -0.003 | -0.001 | **0.012** | **1.48** | 0.36 | 0.01 | 0.01 | 0.62 |
| | Measuring & Control | -0.003 | -0.001 | **0.010** | **1.39** | 0.36 | 0.03 | 0.02 | 0.59 |
| | Shipping Containers | 0.000 | -0.001 | 0.003 | **0.95** | 0.21 | 0.11 | 0.19 | 0.49 |
| | Transportation | -0.001 | -0.003 | **0.012** | **1.08** | 0.08 | 0.00 | 0.01 | 0.90 |
| **Middle Expansion** | Chemicals | 0.000 | -0.002 | **0.010** | **0.97** | 0.14 | 0.01 | 0.01 | 0.85 |
| | Steel Works | -0.003 | **0.004** | 0.005 | **1.23** | 0.77 | 0.19 | 0.00 | 0.05 |
| | Precious Metals | -0.002 | -0.004 | 0.014 | **0.72** | 0.19 | 0.04 | 0.10 | 0.66 |
| | Mining | 0.000 | 0.001 | **0.015** | **1.02** | 0.64 | 0.01 | 0.00 | 0.35 |
| | Fabricated Products | **-0.006** | 0.001 | 0.009 | **1.09** | 0.60 | 0.05 | 0.02 | 0.33 |
| | Machinery | -0.001 | 0.002 | **0.008** | **1.18** | 0.88 | 0.01 | 0.00 | 0.11 |
| | Electrical Equipment | 0.002 | -0.002 | **0.010** | **1.16** | 0.08 | 0.00 | 0.01 | 0.90 |
| | Aircraft | 0.000 | -0.001 | **0.018** | **1.14** | 0.43 | 0.01 | 0.00 | 0.56 |
| | Shipbuilding & Railroad | -0.001 | 0.002 | 0.008 | **1.00** | 0.62 | 0.10 | 0.03 | 0.24 |
| | Defense | 0.003 | -0.002 | 0.005 | **0.83** | 0.19 | 0.08 | 0.19 | 0.54 |
| | Personal Services | -0.004 | **-0.007** | 0.009 | **1.16** | 0.05 | 0.01 | 0.09 | 0.86 |
| | Business Services | -0.001 | **-0.003** | **0.006** | **1.20** | 0.04 | 0.01 | 0.04 | 0.91 |
| **Late Expansion** | Agriculture | 0.001 | 0.000 | 0.002 | **0.90** | 0.28 | 0.20 | 0.19 | 0.33 |
| | Food Products | **0.004** | **-0.005** | **-0.008** | **0.70** | 0.00 | 0.00 | 0.96 | 0.03 |
| | Candy & Soda | 0.001 | -0.001 | **-0.015** | **0.84** | 0.01 | 0.41 | 0.57 | 0.01 |
| | Beer & Liquor | 0.003 | **-0.005** | -0.007 | **0.80** | 0.00 | 0.04 | 0.86 | 0.10 |
| | Tobacco Products | **0.006** | -0.004 | **-0.025** | **0.65** | 0.00 | 0.10 | 0.90 | 0.00 |
| | Healthcare | -0.001 | **-0.010** | 0.004 | **1.16** | 0.01 | 0.05 | 0.38 | 0.57 |
| | Medical Equipment | 0.002 | **-0.004** | -0.003 | **0.89** | 0.01 | 0.03 | 0.68 | 0.28 |
| | Pharmaceutical | 0.002 | 0.000 | **-0.012** | **0.82** | 0.00 | 0.50 | 0.49 | 0.00 |
| | Coal | 0.002 | -0.005 | -0.006 | **1.10** | 0.02 | 0.16 | 0.56 | 0.26 |
| | Petroleum & Natural Gas | 0.003 | **0.005** | 0.000 | **0.78** | 0.51 | 0.46 | 0.01 | 0.02 |

***Continued:***

| | | | | | | Joint probability of regression coefficient signs | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | CFNAI ≥ 0 and ΔCFNAI ≥ 0 | CFNAI ≥ 0 and ΔCFNAI < 0 | CFNAI < 0 and ΔCFNAI < 0 | CFNAI < 0 and ΔCFNAI ≥ 0 |
| **Stage** | **Industry** | **constant** | **CFNAI** | **ΔCFNAI** | **(Mkt-Tbl)** | | | | |
| **Early Recession** | Utilities | 0.002 | -0.002 | -0.005 | **0.51** | ` | 0.10 | 0.74 | 0.14 |
| | Communication | 0.000 | 0.002 | **-0.010** | **0.75** | 0.03 | 0.87 | 0.10 | 0.00 |
| **Late Recession** | Recreation | -0.003 | **-0.007** | **0.017** | **1.18** | 0.00 | 0.00 | 0.01 | 0.98 |
| | Entertainment | 0.002 | -0.004 | -0.004 | **1.31** | 0.03 | 0.18 | 0.56 | 0.23 |
| | Printing & Publishing | -0.001 | **-0.005** | **0.012** | **1.02** | 0.02 | 0.00 | 0.01 | 0.97 |
| | Consumer Goods | 0.000 | **-0.004** | 0.003 | **0.83** | 0.02 | 0.01 | 0.22 | 0.76 |
| | Apparel | 0.000 | **-0.010** | **0.018** | **1.11** | 0.00 | 0.00 | 0.00 | 1.00 |
| | Rubber & Plastic | 0.000 | -0.002 | **0.010** | **1.05** | 0.15 | 0.01 | 0.03 | 0.82 |
| | Textiles | -0.001 | **-0.008** | **0.018** | **0.98** | 0.00 | 0.00 | 0.00 | 1.00 |
| | Construction Materials | 0.000 | -0.003 | 0.003 | **1.10** | 0.02 | 0.01 | 0.24 | 0.72 |
| | Construction | -0.001 | -0.004 | **0.023** | **1.30** | 0.12 | 0.00 | 0.00 | 0.88 |
| | Automobiles & Trucks | -0.002 | -0.004 | 0.007 | **1.02** | 0.06 | 0.01 | 0.13 | 0.80 |
| | Business Supplies | 0.000 | -0.001 | 0.007 | **0.95** | 0.34 | 0.06 | 0.04 | 0.56 |
| | Wholesale | 0.000 | -0.002 | **0.012** | **1.09** | 0.12 | 0.00 | 0.00 | 0.88 |
| | Retail | 0.001 | **-0.008** | 0.004 | **1.03** | 0.00 | 0.00 | 0.20 | 0.80 |
| | Restaurants & Hotels | 0.001 | **-0.005** | 0.008 | **1.14** | 0.06 | 0.02 | 0.11 | 0.81 |
| | Banking | 0.001 | -0.001 | **-0.010** | **1.02** | 0.00 | 0.25 | 0.72 | 0.03 |
| | Insurance | 0.002 | -0.002 | 0.000 | **0.90** | 0.09 | 0.14 | 0.37 | 0.40 |
| | Real Estate | **-0.005** | -0.002 | **0.013** | **1.09** | 0.28 | 0.01 | 0.02 | 0.70 |
| | Trading | 0.002 | 0.002 | -0.002 | **1.23** | 0.28 | 0.61 | 0.05 | 0.07 |

Notes: Table 4.12 reports regression coefficients estimated with Equation 4.7 over the full sample period 1968-2007. CFNAI data availability determines the truncated 1968-2007 sample size. The CFNAI level and change regression coefficients effectively measure the sensitivity of industry outperformance attributable to business cycle conditions. For ease of comparison with previous tables, the table reports results by the business cycle stage where popular belief anticipates industry outperformance will occur. Additionally, Table 4.12 reports block bootstrapped p-values estimated with 10,000 replications for the joint probability of CFNAI level and change coefficient signs. Shaded areas indicate the anticipated sign of CFNAI level and change coefficients. As an example, the computer industry should experience early expansion performance. Furthermore, by construction, the CFNAI has positive levels and positive changes in early expansion. Thus, the results should indicate a high probability of positive CFNAI level and positive CFNAI change coefficients for the computer industry in early expansion, which Table 4.12 reports at 61 percent probability.

$$r_{it} - rf_t = \alpha_0 + \alpha_{1i} CFNAI_t + \alpha_{2i} \Delta CFNAI_t + \beta_i^m (r_{mt} - rf_t) + \varepsilon_{it} \qquad \text{(Eq. 4.7)}$$

### 4.6.4 Timing the business cycle in advance or with a delay

Investors might profit from consistently timing the business cycle incorrectly. Suppose that investors consistently assume that turning points occur earlier or with a delay from actual NBER business cycle dates. If so, the base-case scenario might underestimate actual sector rotation outperformance. To explore that possibility, the analysis advances the implementation of sector rotation by one month, two months, and three months prior to NBER business-cycle turning points. Similarly, the analysis considers delays from one to three months. Table 4.13 presents results before transactions costs.

**Table 4.13 Comparison of strategy performance with different timing**

| | Full Period 1948:01 - 2007:12 | | | | | |
|---|---|---|---|---|---|---|
| **Strategy Implementation** | **mean** | **std.dev.** | **beta** | **Sharpe ratio** | **Jensen's alpha** | **t-statistic** |
| **Market** | 11.6% | 14.5% | 1.00 | 0.13 | | |
| | | | | | | |
| **Sector Rotation:** | | | | | | |
| - 3 months | 13.2% | 16.5% | 0.98 | 0.14 | 1.5% | 1.27 |
| - 2 months | 13.7% | 16.6% | 0.99 | 0.14 | 1.8% | 1.53 |
| - 1 month | 14.1% | 16.8% | 1.00 | 0.15 | 2.2% | 1.81 |
| at turning point | 14.2% | 16.8% | 1.00 | 0.15 | 2.3% | 1.94 |
| + 1 month | 13.8% | 16.8% | 1.00 | 0.14 | 1.9% | 1.63 |
| + 2 months | 13.1% | 17.1% | 1.03 | 0.13 | 1.0% | 0.85 |
| + 3 months | 13.0% | 17.1% | 1.02 | 0.13 | 1.0% | 0.86 |
| | | | | | | |
| **Market Timing:** | | | | | | |
| - 3 months | 11.6% | 14.1% | 0.95 | 0.13 | 0.3% | 0.63 |
| - 2 months | 12.5% | 14.2% | 0.96 | 0.15 | 0.9% | 2.25 |
| - 1 month | 12.8% | 14.2% | 0.97 | 0.15 | 1.2% | 3.10 |
| at turning point | 13.6% | 13.6% | 0.89 | 0.17 | 2.5% | 3.57 |
| + 1 month | 13.9% | 13.5% | 0.87 | 0.18 | 2.9% | 3.75 |
| + 2 months | 13.7% | 13.6% | 0.88 | 0.18 | 2.6% | 3.54 |
| + 3 months | 12.8% | 13.7% | 0.89 | 0.16 | 1.7% | 2.44 |

Notes: Table 4.13 reports the performance of sector rotation and market timing with advanced or delayed strategy implementation at business cycle stage turning points by the indicated months. The strategy rotates the Fama and French 49 industry portfolios according to Table 4.1. Table 4.13 reports mean returns, standard deviations, Sharpe ratios, and Jensen's alphas as annualized rates with White (1980) heteroskedasticity consistent t-statistics. Beta estimates come from a single-index model. The reported performance results are before transaction costs.

Overall, strategy performance declines monotonically and becomes insignificant, implementing sector rotation further away from NBER business-cycle stage turning points. The 2.3 percent sector rotation Jensen's alpha decreases to 1.9 and then 1.0 percent when strategy implementation occurs one, two, and three months earlier. The alphas similarly decrease if investors respond with a delay to business-cycles stages. The results suggest the importance of precisely timing sector rotation with business-cycle stages.

### 4.6.5 Different business-cycle proxies

The literature shows certain economic variables track business cycles. The most common variables found in the literature are term-spread, default-spread, and dividend yield.[100] If investors use these variables to time sector rotation, it is possible to directly test whether a model that predicts relative outperformance, based on these proxies, aligns itself with popular belief on sector performance.

The analysis creates a forecast model with the one-month Treasury bill, term-spread, default-spread, and dividend yield as business-cycle variables *(BCV)*.[101] Chordia and Shivakumar (2002) find that these variables lagged one period predict momentum profits related to business cycles. The literature shows that changes in the business-cycle variables are a proxy for unexpected economic shocks and provide the best asset price forecasts.[102] As such, the forecast model uses monthly business-cycle variable changes. Equation 4.8 first estimates excess industry performance related to changes in the business-cycle variables ($\Delta BCV$) lagged one period, after a correction for contemporaneous systematic market risk.

$$r_{it} - rf_t = c_0 + \sum_{j=1}^{4} \gamma_i \Delta BCV_{jt-1} + \beta_i^m (r_{mt} - rf_t) + \varepsilon_{it} \qquad \text{(Eq. 4.8)}$$

The model represents a single-index model modified with the inclusion of lagged business-cycle variables. Lagged changes in the business-cycle variables capture the relation between business-cycle determinants and future industry Jensen's alpha performance. The forecast model uses the gamma parameter estimates ($\gamma_i$) obtained from changes in the business-cycle variables to predict a period-ahead Jensen's alpha. Essentially, the gamma estimates represent a decomposed Jensen's alpha, which allows for the contribution of business-cycle determinants to industry outperformance. Following the methodology of Chordia and Shivakumar (2002), the forecast model estimates the gamma forecast parameters using a 60-month rolling window. The rolling window moves forward each month to obtain gamma estimates from the most recent 60-month window. The model then uses parameter estimates from Equation 4.8 to

[100] See for instance, Campbell (1987), Chen (1991), Chen, Roll, and Ross (1986), Fama and French (1989), Jensen, Mercer, and Johnson (1996), Keim and Stambaugh (1986), Lewellen (2004), and Petkova (2006).
[101] The analysis calculates the term-spread as the difference between the 10-year Treasury constant maturity yield and the three-month Treasury yield. The term-spread is smallest (largest) at NBER defined business cycle peaks (troughs). The analysis calculates the default-spread as the difference between low-grade Baa and high-grade Aaa corporate bonds. The default-spread increases during periods of recession as investors require greater rates of return.
[102] See, for example, studies by Chen, Roll, and Ross (1986) and Keim and Stambaugh (1986), among others.

forecast period-ahead outperformance $(\hat{\alpha}_{jt+1})$. Equation 4.9 calculates expected industry outperformance as the sum of gamma estimates multiplied by current business-cycle variable changes. A sector rotation strategy then invests in a portfolio that holds equal weights in all industries forecast to have positive outperformance. The following month, the process repeats itself once again. The process continues over the entire sample period.

$$\hat{\alpha}_{jt+1} = \sum_{i=1}^{4} \hat{\lambda}_i \Delta BCV_t \qquad \text{(Eq. 4.9)}$$

An example clarifies the procedure. First, in month 61 the model estimates the $\gamma_i$ parameters from months 1–60. Next, the model multiplies the $\gamma_i$ parameter estimates by $\Delta BCV_{i,61}$, measured as the ($BCV_{i,61}$-$BCV_{i,60}$) difference. The $\gamma_i$ and $\Delta BCV_{i,61}$ product forecasts a Jensen's alpha attributable to business-cycle determinants. Lastly, the model includes all industries with positive forecast outperformance ($\sum_{i=1}^{4} \hat{\lambda}_i BCV_t > 0$) in a one-month sector rotation portfolio. The following month, the model moves the rolling window forward one month and then repeats the entire process.

Panel A and Panel B in Table 4.14 overlay results from the forecast model on industry performance with NBER delineated business-cycle stages, for expositional purposes. The intention is to observe whether forecast industry performance coincides with the period expected by sector rotation investors.[103] Panel A reports the average number of industries selected for inclusion in the sector rotation portfolio by business-cycle stage. On average, the forecast model selects approximately half of all industries for inclusion in the sector rotation portfolio during any given business-cycle stage, suggesting a 50/50 chance of inclusion for each of the 48 industry portfolios.

Panel B reports the percentage of time the forecast model includes a particular industry in the sector rotation portfolio, for the full period and business-cycle stages. If

[103] The analysis also overlays the forecast model results on NBER business cycle sub-stages, with each stage divided into early and late stages and the sample divided into sub-periods. There is no change in the basic results for both sub-stages and sub-periods.

business-cycle variables forecast business cycle-related performance and if performance aligns with popular belief, the sector rotation portfolio should contain industries during the expected stage a high percentage of the time. However, the forecast model selects industries for inclusion, more or less, evenly across the business cycle, seemingly independent of business-cycle stages. The analysis calculates t-statistics for the percentage of time forecast industry performance differs from a 50/50 coin toss. Bold indicates percentages significantly different from 50 percent at a 10 percent level of statistical significance. Overall, future industry outperformance thus appears unrelated to changes in variables known to track the business cycle.[104]

**Table 4.14 Forecast model sector rotation**

| Panel A: | | Average number of industries selected for inclusion by model | | | | | |
|---|---|---|---|---|---|---|---|
| | | Full Period | Early Expansion | Middle Expansion | Late Expansion | Early Recession | Late Recession |
| | | 23 | 23 | 23 | 23 | 22 | 23 |

Panel B: Percentage of time model forecasts period-ahead excess industry returns

| Period | Industry | Full Period | Early Expansion | Middle Expansion | Late Expansion | Early Recession | Late Recession |
|---|---|---|---|---|---|---|---|
| Early Expansion - Stage I | Computers | **46** | 48 | 48 | **43** | 40 | 48 |
| | Computer Software | **38** | **38** | **37** | **40** | 38 | **33** |
| | Electronic Equipment | 47 | 47 | 47 | 47 | 49 | 50 |
| | Measuring & Control | 50 | 50 | 52 | 47 | 43 | 54 |
| | Shipping Containers | 48 | 48 | **42** | 54 | 55 | 46 |
| | Transportation | 49 | 56 | 46 | 44 | 51 | 57 |
| Middle Expansion - Stage II | Chemicals | 50 | 53 | 49 | 46 | 55 | 46 |
| | Steel Works | **54** | **57** | **56** | 48 | 43 | **67** |
| | Precious Metals | **40** | **38** | **42** | **40** | **36** | 43 |
| | Mining | 51 | 53 | 52 | 48 | 51 | 52 |
| | Fabricated Products | **40** | **34** | 45 | **44** | **30** | 39 |
| | Machinery | 48 | **56** | 45 | 47 | 45 | 39 |
| | Electrical Equipment | 47 | 47 | 47 | 45 | 62 | 43 |
| | Aircraft | 48 | 53 | 48 | 47 | **36** | 50 |
| | Shipbuilding & Railroad | 50 | 48 | 50 | 54 | **36** | 54 |
| | Defense | **40** | **39** | **41** | **41** | **36** | 39 |
| | Personal Services | 48 | 46 | 52 | 47 | 53 | 43 |
| | Business Services | 52 | 54 | 55 | 49 | **36** | 57 |

[104] Analogously, in unreported results, additional tests verify whether the CFNAI provides period ahead forecasts of industry performance. The results are the same; neither the CFNAI nor the business-cycle variable model provides investors with guidance on sector rotation or supports popular belief on business cycle linked performance.

***Continued:***

| Panel B: Period | Industry | Full Period | Early Expansion | Middle Expansion | Late Expansion | Early Recession | Late Recession |
|---|---|---|---|---|---|---|---|
| Late Expansion - Stage III | Agriculture | **53** | 53 | **57** | 51 | 53 | 52 |
| | Food Products | 49 | 48 | 46 | 52 | 49 | 52 |
| | Candy & Soda | **39** | **33** | **38** | **43** | 53 | **33** |
| | Beer & Liquor | 49 | 49 | 45 | 50 | 60 | 50 |
| | Tobacco Products | 49 | 47 | 47 | 54 | 49 | 52 |
| | Healthcare | **32** | **31** | **37** | **34** | **21** | **22** |
| | Medical Equipment | 48 | **40** | 49 | **57** | 53 | **37** |
| | Pharmaceutical | 51 | 45 | 49 | **57** | 57 | 48 |
| | Coal | 49 | 47 | 49 | 49 | **64** | 41 |
| | Petroleum & Natural Gas | 52 | 54 | 51 | 51 | 51 | 59 |
| Early Recession - Stage IV | Utilities | 47 | **39** | 48 | 52 | 55 | 48 |
| | Communication | 51 | 45 | **57** | 52 | 55 | 52 |
| Late Recession - Stage V | Recreation | 48 | 55 | **43** | 47 | **36** | 52 |
| | Entertainment | **46** | 47 | 48 | **42** | 43 | 57 |
| | Printing & Publishing | 48 | 51 | 48 | 48 | **36** | 43 |
| | Consumer Goods | 48 | 48 | 47 | 45 | 51 | 54 |
| | Apparel | 52 | 55 | 51 | 52 | 45 | 50 |
| | Rubber & Plastic | 50 | **60** | 48 | 48 | 40 | 39 |
| | Textiles | 49 | **57** | 47 | 46 | 40 | 43 |
| | Construction Materials | 48 | 49 | **42** | 49 | 47 | 54 |
| | Construction | 49 | 51 | 49 | 50 | 40 | 48 |
| | Automobiles & Trucks | 52 | 56 | 49 | 53 | 43 | 54 |
| | Business Supplies | 50 | 55 | 51 | 45 | 49 | 46 |
| | Wholesale | 49 | 50 | 52 | 45 | 51 | 48 |
| | Retail | 48 | 45 | 48 | 48 | 57 | 48 |
| | Restaurants & Hotels | 50 | 52 | 53 | **44** | 49 | 57 |
| | Banking | 51 | 44 | 52 | **57** | 53 | 46 |
| | Insurance | 50 | **41** | 55 | **56** | 55 | **37** |
| | Real Estate | 51 | 56 | 52 | 49 | **36** | 54 |
| | Trading | 53 | 51 | **58** | 51 | 49 | 54 |

Notes: Table 4.14 reports the composition of sector rotation portfolios constructed with a business-cycle variable (*BCV*) forecast model. The model uses variables found in the literature to forecast stock returns over business cycles. The business-cycle variables include lagged changes in the one-month Treasury bill, term-structure, default-spread, and dividend yield. Equation 4.8 estimates gamma ($\gamma_i$) forecast parameters from a regression of excess industry returns ($r_i$-$rf$) on a constant, lagged changes in the business cycle variables ($\Delta BCV_i$), and excess market returns ($r_m$-$rf$). The model estimates forecast parameters with a 60-month rolling window that moves forward each month. The model then uses parameter estimates to forecast period-ahead industry outperformance, calculated with Equation 4.9 as the sum of the gamma estimates multiplied by contemporary business-cycle variable changes ($\Delta BCV$). A period-ahead sector rotation strategy then includes industries with positive forecast outperformance. Panel A of Table 4.14 reports the average number of industries included in the portfolio by business-cycle stage. Panel B of Table 4.14 reports the percentage of time the model selects an industry for inclusion in the portfolio by business-cycle stage. The analysis also tests for any difference between the percentage of time the forecast model actually selects an industry for inclusion in the portfolio and a random 50/50 probability and indicate 10 percent statistical significance in bold. The shaded area in Panel B represents the business-cycle stage where popular belief anticipates outperformance will occur listed in Table 4.1.

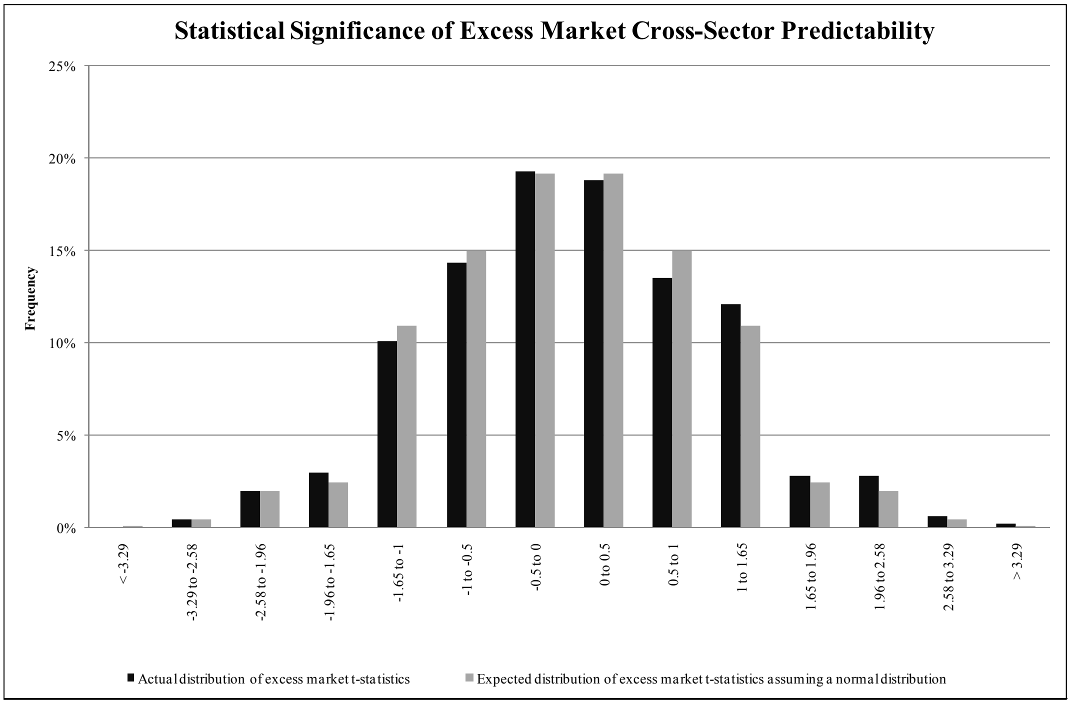
### 4.6.6 Description of other robustness tests

#### 4.6.6.1 Sequential industry performance

Conventional sector rotation presupposes the sequential performance of sectors across business-cycle stages. For instance, Standard & Poor's sequencing in Figure 4.1 shows that performance in the technology sector follows performance in the financial sector, which in turn follows performance in the utilities sector. Figure 4.1 further illustrates other representative sequential patterns of sector performance. While Figure 4.1 depicts largely congruent beliefs on sequential sector performance, other variations are possible. Moreover, although the analysis considers alternative stages, the actual progression of sector performance across business cycles may not fully align with those partitions. To overcome such obstacles, the ultimately analysis relaxes any assumed pattern of sequential performance and completely ignores business-cycle stages. The analysis tests whether the excess market returns of one sector predict future excess market returns of other sectors at different lags. The analysis examines lags from one to 24 months, to allow for different performance sequencing and business-cycle stage durations.

Figure 4.4 illustrates the distribution of t-statistics for cross-sector predictability of excess market sector performance. First, the analysis maps the Fama and French 49 industries to 10 equally weighted sector portfolios following Table 4.1. Next, the analysis runs individual regressions of excess market sector returns on the excess market returns of the remaining sectors at lags from one to 24 months. In total, there are 2,160 (10 x 9 x 24) t-statistics, covering all possible combinations of sectors and lags. Figure 4.4 compares the resultant t-statistic distribution against an expected normal distribution. The figure illustrates that the distribution of t-statistics for excess market predictability follows a normal distribution. Under a normal distribution and a 10 percent significance level, the estimations should indicate 5 percent positive significance and 5 percent negative significance – even in the absence of actual excess market predictability. The bottom of Figure 4.4 reports the percentage of positive and negative t-statistics significant at 10 percent for each lag and for collectively for all lags. In total, t-statistics are significantly positive 6 percent of the time and significantly negative 5 percent of the time. Most significant predictability occurs at a one-month lag, indicating some short-term cross-sector momentum. Cross-sector predictability is only marginally higher than a normal distribution. As such, the results suggest that cross-sector predictability occurs only randomly, without indicating any real evidence of statistically significant sequential sector performance.

**Figure 4.4 Predictability of excess market industry performance**




| | L(1) | L(2) | L(3) | L(4) | L(5) | L(6) | L(7) | L(8) | L(9) | L(10) | L(11) | L(12) | L(13) | L(14) | L(15) | L(16) | L(17) | L(18) | L(19) | L(20) | L(21) | L(22) | L(23) | L(24) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Positive (% )** | 0.16 | 0.08 | 0.10 | 0.06 | 0.02 | 0.12 | 0.04 | 0.06 | 0.03 | 0.03 | 0.07 | 0.02 | 0.10 | 0.08 | 0.09 | 0.06 | 0.08 | 0.04 | 0.04 | 0.04 | 0.07 | 0.06 | 0.01 | 0.07 |
| **Negative (% )** | 0.09 | 0.02 | 0.02 | 0.06 | 0.08 | 0.04 | 0.03 | 0.03 | 0.07 | 0.03 | 0.02 | 0.06 | 0.10 | 0.09 | 0.07 | 0.04 | 0.02 | 0.06 | 0.03 | 0.12 | 0.06 | 0.02 | 0.09 | 0.03 |
| **Total Positive (% )** | 0.06 | | | | | | | | | | | | | | | | | | | | | | | |
| **Total Negative (% )** | 0.05 | | | | | | | | | | | | | | | | | | | | | | | |

Notes: Figure 4.4 illustrates the distribution of t-statistics for cross-sector predictability of excess market performance. The analysis constructs sector rotation portfolios from the Fama and French 49 industries mapped to one of 10 GICS sectors reported in Table 4.7. The analysis tests lags from one to 24 months to allow for the possibility of different performance sequencing and business-cycle stage durations. To illustrate, the Standard & Poor's sequence in Figure 4.1 shows financial sector performance precedes technology sector performance. As such, financial sector returns should predict subsequent technology sector returns. There are 2,160 t-statistics, covering all possible combinations of cross-sector predictability at up to 24 lags. The bottom of Figure 4.4 reports the total percentage of positive and negative t-statistics by lag and in total that are significant at 10 percent.

### 4.6.6.2 Sub-stages

Further analysis also considers different variations of business-cycle stages that might improve the base-case scenario. Outperformance potentially occurs at the beginning or end of each stage. Considering this, the analysis divides all stages into early and late halves then reruns the main tests for sub-stages. There is no significant difference between first- and second-half returns across stages. Investors might anticipate different stages and react in shorter intervals around business-cycle turning points, rather than over the full length of a stage. The analysis also considers shorter periods, testing for significant outperformance two, four and six months around turning points only. Again, there is no evidence of significant outperformance.

#### 4.6.6.3 Sub-samples

Significant events over the full 60-year sample, like the 1970s bear market and 1990s dot.com bubble could potentially drive the results. Unreported analysis also compares average industry performance for each business-cycle stage over the 1948–1977 and 1978–2007 sub-periods. Industry outperformance appears relatively constant across all sub-periods and business-cycle stages, regardless of the performance metric. Consistent with the previous analysis, early-expansion and middle-expansion industries provide inferior outperformance across sub-periods. Overall, the results are not specific to a particular sub-period.

#### 4.6.6.4 Alternative performance measures

This section evaluates two alternative performance measures to compare base-case sector rotation, market-timing, and buy-and-hold strategies. The Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure (MPPM) eliminates any bias in strategy performance attributable to non-normal iid return distributions. Goetzmann, Ingersoll, Spiegel, and Welch (2007) show the MPPM is superior to standard performance metrics, such as Sharpe ratios and Jensen's alphas, when return distributions are potentially non-normal. The MPPM estimates portfolio performance after adjusting for benchmark risk and is comparable with the proprietary Morning Star Risk Adjusted Rating (MRAR).[105] Equation 4.10 defines the MPPM performance measure ( $\Theta$ ) as follows:

$$\Theta \equiv \frac{1}{(1-\rho)\Delta t} \ln\left(\sum_{t=1}^{T} [(1+r_t)/(1+rf_t)]^{1-\rho}\right) \qquad \text{(Eq. 4.10)}$$

[105] For an explanation of widely used MRAR see http://www.morningstar.se/aboutus/MRAR_defined.pdf

where $\Delta t$ is the strategy holding period measured as a percentage of a full year, $r_t$ strategy returns, $rf_t$ the risk-free rate, and $\rho$ benchmark risk. The interpretation of the MPPM performance measure is the annualized strategy return premium after adjusting for benchmark risk. Goetzmann, Ingersoll, Spiegel, and Welch (2007) estimate that benchmark risk ranges from 2 to 4 for the CRSP value-weighted market index. Unreported MPPM test results show that the market-timing strategy outperforms both the buy-and-hold and sector rotation strategies for a normal range of performance risk measures. For instance, when benchmark risk equals 3, market-timing has an annualized risk-adjusted performance of 5.2 percent, in comparison to 3.1 percent and 4.1 percent for the buy-and-hold and sector rotation strategies. Moreover, MPPM performance results show that sector rotation is inferior to market-timing at all levels of benchmark risk.

As another alternative measure, the Barrett and Donald (2003) stochastic dominance test evaluates strategy performance independent of benchmarks. Barrett and Donald (2003) argue that a stochastic dominance approach is suitable for investors who seek to maximize expected utility. Barrett and Donald (2003) show that, due to omitted risk factors, a stochastic dominance performance ranking is superior to mean-variance measures, such as Jensen's alphas and Sharpe ratios. Based on unreported test results, the market-timing strategy second-order stochastically dominates both base-case sector rotation and buy-and-hold strategies. Interestingly, results show, from a stochastic dominance perspective, that an investor would be indifferent between sector rotation and a buy-and-hold strategy. In conclusion, both the MPPM and second-order stochastic dominance performance metrics show that base-case sector rotation is an inferior strategy – even for investors who are able to accurately time all business-cycle stages.

### 4.7 General Sector Performance across the Business Cycle

So far, the base-case analysis uncovers no evidence supporting popular belief on sector performance or the practicality of conventional sector rotation. There are alternative sector rotation variations, as Figure 4.1 illustrates. Thus, the base-case results are subject to the criticism of being limited to a specific sector rotation model. What is more, the popularity of sector rotation suggests investors can profit from its implementation. To account for such possibilities, this section focuses on a general analysis of sector performance. The analysis tests for the systematic performance of *any* sector across *any* business-cycle stage seeking evidence of an alternative sector rotation strategy.

### 4.7.1 Relative industry performance rankings

Initially, the analysis takes a simple, non-parametric view of relative industry performance across business cycles. At a basis, sector rotation holds that the relative outperformance of sectors/industries shifts across business-cycle stages – for example, that early recession performance in transportation precedes middle expansion performance in industrials. If so, the excess market performance of certain industries, on average, should rank highly during particular stages of the business cycle.

Table 4.15 reports the average monthly excess market rankings from highest (1) to lowest (48) for 48 Fama and French industries, over both the full 1948–2007 sample and the original five business-cycle stages. As a guide, the table shades the business-cycle stage where popular belief anticipates industry performance will occur. The results reported in Table 4.15 are striking: The ranking of excess market industry performance is, on average, average. There is no evidence of either consistent outperformance or underperformance for any industry. Most industry performance ranks in the middle (24) for the full period and all stages. An industry that provides systematic performance during a particular stage should rank, for example, consistently in the upper quartile, or top 12 industries. Rather, the results indicate that relative industry performance occurs randomly.

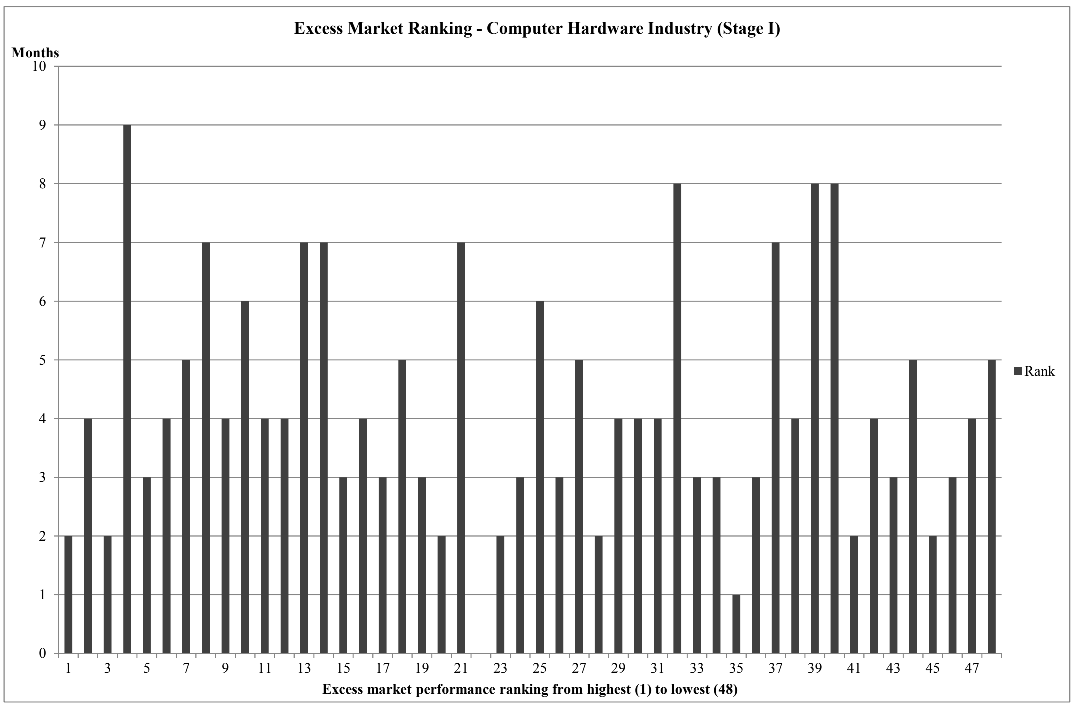
**Table 4.15 Average ranking of excess market industry performance**

| Sector/Industry | Full | Stage I | Stage II | Stage III | Stage IV | Stage V |
|---|---|---|---|---|---|---|
| Computers | 23 | 24 | 23 | 23 | 23 | 22 |
| Computer Software | 25 | 27 | 24 | 24 | 28 | 23 |
| Electronic Equipment | 24 | 23 | 23 | 24 | 26 | 21 |
| Measuring & Control | 23 | 25 | 22 | 23 | 25 | 22 |
| Shipping Containers | 23 | 23 | 23 | 23 | 19 | 23 |
| Transportation | 24 | 22 | 24 | 26 | 27 | 25 |
| Chemicals | 24 | 23 | 25 | 25 | 21 | 27 |
| Steel Works | 24 | 23 | 24 | 24 | 27 | 26 |
| Precious Metals | 25 | 25 | 26 | 25 | 23 | 24 |
| Mining | 24 | 23 | 25 | 22 | 25 | 26 |
| Fabricated Products | 26 | 26 | 26 | 25 | 30 | 27 |
| Machinery | 24 | 23 | 22 | 24 | 27 | 25 |
| Electrical Equipment | 23 | 23 | 22 | 22 | 24 | 25 |
| Aircraft | 23 | 22 | 22 | 25 | 24 | 23 |
| Shipbuilding & Railroad | 24 | 23 | 26 | 24 | 25 | 26 |
| Defense | 24 | 24 | 24 | 26 | 23 | 23 |
| Personal Services | 24 | 24 | 24 | 25 | 23 | 21 |
| Business Services | 24 | 24 | 24 | 23 | 24 | 22 |
| Agriculture | 24 | 25 | 23 | 23 | 26 | 25 |
| Food Products | 23 | 24 | 24 | 24 | 17 | 23 |
| Candy & Soda | 24 | 25 | 21 | 25 | 23 | 24 |
| Beer & Liquor | 23 | 24 | 24 | 22 | 20 | 23 |
| Tobacco Products | 23 | 25 | 23 | 22 | 17 | 24 |
| Healthcare | 24 | 25 | 25 | 23 | 27 | 20 |
| Medical Equipment | 23 | 24 | 23 | 23 | 19 | 22 |
| Pharmaceutical | 23 | 25 | 22 | 23 | 19 | 25 |
| Coal | 24 | 23 | 24 | 22 | 27 | 23 |
| Petroleum & Natural Gas | 23 | 22 | 24 | 23 | 25 | 25 |
| Utilities | 24 | 24 | 25 | 24 | 17 | 26 |
| Communication | 24 | 24 | 25 | 23 | 19 | 28 |
| Recreation | 24 | 24 | 25 | 24 | 24 | 21 |
| Entertainment | 23 | 24 | 24 | 23 | 20 | 24 |
| Printing & Publishing | 23 | 24 | 23 | 25 | 24 | 19 |
| Consumer Goods | 24 | 24 | 23 | 25 | 20 | 23 |
| Apparel | 24 | 24 | 24 | 25 | 24 | 20 |
| Rubber & Plastic | 23 | 23 | 22 | 24 | 26 | 25 |
| Textiles | 24 | 23 | 25 | 25 | 24 | 22 |
| Construction Materials | 24 | 23 | 23 | 25 | 24 | 23 |
| Construction | 24 | 25 | 24 | 23 | 29 | 22 |
| Automobiles & Trucks | 24 | 21 | 25 | 25 | 24 | 24 |
| Business Supplies | 24 | 22 | 25 | 25 | 24 | 24 |
| Wholesale | 24 | 24 | 24 | 24 | 25 | 23 |
| Retail | 24 | 23 | 25 | 23 | 21 | 22 |
| Restaurants & Hotels | 23 | 24 | 23 | 23 | 26 | 23 |
| Banking | 23 | 23 | 24 | 24 | 18 | 23 |
| Insurance | 24 | 23 | 25 | 24 | 22 | 24 |
| Real Estate | 25 | 24 | 25 | 24 | 28 | 22 |
| Trading | 23 | 21 | 23 | 24 | 25 | 21 |

Notes: Table 4.15 reports realized industry rankings from the highest excess market performance (1) to the lowest excess market performance (48). Shading indicates the business-cycle stage where popular belief anticipates excess market outperformance will occur.

Figure 4.5 provides a representative illustration, using the computer hardware industry ranking over 201 months of early recession. The figure illustrates, for instance, that the performance ranking of computer hardware ranges from the highest rank for two months to the lowest rank for 5 months, with an average early expansion rank of 24. The performance ranking of computer hardware in early recession repeats a similar pattern for the other business-cycle stages. The remaining industries also repeat similar patterns of realized performance rankings across all business-cycle stages. Thus, the ranking of excess market returns provides no additional insight into where a particular industry provides relative business-cycle performance.

**Figure 4.5 Performance ranking for the computer hardware industry**




Notes: Figure 4.5 illustrates the excess market performance ranking of the computer hardware industry during 201 months of early expansion.

### 4.7.2 Percentage of months with excess market performance

This section examines the percentage of months that industries generate excess market returns for all business-cycle stages. The intention is to observe whether *any* industry realizes outperformance a high percentage of the time during *any* business-cycle stage. Such evidence would suggest an alternative sector rotation strategy. For instance, an industry that outperforms the market 90 percent of early recession months would provide a relatively certain sector rotation investment during that stage.

Table 4.16 reports the percentage of months realized industry returns exceed the market, for all industries, for all business-cycle stages, and for the full sample. The analysis tests the statistical significance of realized excess market performance against a 50/50 random probability, where bold indicates 10 percent statistical significance. Table 4.16 also reports annualized excess market industry performance estimated with Equation 4.3, where bold indicates 10 percent statistical significance based on White (1980) heteroskedasticity consistent t-statistics.

Some industries do indicate statistically significant market outperformance a high percentage of the time during certain stages. Food products, for instance, provide 19 percent annual excess market performance 77 percent of early recession months. Interestingly, popular belief suggests food products provide late expansion rather than early recession performance. Similarly, utilities outperform the market 72 percent of early recession months, with an average 20 percent annual excess market performance. Here the performance occurs precisely where popular belief suggests. Other industries also significantly outperform the market a high percentage of the time during different business-cycle stages. A majority of significant industry outperformance occurs during the stages of early and late recession. Overall, 8 percent of all industries realize market outperformance statistically different from random chance at the 10 percent significance level for more than 50 percent of the business-cycle stage months. At the same time, 15 percent of all industries realize systematic excess market performance across full business-cycles stages. However, with exceptions, the observed patterns of industry performance are largely unsupportive of conventional views on sector rotation. The evidence, nonetheless, suggests the possibility of an alternative sector rotation strategy, which the next section explores.

### Table 4.16 Percentage of months realized industry returns exceed the market

| | full period | | early expansion | | middle expansion | | late expansion | | early recession | | late recession | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Industries | % month positive | excess market | % month positive | excess market | % month positive | excess market | % month positive | excess market | % month positive | excess market | % month positive | excess market |
| Computers | 0.52 | 0.014 | 0.47 | -0.034 | 0.50 | 0.022 | 0.55 | 0.038 | 0.47 | -0.025 | **0.63** | 0.118 |
| Computer Software | 0.49 | -0.073 | 0.45 | -0.120 | 0.52 | -0.020 | 0.50 | -0.069 | 0.39 | -0.340 | 0.56 | 0.214 |
| Electronic Equipment | 0.51 | -0.003 | 0.49 | -0.003 | 0.53 | 0.025 | 0.48 | -0.021 | 0.49 | **-0.116** | 0.61 | 0.092 |
| Measuring & Control | 0.49 | 0.004 | 0.45 | **-0.060** | 0.53 | 0.046 | 0.50 | 0.029 | 0.45 | -0.097 | 0.49 | 0.116 |
| Shipping Containers | 0.53 | 0.007 | 0.51 | 0.006 | 0.52 | 0.019 | 0.53 | -0.029 | **0.66** | **0.110** | 0.49 | 0.009 |
| Transportation | 0.48 | -0.011 | 0.55 | **0.071** | 0.50 | -0.008 | **0.44** | **-0.066** | **0.28** | **-0.120** | 0.47 | 0.030 |
| Chemicals | 0.50 | -0.005 | 0.51 | 0.030 | 0.51 | -0.018 | 0.47 | -0.030 | 0.55 | **0.071** | 0.47 | **-0.062** |
| Steel Works | **0.46** | -0.017 | 0.51 | 0.000 | 0.48 | -0.007 | **0.43** | -0.010 | **0.32** | **-0.111** | 0.43 | -0.055 |
| Precious Metals | 0.48 | -0.027 | 0.47 | -0.052 | 0.44 | -0.050 | 0.50 | -0.021 | 0.48 | 0.052 | 0.56 | 0.094 |
| Mining | 0.50 | 0.001 | 0.54 | -0.005 | 0.45 | -0.012 | 0.55 | **0.080** | 0.42 | **-0.165** | 0.45 | -0.053 |
| Fabricated Products | **0.45** | **-0.051** | 0.47 | -0.056 | 0.46 | -0.012 | 0.46 | -0.026 | **0.27** | **-0.274** | 0.47 | -0.095 |
| Machinery | 0.48 | -0.005 | 0.46 | 0.009 | 0.55 | 0.027 | 0.47 | -0.013 | **0.36** | **-0.126** | 0.49 | -0.017 |
| Electrical Equipment | 0.53 | **0.024** | 0.50 | 0.013 | **0.58** | **0.047** | 0.53 | 0.042 | 0.45 | -0.071 | 0.47 | -0.001 |
| Aircraft | 0.52 | 0.023 | 0.55 | 0.052 | 0.55 | 0.049 | 0.47 | -0.013 | 0.49 | -0.044 | 0.55 | 0.036 |
| Shipbuilding & Railroad | 0.49 | -0.018 | 0.50 | 0.013 | 0.47 | **-0.053** | 0.51 | 0.002 | 0.45 | -0.078 | 0.51 | -0.024 |
| Defense | 0.50 | 0.014 | 0.52 | 0.031 | 0.53 | 0.014 | **0.43** | -0.037 | 0.52 | 0.026 | 0.63 | 0.220 |
| Personal Services | 0.49 | -0.025 | 0.46 | -0.023 | 0.51 | -0.016 | **0.43** | -0.047 | 0.51 | -0.118 | **0.71** | **0.138** |
| Business Services | 0.49 | -0.010 | 0.46 | **-0.044** | 0.53 | -0.004 | 0.51 | 0.007 | **0.34** | -0.066 | 0.49 | **0.090** |
| Agriculture | 0.49 | -0.013 | 0.45 | -0.061 | 0.51 | 0.016 | 0.51 | 0.042 | 0.43 | -0.131 | 0.47 | -0.028 |
| Food Products | 0.49 | 0.009 | 0.45 | -0.037 | 0.45 | 0.001 | 0.49 | 0.003 | **0.77** | **0.194** | 0.53 | 0.072 |
| Candy & Soda | 0.52 | 0.015 | 0.46 | -0.024 | **0.63** | **0.091** | 0.46 | -0.034 | 0.48 | 0.011 | 0.59 | 0.069 |
| Beer & Liquor | 0.52 | 0.009 | 0.48 | -0.034 | 0.51 | 0.009 | 0.55 | 0.029 | 0.58 | 0.069 | 0.55 | 0.037 |
| Tobacco Products | 0.53 | 0.027 | **0.43** | **-0.077** | 0.54 | 0.020 | **0.56** | 0.081 | **0.70** | **0.275** | 0.55 | 0.040 |
| Healthcare | 0.49 | -0.017 | 0.49 | -0.015 | 0.47 | -0.043 | 0.51 | 0.014 | 0.39 | -0.314 | **0.66** | 0.359 |
| Medical Equipment | **0.53** | 0.022 | 0.47 | **-0.051** | 0.53 | 0.014 | 0.55 | **0.050** | **0.62** | **0.137** | 0.59 | 0.131 |
| Pharmaceutical | 0.52 | 0.017 | 0.48 | **-0.067** | 0.55 | **0.064** | 0.51 | 0.032 | **0.66** | **0.136** | 0.47 | -0.001 |
| Coal | 0.49 | 0.022 | 0.50 | 0.001 | 0.49 | -0.028 | 0.53 | **0.139** | **0.36** | **-0.202** | 0.49 | 0.111 |
| Petroleum & Natural Gas | 0.51 | 0.020 | 0.53 | 0.035 | 0.49 | 0.017 | 0.53 | 0.046 | 0.43 | -0.037 | 0.53 | -0.067 |
| Utilities | 0.49 | -0.002 | 0.46 | -0.029 | 0.48 | -0.013 | 0.50 | 0.003 | **0.72** | **0.199** | 0.41 | -0.062 |
| Communication | 0.47 | -0.013 | 0.47 | -0.037 | **0.43** | -0.028 | 0.53 | 0.007 | 0.58 | **0.151** | **0.31** | -0.099 |
| Recreation | 0.48 | -0.023 | 0.48 | -0.040 | 0.46 | -0.024 | 0.48 | -0.038 | 0.43 | -0.060 | 0.55 | 0.178 |
| Entertainment | 0.51 | 0.018 | 0.46 | -0.011 | 0.51 | 0.027 | 0.52 | 0.006 | 0.57 | 0.096 | 0.53 | 0.073 |
| Printing & Publishing | 0.51 | 0.001 | 0.49 | -0.017 | 0.51 | 0.031 | 0.49 | -0.034 | 0.47 | -0.040 | **0.71** | **0.161** |
| Consumer Goods | 0.49 | 0.005 | 0.45 | -0.004 | 0.49 | 0.010 | 0.46 | -0.025 | **0.64** | 0.081 | 0.55 | 0.066 |
| Apparel | **0.46** | -0.016 | **0.42** | -0.012 | 0.47 | -0.020 | **0.44** | -0.048 | 0.43 | -0.054 | **0.63** | **0.169** |
| Rubber & Plastic | 0.49 | 0.003 | 0.51 | -0.002 | **0.57** | 0.042 | 0.46 | -0.011 | **0.36** | -0.071 | 0.41 | 0.013 |
| Textiles | 0.48 | -0.018 | 0.53 | 0.029 | 0.50 | -0.036 | **0.41** | -0.054 | 0.47 | -0.047 | 0.55 | 0.054 |
| Construction Materials | 0.48 | -0.003 | 0.48 | -0.001 | 0.51 | 0.022 | 0.46 | -0.036 | 0.51 | -0.054 | 0.45 | 0.083 |
| Construction | 0.48 | 0.001 | 0.46 | -0.036 | 0.50 | 0.009 | 0.53 | 0.051 | **0.28** | **-0.209** | 0.53 | 0.166 |
| Automobiles & Trucks | 0.50 | -0.007 | **0.57** | **0.078** | 0.46 | -0.040 | 0.47 | -0.040 | 0.43 | -0.053 | 0.53 | -0.014 |
| Business Supplies | 0.48 | -0.004 | 0.52 | **0.053** | 0.46 | -0.028 | 0.45 | -0.034 | 0.45 | -0.037 | 0.55 | 0.029 |
| Wholesale | 0.48 | -0.005 | 0.45 | -0.011 | 0.51 | 0.006 | 0.45 | 0.004 | 0.42 | **-0.082** | 0.61 | 0.020 |
| Retail | 0.50 | 0.000 | 0.50 | -0.016 | 0.45 | -0.038 | 0.52 | 0.012 | 0.57 | 0.062 | 0.55 | **0.111** |
| Restaurants & Hotels | 0.51 | 0.006 | 0.48 | -0.005 | 0.54 | 0.025 | 0.53 | 0.008 | 0.42 | -0.099 | 0.51 | 0.090 |
| Banking | 0.52 | 0.006 | 0.53 | -0.011 | 0.45 | -0.004 | 0.51 | -0.004 | **0.72** | 0.114 | 0.53 | 0.056 |
| Insurance | 0.49 | 0.001 | 0.50 | -0.015 | 0.50 | -0.011 | 0.46 | 0.009 | 0.55 | 0.040 | 0.51 | 0.031 |
| Real Estate | 0.48 | **-0.038** | 0.49 | -0.030 | 0.48 | -0.025 | 0.47 | -0.038 | 0.45 | **-0.237** | 0.57 | 0.115 |
| Trading | **0.54** | **0.023** | **0.56** | **0.048** | 0.55 | **0.034** | 0.50 | 0.001 | 0.45 | **-0.089** | 0.61 | **0.098** |
| **Outperform** | 2.00 | 2.00 | 2.00 | 4.00 | 3.00 | 4.00 | 1.00 | 3.00 | 8.00 | 8.00 | 5.00 | 6.00 |
| **Underperform** | 3.00 | 2.00 | 2.00 | 5.00 | 1.00 | 1.00 | 6.00 | 1.00 | 8.00 | 11.00 | 1.00 | 1.00 |

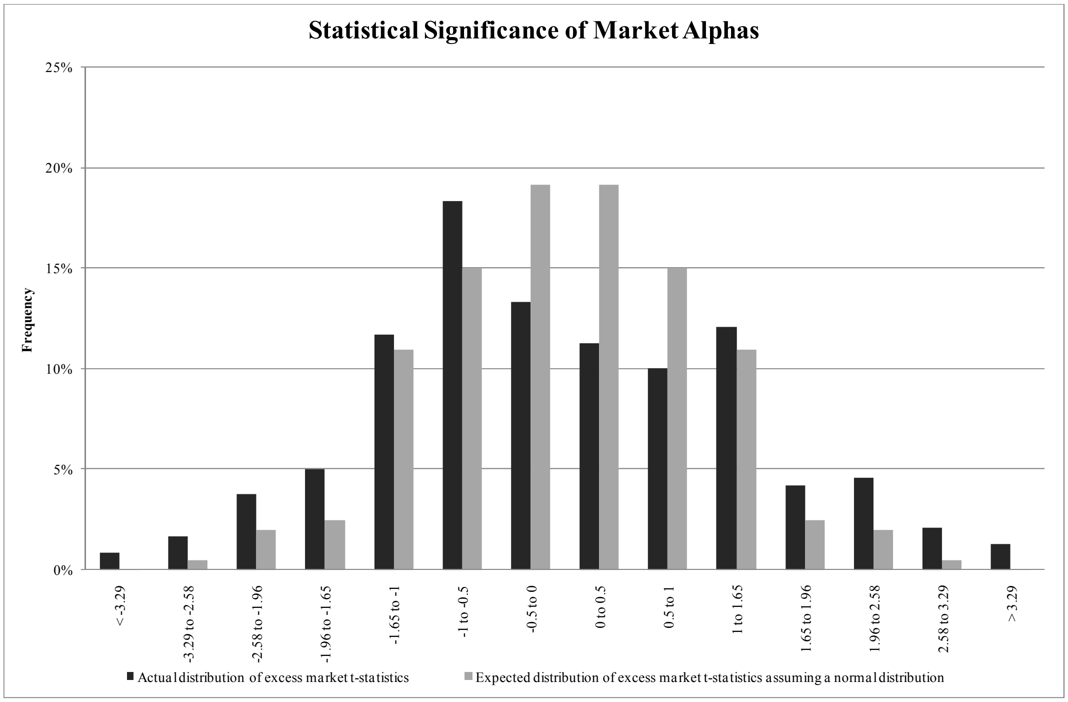
Notes: Table 4.16 reports the percentage of months realized industry returns exceed the market. The analysis tests the statistical significance of realized excess market performance against a 50/50 random probability, where bold indicates 10 percent statistical significance. The table also reports annualized excess market performance estimated with Equation 4.3. Bold indicates White (1980) heteroskedasticity consistent t-statistics significant at 10 percent.

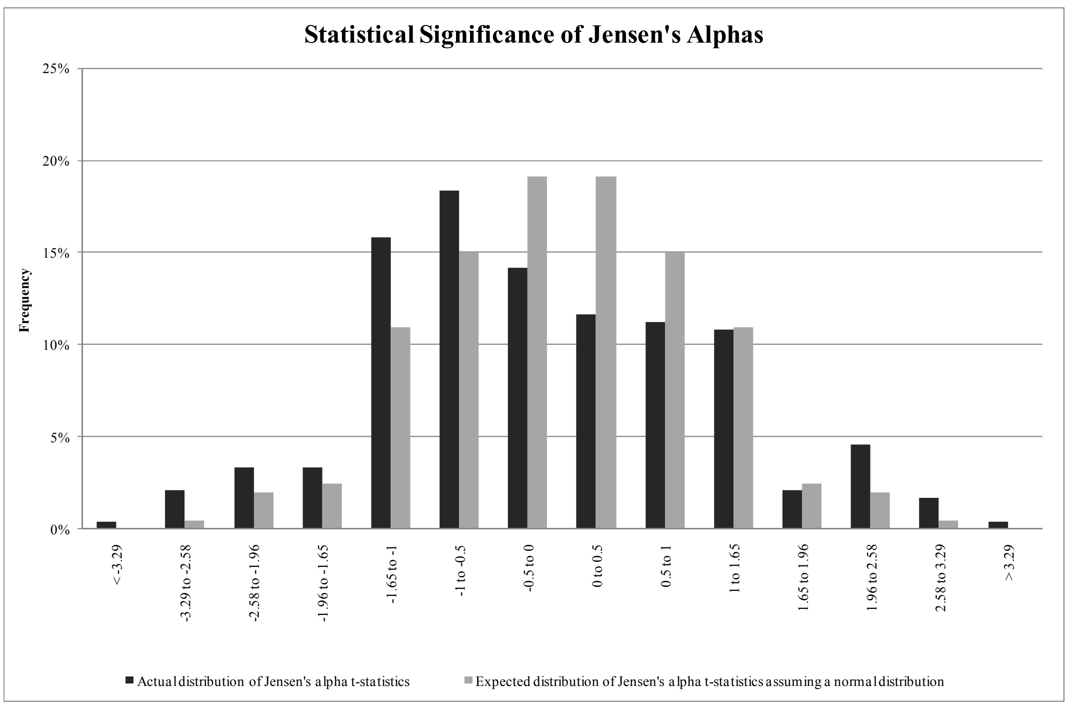
### 4.7.3 Alternative sector rotation strategy

As a final step, the analysis investigates whether the opportunity exists for an alternative sector rotation strategy. Previously, the results show limited evidence of systematic industry performance over 10 business cycles from 1948 to 2007. The true test, of course, is whether evidence of in-sample industry performance leads to profitable out-of-sample sector rotation. To explore that possibility, the analysis first identifies the industries that provide systematic performance over the first nine business cycles since 1948. The analysis then uses the most recent business cycle to test whether any identified industries translate into a profitable out-of-sample alternative rotation strategy.

First, the analysis examines the Fama and French 48 industries for evidence of statistically significant excess market and Jensen's alpha performance across all five business-cycle stages. Figure 4.6 plots the actual distribution of outperformance t-statistics against the expected distribution under a normal distribution. Under the null hypothesis of no significant outperformance, the outperformance t-statistics should follow a normal distribution centered on zero. Slightly more industries provide systematic outperformance than expected under the null hypothesis at a 10 percent confidence level. In total, the results show significant excess market and Jensen's alpha outperformance for 29 and 21 industries, rather than 12 each as expected under a normal distribution. An alternative sector rotation strategy includes those industries with *jointly* significant excess market and Jensen's alpha performance.

**Figure 4.6 Distribution of excess market and Jensen's alpha performance**




Note: Figure 4.6 illustrates the percentage of time that the actual t-statistics for excess market and Jensen's alpha outperformance fall within the indicated range in comparison with a normal distribution. The analysis calculates excess market and Jensen's alpha outperformance for all industries across all business cycle stages with Equation 4.3 and Equation 4.4 for a total of 240 (5 x 48) corresponding t-statistics for each performance measure.

Panel A of Table 4.17 reports industries by the business-cycle stage identified as providing jointly systematic excess market and Jensen's alpha performance, over the nine business cycles from January 1948 to March 2001. The table reports excess market and Jensen's alpha performance as annual rates, where bold indicates 10 percent statistical significance using White (1980) heteroskedasticity consistent t-statistics. Column 4 of Panel A reports the percentage of months an industry realizes positive market performance. The analysis tests the percentage of months an industry realizes excess performance against a 50/50 random probability, where bold again indicates 10 percent statistical significance. There are three industries included in each business-cycle stage, with the exception of five industries in early recession, which meet the criterion for alternative sector rotation. Notably, seven of those industries do correspond with popular belief on anticipated industry performance. For example, the gas and electric, and communication industries have proven consistently to provide early recession performance, both in the base-case analysis and robustness tests.

Panel B of Table 4.17 reports performance results for the alternative sector rotation strategy. The out-of-sample period covers the NBER business cycle that runs from January 2001 to December 2007. Panel B reports mean returns, standard deviations, and Jensen's alphas as annual rates, along with single-index betas and Sharpe ratios. Bold indicates Jensen's alpha performance statistically significant at 10 percent using White (1980) heteroskedasticity consistent t-statistics. The alternative sector rotation industries realize in-sample excess market performance approximately 62 percent of all months for the selected stages. Nonetheless, the alternative strategy, which showed such in-sample promise, actually realizes a negative 4.4 percent annual Jensen's alpha out-of-sample, although this is statistically indistinguishable from zero. Transaction costs further diminish strategy performance. Notably, the market-timing Jensen's alpha also drops from 2.5 percent for the full period to a negative 0.4 percent, although here again insignificantly so. One could argue that the 2001–2007 business cycle is not representative of typical business cycles and thus is an unfair test of any sector rotation strategy. Alternatively, one might conclude that industry fundamentals vary from one business cycle to the next, making it impracticable to implement profitable sector rotation. Evidence of unsystematic sector performance across business cycles suggests the latter.

**Table 4.17 Alternative sector rotation strategy**

| Panel A: | | Performance | | |
|---|---|---|---|---|
| | | excess | % month | Jensen's |
| Period 1948:01 - 2001:03 | Sector/Industry | market | positive | alpha |
| Early Expansion - Stage I | Transportation | **0.073** | **0.568** | **0.060** |
| | Automobiles & Trucks | **0.081** | **0.580** | **0.088** |
| | Trading | **0.048** | **0.574** | **0.042** |
| Middle Expansion - Stage II | Candy & Soda | **0.115** | **0.638** | **0.128** |
| | Pharmaceutical | **0.088** | **0.582** | **0.088** |
| | Printing & Publishing | **0.060** | 0.548 | **0.057** |
| Late Expansion - Stage III | Medical Equipment | **0.061** | **0.568** | **0.062** |
| | Coal | **0.150** | 0.526 | **0.150** |
| | Construction | **0.088** | 0.553 | **0.087** |
| Early Recession - Stage IV | Shipping Containers | **0.089** | **0.653** | **0.079** |
| | Chemicals | **0.088** | 0.571 | **0.079** |
| | Food Products | **0.214** | **0.776** | **0.171** |
| | Gas & Electric | **0.246** | **0.776** | **0.177** |
| | Communication | **0.186** | 0.612 | **0.085** |
| Late Recession - Stage V | Personal Services | **0.154** | **0.723** | **0.157** |
| | Apparel | **0.190** | 0.617 | **0.198** |
| | Printing & Publishing | **0.173** | **0.702** | **0.162** |

| Panel B: | | | | | |
|---|---|---|---|---|---|
| Period 2001:04 - 2007:12 | | | | Sharpe | Jensen's |
| Strategy Performance | mean | std. dev. | beta | ratio | alpha |
| Market | 7.44% | 13.10% | 1.00 | 0.10 | |
| ***0% round-trip transaction costs*** | | | | | |
| Alternative Sector Rotation | 3.03% | 17.64% | 1.07 | 0.00 | -4.44% |
| Market-timing | 6.77% | 12.71% | 0.94 | 0.09 | -0.36% |
| ***0.5% round-trip transaction costs*** | | | | | |
| Alternative Sector Rotation | 2.73% | 17.57% | 1.07 | 0.00 | -4.70% |
| Market-timing | 6.69% | 12.71% | 0.94 | 0.09 | -0.44% |
| ***1.0% round-trip transaction costs*** | | | | | |
| Alternative Sector Rotation | 2.42% | 17.51% | 1.06 | -0.01 | -4.96% |
| Market-timing | 6.61% | 12.72% | 0.94 | 0.08 | -0.52% |
| ***1.5% round-trip transaction cost*** | | | | | |
| Alternative Sector Rotation | 2.12% | 17.46% | 1.06 | -0.01 | -5.22% |
| Market-timing | 6.54% | 12.73% | 0.95 | 0.08 | -0.60% |

Notes: Panel A of Table 4.17 reports industries that over the period from January 1948 to March 2001 provided jointly statistically significant excess market returns and Jensen's alphas during the indicated business-cycle stage. The table reports excess market returns and Jensen's alphas as annualized rates and indicate White (1980) heteroskedasticity consistent t-statistics significant at 10 percent in bold. Column 4 reports the percentage of months realized industry returns exceed the market. The analysis tests for the percentage of months an industry provides realized outperformance against a random 50/50 chance and indicates 10 percent statistical significance in bold. Panel B of Table 4.17 reports mean returns, standard deviations, single-index betas, Sharpe ratios, and Jensen's alphas for an out-of-sample performance of an alternative sector rotation strategy based on Panel A. Panel B reports mean returns, standard deviations, and Jensen's alphas as annual rates. Bold indicates Jensen's alpha performance significant at 10 percent using White (1980) heteroskedasticity consistent t-statistics.

## 4.8 Conclusion

Despite thorough empirical tests, there is scant evidence that conventional sector rotation across business cycles generates systematic excess returns. The base-case analysis assumes that sector rotation investors perfectly time business cycles and rotate sectors in accordance with popular belief on sector performance. Even then, sector rotation generates, at best, 2.3 percent annual outperformance. Performance quickly diminishes with the introduction of transaction costs or business cycle mistiming. In comparison, a similar investor, with perfect market timing ability, would realize 2.5 percent annual outperformance by simply switching to cash during early recession. Lastly, the analysis generalizes the base case to allow for all possible sector rotation variations. The analysis explores whether any industry provides systematic performance across any business-cycle stage. The general results again provide limited evidence of systematic industry performance over business cycles. A group of industries does generate in-sample systematic outperformance, which is marginally different from that expected to occur randomly, absent any systematic outperformance. However, an out-of-sample sector rotation strategy, based on those same industries, fails to generate significant outperformance. The results suggest that no variation of sector rotation provides systematic outperformance, questioning the popular belief that timing sector investments with business cycles generate excess returns. The results do not necessarily preclude investors from profiting through sector rotation. Different investments in sector and industry funds, beyond the scope of this study, may outperform the market. The results simply show that sectors fail to provide systematic performance across the business cycle and question the viability of popular sector rotation.

# Chapter 5 Conclusions

## 5.1 Summary of Contributions

The efficient market hypothesis is the cornerstone of modern finance. In perfectly efficient markets, stock prices fully and instantaneously reflect all available information. Theoretically, investors should be unable to earn excess returns trading on systematic cycles in the stock market, especially after deducting transaction costs. While the efficient market hypothesis remains the principal tenet of finance, evidence of periodic stock market cycles and speculative investor sentiment appear to contradict theory.

Behavioral finance provides an alternative financial theory that describes inefficient markets, which allows for market cycles and strategies that earn excess returns. The Hong and Stein (1999) model portrays investors who are boundedly rational, due to their inability to fully process fundamental news. Other theoretical studies, such as Barberis and Shleifer (2003) and Peng and Xiong (2006), argue that limited investor attention leads to categorized learning and style investing. Importantly, Kumar and Lee (2006) confirm that the collective trades of uninformed investors — those who trade on sentiment rather than fundamental value — result in mispricing and return predictability. Research by Baker and Wurgler (2006), among others, provides empirical evidence that investor sentiment leads to speculative mispricing, especially in particular styles. Behavioral finance studies support the occurrence of stock market cycles and sentiment-driven mispricing, topics this dissertation explores.

Specifically, this dissertation examines industry returns for evidence of cyclical performance. Evidence of cyclical industry performance is interesting from two perspectives. Firstly, stock market cycles, unrelated to fundamental value, challenge the efficient market hypothesis. Nonetheless, an evolving literature, coupled with anecdotal evidence, indicates that stock prices, at times, do not fully reflect fundamental value. Investigating industry performance provides additional insight into stock market cycles previously documented. Secondly, popular belief suggests that predictable industry cycles facilitate profitable investment strategies. The capital that such strategies attract makes the topic interesting from a practical perspective. Taken together, both perspectives suggest the need for an investigation of whether there are systematic cycles in industry performance. Each of the three empirical studies investigates industry returns for evidence of different cycles. The three industry cycles investigated are investor-sentiment cycles, political cycles, and business cycles. The following sub-sections summarize each of the empirical studies. The last section discusses limitations, and outlines an intended agenda for future research.

### 5.1.1 Investor sentiment and industry returns

The first study investigates the relationship between investor sentiment and industry returns. The efficient market hypothesis makes no provision for investor sentiment in asset pricing. However, anecdotal evidence periodically suggests that investor sentiment drives stock market performance. The financial media also widely report on investor-sentiment measures as predictors of market direction. Particular industries, outlined in Baker and Wurgler (2006), appear especially sensitive to speculative investor sentiment. Empirical research provides some evidence that investor sentiment does predict stock market returns. Research shows that investor sentiment positively predicts short-term market overreaction and long-term market reversals. Evidence that investor sentiment predicts stock returns presents another challenge to market efficiency, which the first study endeavors to understand through industry analysis. The study examines investor sentiment predictability of industry performance and its practical application in industry rotation.

The first study documents investor sentiment predictability of industry returns. However, timing industry investments with sentiment generates only marginal outperformance. The study investigates the interaction between industry performance and three investor-sentiment measures, over the sample period 1987–2007. Confirming other empirical research, it finds that investor sentiment positively predicts short-term and negatively predicts long-term market returns. Predictability is more evident in equal-weighted indices, given the greater influence of small-cap stocks. Investor sentiment similarly has a predictable effect on industry performance. The study documents universal predictability of short-term industry performance. However, long-term predictability is limited over the full sample. Long-term predictability is greater for bearish sentiment than it is for bullish sentiment. Study one finds that difficult-to-value industries are no more susceptible to speculative investor sentiment than others are. Investor sentiment predictability of industry returns does not readily translate into a profitable investment strategy, due to high strategy turnover. Study one documents 3 to 6 percent annual outperformance to strategies that use investor sentiment to rotate industries, which transaction costs would largely consume. Overall, the first study concludes that the effect of investor sentiment is market-wide rather than industry-specific. Industry returns thus provide no additional explanation for investor sentiment predictability of stock returns.

### 5.1.2 Political cycles in U.S. industry returns

Study two investigates industry returns for evidence of two well-known presidential election cycles. Prior empirical studies document stock market cycles related to a president's political affiliation (presidential election cycle) and the years of a four-year presidential term (quadrennial cycle). Generally, research shows that the market performs best under Democratic presidents and in the last two years of any presidential term. Research, thus, contradicts popular belief that the stock market performs best under Republican presidents. There is also widespread belief that certain industries systematically perform best under Republican presidents and other industries perform best under Democratic presidents. Predictable political stock market cycles challenge market efficiency and remain an unanswered puzzle in the financial literature. The second study investigates political cycles in industry returns for two reasons: to provide a possible explanation for political stock market cycles, and to test the popular belief that political cycles drive industry performance.

The second study documents political stock market cycles in the market and in unadjusted industry returns. The sample covers 21 presidential election cycles from 1926 to 2006. Confirming prior studies, such as Booth and Booth (2003) and Santa-Clara and Valkanov (2003), study two provides evidence of political cycles in the general market. Stock market returns are 8.6 percent higher under Democratic presidents and 10 percent higher in the second half of any presidential term. Unadjusted industry returns exhibit similar political cycles. However, evidence of presidential and quadrennial cycles mostly dissipates in industry returns after a Fama and French three-factor risk correction. Size and value risk factors thus largely explain political cycles in industry performance. The second study also tests differences in expected industry performance, using an event study to analyse the closely contested 2004 presidential election. The event study analysis groups industries by political orientation, political contributions, and analyst recommendations. Statistically insignificant excess returns, for all groups, indicate that election outcomes provide a noisy signal of differences in expected industry performance. Contrary to popular belief, study two provides no evidence of a relationship between industry performance and political cycles. The second study concludes that political cycles remain a market-wide puzzle, unexplained by industry performance.

### 5.1.3 Sector rotation across business cycles

The third study investigates the two fundamental assumptions of a popular investment strategy known as sector rotation: that industries provide systematic business-cycle performance, and that sector rotation generates excess risk-adjusted performance. Profitable sector rotation further requires perfectly timing industry investments with business-cycle stages. To overcome that obstacle, study three makes the simplifying assumption of an investor who has perfect business-cycle foresight. Study three initially examines a common variation of sector rotation, which rotates specific industry investments over NBER-delineated business-cycle stages. Extended analysis investigates the performance of all industries across all business-cycle stages, as a generalization that covers any possible variation of sector rotation. The third study includes additional robustness tests in order to account for alternative business-cycle stage delineations; sector and industry classifications; risk-correction measures, and strategy implementations.

The third study documents limited evidence that industry performance systematically varies over business cycles in a way that facilitates profitable sector rotation strategies. The full sample covers 10 NBER business cycles from 1948 to 2007. A sector rotation strategy that follows popular guidance on industry performance generates at best 2.3 percent annual outperformance. Performance does not improve rotating industries one to three months before or after business-cycle turning points. Moreover, imperfectly timing business cycles and deducting transaction costs would quickly eliminate outperformance. The third study shows that an investor with business-cycle foresight would do better by simply switching from the market index to cash in recessions. More generally, there is only limited evidence that any industry systematically performs better during any business-cycle stage. The unsystematic performance of industries over business-cycle stages questions the popular belief that sector rotation generates outperformance, while also confirming market efficiency.

### 5.2 Limitations and Future Research Agenda

This section discusses limitations and an intended agenda for future research. The dissertation examines industry performance related to sentiment cycles, political cycles, and business cycles. While market efficiency maintains that stock returns follow a random walk, widespread belief persists that there are predictable cyclical patterns in industry returns. Shiller (2003) discusses the importance of better understanding such irrational expectations, which ultimately result in speculative asset pricing. To that end, there are aspects of industry performance that deserve further exploration.

The first study documents that the effect of investor sentiment on market returns extends, almost universally, to industry performance. Moreover, industry characteristics fail to explain investor sentiment predictability of industry returns. This result runs contrary to market studies, which show speculative mispricing related to certain stocks' characteristics. As such, future research will seek to understand better the relationship between industry mispricing and investor sentiment. An intended approach is to disentangle industry sentiment from market-wide investor sentiment. This approach will require the construction of an industry-specific investor-sentiment measure, similar to the Baker and Wurgler (2006) sentiment index. A direct industry sentiment measure, thus, could better explain industry return predictability and industry boom-and-bust cycles.

Political cycles in the U.S. stock market remain an unexplained puzzle, in contradiction of the efficient market hypothesis. The first essay shows that systematic sources of risk largely explain presidential cycles in U.S. industry returns, leaving political stock market cycles a puzzle. There are at least two alternative explanations of political stock market cycles. In the U.S., the Congress controls government expenditures. A later study will further examine industry performance related to the interaction between political control of Congress and the presidency. The question also remains of causality – does politics determine stock market cycles, or the reverse? For instance, influential industries could determine presidential election outcomes. Santa-

Clara and Valkanov (2003) additionally recognize the possibility that macro-economic conditions drive political cycles. Future research will thus further examine these possible explanations of political stock market cycles.

The third essay documents no evidence of systematic industry performance corresponding with business cycles. A remaining question is whether rotating across alternative investment styles (e.g. size, growth, value, and international) provides predictable business-cycle outperformance. Lucas, van Dijk, and Kloek (2002) and Ammann and Verhofen (2006) observe that the returns of certain investment styles do exhibit pro-cyclical patterns. Næs, Skjeltorp, and Ødegaard (2011) also observe that time-variant investor preferences correspond with business cycles. Their study particularly documents a "flight to quality" as business cycle conditions worsen, affecting market liquidity and valuations. During an economic downturn, for instance, investor participation in small-cap stocks diminishes. Additionally, Vardharaj and Fabozzi (2007) show that time-variant asset allocations account for 90 percent of investment returns. Consequently, differences in cross-sectional style performance across business cycles potentially result in profitable investment allocation strategies. A future study explores this possibility.

A further extension of study three will examine the relationship between industry values and credit cycles. Research shows that credit cycles are distinct from traditional business cycles. Bordo and Haubrich (2009) find that phases of credit and business cycles overlap only about 34.4 percent of the time. Moreover, Claessens, Kose, and Terrones (2008) show that credit cycles generally lead business cycles. Their study also shows that economic contractions are more severe when traditional business cycles coincide with credit cycles. Minsky (1992) describes credit availability as the driver of financial market boom-and-bust cycles. From a Minsky perspective, cycles of credit expansion and contraction underlie business cycles and financial market fragility. Minsky delineates stages of expanding credit, diminishing risk aversion, and speculation that potentially lead to industry valuation cycles and subsequent mispricing. An analysis of the interaction between Minsky credit-cycle stages and industry performance may provide an alternative explanation of popular rotation strategies.

Finding spurious patterns in market returns does not provide conclusive evidence of violations of the efficient market hypothesis. A limitless number of variables are available that can potentially describe statistical patterns in the data – even where none exist. The extant literature documents a number of apparently systematic patterns, which might simply represent artifacts of the data. A true test of cyclical patterns is whether trading on them generates systematic outperformance. This thesis tests industry returns for evidence of sentiment cycles, political cycles, and business cycles. In all instances, unsystematic industry performance provides no evidence that investors can generate excess returns by timing their investments with these cycles. Rational explanations, such as corrections for well-known sources of risk, largely explain any apparent evidence of systematic industry performance. Additionally, trading costs further explain any excess returns that timing industry investments with the examined cycles accrue. It appears that if investors do profit from cyclical trading strategies, they are trading on noise rather than systematic industry performance. Ultimately, the results of this thesis are not encouraging for those who seek to exploit apparent deviations from market efficiency. To that extent, industry performance appears transactionally efficient, despite an extensive literature that documents cyclical market performance. Nonetheless, the absence of systematic industry cycles leaves unanswered the puzzle of cycles documented in the general market. However, perhaps as Black (1986) suggests, such apparent deviations from market efficiency merely represent unexploitable noise, from which traders are unable to economically benefit. If so, one can conclude that markets are efficient, as traditional financial theory prescribes.

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