R^2 and Stock Price Informativeness: New Empirical Evidence

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CHAPTER ONE: INTRODUCTION

This chapter presents an introduction of the thesis. It contains an overview of the topic background and a discussion of research motivation, a theoretical review of R^2 interpretation debate, and a brief overview of the three essays presented. The thesis structure is presented in the last section.

1.1 Background and Motivation

R^2, also commonly referred to as stock price synchronicity, continues to be an active area of study in the finance and accounting literature. R^2 is the regression statistic derived from the common asset pricing model, while stock price synchronicity is estimated as a log-transformed R^2. A review of the literature yielded 32 published papers that focused on the topic of R^2 or stock price synchronicity in top-tier finance and accounting journals. At least 40 working papers that examined R^2 or stock price synchronicity and its associated effects were listed on the Social Science Research Network (SSRN). Despite wide exploration and application of R^2 or stock price synchronicity in the studies of corporate finance, corporate governance, investment, emerging markets, and other areas of finance, the interpretation of R^2 or stock price synchronicity is still unclear in terms of measuring price informativeness, according to the existing literature. One strand of literature interprets low R^2 stocks as having more informative stock prices due to greater amount of firm-specific information incorporation. While an opposite view proposes that low R^2 stocks have less informative stock prices due to prediction errors and price noisiness. In recent years, the popularity of using low R^2 or stock price synchronicity as a proxy of price informativeness and information efficiency has increased. As summarised in Table 1.1, among the 32 published journal articles, 26 articles are in favor of the information-based interpretation of R^2, while only 6 articles are in favor of the noisiness-based interpretation of R^2. Given the popularity of this topic and its wide application in the empirical studies, it is important to distinguish between the contradicting explanations of R^2 and to empirically investigate the question as to whether low R^2 is a proxy for price informativeness or noisiness. Studies on R^2 that are based on an incorrect interpretation could generate

Table 1.1 Published Journal Articles of R^2

Panel A Journal articles supporting the information-based interpretation

Published Journal	**Year**	**Article Title**
Journal of Financial Economics	2000	Morck, R., Yeung, B., & Yu, W. The information content of stock markets: Why do emerging markets have synchronous stock price movements?
Journal of Financial Economics	2000	Wurgler, J. Financial markets and the allocation of capital.
Journal of Accounting Research	2003	Durnev, A., Morck, R., Yeung, B., & Zarowin, P. Does greater firm-specific return variation mean more or less informed stock pricing?
Journal of Finance	2004	Durnev, A., Morck, R., & Yeung, B. Value-enhancing capital budgeting and firm-specific stock return variation.
The Accounting Review	2004	Piotroski, J. D. & Roulstone, D. T. The influence of analysts, institutional investors and insiders on the incorporation of market, industry and firm-specific information into stock prices.
Journal of Financial Economics	2006	Jin, L., & Myers, S. R^2 around the world: New theory and new tests.
Journal of Financial Economics	2006	Chan, K., & Hameed, A. Stock price synchronicity and analyst coverage in emerging markets.
The Review of Financial Studies	2007	Chen, Q., Goldstein, I., & Jiang, W. Price informativeness and investment sensitivity to stock price.
Journal of Finance	2007	Ferreira, M., & Laux, P. Corporate governance, idiosyncratic risk, and information flow.
Journal of Financial Economics	2008	Chun, H., Kim, J., & Morck, R., & Yeung, B. Creative destruction and firm-specific performance heterogeneity.
Journal of Financial Economics	2008	Fernandes, N., & Ferreira, M. Does international cross-listing improve the information environment.
Journal of Financial Economics	2009	Hutton, A.P., Marcus, A. J., & Tehranian, H. Opaque financial reports, R^2, and crash risk.

Panel A. (Continued)

Published Journal	**Year**	**Article Title**
Journal of Financial Economics	2009	Khanna, T., & Thomas, C. Synchronicity and firm interlocks in an emerging market.
Journal of Banking and Finance	2009	Brockman, P., & Yan, X. Block ownership and firm-specific information
Journal of Financial Economics	2010	Gul, F., & Kim, J., & Qiu, A. Ownership concentration, foreign shareholding, audit quality, and stock price synchronicity: Evidence from China.
Review of Accounting Studies	2011	Brown, N., & Kimbrough, M. Intangible investment and the importance of firm-specific factors in the determination of earnings
Journal of Financial Economics	2011	Ferreira, D., Ferreira, M. & Raposo, C. Board structure and price informativeness.
The Financial Review	2011	Stowe, J.D. & Xing, X. R^2: Does it matter for firm valuation?
The Accounting Review	2012	Crawford, S. S., & Roulstone, D. T., So, E. C. Analyst Initiations of Coverage and Stock Return Synchronicity.
Review of Accounting Studies	2012	Kim, J., & Shi. S. IFRS reporting, firm-specific information flows and institutional environment: International evidence.
Journal of Corporate Finance	2013	An, H., & Zhang, T. Stock price synchronicity, crash risk, and institutional investors.
Journal of Banking and Finance	2013	Sun, Q., Tong, W.H.S., & Zhang, X. How cross-listings from an emerging economy affect the host market?
Journal of Banking and Finance	2013	Jones, J. S., Lee, W. Y., & Yeager, T. J. Valuation and systemic risk consequences of bank opacity.
Journal of Banking and Finance	2014	Boubaker, S., Mansali, H., & Rjiba, H. Large controlling shareholders and stock price synchronicity.
Journal of Financial Economics	2015	Eun, C. S., Wang, L., & Xiao, S. C. Culture and R^2.
Journal of Financial and Quantitative Analysis	2015	Dong, Y., Li, Z., Lin, Y., & Ni, C. Does information processing cost affect firm-sepcific information acquisition? Evidence from XBRL adoption.

Panel B Journal articles supporting the noisiness-based interpretation

Published Journal	Year	Paper Title
Journal of Financial and Quantitative Analysis	2010	Dasgupta,S., Gan, J., & Gao, N. Transparency, Price Informativeness, and Stock Return Synchronicity: Theory and Evidence.
Journal of Accounting and Economics	2011	Rajgopal, S. & Venkatachalam. M. Financial reporting quality and idiosyncratic return volatility
Journal of Financial Markets	2013	Chan, K., Hameed, A., & Kang, W. Stock price synchronicity and liquidity.
Journal of Financial Economics	2014	Chan, K., & Chan, Y. Price informativeness and stock return synchronicity: Evidence from the pricing of seasoned equity offers.
Accounting Review	2014	Li, B., Rajgopal, S. and Venkatachalam, M. R^2 and idiosyncratic risk are not interchangeable
Quarterly Journal of Finance	2014	Kelly, P. Information efficiency and firm-specific return variation.

mistaken results, and the inferences drawn from the research findings could be misleading.

This thesis aims to answer the question of whether low R^2 indicates more or less informative stock price from three aspects: by focusing on the firm-specific information produced by stock analysts outside a company (essay one); by focusing on the firm-specific information conveyed by dividend announcements made by managers inside a company (essay two); and by investigating R^2 and its relation to bond pricing and bond structure in the bond market (essay three). Taken together, the three independent but related essays present a comprehensive analysis on R^2 and provide insightful empirical evidence to the implication of R^2. Consistent findings from three essays are documented to support the contention that low R^2 stocks are actually associated with less informative stock prices.

1.2 Debate on R^2 Interpretation

An important research question in finance literature is to what extent stock price movement is related to firm-specific information. In a seminal work, Roll (1988) investigates how effectively systematic factors could explain stock price movement. He does this by measuring and observing regression statistic R^2 values that are obtained from running single-factor and multiple-factor regression models. His underlying rationale is that R^2 should be close to 1 if the price movement can be largely and accurately estimated by the systematic factors. Surprisingly, he finds that when using monthly data, the average adjusted R^2 is only about 35%, and when using daily data, the average adjusted R^2 is about 20%, indicating that a large portion of stock price movement is unrelated to contemporaneous public news and systematic economic influences. Roll (1988) attributes these low R^2 statistics to the existence of private information and suggests that "the financial press misses a great deal of relevant information generated privately."

Extending Roll's (1988) work, Durnev, Morck, Yeung, and Zarowin (2003) empirically examine the importance of firm-specific information incorporation in explaining the low R^2 statistics from a common asset pricing model by relating firm-specific stock price variation to accounting measures of stock price informativeness. Specifically, firm-specific return variation is defined as the proportion of a firm's stock return variation left unexplained by market and industry returns, which is precisely equivalent to ($1-R^2$). They find that firm-specific return variation has a positive association with stock price informativeness measures, suggesting that a greater amount of firm-specific information is incorporated into stock prices of lower R^2 firms. These findings support the information-based explanation of low R^2 and suggest that R^2 is an inverse measure of stock price informativeness.

Subsequently, Durnev, Morck, and Yeung (2004) relate firm-specific return variation (i.e. $1-R^2$) to the corporate investment efficiency and document a cross-sectional positive relation between them. Their findings suggest that firm-specific return variation is a good gauge of how much firm-specific information being quickly and accurately incorporated into stock price, and capital investment decisions become more efficient when stock prices are more informative as indicated by higher firm-specific return variation (i.e. lower R^2).

In an international context, Morck, Yeung, and Yu (2000) further investigate Roll's (1988) findings by examining and comparing stock price co-movements across countries. Using R^2 as a direct measure of price synchronicity, they demonstrate that stock prices move in a less synchronized manner in high GDP countries compared to low GDP countries. To the extent that stock prices move together as a consequence of greater amounts of market-wide information being capitalized into stock prices, Morck, Yeung, and Yu (2000) attribute the low price synchronicity identified in high GDP countries to greater firm-specific information capitalization and higher level of firm-specific variation as a result of stronger property rights protection.

Building on these seminal works, a large body of finance and accounting literature has widely employed R^2 as an inverse measure of stock price informativeness. For example, more informative stocks are associated with increased information transparency (Jin & Myers, 2006), lower board independence (Ferreira, Ferreira, & Raposo, 2011), lower firm valuation (Stowe & Xing, 2010), fewer analyst forecasting activities (Piotroski & Roulstone, 2004; Chan & Hameed, 2006), and less separation between control and cash flow rights (Boubaker, Mansali, & Rjiba, 2014).

Despite Roll (1988) positing the importance of firm-specific information in explaining the low R^2 statistics obtained based on the common asset pricing models, he also acknowledges the existence of "else occasional frenzy unrelated to concrete information." Therefore, while the former line of research attributes lack of synchronicity to an environment where there is more firm-specific information, lower R^2 from a market-model regression implies greater firm-specific volatility, which a growing body of research attributes to noise and poor information quality. In early work, West (1988) develops a theoretical model where prices converge towards fundamental value when there is more information flow. As a result, new information has less marginal effect on price, and subsequently, there is less firm-specific volatility (i.e., higher R^2). West (1988) provides empirical support for this view by showing that when there is more information about future dividends impounded into stock price, firm-specific volatility is lower.

In addition, Kelly (2014) adds to this premise by showing that firms with low R^2 are associated with attributes that are consistent with poor information environment.

Typically, low R^2 firms are smaller, younger, and have fewer institutional holdings, less analyst coverage, higher bid-ask spread, greater short-sell constraints, and lower trading frequency. Hou, Peng, and Xiong (2013) further explore the effectiveness of using R^2 as a measurement of market efficiency and find that stock price fluctuation driven by investor sentiment related noise is a key driver of lower R^2. Low R^2 is found to be correlated with stronger positive short-term (and greater negative long-term) return autocorrelation, indicating low R^2 is an indicator of greater price inefficiency.

By linking R^2 to post-earnings-announcement drift, V/P (fundamental value over stock price), accruals, and net operating assets anomalies, Teoh, Yang, and Zhang (2007) show that R^2 is inversely related to all these accounting-based anomalies. Their findings support the view that low R^2 reflects greater noisiness and less information about future fundamentals. Moreover, Rajgopal and Venkatachalam (2011) provide additional evidence by investigating if idiosyncratic return volatility is associated with financial reporting quality as measured by accrual-based measures. Their findings exhibit that lower earnings quality is linked to higher idiosyncratic volatility, implying lower R^2 actually represents deteriorating disclosure quality and a poor information environment.

In addition, Chan and Chan (2014) further explore what stock price synchronicity measures in terms of stock price informativeness by linking synchronicity to the pricing of seasoned equity offers (SEO). They document a significant negative relation between synchronicity and SEO discounts, and such negative relation is found to be the strongest without analyst coverage and dissipates with the increase of analyst coverage. To the extent that SEO discounts are commonly used as proxy for information asymmetry between inside managers (with possession of private information) and uninformed outside investors, their findings confirm the role of stock price synchronicity as an inverse measurement of information asymmetry, rather than as an inverse measurement of price informativeness.

Taking an alternative tack, Dasgupta, Gan, and Gao (2010) hypothesize that investors of more transparent firms learn about events early, resulting in lower prior R^2. When the event occurs, there is little additional priced information resulting in higher R^2. They show that older firms have higher R^2, supporting the notion that the information environment improves as firms are exposed to the market longer and value-impacting events become more anticipated. They provide further empirical support by examining R^2 surrounding seasoned equity offerings and ADR listings. Firm-specific return variation changes little around both announcements, supporting the view that key information is distributed prior to the event, leading to lower pre-event R^2. Consequently, R^2 is higher at the time of the event, providing evidence for the intuition that R^2 varies over time according to the degree of firm transparency and the nature of the event.

1.3 Overview of the Three Essays

1.3.1 Essay One: R^2 and market response to analyst recommendation revisions

Essay one examines how the informational impact of analyst recommendation revisions on stock price, stock trading volume, and return volatility varies with stock R^2 levels. Stock analysts are independent information intermediaries outside the company who collect, analyse information that is specific to a company, and disseminate the information through issuing regular stock recommendations. In focusing on the analyst recommendations issued between 1993 and 2012 in the U.S. stock market, this essay finds that stock prices react to upgrade recommendation revisions positively and react to downgrade recommendation revisions negatively. More importantly, the price reaction is prominently stronger among stocks with lower R^2. This primary finding is consistent with Dasgupta, Gan, and Gao (2010) and provides initial evidence to the notion that low R^2 stocks are associated with less informative stock prices. According to Dasgupta, Gan, and Gao (2010), stock return R^2 reflects how much firm-specific information has been captured previously. As the information is less likely to have been previously anticipated and incorporated into the prices of lower R^2 stocks, lower R^2 stocks will demonstrate stronger price reaction when the information event actually occurs.

An examination of how the reaction of stock trading volume and return volatility changes according to stock R^2 levels provides additional evidence. Consistent with the price reaction, lower R^2 stocks exhibit stronger volume and volatility reaction compared to higher R^2 stocks. To the extent that abnormal volume and volatility are metrics for information-based trading, results of this examination suggest that lower R^2 stocks experience greater improvement in information flow upon the arrival of new information conveyed by the recommendation revisions.

Further demonstration of this point is found in presenting findings of a test of analyst impact on information asymmetry improvement conditional on different R^2 levels.

Lower R^2 stocks again experience greater reduction in information asymmetry, suggesting that the information content of analyst recommendations improves the stock information environment, especially for lower R^2 stocks.

Overall, essay one shows that the new firm-specific information contributed by analyst recommendation revisions results in a greater reaction in stock price, greater improvement in informed trading, and a greater improvement in information asymmetry among lower R^2 stocks. All these results remain robust and consistent in multivariate regression tests when using the stock price synchronicity as the independent variable and with the inclusion of other firm-level control variables.

Essay one contributes to the existing literature in two major ways: first, it contributes to the ongoing debate on R^2 interpretation by providing empirical evidence that lower R^2 stocks are actually associated with a noisier and less informative information environment. Secondly, essay one contributes to the debate on the nature of the information provided by analyst recommendations. By relating the information content of analyst recommendations to the measure of firm-specific information, essay one supports the view that analysts serve as an information mechanism and contribute firm-specific information, rather than market-wide information, to the public.

1.3.2 Essay Two: R^2 and the corporate signaling effect

Essay two explores how dividend signaling effect varies with stock R^2 levels. Dividend change announcements are informational events that convey signals to the stock market regarding firms' future prospects. By relating R^2 to the firm-specific information conveyed by dividend announcements, essay two provides further empirical evidence to the interpretation debate on R^2. The analysis in essay two comprises two parts. The first part, or preliminary test, focuses on the dividend announcements and the immediate stock price reaction. Based on the dividend announcements for U.S. stocks during the 1950–2012 period, both dividend increase announcements and decrease announcements indeed have a stronger signaling effect on stock prices among lower R^2 stocks. This finding is consistent with the notion that lower R^2 stocks are associated with a poorer information environment, and the firm-specific information conveyed by the dividend announcements is less likely to have been previously anticipated and incorporated into the prices of lower R^2 stocks (Dasgupta, Gan, & Gao, 2010).

The second part, the extension test, further examines if the predicting ability of current dividend changes on a firm's earnings prospects changes with stock R^2 levels. To the extent that lower R^2 stocks are less informative and experience stronger price reaction to changes in dividend payout policy, inside managers should be more cautious in sending such a costly signal and require more confidence around future earnings before doing so. The results of this test lend partial support to this hypothesis. Current dividend decrease changes are found to provide reliable signals about firms' future prospects and the positive correlation between current dividend decreases and future earnings changes is indeed stronger for stocks with lower stock price synchronicity. This finding sheds further light on the noisiness-based interpretation of low R^2 from two aspects: first, lower R^2 stocks have a poorer information environment in which their earnings prospects are better predicted by current dividend decrease changes, consistent with the view that dividend changes do convey information about future earnings, but only in conditions of market imperfection or uncertainty (Miller & Modigliani; 1961). Secondly, lower R^2 stocks have a poorer information environment, which leads to greater stock price changes in response to the dividend announcements. As suggested by the learning hypothesis (Chen, Goldstein, & Jiang, 2007; Foucault & Fresard, 2014), the greater price reaction enables inside managers to learn more information and use it in shaping their investment decisions, which ultimately leads to a greater impact on the firm's future profitability.

Essay two makes contributions to current literature from two aspects: first, it documents empirical evidence consistent with essay one, and it adds to the interpretation debate of R^2. Secondly, by directly relating the dividend signaling effect to the relative importance of firm-specific information measured by R^2, essay two confirms the view that the presence of dividend announcements conveys reliable signals to investors regarding firms' future prospects. These findings are contrary to some recent studies that posit the dividend signaling effect is disappearing (DeAngelo, DeAngelo, & Skinner, 1996; Benartzi, Michaely, & Thaler, 1997; and Grullon, Michaely, Benartzi, & Thaler, 2005).

1.3.3 Essay Three: Does R^2 mean more or less informative stock price? Evidence from bond market

Essay one and essay two provide empirical evidence to the interpretation debate on R^2 by directly relating it to informational events, while essay three aims to provide additional evidence from the perspective of the corporate bond market. Specifically, it aims to investigate whether a firm's stock return R^2 has a role in explaining corporate bond pricing and bond structure. If lower R^2 indicates greater price noisiness and a less efficient information environment, firms with lower stock return R^2 should be associated with higher risk, resulting in lower credit ratings and greater yield spreads. Using stock price synchronicity as a proxy for the information environment surrounding a firm, essay three finds a negative relation between stock price synchronicity and yield spread and a positive relation between stock price synchronicity and credit ratings for both corporate at-issue (i.e. newly issued) bonds and seasoned bonds. These results suggest that stock price synchronicity is a priced risk factor, for which bond investors demand a higher premium as compensation.

In addition, a firm's information environment can explain the presence of callable features for newly issued bonds. Given that bonds issued with callable provisions offer the issuers call-back rights and enable them to refinance at a later time, firms under great information asymmetry send positive signals to bond investors about their future prospects through callable bonds issuance (Banko & Zhou, 2011). Consistent with this view, essay three finds that stock price synchronicity has a negative relation with the probability of callable bond issuance for at-issue bonds; this supports the notion that lower synchronicity firms (or lower R^2 firms) are associated with a less efficient information environment.

To further confirm this view, the information asymmetry explanation of synchronicity is directly related to the incidence of corporate bonds receiving split credit ratings from the two major rating agencies: S&P and Moody's. The negative relation between synchronicity and levels of rating splits confirms the view that firms with lower synchronicity have poor information environments, which impedes rating agencies in evaluating the credit quality of these firms, consequently causing greater deviation in rating assessments.

Overall, essay three provides additional empirical evidence that is contrary to the conventional information-based interpretation of R^2, and it further supports the new proposition that low R^2 actually represents less informative stock price and greater information asymmetry.

1.4 Structure of the Thesis

This thesis is structured as follows: In chapter two, essay one is presented, which investigates R^2 in the context of analyst recommendation revisions. Essay two and essay three are presented in chapters three and four, respectively. Finally, chapter five concludes the thesis by summarising the major findings of each essay and discussing the implications of their results.

CHAPTER TWO: ESSAY ONE

R^2 AND THE MARKET RESPONSE TO ANALYST RECOMMENDATION REVISIONS

This chapter presents essay one, which studies R^2 (or stock price synchronicity) and its effects on market response to analyst recommendation revisions. Section 2.1 presents the introduction of this study and highlights the research motivation and contribution. Section 2.2 reviews the related literature of analyst recommendation revisions. Section 2.3 presents hypotheses development. Section 2.4 provides details of data collection, sample filtering process, and research methodology. Section 2.5 discusses empirical results and findings. Section 2.6 outlines the conclusions of this study.

Abstract

This paper examines how R^2 impacts the information diffusion process associated with analyst recommendation revisions. It shows that the market response to analyst recommendation revisions varies according to R^2: Stocks with lower R^2 experience stronger price, volume and volatility reactions in response to revisions of analyst recommendations, and the magnitudes of these measures decrease monotonically with R^2 levels. Information asymmetry, as measured by bid-ask spread, likewise decreases more for low R^2 stocks. In a multivariate context, these results are robust to the inclusion of additional explanatory variables including firm size. These results support the view that R^2 is inversely related to the noisiness of the information environment.

2.1 Introduction

R^2 (or stock price synchronicity) and its association with price informativeness continues to be an active area of debate. In seminal work, Morck, Yeung, and Yu (2000) show that stocks have higher synchronicity in developing markets with weak institutional and regulatory frameworks, leading to a greater likelihood that trades are less likely to be information-based; as a consequence, high R^2 stocks are less informative, and low R^2 stocks are more informative. In contrast, other researchers (e.g., Kelly, 2014; West, 1988) argue that low R^2 is symptomatic of less informativeness due to pricing errors and other forms of noise trading that contribute to lower price synchronicity. In particular, Kelly (2014) finds that low R^2 firms are associated with attributes consistent with a poor information environment: For example, firms with lower R^2 tend to be smaller, younger, and have lower institutional ownership, among other characteristics. Dasgupta, Gan, and Gao (2010) take an alternative tack by arguing that R^2 should be viewed intertemporally according to the nature of the event; for events that feature "lumpy" information dissemination, such as seasoned equity offerings and ADR listings, R^2 is lower prior to the event, as information is absorbed and increases around and subsequently to the event as additional public information diminishes. In other words, current period R^2 may reflect the relative amount of previously priced information and not necessarily how much information is contemporaneously priced.

This essay contributes to the literature by investigating the association between changes in market-based measures of information-based trading in response to new information conditioned on prior stock price synchronicity. In contrast to Dasgupta, Gan, and Gao (2010), focusing on infrequent announcements that are preceded by an information dissemination process, this essay examines analyst recommendation revisions as information events that convey unanticipated information to the market. In contrast to existing work, event study methodology is used as the empirical approach in this essay, which allows to examine if abnormal changes in the information environment in response to the exogenous arrival of new information are causally associated with R^2. To ensure that the R^2 estimates are not commingled with the contemporaneous market response to the event, and to provide comparability with the intertemporal findings of Dasgupta, Gan, and Gao (2010), this essay estimates R^2 over the year preceding the event date. The analysis of U.S. stocks during the 1993 to 2012 period illustrates that abnormal stock returns associated with analyst recommendation upgrade and downgrade announcements are significantly greater for stocks with lower prior levels of R^2. It shows that, in a multivariate setting, the greater price response to analyst recommendation revisions among lower R^2 stocks is not merely a manifestation of the firm size effect (e.g., Womack, 1996; Barber, Lehavy, McNichols, & Trueman, 2001; Jegadeesh & Kim, 2006). Furthermore, this essay demonstrates that low R^2 stocks exhibit relatively greater improvements in informed trading and measures associated with information flow and reduced information asymmetry compared to high R^2 stocks; abnormal trading volume and return volatility increase, while abnormal bid-ask spread diminishes in response to recommendation revisions. Overall, the findings show that new information results in greater price reactions and improvements in information asymmetry among firms with lower prior price synchronicity, hence providing support for the interpretation that low R^2 proxies for a noisier, less informative information environment.

In addition, this essay contributes to the debate on the nature of information provided by analyst recommendations, i.e. whether analysts provide firm-specific or market-wide information. On one hand, Mikhail, Walther, and Willis (1997), Park and Stice (2000), and Liu (2011) suggest that information produced by analysts is firm-specific rather than market-wide.[1] On the other hand, Piotroski and Roulstone (2004), Chan and Hameed (2006), and Cheng, Gul, and Sinidhi (2012) provide empirical evidence that security analysts produce more industry-level and market-level information to investors relative to firm-specific information. By demonstrating that analyst recommendation revisions are directly associated with improvements of the firm's information environment, this essay provides additional evidence corroborating the view that analyst recommendations serve as a mechanism to disperse firm-specific information to the public.

The remainder of this essay is organised as follows: Section 2.2 reviews related literature, and Section 2.3 develops the hypotheses. Section 2.4 describes data and methodology, and Section 2.5 presents empirical results. Section 2.6 presents the conclusions for this essay.

2.2 Literature Review: Analyst Recommendations and New Information

Analyst recommendations convey important information to investors, as is evidenced by price effects. Womack (1996) identifies analysts' market timing and stock picking abilities by investigating the stock price reactions to recommendations and post-

[1] Market-wide information refers to macroeconomic information, such as unemployment statistics, inflation, etc.

recommendation price drift. Womack documents positive price reactions to buy recommendations and negative price reactions to sell recommendations. For buy recommendations, subsequent drift persists for one month, while for sell recommendations, it persists for six months. The reactions to buy and sell recommendations differ in magnitude: stock price reactions are greater in magnitude to sell recommendations than to buy recommendations, and they are significantly larger for small firms than for large firms. The value of stock recommendations is further investigated in Barber, Lehavy, McNichols, and Trueman (2001). They find that an investment strategy of buying stocks with the most favourable consensus recommendations, and selling stocks with the least favourable consensus recommendations generates abnormal gross returns that are greater than 4% annually. In line with Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001) also show that small firms experience greater price effects than large firms.

Instead of studying the long-term stock price response, Green (2006) focuses on the short-term profitability associated with early access to analyst recommendations. After controlling for transaction cost, Green concludes that investors who have early access to recommendation changes could earn a two-day return of 1.02% following upgrade recommendations and 1.5% following downgrade recommendations.

Moreover, Jegadeesh, Kim, Krische, and Lee (2004) focus on studying the characteristics of analyst recommended stocks. They find that analysts prefer to recommend glamour stocks, which have positive momentum, high growth, high volume, and are relatively expensive. Consensus recommendations add value to investors only among stocks with favourable characteristics, such as value stocks and positive momentum stocks, and the value added appears to be greater for small firms than for large firms.

Jegadeesh and Kim (2006) analyse the informational role of analyst recommendations in an international (i.e., G7) context. Stock prices of all countries, except for Italy, are found to react significantly in response to recommendation revisions. Among these countries, analyst recommendation revisions in the U.S. market are associated with the strongest abnormal performance in immediate price reaction and in post-revision price drift. They attribute this to analysts' superior skills and abilities in selecting mispriced stocks in the US market. Jegadeesh and Kim (2006) also document that the price impact appears to be the most pronounced for small firms and growth firms.

Analyst recommendations also affect the information environment, as is evidenced by stock trading volume, return volatility, and other measures. Liu, Smith, and Syed (1990), Womack (1996), and Green (2006) document significant volume reactions in response to analyst recommendations. Jegadeesh and Kim (2006) suggest that investors' trading behaviour is influenced by analysts, and the magnitude of changes depends on the value of their recommendations. Among G7 countries, they find analyst recommendations have the highest value in the US and in Japan, and investors in these two countries trade more intensely after the recommendations than in other countries.

The information content conveyed by analyst recommendations has been well documented in previous literature; nevertheless, whether analysts contribute firm-specific or industry/market-wide information to the stock market is still a controversial question. Literature such as that contributed by Mikhail, Walther, and Willis (1997), Park and Stice (2000), and Liu (2011) suggests that information produced by analysts is mainly at firm-level, while Piotroski and Roulstone (2004), Chan and Hameed (2006), and Cheng, Gul, and Sinidhi (2012) provide contradicting empirical evidence supporting the industry- and market-wide information argument.

Crawford, Roulstone, and So (2012) extend this debate by relating stock price synchronicity to the initiation of analyst coverage. Using higher price synchronicity as a measurement of a greater amount of market-wide information incorporation, and lower price synchronicity as a measurement of a greater amount of firm-specific information incorporation, they posit that analysts initiate their coverage by providing low-cost market- and industry-level information to enable themselves to follow more stocks; subsequently, the analysts' coverage conveys firm-level information. This inclusion of firm-level information is a strategy analysts use to distinguish themselves from each other.

Potential biases existing among stock analysts may result in imbalances between buy and sell recommendations, which in turn affect their relative informativeness. For example, Womack (1996) shows that buy recommendations are 7 times more likely than sell recommendations; on one hand, analysts have a responsibility to make accurate investment recommendations to investors. On the other hand, analysts have strong economic incentives to maintain positive recommendations on stocks that have been underwritten by their brokerage houses in order for analysts to maintain business relationships and to boost their brokerage house revenues (Michaely & Womack, 1999). Brokerage houses also reward optimistic analysts who promote stocks (Hong and Kubik, 2003). As a result, analysts are reluctant to issue unfavourable comments or recommendations; if stocks are expected to perform poorly, analysts typically drop them from their coverage (McNichols & O'Brien, 1997). Thus, buy recommendations may be less informative than sell recommendations, as the former are more likely to be motivated by reasons other than information.

2.3 Hypotheses Development

This essay analyses stock price reactions and changes in the information environment surrounding analyst recommendation changes. Analysts gather, process, and disseminate information that is specific to firms. The value of analyst recommendations could stem from two potential sources: First, analysts have superior skills, comparative advantages, and innate ability in analysing certain stocks based on public information (Cooper, Day, & Lewis, 2001). Second, analysts have the ability to collect and process private information that is not readily available in the market (Ivkovic′ & Jegadeesh, 2004). The extent to which analyst recommendations increase the information content of prices is conditional on the pre-existing quality of the information environment: Kelly (2014) posits that low R^2 is a symptom of underlying firm characteristics associated with greater information asymmetry. Therefore, it is hypothesized that low R^2 firms should be associated with the greatest improvement in price informativeness, as reflected by abnormal price reactions and metrics associated with information-based trading. To the extent that R^2 is directly related to transparency, *H1: Analyst recommendation revisions have a greater price effect on lower prior-R^2 firms.*

Cready and Hurtt (2002) find that abnormal volume and return volatility are superior metrics for capturing investors' responses to information events. Accordingly, to the extent that price reactions are conditional on prior R^2, the information incorporation process should also result in differing changes in metrics associated with the information environment in year *t* conditional on prior R^2. Specifically, this essay focuses on abnormal trading volume and return volatility surrounding the announcements, leading to the second and third hypotheses. To the extent that R^2 is directly related to transparency,

H2: Analyst recommendation revisions have a greater abnormal volume effect on lower prior-R^2 firms.

H3: Analyst recommendation revisions have a greater abnormal return volatility effect on lower prior-R^2 firms.

Finally, bid-ask spreads are employed to examine if recommendation revisions impact the balance of informed versus uninformed market participants by increasing the amount of *ex ante* unanticipated public information. Following hypotheses 1–3, to the extent that R^2 is directly related to transparency,

H4: Analyst recommendation revisions have a greater abnormal bid-ask spread effect on lower prior-R^2 firms.

2.4 Data and Methodology

2.4.1 Analyst recommendations and R^2

The sample of analyst recommendations is based on the 1993–2012 period.[2] Recommendations are collected from the International Brokers' Estimate System (I/B/E/S) and classified into upgrades and downgrades. First, 100,462 recommendation events are collected and these recommendations are scored between 1 and 5, where 1 refers to strong buy recommendation, 2 refers to buy recommendation, 3 refers to hold recommendation, 4 refers to sell recommendation and 5 refers to strong sell recommendation. Analyst recommendation for a particular stock is compared with its preceding recommendation. If the recommendation issued is more favourable (i.e., has a lower score) than its preceding recommendation, then it is classified as an upgrade; if the recommendation issued is less favourable (i.e., has a higher score) than its preceding recommendation, then it is classified as a downgrade. Returns and other price-related data are collected from the Center for Research in Security Prices (CRSP). Other accounting data are collected from Datastream and Compustat. To minimise biases related to outliers, key variables are winsorized at the 1% tails of their distributions. The sample is selected according to the following criteria:

1. Each sample firm must have price, accounting, and recommendation information simultaneously available on all databases (Womack, 1996; Jegadeesh & Kim, 2006).
2. Stocks listed on NYSE are restricted to ordinary shares with their prices over $1 before the recommendation day (Jegadeesh & Kim, 2006).
3. Only new recommendations are included; reiterations of existing recommendations are

[2] Analyst recommendation data begins in I/B/E/S in 1993.

excluded (Jegadeesh & Kim, 2006).

4. Multiple same-direction recommendations on same day for same stock are considered as a single recommendation. Opposite-direction recommendations are excluded to avoid confounding results.
5. Stocks are excluded if other firm-specific events, e.g., earning announcements, occur within the event window period.

Table 2.1 provides a general description of the sample events. As illustrated in Table 2.1 Panel A, analysts are more likely to issue either favourable or neutral recommendations. On average, strong buy recommendations are issued about 13 times more often than strong sell recommendations. In contrast to the findings of Womack (1996), who documented a ratio of 7:1 of strong buy to strong sell recommendations over the period from 1989 to 1992, this gap nearly doubled for the more recent period from 1993 to 2012. This indicates that analysts' upward bias has significantly increased since 1992. Panel A also demonstrates that the frequency of issuing unfavourable recommendations is considerably greater for the 2003–2012 period compared with the 1993–2002 period. This is consistent with the findings of prior literature on the effects of changes in the regulatory environment: The imbalance between positive and negative recommendations has declined sharply since 2003 when the Regulation Fair Disclosure and Global Analyst Research Settlement became effective. Specifically, Hovakimian and Saenyasiri (2010) and Kadan, Madureira, Wang, and Zach (2009) find that analyst forecast bias and the prevalence of issuing optimistic recommendations dropped significantly following commencement of the regulations.

R^2 is estimated for each sample stock on year t-1 basis. For example, if an analyst recommendation is issued in 1993, the stock's R^2 is calculated using daily returns over year 1992. Using a predetermined R^2 to match the testing period of analyst recommendation reduces the likelihood of endogeneity between the price reaction and contemporaneous price synchronicity (Durnev, Morck, & Yeung, 2004). In this essay, R^2 is estimated using a four-factor model, which allows more risk factors to be included in addition to market risk[3]. Specifically, the four-factor model is defined as:

$$R_{jt} - R_{ft} = \alpha_j + \beta_j (R_{mt} - R_{ft}) + \delta_j SMB_t + h_j HML_t + m_j PMOM_t + \varepsilon_{jt} \qquad (1)$$

where R_{jt} is the daily return of stock j and R_{jt} is the daily risk-free T-Bill return; R_{mt} is the return on the CRSP daily value-weighted index; SMB_t is the difference between returns of value-weighted portfolio of small stocks and large stocks on day t; HML_t is the difference between returns of a value-weighted portfolio of high book-to-market stocks and low book-to-market stocks on day t, and $PMOM_t$ is the difference of average returns between a high prior return portfolio and a low prior return portfolio on day t.[4] Sample stocks are then sorted according to their R^2 levels within each year and divided into three groups: low R^2, representing stocks with R^2 at or below the first R^2 tercile, and high R^2, representing stocks with R^2 at or above the third R^2 tercile.

[3] To ensure results are not driven by the way R^2 is estimated, sample stock's return R^2 is also estimated using market-industry model based on weekly returns (see e.g., Durnev, Morck, & Yeung, 2004; Chen, Goldstein & Jiang, 2007; Stowe & Xing, 2011). The results are checked and found to be qualitatively similar to those presented here.

[4] *SMB*, *HML*, and *PMOM* are obtained from Kenneth French's data library, at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2.1 Sample Description

Panel A describes the distribution of analyst recommendations that are originally collected from IBES. Analyst recommendations including strong buy, buy, hold, sell and strong sell recommendations are summarised in Columns 2-6. Column 7 shows the total number of recommendations and Column 8 presents the ratio of strong buys to strong sells. The last column provides the ratio of favourable- to unfavourable recommendations. Panel B reports the final sample distribution across three R^2 groups.

Panel A: Frequency of Analyst Recommendations by Time Period

Recommendation Type								
Years	Strong Buy	Buy	Hold	Sell	Strong Sell	Total	Strong Buy vs. Strong Sell	Favourable vs. Unfavourable
1993-1997	4,794	5,295	6,636	307	283	17,315	16.9	17.1
1998-2002	6,761	8,689	9,153	861	219	25,683	30.9	14.3
2003-2007	5,988	7,349	14,605	1,813	768	30,523	7.8	5.2
2008-2012	5,643	6,701	12,510	1,629	458	26,941	12.3	5.9
Total	23,186	28,034	42,904	4,610	1,728	100,462	13.4	8.1

Panel B: Frequency of Analyst Recommendation Revisions by R^2

Years	Upgrades	Downgrades	Total
1993-1997	3,746	3,710	7,456
1998-2002	5,480	5,841	11,321
2003-2007	7,332	7,275	14,607
2008-2012	7,125	7,112	14,237
Low R^2	7,910	7,993	15,903
Medium R^2	7,842	7,922	15,764
High R^2	7,931	8,023	15,954
Total	23,683	23,938	47,621

Table 2.1 Panel B presents the distribution of upgrades and downgrades for every five years and across the three R^2 subsets. The final sample of recommendations is reduced to 47,621 with non-missing values of R^2. Overall, there are 23,683 upgrades and 23,938 downgrades during the sample period. Unlike the five groups of recommendations as reported in Panel A, upgrade and downgrade revisions capture changes of analyst opinion on a particular sample stock and are therefore more likely to convey new information to the market. Numbers of observations for each low R^2, medium R^2, and high R^2 subset used in the primary event study analyses are also reported in Panel B. The tercile grouping method on R^2 generates a relatively equivalent number of observations for each group, therefore ensuring the reliability of results from the comparison.

2.4.2 Empirical Methodology

2.4.2.1 Abnormal returns

A single-index market model is used in the event study methodology to examine market responses to analyst recommendations. As described by Brown and Warner (1980), the market model is a simple but well-specified methodology that is relatively powerful under a wide variety of conditions. This methodology has been widely used to evaluate stock reactions in response to analyst recommendations (see for example, Liu, Smith, & Syed, 1990; Stickel, 1995; Barber, Lehavy, McNichols, & Trueman, 2001; Jegadeesh, Kim, Krische, & Lee, 2004; Jegadeesh & Kim, 2006).

Consistent with previous literature, R_{jt} is calculated as:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt} \tag{2}$$

where R_{jt} is the return of stock *j* on day *t*, R_{mt} is the return of the CRSP value-weighted market index on day *t*, and α_j, β_j are estimated parameters. Differently from Brown and Warner (1980, 1985) and Liu et al. (1990), a value-weighted market index, rather than an equal-weighted market index, is used to better capture the economic significance of each index stock. The market model parameters are estimated over the (-131, -31) time period relative to the announcement day. The abnormal return of stock *j* is as follows:

$$AR_{jt} = R_{jt} - (\alpha_j + \beta_j R_{mt}) \tag{3}$$

A standardized cross-sectional test (Boehmer, Musumeci & Poulsen, 1991) is used to test the null hypothesis that the event period abnormal return is zero. The cross-sectional test adjusts for event-induced changes in variance around the event date.

2.4.2.2 Abnormal trading volume

When testing market responses to information disclosure or public events, prior studies focus not only on the abnormal return, but also on the reaction in trading volume around the event as an indication of information flow. Beaver (1968) tests if the value of earning announcements is reflected in stock trading volume and return volatility. Berry and Howe (1994) also document a positive relation between public information arrival and trading volume. Trading volume changes directly mirror investors' trading decisions in responses to improvement in the information environment. As Cready and Hurtt (2002) conclude, the volume-based metric is more likely to detect the presence of investors' responses than return-based metrics, and therefore is a more powerful measure of the impact of public disclosure than the return-based metric.

To estimate abnormal trading volumes around analyst recommendations, this essay follows Beaver (1968), Morse (1981) and Palmon, Sun and Tang (1994) who define market-model abnormal volume as:

$$AV_{jt} = V_{jt} - (\alpha_j + \beta_j V_{mt}) \tag{4}$$

where V_{jt} is the number of shares of firm *j* traded on day *t* divided by the number of shares outstanding, and V_{mt} is the aggregate number of shares traded on day *t* divided by the total shares outstanding on day *t*. AV_{jt} is (actual - predicted) volume, where predicted volume is based on the parameters α_j and β_j estimated over the (-131,-31) period relative to the announcement date. As Campbell and Wasley (1996) describe, the non-parametric rank test is more powerful in detecting abnormal trading volume than the parametric test. Therefore, the rank test (Corrado, 1989) is used to gauge the statistical significance of abnormal volume over each event day and window.

2.4.2.3 Abnormal return volatility

Along with abnormal volume, abnormal return volatility has also been employed as an indicator of increased information flow. To examine the impact of analyst recommendations as reflected by stock return volatilities, this essay follows Beaver (1968), Landsman and Maydew (2002), DeFond, Hung, and Trezevant (2007), and Landsman, Maydew, and Thornock (2012) by defining abnormal return volatility as:

$$AVAR_{jt} = \overline{AR_{jt}^2} / \sigma_j^2 \qquad (5)$$

where $AR_{jt} = R_{jt} - (\alpha_j + \beta_j R_{mt})$ as defined by Equation 3. Abnormal return volatility measures the stock return variance over the event window period compared to the stock return variance over the estimation period. The denominator is the variance of stock *j*'s market model residuals calculated over the (-131,-31) estimation period. If abnormal volatility is between 0 and 1, the stock is considered to have smaller than normal volatility. If abnormal volatility is greater than 1, the stock is considered to have greater than normal volatility. One-tailed *t*-statistics are calculated to test the null hypothesis that abnormal volatility is smaller than or equal to 1.

2.5 Empirical Results

2.5.1 Transparency and information asymmetry characteristics across R^2 subsets

The first question addressed is preliminary: Is there a more noisy or less noisy information environment for firms ranked according to their prior R^2 levels? Clarke and Shastri (2000) suggest that proxies for transparency and information asymmetry generally fall into categories based on market microstructure, analyst forecasts, and firm-level measures that are reflective of growth opportunities; while each category has merits and drawbacks, there is no single best measure. Accordingly, multiple proxies are employed and compared between low R^2 and high R^2 stocks. Results are presented in Table 2.2.

Table 2.2 Characteristics of Subsets Classified by R^2

Table 2.2 reports means and medians for various measures classified by market microstructure (Panel A), analyst based measures (Panel B), and other firm-level characteristics (Panel C) for terciles sorted by R^2. The mean (median) estimate of each measure among each R^2 subset is reported in Table 2.2, columns 2-4. The difference between low R^2 subset and high R^2 subsets is reported in Column 5. The *p*-values for the difference in means between low R^2 and high R^2 subsets are adjusted for clustering at the firm level, and differences in medians are assessed using the Wilcoxon test. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Low R^2	Medium R^2	High R^2	Low - High	*P*- value for Difference in Mean (Median)
Panel A: Microstructure-based measures					
Bid-Ask Spread	0.009	0.007	0.005	0.004***	<0.000
	(0.003)	(0.002)	(0.002)	(0.001)***	(<0.000)
Trading Volume	7.572	8.178	8.017	-0.444*	0.076
	(5.664)	(5.989)	(5.886)	(-0.222)***	(<0.000)
Return Volatility	0.025	0.024	0.024	0.001***	<0.000
	(0.022)	(0.021)	(0.020)	(0.002)***	(<0.000)
Panel B: Analyst-based measures					
Number of Analysts	8.849	10.303	12.245	-3.396***	<0.000
	(7)	(9)	(11)	(-4)***	(<0.000)
Analyst Forecast Dispersion	0.0034	0.0027	0.0022	0.0012***	<0.000
	(0.0011)	(0.0009)	(0.0007)	(0.0004)***	(<0.000)
Analyst Forecast Accuracy	-0.0073	-0.0056	-0.0054	-0.0020***	0.001
	(-0.0015)	(-0.0012)	(-0.0010)	(-0.0005)***	(<0.000)
Panel C: Firm level measures					
Total Assets ($MM)	5,889	9,818	32,414	-26,520***	<0.000
	(1,487)	(2,477)	(4,834)	(-3,347)***	(<0.000)
Market-book Ratio	1.752	1.758	1.741	0.011***	<0.000
	(1.428)	(1.407)	(1.374)	(0.054)	(0.234)
Market Competition	22.322	29.266	55.062	-32.734***	<0.000
	(2.951)	(4.892)	(9.289)	(-6.338)***	(<0.000)

Table 2.2 compares characteristics for low vs. high R^2 stocks after reducing the primary recommendation-level dataset to one firm-level observation per year. Table 2.2 Panel A provides comparison of microstructure-based measures of noise and asymmetry. Consistent with Leuz and Verrecchia (2000), these measures include *Bid-Ask Spread*, *Trading Volume*, and *Return Volatility*. Following the methodology of Chung and Zhang (2014), a daily *Bid-Ask Spread* measure is calculated as $(Ask_{i,t} - Bid_{i,t})/M_{i,t,}$ where $Ask_{i,t}$ and $Bid_{i,t}$ are the daily closing stock ask and bid prices for firm *i* on day *t,* and $M_{i,t}$ is the mean of the corresponding ask and bid prices obtained from the CRSP database. A yearly average *Bid-Ask Spread* is calculated as the mean of the daily *Bid-Ask Spread* measure over the event year. *Trading Volume* is defined as average daily shares traded scaled by shares outstanding over the event year, and *Return Volatility* is the standard deviation of daily returns measured over the event year. Table 2.2 Panel A demonstrates that low prior-R^2 stocks exhibit characteristics associated with a relatively noisier information environment; they have the highest average bid-ask spread, the lowest average trading volume, and the highest return volatility of the three subsets. As reported, the difference in means between low R^2 and high R^2 subsets is significant for all three measures, suggesting that low R^2 firms have the noisiest information environments according to the microstructure-based measures.[5]

Table 2.2 Panel B provides further evidence, and effects, of the paucity in the supply of information for low R^2 stocks. The analysis examines the number of analysts posting forecasts (*Analyst Coverage*), standard deviation of earning forecasts (*Analyst*

[5] The test statistics for the differences in means in Table 2.2 are based on the SAS procedure SURVEYREG and are clustered at the firm level.

Forecast Dispersion), and analyst forecast accuracy (*Analyst Forecast Accuracy*) across different R^2 groups. Following Mansi, Maxwell, and Miller (2011), *Analyst Forecast Dispersion* is the standard deviation of analyst forecasts supplied by IBES scaled by stock price, and *Analyst Forecast Accuracy* is calculated as the negative of the absolute value of (actual EPS - median EPS forecast) scaled by the stock price (i.e., the more negative the number, the less precise). The results show that the precision of information gathered by analysts, and the quality of the signal provided to the market, is lower for stocks with less price synchronicity: Low R^2 firms are associated with significantly lower analyst coverage, greater forecast dispersion, and lower forecast accuracy. These findings suggest that the supply of information available to analysts and other market participants is lower for low R^2 stocks, implying that low R^2 stocks are less transparent even from the perspective of analysts.

Table 2.2 Panel C provides firm-level characteristics associated with growth opportunities and other indicators of information asymmetry. These include *Firm Size* (total assets), *Market-Book Ratio* (sum of book value of debt plus market value of equity plus liquidating value of preferred stock, scaled by total assets), and *Market Competition* (number of common shareholders)[6]. Low R^2 firms are associated with characteristics that are consistent with more noisy information environments and greater asymmetry; they tend to be smaller than their high R^2 counterparts, have higher growth prospects, and have lower numbers of common shareholders. Viewed collectively, the results of Table 2.2 are

[6] Armstrong, Core, Taylor and Verrecchia (2011) use number of shareholders to measure the degree of market competition. They find that information asymmetry has an impact on expected stock returns under imperfect market competition as proxied by a small number of shareholders, indicating information asymmetry is more severe when market competition is low.

consistent with earlier findings that firms with lower prior R^2 have opaque information environments and less informed stock prices.

2.5.2 Abnormal return, trading volume, and return volatility across R^2 subsets

Table 2.3 Panel A provides daily and cumulative average abnormal returns across the three R^2 groups. The table shows an inverse relationship between the day-0 price reaction and R^2 in both upgrade and downgrade groups. For upgrades, mean abnormal returns are the largest (0.30 %) among low R^2 stocks and decrease to 0.22 % among high R^2 stocks. For downgrades, mean abnormal returns are the strongest in magnitude (-0.26 %) among low R^2 stocks and decrease monotonically to the weakest in magnitude (-0.06 %) among high R^2 stocks. These results are consistent with *Hypothesis 1* and the univariate results of Table 2.2: Low R^2 stocks have fundamentally noisier information environments and therefore experience greater price reactions as new firm-specific information is conveyed to the market. The inverse relation between abnormal returns and R^2 continues to hold for wider periods of time around the announcement date. Within the downgrade group, the monotonic relation between abnormal returns and R^2 emerges three days before the announcement: mean abnormal returns are highly significant on days -3, -2, and -1, indicating the possibility of information leakage among unfavourable recommendations (e.g., Liu, Smith, & Syed (1990) and Schlumpf, Schmid, & Zimmermann (2008) provide evidence suggesting analysts may release information to some institutional investors earlier than to individual investors). The cumulative average abnormal return (CAAR) is also decreasing with R^2; within the upgrade group, the (-1, 0) and (-1, 1) window CAARs decrease across the three R^2 subsets. For downgrades, the (-1, 0), (-1, 1), and (-5, 5) window CAARs all decrease monotonically in magnitude across R^2 groups. The CAARs over the different event windows also suggest that the cumulated market response is stronger for downgrade revisions than for upgrade revisions, indicating that investors place greater weight on unfavourable information.

Table 2.3 Panel B reports abnormal trading volume results. As with the abnormal return results, the significantly positive abnormal trading volume around recommendation revisions is consistent with the view that investors perceive changes in analysts' opinions as information that is relevant to their trading decisions. As shown in the table, abnormal trading volume begins to increase five days prior to the announcement, peaks at day-0, and then dissipates thereafter. Consistent with *Hypothesis 2*, positive abnormal trading volume is the strongest among stocks that are less synchronous and decreases monotonically with the increase of R^2 levels on days around the upgrade and downgrade revisions, implying that recommendations result in increased information-based trading. Specifically on day-0, abnormal trading volumes are 30.23% among low R^2 stocks, 26.16% among medium R^2 stocks, and 18.34% among high R^2 stocks in response to upgrade recommendations. For downgrades, abnormal trading volumes are 30.63% among low R^2 stocks, 26.64% among medium R^2 stocks, and 20.35% among high R^2 stocks. These changes are statistically significant at the 1% level, providing evidence that the improvement in information-based trading is the strongest for low R^2 stocks. Consistent results are also identified for the cumulative abnormal volumes over (-1, 0), (-1, 1), and (-5, 5) event windows for both upgrades and downgrades. The effect is larger for downgrades, supporting the view that downgrades are perceived as more informative than upgrades.

Table 2.3 Market Reactions across R^2 Groups

The tables below show the results of market reaction in response to analyst upgrade and downgrade recommendations conditional on the level of R^2. Panel A presents results using the standardized cross-sectional z-statistic. Panel B reports abnormal trading volume, and assesses the significance of each day (window) using the rank test statistic. Finally Panel C reports abnormal return volatility, and assesses the significance for each day (window) using one tail t-tests to test if abnormal volatilities are significantly greater than 1. The difference between Low R^2 and High R^2 is assessed based on t-test. The symbols *, **, and *** indicate significance at 10%, 5%, and 1% levels respectively.

Panel A: Abnormal returns

Upgrade								
	Low R^2		Medium R^2		High R^2		Low R^2 - High R^2	
Days	Abnormal Return	StdCsect Z	Abnormal Return	StdCsect Z	Abnormal Return	StdCsect Z	Abnormal Return	T test
-5	0.00%	0.124	0.01%	0.035	0.10%	2.602***	-0.10%	-2.476**
-4	0.00%	-1.792*	-0.01%	-0.494	0.04%	0.626	-0.04%	-0.822
-3	-0.06%	-2.733***	-0.01%	-0.301	0.02%	0.319	-0.08%	-1.913*
-2	0.02%	-0.367	0.01%	0.101	0.08%	1.863*	-0.06%	-1.452
-1	0.06%	0.888	0.02%	0.84	0.07%	1.297	-0.01%	-0.328
0	0.30%	7.670***	0.19%	5.316***	0.22%	7.613***	0.08%	1.334
1	0.07%	2.715***	0.05%	1.451	0.03%	1.448	0.04%	0.998
2	-0.05%	-2.350**	0.00%	-0.193	0.03%	1.707**	-0.08%	-1.921*
3	-0.01%	0.962	0.01%	-0.704	-0.01%	-1.279	0.00%	0.250
4	-0.02%	-0.726	-0.02%	0.092	0.04%	0.944	-0.06%	-1.678*
5	0.01%	1.188	0.03%	0.759	0.04%	0.896	-0.03%	-0.703
(-1, 0)	0.36%	7.833***	0.21%	5.131***	0.29%	6.913***	0.07%	1.648*
(-1,+1)	0.42%	6.819***	0.25%	4.537***	0.32%	6.222***	0.10%	1.124
(-5,+5)	0.31%	2.621***	0.28%	2.662***	0.66%	6.040***	-0.35%	-2.366**

Downgrade								
	Low R^2		Medium R^2		High R^2		Low R^2 - High R^2	
Days	Abnormal Return	StdCsect Z	Abnormal Return	StdCsect Z	Abnormal Return	StdCsect Z	Abnormal Return	T test
-5	-0.09%	-2.738***	0.04%	1.109	0.00%	-0.328	-0.09%	-2.222**
-4	-0.06%	-3.280***	-0.10%	-2.864***	0.02%	0.87	-0.08%	-1.597
-3	-0.10%	-3.749***	-0.09%	-2.280**	-0.01%	-1.101	-0.09%	-2.053**
-2	-0.09%	-3.182***	-0.12%	-3.102***	-0.04%	-1.145	-0.05%	-1.092
-1	-0.26%	-5.509***	-0.20%	-3.862***	-0.09%	-1.838*	-0.17%	-3.022***
0	-0.26%	-6.182***	-0.16%	-4.857***	-0.06%	-2.129**	-0.20%	-3.092***
1	0.01%	0.182	0.01%	0.427	-0.06%	-1.274	0.07%	1.448
2	-0.06%	-2.098**	-0.04%	-0.937	0.00%	-0.499	-0.06%	-1.431
3	-0.04%	-1.686*	-0.01%	-0.271	-0.01%	-1.345	-0.03%	-0.788
4	-0.06%	-2.248**	-0.05%	-1.930*	0.04%	1.236	-0.10%	-2.572**
5	0.00%	0.632	-0.04%	-1.581	0.00%	-0.08	0.00%	-0.122
(-1, 0)	-0.52%	-4.970***	-0.36%	-3.718***	-0.15%	-2.460**	-0.37%	-1.694*
(-1,+1)	-0.51%	-7.261***	-0.36%	-5.272***	-0.21%	-3.028***	-0.30%	-3.190***
(-5,+5)	-1.00%	-10.040***	-0.76%	-6.656***	-0.21%	-2.665***	-0.79%	-5.348***

Panel B: Abnormal trading volume

Upgrade								
	Low R^2		Medium R^2		High R^2		Low R^2 - High R^2	
Days	Abnormal Volume	Rank Test	Abnormal Volume	Rank Test	Abnormal Volume	Rank Test	Abnormal Volume	T test
-5	1.93%	1.741*	2.20%	3.401***	0.06%	0.337	1.87%	1.932*
-4	3.79%	3.060***	3.45%	4.469***	1.36%	2.234**	2.43%	2.570***
-3	5.81%	4.716***	4.58%	5.525***	2.33%	3.848***	3.48%	3.562***
-2	8.98%	6.624***	7.47%	7.093***	4.78%	7.489***	4.20%	4.106***
-1	17.01%	8.237***	14.60%	8.630***	11.77%	16.387***	5.24%	4.854***
0	30.23%	9.308***	26.16%	9.500***	18.34%	26.454***	11.89%	10.790***
1	17.91%	8.675***	13.66%	8.852***	9.43%	14.972***	8.48%	8.636***
2	11.10%	7.603***	8.11%	7.649***	3.86%	6.277***	7.24%	7.470***
3	8.16%	6.530***	6.58%	6.930***	2.62%	4.568***	5.54%	5.827***
4	7.03%	6.116***	5.65%	6.450***	1.98%	3.892***	5.05%	5.282***
5	6.01%	5.461***	4.73%	6.147***	1.15%	2.049**	4.86%	5.195***
(-1, 0)	47.24%	9.211***	40.76%	9.401***	30.11%	9.218***	17.13%	8.710***
(-1,+1)	65.14%	9.167***	54.43%	9.376***	39.53%	9.197***	25.61%	8.300***
(-5,+5)	117.94%	8.392***	97.19%	8.800***	57.69%	7.949***	60.25%	9.784***

Downgrade								
	Low R^2		Medium R^2		High R^2		Low R^2 - High R^2	
Days	Abnormal Volume	Rank Test	Abnormal Volume	Rank Test	Abnormal Volume	Rank Test	Abnormal Volume	T test
-5	2.34%	1.752*	2.74%	3.728***	0.21%	0.265	2.13%	2.200**
-4	4.63%	3.551***	2.68%	3.491***	1.51%	1.988**	3.12%	3.195***
-3	5.66%	4.365***	3.83%	4.619***	2.70%	3.330***	2.96%	3.094***
-2	8.77%	6.249***	7.22%	6.601***	5.50%	5.590***	3.27%	3.189***
-1	19.14%	8.288***	16.05%	8.498***	12.37%	8.195***	6.77%	6.100***
0	30.63%	9.277***	26.64%	9.360***	20.35%	9.221***	10.28%	9.171***
1	17.08%	8.548***	14.72%	8.690***	10.67%	8.207***	6.41%	6.497***
2	10.48%	7.152***	8.72%	7.438***	5.95%	6.648***	4.53%	4.674***
3	8.54%	6.498***	7.35%	7.056***	4.17%	5.301***	4.37%	4.530***
4	7.38%	5.770***	6.16%	6.371***	2.95%	4.461***	4.43%	4.657***
5	5.56%	4.973***	5.77%	6.207***	2.15%	3.344***	3.41%	3.629***
(-1, 0)	49.77%	9.168***	42.69%	9.259***	32.72%	9.045***	17.05%	8.310***
(-1,+1)	66.85%	9.150***	57.40%	9.246***	43.39%	9.041***	23.46%	7.150***
(-5,+5)	120.21%	8.297***	101.86%	8.655***	68.54%	7.840***	51.67%	8.805***

Panel C: Abnormal return volatility

Upgrade								
	Low R^2		Medium R^2		High R^2		Low R^2 - High R^2	
Event Window	Abnormal Volatility	T test	Abnormal Volatility	T test	Abnormal Volatility	T test	Abnormal Volatility	T test
(-1, 0)	4.59	18.75***	4.13	17.97***	3.05	18.47***	1.55	6.99***
(-1,+1)	5.79	23.70***	5.29	22.14***	3.91	22.15***	1.87	7.81***
(-5,+5)	14.50	36.17***	13.21	34.06***	10.78	36.88***	3.72	8.24***

Downgrade								
	Low R^2		Medium R^2		High R^2		Low R^2 - High R^2	
Event Window	Abnormal Volatility	T test	Abnormal Volatility	T test	Abnormal Volatility	T test	Abnormal Volatility	T test
(-1, 0)	5.55	17.74***	4.48	22.57***	3.71	11.84***	1.84	5.36***
(-1,+1)	6.84	18.75***	5.60	26.24***	4.77	16.47***	2.07	4.99***
(-5,+5)	15.53	32.45***	14.48	33.89***	12.11	20.10***	3.42	4.94***

Table 2.3 Panel C provides results of abnormal return volatility. As with abnormal trading volume, the magnitude of abnormal volatilities diminishes monotonically with higher R^2 levels in response to upgrade and downgrade recommendations. For example, within the upgrade recommendation group, abnormal volatilities over the (-1, 0) window for low R^2 stocks, medium R^2 stocks, and high R^2 stocks are 4.59, 4.13, and 3.05, respectively. Within the downgrade recommendation group, abnormal volatilities over the (-1, 0) window for low R^2 stocks, medium R^2 stocks, and high R^2 stocks are 5.55, 4.48, and 3.71, respectively. All abnormal volatilities are significantly greater than 1. These results are consistent with *Hypothesis 3* and provide additional evidence that the improvement in the information environment is the strongest for low R^2 stocks.

Viewed collectively, these results support the univariate findings that lower R^2 is associated with lower transparency and information flow. The findings show that abnormal returns of low R^2 stocks exceed high R^2 stocks, indicating more of an informational surprise associated with the recommendation announcements. Furthermore, abnormal trading volume and return volatility of low R^2 stocks exceed high R^2 stocks around the announcement dates, indicating a greater impact on informed trading.

The event study analysis establishes that there is an inverse relationship between R^2 and the market response to recommendation revisions. Changes in opinion by analysts play a greater informational role for lower R^2 stocks, whose prices are *ex ante* less efficient. However, prior studies have directly associated firm size with R^2 (e.g., Kelly, 2014), and since firm size is also correlated with analyst impact as evidenced by larger price reaction to analyst recommendations for smaller firms (e.g., Womack, 1996; Jegadeesh & Kim, 2006; among others), there is a need to make sure that the R^2 effect is not totally subsumed by the size effect, i.e., that the greater market response identified among lower R^2 stocks is not merely a small firm size effect.

To check this, a series of two-way sorts is conducted where the samples of upgrades and downgrades are first sorted into terciles based on firm size in each year, and then further sorted within each size tercile using R^2. Table 2.4 provides the (-1, 0) event window results for the three market response metrics employed in Table 2.3, for low and high R^2 terciles within each size tercile. Viewed collectively, these results provide univariate support for previous findings and establish that the negative relation between R^2 and the market response to analyst recommendation revisions is not totally subsumed by firm size. As shown in Table 2.4, the R^2 effect is generally stronger for small firms compared to large firms, and for downgrade recommendation revisions compared to upgrade recommendation revisions. In Panel A1, variation in R^2 does not significantly impact abnormal returns within the top and bottom terciles for upgrades; however, Panel A2 shows that abnormal returns associated with downgrades are significantly stronger for low vs. high R^2 firms within the lowest size tercile.

Table 2.4 Panel B demonstrates that the association between R^2 and abnormal trading volume is not driven by the underlying size effect, and that variation in R^2 has a greater impact on small firms than on large firms. In Panel B, abnormal volume around upgrades is significantly stronger for low R^2 firms within both small and large firm subsets, and the magnitude is approximately twice as large for small firms. For downgrades, the difference in abnormal volume between low and high R^2 firms is significant at the 1% level within the small firm subset and is positive albeit insignificant within the largest firms. Likewise, Panel C shows that variation in R^2 has the greatest impact on abnormal return volatility among small firms, with the largest magnitude for downgrades. In short, the findings suggest that the R^2 effect is not totally subsumed by firm size effect. However, variation in R^2 has a relatively larger effect on the market response to new information for small firms, indicating that R^2 complements size effect by augmenting the explanatory value of firm size on the market response measures.

Table 2.4 Impact of R^2 on the Market Response to Analyst Recommendation Changes: Size Effect

This table reports differences in abnormal return (Panel A), abnormal volume (Panel B), and abnormal return volatility (Panel C) by subsets sorted by size (in terciles) and then by R^2 (in terciles) for analyst recommendation upgrades and for downgrades. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A: (-1, 0) Cumulative Average Abnormal Returns Sorted By Size and R^2

	Panel A1: Upgrades (%)				Panel A2: Downgrades (%)			
	Low R^2	High R^2	Low R^2 – High R^2	T test	Low R^2	High R^2	Low R^2 – High R^2	T Test
Small Size	0.36	0.37	-0.00	-0.08	-0.85	-0.39	-0.46	-2.70***
Large Size	0.11	0.20	-0.09	-0.86	-0.12	-0.07	-0.05	-0.42

Panel B: (-1, 0) Cumulative Average Abnormal Volume Sorted By Size and R^2

	Panel C1: Upgrades (%)				Panel C2: Downgrades (%)			
	Low R^2	High R^2	Low R^2– High R^2	T test	Low R^2	High R^2	Low R^2 – High R^2	T Test
Small Size	56.21	43.94	12.27	3.28***	60.94	43.89	17.05	4.49***
Large Size	28.12	21.59	6.53	2.57**	29.44	26.67	2.79	1.10

Panel C: (-1, 0) Abnormal Return Volatility Sorted By Size and R^2

	Panel D1: Upgrades (%)				Panel D2: Downgrades (%)			
	Low R^2	High R^2	Low R^2– High R^2	T test	Low R^2	High R^2	Low R^2 – High R^2	T Test
Small Size	5.52	3.90	1.62	2.67***	6.69	4.18	2.51	4.80***
Large Size	3.58	2.71	0.87	2.47**	3.78	3.61	0.17	0.28

2.5.3 Multivariate regression analysis

The robustness of the univariate relation between R^2 and changes in the information environment is tested by controlling for firm- and revision-level control variables that may also impact the abnormal market response to analyst recommendation revisions. Since the price effects of upgrade or downgrade revisions have opposite signs, the OLS regression model for upgrades and downgrades is estimated separately using the (-1, 0) CAAR as the dependent variable. The regression model is specified as follows:

$$Abnormal\ Return = a_0 + a_1 Synchronicity + a_2 FirmSize + a_3 TradingVolume + a_4 MarektBookRatio + a_5 PriceMomentum + a_6 AnalystCoverage + a_7 No.Recommendation + a_8 MagnitudeofChange + a_9 FirmAge + a_{10} MarketCompetition + a_{11} RegFD + \sum_i a_i\, FamaFrench30IndustryFixedEffects + \sum_i a_i\, YearFixed\ Effects \quad (6)$$

Because R^2 is bounded between 0 and 1, the convention in Morck, Yeung, and Yu, 2000; Durnev, Morck, Yeung, and Zarowin, 2003; and Durnev, Morck, and Yeung, 2004 is followed by converting R^2 to the *Synchronicity* measure using log $(R^2/(1-R^2))$. Following Loh and Stulz (2011), the control variables included in the regression model are proxies for information asymmetry and characteristics associated with the recommendation revisions. The control variables include *Firm Size*, *Trading Volume*, *Market-to-book Ratio*, *Price Momentum*, *Analyst Coverage*, *Firm Age*, and *Market Competition*. Among the recommendation-level control variables, *No. of Recommendations* tests if recommendation breadth impacts investor response to revisions, and *Magnitude of Change* tests if the intensity of the signal provided by the revisions affects the market response (Stickel, 1995; Brav and Lehavy, 2003). Finally, *Reg FD* (Regulation Fair Disclosure) controls for a systematic effect between the post-regulatory time period and the market response. *Reg FD* is indicated by a dummy variable, which takes the value of one if the recommendation revision occurs in November 2000 or thereafter, and zero otherwise. The regression model also includes *Fama-French 30 Industry*- and *Year-Fixed Effects*. Further details about the construction of these variables are provided in the Appendix.

It is common in finance application that the residuals of a given firm may be correlated across years or the residuals of a given year may be correlated across different firms. As such, a method fails to take into account of the time-series correlation and cross-sectional correlation will severely understate standard errors and overstate the result significance. As pointed out by Petersen (2009), when there is a fixed or temporary firm effect in both independent variables and residuals, the standard errors of coefficients are biased when using approaches such as Newey-West statistics or the Fama and Macbeth approach (1973). However, the standard errors of coefficients are unbiased when using the approach to correct standard errors clustering at firm-level and time-level. This approach can produce correctly sized confidence intervals whether or not the time-series correlation or the cross-sectional correlation in both independent variables and residuals is permanent or temporary. This approach is particularly appropriate when dealing with corporate finance and asset pricing panel data. Therefore in this essay, the time-series correlation and cross-sectional correlation of residuals are taken into account by adjusting the standard errors for clustering at both firm-level and year-level in the multivariate regression analysis.

Table 2.5 Correlation Matrix of Independent Variables

This table provides pairwise correlations between the independent variables used in the multivariate regression analysis. Additional variable details are provided in the Appendix. * indicates significance at the 5% level or lower.

	Synchronicity	Firm size	Trading volume	Market-book Ratio	Price momentum	Analyst Coverage	No. of Recommendation	Magnitude	Firm age	Market competition	Reg FD
Synchronicity	1										
Firm Size	0.409*	1									
Trading Volume	0.294*	-0.069*	1								
Market-book Ratio	-0.040*	-0.211*	-0.01*	1							
Price Momentum	0.031*	-0.023*	-0.004	0.075*	1						
Analyst Coverage	0.234*	0.277*	0.158*	0.131*	0.003	1					
No. of Recommendations	0.469*	0.547*	0.345*	-0.032*	-0.013*	0.389*	1				
Magnitude	0.027*	-0.004	0.037*	-0.008*	0.011*	0.015*	0.027*	1			
Firm Age	0.486*	0.301*	0.411*	-0.102*	0.004	0.197*	0.691*	0.035*	1		
Market Competition	0.135*	0.58*	-0.262*	-0.015*	-0.018*	0.155*	0.316*	-0.005	0.118*	1	
Reg FD	0.364*	0.137*	0.492*	-0.073*	-0.023*	0.173*	0.462*	0.049*	0.570*	-0.127*	1

Pairwise correlation coefficients are reported in Table 2.5 between *Synchronicity* and the independent variables used in the proceeding regression models. Consistent with the univariate comparison of Table 2.2, less synchronous firms exhibit high correlations with firm-level variables associated with greater opacity (e.g., smaller firm size, decreased average trading volume, less analyst coverage, lower age, and fewer shareholders). Consistent with the positive correlation between *Analyst Coverage* and *Synchronicity*, there are also more recommendations issued for firms with higher price synchronicity. Pairwise correlation between the magnitude of the revisions and *Synchronicity* is also positive, providing evidence that analysts do not condition the magnitude of their recommendation revisions on the underlying noisiness of the stock's trading environment as reflected by the R^2.

Regression coefficient estimates are reported in Table 2.6. While *Synchronicity* has no systematic effect on upgrade abnormal returns in Model 1, *Synchronicity* is significantly positively related to downgrade abnormal returns in Model 3. This is consistent with the event study results above and demonstrates that stocks with lower R^2 are inversely associated with stronger price responses to downgrades. Models 2 and 4 include an interaction between *Firm size* and *Synchronicity* to test if the impact of *Synchronicity* varies with the magnitude of *Firm size*. This interaction is negative and significant at the 10% level for downgrades, indicating that the magnitude of the marginal effect of *Synchronicity* on the price reaction to downgrades is significantly greater for

Table 2.6 Regressions of Cumulative Average Abnormal Stock Returns on Synchronicity and Additional Control Variables

This table provides coefficient estimates using two-day (-1, 0) cumulative average abnormal returns as the dependent variable, for recommendation upgrades (Models 1-2) and for downgrades (Models 3-4). The standard errors are adjusted for clustering at firm-level and year-level. Additional variable details are provided in the Appendix. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Upgrades		Downgrades	
	Abnormal Returns		Abnormal Returns	
	Model (1)	Model (2)	Model (3)	Model (4)
Intercept	-0.0008	-0.0005	-0.0019	-0.0051
	(-0.07)	(-0.04)	(-0.17)	(-0.43)
Synchronicity	0.0001	0.0004	0.0013*	0.0014**
	(0.38)	(0.31)	(1.78)	(1.98)
Firm Size	-0.0004	-0.0004	0.0005	-0.0010
	(-1.23)	(-1.30)	(0.82)	(0.97)
Synchronicity × Firm Size		-0.0000		-0.0007*
		(-0.24)		(1.85)
Trading Volume	0.0001	0.0001	-0.0000	-0.0000
	(0.49)	(0.52)	(-0.07)	(-0.18)
Market-book Ratio	0.0003	0.0003	0.0011	0.0011
	(0.59)	(0.59)	(1.42)	(1.42)
Price Momentum	0.0080***	0.0080***	0.0617***	0.0617***
	(3.36)	(3.37)	(12.77)	(12.78)
Analyst Coverage	0.0002	0.0002	0.0010*	0.0012*
	(1.53)	(1.52)	(1.68)	(1.75)
No. of Recommendations	0.0000	0.0000	0.0002*	0.0002*
	(1.01)	(1.03)	(1.70)	(1.82)
Magnitude of Change	0.0009**	0.0009**	-0.0005**	-0.0005**
	(2.36)	(2.36)	(-2.40)	(-2.39)
Firm Age	-0.0001	-0.0001	0.0000	0.0000
	(-1.33)	(-1.32)	(0.18)	(0.10)
Market Competition	0.0001	0.0001	-0.0003	-0.0003
	(0.53)	(0.53)	(-1.43)	(-1.44)
Reg FD	-0.0010	-0.0010	-0.0005	-0.0005
	(-0.09)	(-0.07)	(-0.15)	(-0.12)
Fama-French 30 Industry Fixed Effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. Obs.	20509	20509	20754	20754
R-squared	0.035	0.035	0.030	0.030

smaller firms than for larger firms.[1] Similar to Hong, Lim, and Stein (2000), *Price Momentum* is positively significantly related to abnormal returns around downgrades, indicating high price momentum stocks experience smaller changes in magnitude for abnormal returns. In their context, momentum is a symptom of under-reaction, i.e., stocks adjust to new information too slowly; stocks with greater momentum exhibit slower information diffusion (i.e., greater under-reaction) to new information and are therefore associated with smaller price reactions. Also, consistent with Loh and Stulz (2011), the findings show that number of recommendations reduces the magnitude of abnormal returns around downgrades. Similarly, analyst coverage also mitigates the magnitude of return reaction for downgrades. Finally, the magnitude of price response is found to increase with the magnitude of revision changes for both upgrades and downgrades.

In Table 2.7, the multivariate impact of *Synchronicity* on alternative measures of changes in the information environment is evaluated using OLS regressions. Using the independent variables specified in Equation 6, the relationship between *Synchronicity* and abnormal volume and the relationship between *Synchronicity* and abnormal volatility is examined, controlling for additional firm- and recommendation-level measures. As *Synchronicity* has the same hypothesized effect on abnormal volume and volatility for upgrades and downgrades, upgrade and downgrade samples are pooled together. Several interaction terms are included to the specification of Equation 6. First, the relative impact

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[1] It is possible that analysts issue only large revisions on smaller or more illiquid stocks if they expect minor revisions to have minimal economic impact. To insure that stronger price responses among low R^2 stocks do not simply reflect analysts' preference to issue large revisions, Equation (6) is re-estimated with inclusion of an interaction between *Synchronicity* and *Magnitude of change* to test if the impact of the magnitude of the revision varies for higher and lower levels of *Synchronicity*. This interaction is statistically insignificant across all regression models.

of variation downgrades relative to upgrades is tested, with the indicator variable *Downgrade*. Then the impact of *Synchronicity* within the downgrade subset is tested by including the interaction term *Synchronicity* × *Downgrade*. These variables are specified in Equation 7. Similarly to Equation 6, standard errors are adjusted for clustering at firm-level and year-level.

$$Abnormal\,Volume\ (or\ Volatility) = a_0 + a_1 Synchronicity + a_2 Downgrade + a_3 Synchronicity * Downgrade + a_4 FirmSize + a_5 TradingVolume + a_6 MarektBookRatio + a_7 PriceMomentum + a_8\,AnalystCoverage + a_9 No.Recommendation + a_{10} MagnitudeofChange + a_{11} FirmAge + a_{12} MarketCompetition + a_{13} RegFD + \sum_i a_i\,FamaFrench30IndustryFixedEffects + \sum_i a_i\,YearFixed\ Effects \qquad (7)$$

The coefficient estimates for abnormal volume and abnormal volatility are provided in Table 2.7, Model 1 and Model 3, respectively. In Model 2 and Model 4, the interaction *Synchronicity* × *Firm Size* is included to test if the sensitivity of *Synchronicity* to the response of abnormal volume and abnormal volatility varies as *Firm Size* changes. An interaction term of *Synchronicity* × *Downgrade* is also included in Models 2 and 4 to test if the synchronicity effect on abnormal volume and abnormal volatility is stronger among downgrade revisions. The dependent variables are the two-day (-1, 0) cumulative abnormal volume in Models 1 and 2, and abnormal volatility over (-1, 0) event window in Models 3 and 4. Consistent with *Hypotheses 2 & 3*, Table 2.7 demonstrates that *Synchronicity* is negative and significant across all Models. Models 1–2 demonstrate that *Firm Size, No. of Recommendations* and *Market-to-book Ratio* are significantly and negatively related to abnormal volume, while *Trading Volume* and *Magnitude of Change*

Table 2.7 Regressions of Abnormal Trading Volume and Return Volatility on Synchronicity and Additional Control Variables

This table provides coefficient estimates using two-day (-1, 0) cumulative average abnormal trading volume (Models 1-2) and abnormal volatility over the (-1, 0) event window period (Models 3-4) as the dependent variables, respectively. The standard errors are adjusted for clustering at firm-level and year-level. Additional variable details are provided in the Appendix. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Abnormal Volume		Abnormal Volatility	
	Model (1) Upgrades + Downgrades	Model (2) Upgrades + Downgrades	Model (3) Upgrades + Downgrades	Model (4) Upgrades + Downgrades
Intercept	0.1584*	0.2206**	2.5062	2.4729
	(1.81)	(2.98)	(0.95)	(0.93)
Synchronicity	-0.0322**	-0.0298**	-0.5959***	-0.5737***
	(-2.18)	(-2.03)	(-4.07)	(-3.82)
Downgrade	-0.0112	-0.0113	-0.1696	-0.1716
	(-0.67)	(-0.68)	(-0.76)	(-0.77)
Synchronicity × Downgrade	-0.0157	-0.0157	-0.3341*	-0.3355*
	(-1.04)	(-1.04)	(-1.78)	(-1.79)
Firm Size	-0.0548**	-0.0343*	-0.1844	-0.0239
	(-2.84)	(-1.72)	(-1.14)	(-0.15)
Synchronicity × Firm Size		0.0191**		0.1605*
		(2.31)		(1.89)
Trading Volume	0.0033*	0.0034*	0.0048	0.0002
	(1.79)	(1.85)	(0.39)	(0.02)
Market-book Ratio	-0.0359***	-0.0358***	-0.3305***	-0.3331***
	(-3.30)	(-3.28)	(-3.39)	(-3.42)
Price Momentum	-0.0147	-0.0163	-0.2270	-0.2352
	(-0.28)	(-0.30)	(-0.87)	(-0.89)
Analyst Coverage	-0.0220	-0.0237	-0.1821*	-0.1918*
	(-1.50)	(-1.60)	(-1.80)	(-1.86)
No. of Recommendations	-0.0008**	-0.0009**	-0.0134***	-0.0141***
	(-2.15)	(-2.40)	(-3.55)	(-3.76)
Magnitude of Change	0.0202*	0.0208*	0.0006	0.0005
	(1.76)	(1.81)	(0.00)	(0.00)
Firm Age	-0.0038	-0.0035	0.0580*	0.0621**
	(-0.99)	(-0.88)	(1.93)	(2.09)
Market Competition	-0.0050	-0.0048	-0.1821*	-0.1918*
	(-1.16)	(-1.13)	(-1.80)	(-1.86)
Reg FD	0.0060	0.0076	0.0151	0.0109
	(0.36)	(0.45)	(0.33)	(0.35)
Fama-French 30 Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
No. Obs	43002	43002	42840	42840
R-squared	0.024	0.024	0.015	0.015

are significantly and positively related to abnormal volume. Consistent with the univariate results above, the *Synchronicity* × *Firm Size* interaction is positive and significant at the 5% level in Model 2; the marginal sensitivity of abnormal volume to *Synchronicity* varies significantly with *Firm Size*. Across all models, *Downgrade* is negative and insignificant, indicating the magnitudes of abnormal volume and abnormal volatility are not greater for downgrade revisions. However, as shown in Models 3–4, *Synchronicity* does have a significantly different effect on abnormal volatility within the downgrade subset compared with the upgrade subset; the incremental effect of *Synchronicity* on abnormal volatility varies significantly within the downgrade component as evidenced by the significantly negative *Synchronicity* × *Downgrade* regression coefficients. Similar to Model 2, the *Synchronicity* × *Firm Size* interaction term is positive and significant on abnormal volatility in Model 4, suggesting the marginal sensitivity of abnormal volatility to *Synchronicity* varies significantly with *Firm Size*.

2.5.4 Multivariate regression analysis: robustness check

It is possible that stock price synchronicity and other independent variables included in Equations 6 and 7 are overlapping in what they proxy for. As shown in Table 2.5, synchronicity has a strong correlation with firm size, trading volume, analyst coverage, number of recommendations, and firm age. Therefore, it is important to ensure that synchronicity captures price noisiness, which is distinct from the remaining firm- and recommendation-level control variables. Despite these variables having been included and controlled in the multivariate regression models, their effects on synchronicity are further separated out by creating a new variable called *Orthogonalized Synchronicity*. Following the methodology introduced in Mansi, Maxwell, and Miller (2004); Klock, Mansi, and Maxwell (2005); and Mansi, Maxwell, and Miller (2011), *Orthogonalized Synchronicity* is the residual from a regression of *Synchronicity* on the remaining independent variables included in Equations 6 and 7. Multivariate regression analyses on abnormal returns, abnormal volume, and abnormal volatility are then replicated using *Orthogonalized Synchronicity* to replace *Synchronicity*. Results are presented in Tables 2.8 and 2.9. Overall, the coefficient estimates of *Orthogonalized Synchronicity* and the interactions with *Downgrade* and *Firm Size* are qualitatively similar to the previous results reported in Tables 2.6 and 2.7. Regression coefficient estimates of other independent variables also remain consistent with those presented in Tables 2.6 and 2.7.

2.5.5 Abnormal bid-ask spread and R^2

Information events such as earnings announcements have been shown to mitigate information asymmetry through the release of new information (e.g., Lee, Mucklow, & Ready, 1993; Brooks, 1996; Yohn, 1998). The prior results imply, but do not directly address, that low R^2 firms are associated with more information asymmetry and high R^2 firms are associated with less information asymmetry. This essay will now proceed to investigate if analyst recommendations are associated with changes in the relative balance of informed to uninformed market participants and if these changes are related to R^2. Following prior results, lower R^2 stocks are expected to benefit more from information asymmetry reduction associated with recommendation revisions.

Table 2.8 Regressions of Cumulative Average Abnormal Stock Returns on Orthogonalized Synchronicity and Additional Control Variables

This table provides coefficient estimates using two-day (-1, 0) cumulative average abnormal returns as the dependent variable, for recommendation upgrades (Models 1-2) and for downgrades (Models 3-4). The independent variable *Synchronicity* is replaced by *Othogonalized Synchronicity*. The standard errors are adjusted for clustering at firm-level and year-level. Additional variable details are provided in the Appendix. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Upgrades		Downgrades	
	Abnormal Returns		Abnormal Returns	
	Model (1)	Model (2)	Model (3)	Model (4)
Intercept	-0.0012	-0.0012	-0.0057	-0.0054
	(-0.10)	(-0.10)	(-0.65)	(-0.61)
Orthg. Synchronicity	0.0001	0.0004	0.0013*	0.0014**
	(0.38)	(0.31)	(1.74)	(1.95)
Firm Size	-0.0003	-0.0003	0.0007	0.0006
	(-1.10)	(-1.06)	(1.19)	(1.12)
Synchronicity × Firm Size		-0.0001		-0.0007*
		(-0.15)		(1.82)
Trading Volume	0.0001	0.0001	-0.0000	-0.0000
	(0.50)	(0.50)	(-0.04)	(-0.06)
Market-book Ratio	0.0003	0.0003	0.0012	0.0011
	(0.59)	(0.58)	(1.50)	(1.45)
Price Momentum	0.0080***	0.0080***	0.0617***	0.0617***
	(3.36)	(3.36)	(12.75)	(12.78)
Analyst Coverage	0.0002	0.0002	0.0009*	0.0008*
	(0.57)	(0.56)	(1.65)	(1.77)
No. of Recommendations	0.0000	0.0000	0.0002*	0.0002*
	(1.02)	(1.02)	(1.70)	(1.80)
Magnitude of Change	0.0009**	0.0009**	-0.0005**	-0.0005**
	(2.35)	(2.35)	(-2.38)	(-2.38)
Firm Age	-0.0001	-0.0001	0.0001	0.0001
	(-1.40)	(-1.41)	(0.29)	(0.38)
Market Competition	0.0001	0.0001	-0.0004	-0.0004
	(0.52)	(0.51)	(-1.60)	(-1.56)
Reg FD	-0.0010	-0.0010	-0.0006	-0.0007
	(-0.09)	(-0.07)	(-0.15)	(-0.12)
Fama-French 30 Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
No. Obs.	20509	20509	20754	20754
R-squared	0.035	0.035	0.030	0.030

Table 2.9 Regressions of Abnormal Trading Volume and Return Volatility on Orthogonalized Synchronicity and Additional Control Variables

This table provides coefficient estimates using two-day (-1, 0) cumulative average abnormal trading volume (Models 1-2) and abnormal volatility over the (-1, 0) event window period (Models 3-4) as the dependent variables, respectively. The independent variable *Synchronicity* is replaced by *Othogonalized Synchronicity*. The standard errors are adjusted for clustering at firm-level and year-level. Additional variable details are provided in the Appendix. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Abnormal Volume		Abnormal Volatility	
	Model (1) Upgrades + Downgrades	Model (2) Upgrades + Downgrades	Model (3) Upgrades + Downgrades	Model (4) Upgrades + Downgrades
Intercept	0.1941**	0.2625***	3.5464	3.4743
	(2.25)	(3.57)	(1.32)	(1.29)
Orthg. Synchronicity	-0.0322**	-0.0298**	-0.5959***	-0.5737***
	(-2.18)	(-2.03)	(-4.07)	(-3.82)
Downgrade	-0.0112	-0.0113	-0.1696	-0.1716
	(-0.67)	(-0.68)	(-0.76)	(-0.77)
Synchronicity × Downgrade	-0.0157	-0.0157	-0.3341*	-0.3355*
	(-1.04)	(-1.04)	(-1.78)	(-1.79)
Firm Size	-0.0657***	-0.0445**	-0.3168**	-0.1514
	(-3.60)	(-2.27)	(-2.21)	(-1.02)
Synchronicity × Firm Size		0.0191**		0.1605*
		(2.31)		(1.89)
Trading Volume	0.0031*	0.0032*	0.0021	-0.0023
	(1.64)	(1.71)	(0.18)	(-0.19)
Market-book Ratio	-0.0397***	-0.0393***	-0.3762***	-0.3771***
	(-3.73)	(-3.67)	(-4.02)	(-4.05)
Price Momentum	-0.0112	-0.0130	-0.2107	-0.2196
	(-0.21)	(-0.24)	(-0.80)	(-0.83)
Analyst Coverage	-0.0261*	-0.0276*	-0.2612***	-0.2680***
	(-1.80)	(-1.87)	(-2.89)	(-2.93)
No. of Recommendations	-0.0007*	-0.0008**	-0.0138***	-0.0144***
	(-1.91)	(-2.16)	(-3.60)	(-3.81)
Magnitude of Change	0.0199*	0.0205*	0.0006	0.0006
	(1.74)	(1.79)	(0.00)	(0.00)
Firm Age	-0.0050	-0.0046	0.0142	0.0198
	(-1.29)	(-1.14)	(0.58)	(0.82)
Market Competition	-0.0052	-0.0051	0.0697	0.0689
	(-1.23)	(-1.20)	(0.76)	(0.75)
Reg FD	0.0061	0.0077	0.0166	0.0112
	(0.36)	(0.45)	(0.43)	(0.41)
Fama-French 30 Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
No. Obs	43002	43002	42840	42840
R-squared	0.024	0.024	0.015	0.015

Table 2.10 Abnormal Bid-Ask Spread and R^2

This table provides abnormal reactions in the daily bid-ask spread measure corresponding to upgrade (Panel A) and downgrade (Panels B) recommendation revisions conditional on the level of R^2. Statistical significance is based on the cross-sectional z-statistic and, alternatively, the rank test statistic. The difference in means between Low R^2 and High R^2 is assessed based on t-test and the difference in medians is assessed using the Wilcoxon test. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A: Upgrades

	Low R^2				Medium R^2				High R^2				Low R^2 - High R^2		
Event Window	Abnormal BAS		StdCsect Z	Rank Test	Abnormal BAS		StdCsect Z	Rank Test	Abnormal BAS		StdCsect Z	Rank Test	Difference (Mean)	T test	Wilcoxon test
	Mean	Median			Mean	Median			Mean	Median					
(-1, 0)	-0.03%	-0.03%	0.254	2.504**	0.01%	-0.03%	1.208	3.562***	-0.02%	-0.03%	0.877	3.401***	-0.01%	-0.726	-1.6416*
(-1, +1)	-0.05%	-0.05%	0.424	2.659***	0.00%	-0.04%	1.169	3.522***	-0.03%	-0.04%	0.997	4.827***	-0.02%	-0.775	-2.3225**
(-5,+5)	-0.19%	-0.11%	0.400	2.248**	-0.05%	-0.09%	1.077	3.266***	-0.12%	-0.09%	1.316	3.903***	-0.07%	-1.163	1.9044*

Panel B: Downgrades

	Low R^2				Medium R^2				High R^2				Low R^2– High R^2		
Event Window	Abnormal BAS		StdCsect Z	Rank Test	Abnormal BAS		StdCsect Z	Rank Test	Abnormal BAS		StdCsect Z	Rank Test	Difference (Mean)	T test	Wilcoxon test
	Mean	Median			Mean	Median			Mean	Median					
(-1, 0)	-0.01%	-0.04%	1.357	3.058***	0.02%	-0.03%	1.005	6.131***	-0.01%	-0.03%	1.248	4.876***	0.00%	0.030	-1.1877
(-1, +1)	-0.01%	-0.04%	1.612	3.894***	0.03%	-0.04%	1.324	5.962***	-0.01%	-0.04%	1.537	5.381***	0.00%	0.350	-0.7189
(-5,+5)	-0.10%	-0.10%	1.299	2.984***	0.01%	-0.08%	1.798*	5.010***	-0.07%	-0.06%	1.909*	5.094***	-0.03%	-0.457	-2.5395**

Stock's information asymmetry is measured using the bid-ask spread measure around each recommendation revision. A mean-adjusted event study methodology is used to test if abnormal bid-ask spreads around upgrades and downgrades are significantly different from zero. As described earlier, the daily bid-ask spread measure is $(Ask_{i,t} - Bid_{i,t})/M_{i,t}$, where $Ask_{i,t}$ and $Bid_{i,t}$ indicate closing ask price and bid prices of stock *i* at day *t* and $M_{i,t}$ is the average of ask and bid prices. Expected bid-ask spread is calculated as the mean daily spread measured over the (-131, -31) estimation period. Abnormal bid-ask spread for event day *t* is defined as the difference between actual and mean bid-ask spread. Cumulative abnormal bid-ask spread (CBAS) is calculated by cumulating daily abnormal bid-ask spreads over the (-1, 0), (-1, 1), and (-5, 5) event windows. Both the standardized cross-sectional test (Boehmer, Musumeci, & Poulsen, 1991) and the nonparametric rank test (Corrado, 1989) are applied to test the null hypothesis that the event period abnormal spread is zero.

For brevity, Table 2.10 only reports the cumulated abnormal bid-ask spread over the (-1, 0), (-1, 1), and (-5, 5) event windows for the three R^2 subsets. Sample means and medians for each R^2 subset are reported and standard *t*-test (Wilcoxon test) statistics are provided to test the significance of the difference in means (medians) between low and high R^2 subsets. Overall, the findings show that lower R^2 stocks experience a larger reduction in bid-ask spread in response to both upgrade and downgrade recommendations. While the low-minus-high differences in means are insignificant, the low-minus-high differences in medians are significant for all event windows for upgrades and for the (-5, 5) event window for downgrades. These results add further support for the view that R^2 reflects divergence of price from fundamental value and that recommendation revisions serve as a corrective mechanism to reduce adverse selection.

2.6 Conclusions

This essay addresses the question of whether lower stock price synchronicity represents more noise or, conversely, greater firm-specific information. The initial results show that low R^2 stocks are associated with characteristics related to a lower-quality information environment. Microstructure-based metrics suggest that lower R^2 firms have less transparency and greater information asymmetry problems than do higher R^2 firms, while other metrics suggest that outside investors have greater difficulty in monitoring and assessing internal corporate policies of low R^2 firms.

The subsequent analyses demonstrate that the market response of low R^2 stocks to new information in the form of analyst recommendation upgrade and downgrade revisions exceeds that of high R^2 stocks: Abnormal returns are larger, abnormal trading volume and return volatility are higher, and abnormal bid-ask spreads are lower when R^2 is lower. These results are consistent with the view that lower R^2 stocks have noisier information environments and less *ex ante* information imputed into their prices, and as a result, there is more surprise and informed trading and a greater reduction in information asymmetry when new information is released. Multivariate regression analysis demonstrates that these results are robust to the presence of additional explanatory variables, including firm size. Overall, findings of this essay highlight the informational value-added role of analyst recommendations, particularly for stocks in noisier trading environments.

Appendix: Description of Variables Used in the Study

Variable Name	Description and Source
Panel A: Variables Used in Comparative Analysis	
Bid-Ask Spread	The mean of the daily bid-ask spread measure (ASK-BID/((ASK+BID)/2), measured over the event year. *Source:* CRSP
Trading Volume	The mean of daily trading volume divided by shares outstanding (VOL / SHROUT), measured over the event year. *Source*: CRSP
Return Volatility	Standard deviation of daily returns measured over the event year. *Source:* CRSP
Number of Analysts	Number of stock analysts covering the sample firms. *Source*: IBES via Datastream
Analyst Forecast Dispersion	Standard deviation of the inter-analyst forecast divided by the fiscal-year-end stock price. Winsorized at the 1% tails. *Source*: IBES via Datastream
Analyst Forecast Accuracy	Negative absolute value of the analyst forecast error (the actual EPS minus the median forecast deflated by the stock price). Winsorized at the 1% tails. *Source*: IBES via Datastream
Firm Size	Total assets (AT). *Source:* Compustat
Market-to-book Ratio	Sum of book value of debt plus market value of equity scaled by total assets (AT - CEQ + (PRCC_F * CSHO))/AT. *Source:* Compustat
Market Competition	Number of common shareholders in thousands (CSHR). *Source:* Compustat
Panel B: Variables Used in Regressions	
Downgrade	A dummy variable taking the value of one for downgrade recommendations and zero otherwise. *Source:* IBES
Firm Size	Logged total assets, measured over the year prior to the event year. *Source:* Compustat
Trading Volume	Logged daily trading volume measured over the event year. *Source:* CRSP
Market–to–book Ratio	Sum of book value of debt plus market value of equity scaled by total assets (AT - CEQ + (PRCC_F * CSHO))/AT, measured over the year prior to the event year. *Source:* Compustat
Price Momentum	Cumulative daily stock return for the 3-month period prior to the recommendation revision date, winsorized at the 1% tails. *Source:* CRSP
Analyst Coverage	Logged one plus number of analysts. *Source:* IBES via Datastream
No. of Recommendations	Logged one plus number of recommendations. *Source:* IBES via Datastream
Magnitude of Change	A dummy variable equal to one if the recommendation revision skips a rank and zero otherwise. *Source:* IBES via Datastream
Firm Age	Fractional number of years from when the firm first appeared in CRSP. *Source:* CRSP
Market Competition	Logged number of shareholders (CSHR in thousands), measured over the year prior to the event year. *Source:* Compustat
Reg FD	A dummy variable taking the value of one if the recommendation revision occurs in November 2000 or thereafter, and zero otherwise.

CHAPTER THREE: ESSAY TWO

R^2 AND THE CORPORATE SIGNALING EFFECT

This chapter presents essay two which studies R^2 (or stock price synchronicity) and the dividend signaling effect. Section 3.1 presents an introduction and discusses the motivation and research contribution. Section 3.2 reviews the related literature on the dividend signaling effect. Section 3.3 presents hypotheses development. Section 3.4 presents details of data collection and research methodology. Section 3.5 discusses empirical results and findings. Finally, Section 3.6 outlines the conclusions of this essay.

Abstract

If corporate announcements provide additional signals about firms' future prospects, the degree of investor dependency on these news events should vary with the relative importance of firm-specific information for such firms. This essay shows that price reactions to dividend change announcements are significantly stronger for low R^2 stocks (e.g., less synchronized firms). This indicates that lower R^2 stocks are less informative and thus more surprises on firm-specific news are experienced. These findings are particularly strong for dividend decrease announcements. This essay also shows that signals about firms' earnings prospects from dividend decrease announcements are more reliable among companies with low R^2.

3.1 Introduction

A firm's stock return R^2 has been well established as the measure of the relative importance of firm-specific information in its stock price movement variations. In the context of event studies, Dasgupta, Gan, and Gao (2010) have argued, based on their theoretical model, that if the market is efficient, there should be less surprise (and thus less reaction) to event announcements among stocks with higher price synchronicity (e.g., higher R^2). In their rationale, higher R^2 stocks are less responsive to announcements, since relatively more firm-specific information would have already been impounded in their stock prices. As a result, there would be less surprise as announcements unfold, giving the impression that stock price movements are more reflective of market factors (e.g., high price synchronicity) over time. By examining dividend change announcements, this essay provides an empirical investigation on such a prediction in a corporate context.

The analysis begins by examining the signaling effects of dividend change announcements (dividend increases and dividend decreases) on stock market reactions conditional on different R^2 levels. Results for U.S. stocks during the 1950–2012 period show that price reactions to both dividend increase and dividend decrease announcements are indeed stronger for stocks with lower levels of R^2, and the magnitude of reactions decreases monotonically with the increase of R^2 levels, not only on the announcement day, but also on days around the announcement. However, this relationship is more prominent among dividend decrease announcements. These findings also hold in the multivariate regression analysis with inclusion of other control variables, including the magnitude of dividend changes and firm size, among others.

These findings extend the existing literature in two major ways. First, while there is established empirical evidence in the dividend signaling literature regarding the positive price responses to dividend increase announcements and the negative prices responses to dividend decrease announcements, no direct link has yet been made between the relative importance of firm-specific information and the magnitude of the price impact. Thus, this study lends further support to the view that investors perceive dividend change announcements as providing signals about specific firms' future prospects (see e.g., Aharony & Swary, 1980; Bajaj & Vijh, 1990; Pettit, 1972; Nissim & Ziv, 2001; and Amihud & Li, 2002). Second, by showing that there is an inverse relationship between price synchronicity and the magnitude of price reaction to firms' announcements, this study adds to the limited empirical evidence for the more recent and radical view that lower R^2 stocks are actually less informative. This view is formalized in the Dasgupta, Gan, and Gao (2010) theoretical model, but has never been formally tested in the context of the corporate signaling effect. Dasgupta, Gan, and Gao (2010) examine the change of the price synchronicity before and after events that should affect stock price informativeness. A higher degree of synchronicity (e.g., higher R^2) is observed after the informativeness promoting events such as seasoned equity issues and ADR listings. In other words, their empirical tests deal with longer term dynamics of R^2. In comparison, the tests of this study focus on the immediate effect of the event with the prediction that the event announcement impact will be higher for stocks with lower synchronicity. This study and the study done by Dasgupta, Gan, and Gao (2010) are complementary with consistent results.

As an important extension, this essay further investigates whether the ability of dividend changes to predict future earnings is stronger among lower R^2 stocks. Classical theoretical work suggests that dividend payments provide a reliable signal (from management) to investors about the firm's earnings prospects in an imperfect capital market. Lintner (1956) suggests that a firm's dividend policy reflects management's view of future earnings, as managers only increase a firm's dividend payments when they believe that the firm will have a substantial increase in earnings. Nevertheless, the empirical findings on this particular issue are, at best, mixed. Studies offering empirical evidence of this include Brickley (1983), Healy and Palepu (1988), Aharony and Dotan (1994), and Nissim and Ziv (2001). Examples of contradicting evidence are those by Watts (1973), Penman (1983), DeAngelo, DeAngelo, and Skinner (1996); and Benartzi, Michaely, and Thaler (1997). In one comprehensive study, Grullon, Michaely, Benartzi, and Thaler (2005) specifically argue that the results of the study by Nissim and Ziv (2001) are biased due to model misspecification problems. Grullon, Michaely, Benartzi, and Thaler (2005) find that dividend changes do not signal future earnings changes after controlling for the non-linear patterns in the behaviour of earnings. Whether dividend changes are positively correlated to future earnings changes is thus an ongoing debate.

As outlined in the next section, this essay also examines whether the quality of dividend signals about firms' future earnings is related to price synchronicity. If managers of low R^2 firms[8] observe stronger price reactions to their corporate announcements through

[8] West (1988), Kelly (2014), Li, Rajgopal, and Venkatachalam, (2014), and Chan and Chan (2014) are examples of studies that indicate low R^2 stocks are operating in a noisier information environment. To the extent that probability of crashes is higher for stocks traded in such an environment (see e.g., Calomiris, Love, & Peria, 2012), managers are motivated to send more reliable signals about firms' prospects to the stock

time, then they should be more cautious in sending such signals and require more confidence around future earnings before doing so. Therefore, this essay re-examines the relationship between changes in current dividend payments and future earnings conditional on price synchronicity. Specifically, it tests whether the correlation between current dividend changes and future earnings varies with synchronicity. The overall results support this proposition for dividend decrease announcements. The findings show current dividend decrease changes provide credible signals about firms' future earnings prospects, and such positive correlation is indeed greater among less synchronized stocks. This is an interesting empirical result in itself, as it is in contrast to recent studies that document the disappearing signals in dividend announcements (e.g., DeAngelo, DeAngelo, & Skinner, 1996; Benartzi, Michaely, & Thaler, 1997; and Grullon, Michaely, Benartzi, & Thaler, 2005). To the extent that low R^2 stocks represent more opaque stocks (e.g., Kelly, 2014), the result on dividend decrease announcements from this essay compliments the view of Miller and Modigliani (1961) that dividend changes do convey information about future earnings, but only in conditions of market imperfection or uncertainty. This result is also consistent with the learning hypothesis, suggesting that stock prices contain information about firms' future prospects, which managers can learn and use in shaping their corporate investment decisions (Chen, Goldstein, & Jiang, 2007; Foucault & Fresard, 2014). As low R^2 stocks are more sensitive to dividend changes (particularly to dividend decrease changes), their greater price changes provide more information to managers to learn and utilize in forming their investment decisions, and ultimately result in greater impact on firms' future performance.

market. This could compensate for lack of analyst coverage, and at the same time, does not increase the probability of stock price crashes for the company.

While this study has documented a significant relation between firms' current dividend decrease changes and future earnings changes, current dividend increase announcements generally do not provide credible signals about firms' future prospects in this study, which is consistent with Grullon, Michaely, Benartzi, and Thaler (2005). This may be because there is a greater degree of certainty around future falls in company profitability as compared to future increases. That is, overconfidence or incentive to convey good news may persist among corporate executives. As shown by the results, the relationship between stock price synchronicity and credibility of signals conveyed by dividend increase announcements is in the expected direction but these results are not statistically significant at the conventional level.

In the next section, related literature of dividend signaling effects is reviewed. Section 3.3 develops the hypotheses. Section 3.4 describes the data and methodology. Section 3.5 reports the empirical results and analysis. Section 3.6 outlines the conclusions of this essay.

3.2 Literature Review of Dividend Signaling Effect

Researchers have long been studying the dividend signaling effect on stock price and have well documented a positive association between dividend change announcements and stock price changes. For example, Pettit (1972) and Aharony and Swary (1980) find that managers use dividend announcement as a signaling vehicle to deliver considerable amounts of information to the market. Investors make use of this information to assess stock value, leading to stock price changes.

Similarly, Brinkley (1983) examines and compares the signaling effect of special labelled dividend increases (e.g., “extra,” “special,” “year-end”) and regular unlabeled dividend increases. He exhibits evidence consistent with the signaling hypothesis and suggests that managers signal to the stock market about firms’ future dividends and earnings through the labelling of dividend increases, and regular dividend increases convey a greater amount of favourable information than special labelled dividend increases.

In addition, Denis, Denis, and Sarin (1994) further investigate stock price reaction to dividend announcements based on three explanation hypotheses, namely the cash flow signaling, the overinvestment, and the dividend clientele hypotheses. By incorporating these three hypotheses into a single testing framework, their empirical results suggest that the stock price reaction to dividend change announcements can be explained by the cash flow signaling and dividend clientele hypotheses.

Moreover, Asquith and Mullins (1983) further confirm the role of dividend announcements in conveying unique and valuable information to the public. They investigate both dividend initiations and subsequent dividend increase announcements and document large positive impacts of such announcements on shareholders’ wealth.

Dividend signaling theory also suggests that dividend changes convey information about firms' future earnings. Lintner (1956) establishes that if management expects future earnings to increase in the next year, management declares higher dividends in the current year. This indicates that firms' future profitability can be predicted by their current dividend changes. Theories by Bhattacharya (1979), John and Williams (1985), and Miller and Rock (1985) imply that dividend increases, in particular, signal better prospects about a firm.

However, unlike the first implication of the theory (i.e. the dividend signaling effect on stock price), the empirical evidence on whether current year dividends provide a credible signal regarding firms' future prospects has been weak, or mixed at best. Most of the empirical studies (see, e.g., Watts, 1973; Gonedes, 1978; Penman, 1983; DeAngelo, DeAngelo, & Skinner, 1996; Grullon, Michaely, & Swaminathan, 2002; Grullon, Michaely, Benartzi, & Thaler, 2005) indicate that there is no strong signal about firms' future prospects from unexpected dividend changes. The only exception to this is the positive finding by Nissim and Ziv (2001), who argue that earlier studies suffer from an omitted variable problem, as they fail to include relevant variables such as return on equity and past change in earnings to account for the mean reversion and autocorrelation process in earnings. Nevertheless, after considering the non-linearity issue, Grullon, Michaely, Benartzi, and Thaler (2005) show that the ability of unexpected dividend changes to forecast future earnings disappears altogether again.

3.3 Hypotheses Development

Based on the premise that R^2 measures the relative importance of firm-specific information in stock price variations, this essay first aims to investigate whether investors' reactions to firm-specific information conveyed by dividend change announcements would vary with the relative importance of firm-specific information to such firms. To the extent that low R^2 firms are associated with attributes of poor information environment (Kelly, 2014), if dividend announcements convey new firm-specific formation about a firm's future value to the market, then lower R^2 stocks are expected to react more to dividend announcements. As the firm-specific information is less likely to have already been previously anticipated and incorporated into their stock prices, there should be more surprise for lower R^2 firms when the informational event actually occurs (Dasgupta, Gan, & Gao, 2010). Therefore, the first hypothesis is:

H1: Firms with lower levels of R^2 experience stronger price reaction to dividend increase and decrease announcements than firms with higher levels of R^2.

Next, this essay aims to add further empirical evidence to the ongoing debate as to whether dividend changes convey information about firms' future earnings by considering stock price synchronicity (R^2) in the analytical framework. Corporate behaviour models (see, e.g., Dow & Gorton, 1997; Subrahmanyam & Titman, 1999) suggest that information contained in firms' stock prices can be observed by managers and consequently used in shaping their behaviours and decisions regarding a firm. In the same vein, Chen, Goldstein and Jiang (2007) specifically show that the investment activities react more to stock prices among less synchronized firms, indicating that managers learn more from less synchronized stock prices and use the information to make investment decisions. Given that dividend signaling is costly, a rational manager should choose to exercise it only when he or she observes that firm-specific information is relatively important in his or her own company's stock price movements, ceteris paribus. In other words, managers of companies with low R^2 should be aware that any signal given through changes in dividends will be perceived to be a strong signal. Managers of companies with low R^2 may therefore be more cautious in sending such a signal and require more confidence around future earnings before doing so. Furthermore, based on the premise that firms with low R^2 are less informative and are associated with a poor information environment (see, e.g., West, 1988; Kelly, 2014; Li, Rajgopal & Venkatachalam, 2014; Chan & Chan, 2014), managers of these firms are motivated to send more genuine signals about their firms' prospects to improve their firms' informational environments and avoid future stock price instability at the same time. Therefore, the second hypothesis is:

H2: Current dividend increases and decreases will have stronger correlation to future earnings for firms with lower levels of R^2 than for firms with higher levels of R^2.

3.4 Data and Methodology

3.4.1 Measuring a firm's R^2 and group categorization

In finance literature, the goodness of fit statistic (R^2) derived from the market model (or some capital asset pricing model) regression on a particular stock is widely referred to as a measure of the relative importance of firm-specific news against market-wide information in explaining variations in stock price movements. Roll (1988) suggests that R^2 measures the capitalization of firm-specific information in a firm's stock price. The more firm-specific news is capitalized into the firm's stock price, the less variation of realized returns around the expected return can be explained by capital asset pricing models which incorporate systematic risk, and the lower the R^2 value will be. Durnev, Morck, Yeung, and Zarowin (2003) and Durnev, Morck, and Yeung (2004) provide further evidence that a stock with lower R^2 incorporates more information about future earnings into current stock returns. Hutton, Marcus, and Tehranian (2009) report that firms with higher levels of earnings management are associated with higher R^2 (e.g., less firm-specific information is available about the firm) and experience higher crash risk. While based on different perspectives or interpretations from traditional studies, Dasgupta, Gan, and Gao (2010) also use R^2 as the measure of relative importance of firm-specific information in the stock price dynamics. In contrast, they find low R^2 stocks are less informative stocks with less firm-specific information being previously incorporated into their stock prices.

The estimation of R^2 in corporate context literature is commonly based on the market model with inclusion of industry returns (see, e.g., studies on R^2 and corporate investment: Durnev, Morck, & Yeung, 2004; Chen, Goldstein, & Jiang, 2007; and on R^2 and firm valuation: Stowe & Xing, 2011). To allow comparison of results with other literature in this particular branch, in this essay each sample stock's return R^2 is estimated using a market-industry model based on weekly returns[9]. The market-industry model is specified as below:

$$R_{i,j,t} = \beta_{i,0} + \beta_{i,m} * R_{m,t} + \beta_{i,j} * R_{j,t} + \varepsilon_{i,t} \tag{1}$$

[9] Estimating R^2 based on a different model does not change the overall empirical findings. Effort has been made to calculate R^2 using a four-factor model consistent with essay one; the empirical findings remain consistent with the results presented here.

where $R_{i,j,t}$ is the return of firm i in industry j at time t, $R_{m,t}$ denotes the market return at time t, and $R_{j,t}$ refers to the return of industry j at time t.

In each year, sample stocks are sorted based on R^2 that is measured in the year before and divided into terciles: low R^2, medium R^2, and high R^2, where each group contains about one-third of the whole sample[10]. To convert R^2 into synchronicity for the multivariate regression analysis, the regression R^2 obtained from Equation 1 for each stock is normalized by logging the ratio of R^2 / (1- R^2) following Morck, Yeung, and Yu (2000); Durnev, Morck, Yeung, and Zarowin (2003); Durnev, Morck, and Yeung (2004); and others.

To measure price reactions to quarterly dividend change announcements for different levels of R^2, quarterly dividend change announcements are classified into dividend increase and dividend decrease groups[11].

[10] To ensure robustness of results, results are checked using a different R^2 grouping method by dividing sample stocks into Low, Medium and High R^2 groups (defined as bottom 30%, medium 40% and top 30% of all sample stocks' return R^2). Results remain qualitatively unchanged.

[11] Dividend initiations are also an important form of dividend signaling. Asquith and Mullins (1983) and Healy and Palepu (1988) document much larger price reactions to dividend initiations than dividend increases, indicating dividend initiations carry a bigger chunk of firm-specific information than dividend increases. Although dividend initiations are not the main focus in this study, the same tests are performed to examine the signaling effect and R^2 on dividend initiation announcements for analysis completeness. A total of 3,490 dividend initiations between 1950 and 2012 are obtained. Results of dividend initiations are consistent with dividend increases and decreases, in which a monotonic pattern of price reaction across three R^2 groups is identified. In the unreported results table, CAR (-1, 1), CAR (-1, 0), and CAR (0, 1) in dividend initiation group are all found to decrease monotonically with the increase of R^2 levels.

3.4.2 Sample selection

The initial sample is selected to examine the magnitude of stock price reaction to dividend change announcements. To test the first hypothesis about the different impacts of dividend change announcements on stocks with different R^2, all dividend announcements reported in the Center for Research in Securities Prices (CRSP) data files for NYSE and AMEX listed securities from 1950 to 2012 are included. Stock price relevant data are collected from CRSP, other accounting data are collected from Compustat. The final sample must satisfy the following criteria:

1. The company is not a financial institution (SIC code from 6000-6999). This criterion is set to increase homogeneity (Nissim & Ziv, 2001).
2. The company must have a valid dividend announcement date.
3. To be included in the sample, a firm's R^2 must be available in the year before the dividend announcement date. The information on daily stock adjusted returns and the daily return of CRSP NYSE/Alternext/Nasdaq Value-Weighted Market Index in the year before dividend announcement date must be available on the CRSP data files.
4. The company must pay a regular quarterly cash dividend in U.S. dollars (distribution code 1232). Special, year-end, interim or non-recurring dividends are excluded.
5. No other distributions or events are announced during the period of 15 days before and after the declaration of the current dividend. The purpose of this exclusion is to ensure that changes in regular quarterly cash dividends are not entangled with impacts from other distributions or events, such as stock dividends or earnings announcements.

6. Dividend changes that are smaller than 0.5% of the previous dividend are excluded. This criterion is set to avoid the record errors (Amihud & Li, 2002).
7. If a dividend change results from mergers or acquisitions, stock splits, and other events that adjust prices, the dividend change is excluded from the sample for which price reactions are analysed.

The final sample firms that satisfy the above criteria result in 26,116 quarterly dividend change announcements for different levels of R^2: 23,439 dividend increases and 2,677 dividend decreases. Table 3.1 provides detailed summary statistics for the sample. Panel A presents the summary statistics of the numbers of quarterly dividend increases and quarterly dividend decreases within each R^2 group throughout the sample period. Interestingly, the low R^2 firms have the smallest number of quarterly dividend increases and the largest number of quarterly dividend decreases over the whole sample period. Panel B reports the summary statistics of the R^2 means and medians for the low, medium, and high groups. Within the quarterly dividend increase group, the low R^2 group has a sample mean of 0.1250 (sample median of 0.1055). The sample means (medians) for the high R^2 and medium R^2 groups are 0.4445 (0.4233), and 0.2667 (0.2484), respectively. For quarterly dividend decreases, the sample means (medians) for the low R^2, medium $R^{2,}$ and high R^2 groups are 0.1240 (0.1015), 0.2724 (0.2474), and 0.4499 (0.4193) respectively.

To test the second hypothesis regarding whether changes in current dividend payments provide a better signal about future earnings among less synchronized (low R^2)

Table 3.1 Summary statistics – dividend announcements and R^2 group

This table reports dividend changes frequency across R^2 groups (Panel A) and the mean and median level of R^2 (Panel B). The final sample of 26,116 quarterly dividend announcements is selected based on dividend announcements reported in the CRSP data files for NYSE and AMEX stocks during the period of July 1950 to 2012. In each year, sample stocks are sorted based on their return R^2 measured in the year before and divided into the low (33.33%), medium (33.34%), and high (33.33%) R^2groups.

Panel A: The frequency of dividend changes in different levels of R^2 over years

	Dividend Increase			Dividend Decreases		
Year	Low R^2	Medium R^2	High R^2	Low R^2	Medium R^2	High R^2
1951-1955	138	141	173	56	66	48
1956-1960	226	219	212	94	102	121
1961-1965	359	427	422	65	53	58
1966-1970	414	460	515	85	101	101
1971-1975	746	841	876	130	103	66
1976-1980	1309	1514	1676	68	51	39
1981-1985	696	726	782	87	75	44
1986-1990	595	709	881	72	47	26
1991-1995	619	656	739	89	57	50
1996-2000	470	427	470	77	57	47
2001-2005	607	536	507	66	58	49
2006-2012	1260	1065	1026	134	125	110
Total	7439	7721	8279	1023	895	759

Panel B: The mean and median level of R^2

	Dividend Increase			Dividend Decreases		
	Low R^2	Medium R^2	High R^2	Low R^2	Medium R^2	High R^2
R^2 Mean	0.1250	0.2667	0.4445	0.1240	0.2724	0.4499
R^2 Median	0.1055	0.2484	0.4233	0.1015	0.2474	0.4193

stocks, the final sample firms need to satisfy Criteria 1–3. Furthermore, companies must also have annual-basis variables in the regressions, including earnings (e.g., income before extraordinary items), book value of equity, annual dividend payments, return on equity, and total assets. As a normal distribution is required in order to conduct the null hypothesis test about the regression model parameters, the top and bottom 1% of regression variables is winsorized to reduce the skewness and kurtosis of the disturbances. The final observations are distributed relatively evenly among stocks with high versus low levels of R^2.

To begin the analysis, firm-level characteristics are estimated and compared across the three R^2 groups. The summary statistics are reported in Table 3.2. Overall, consistent with Kelly (2014), Li, Rajgopal, and Venkatachalam, (2014), and Chan and Chan (2014), the results show that low R^2 stocks demonstrate characteristics associated with a relatively poor information environment; they are smaller in firm size as measured by *Total Assets,* less profitable as measured by *Return on Equity* (median values) and *Earnings*, and associated with greater growth opportunities as measured by *Market-to-Book Ratio*. Firms with low R^2 have lower *Dividend Payout Ratio* but they change their dividend policy more frequently as indicated by higher *Dividend Change Frequency*. This may be because the more volatile business environment for low R^2 firms forces the managers to adjust their dividend policy more often, although they should be aware that a strong price reaction would be caused as a consequence. In contrast, firms with high R^2 are shown to be bigger, more mature, and associated with a more informative environment; managers are therefore more likely to maintain a stable dividend policy. Low R^2 stocks are also found to be associated with higher *Debt Ratio* and lower *Stock Turnover*, which can be viewed as indicators of stock sensitivity to market crash, according to Calomiris, Love, and Peria (2012). These findings provide support for the second hypothesis; given the vulnerability and fragility to market crash of low R^2 firms, managers of these firms will be more cautious and require more confidence when making dividend policy decisions, as any inaccurate dividend changes will, to a great extent, drive their stock prices away from the fundamental values.

Table 3.2 Summary statistics – firm characteristics and R^2 group

This table summarises firm characteristics among each R^2 subset. The mean (median) estimate of each measure among each R^2 subset is reported in Columns 2-4. The differences between low R^2 subset and high R^2 subset are reported in Column 5. Variable details are provided in the Appendix. The *p*-values for the differences in means between low and high R^2 subsets are adjusted for clustering at the firm level, and differences in medians are assessed using the Wilcoxon test. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Low R^2	Medium R^2	High R^2	Low - High	*P*- value for Difference in Mean (Median)
Assets	1428.40	2033.02	3171.41	-1743.01***	<0.000
	(581.11)	(1018.61)	(2150.31)	(-1569.2) ***	(<0.000)
Market-to-Book Ratio	2.0883	1.9236	2.0255	0.0628***	<0.000
	(1.4479)	(1.5876)	(1.6533)	(-0.2054)	(0.7129)
Debt Ratio	0.0411	0.0391	0.0375	0.0036**	0.0353
	(0.0218)	(0.0219)	(0.0204)	(0.0014)	(0.3128)
Stock Turnover	0.0684	0.0334	0.0757	-0.0073	0.7851
	(0.0072)	(0.0076)	(0.0081)	(-0.0009) *	(0.0539)
Return on Equity	0.1168	0.1173	0.1159	0.0009	0.8051
	(0.1185)	(0.1238)	(0.1259)	(-0.0074) ***	(<0.000)
Earnings	61.46	88.08	129.70	-68.24***	<0.000
	(23.23)	(38.50)	(71.29)	(-48.06) ***	(<0.000)
Dividend Change Frequency	1.1681	1.1005	1.0894	0.0787***	<0.000
	(1.00)	(1.00)	(1.00)	(0.00) ***	(<0.000)
Dividend Payout Ratio	2.3665	6.8647	7.8635	-5.497***	0.0039
	(0.3658)	(0.3392)	(0.3507)	(0.0151) **	(0.0397)

3.4.3 Measuring abnormal returns of quarterly dividend change announcements conditional on R^2

This essay follows the approach of Aharony and Swary (1980) to measure the average abnormal returns of quarterly dividend change announcements for the different R^2 groups following dividend announcements. For any security return *q*, a single factor market model is:

$$R_{qt}= \alpha_0+\beta_q R_{mt}+e_{qt} \tag{2}$$

where R_{qt} and R_{mt} are the daily rates of return of security *q* on day *t*, and the daily rate of return of the Value-Weighted Market Index on day *t*; e_{qt} is the zero mean disturbance term and is assumed to be uncorrelated with R_{mt}; and α_0 and β_q are the estimated parameters of the market model.

Assuming parameters are stationary and the security returns are normally distributed, the lengths of the dividend event window are defined as (-5, +5). The market model is estimated over the 80 trading days from t = -100 to t = -21[12]. Sample firms must have at least 60 daily returns in the estimation period. This criteria reduces the total number of quarterly dividend increases from 23,439 to 23,322 during the sample period from 1950 to 2012 (7,380 quarterly dividend increases for low R^2 stocks, 7,686 quarterly dividend increases for medium R^2 stocks, and 8,256 quarterly dividend increases for high R^2 stocks). Total number of quarterly dividend decreases reduces from 2,677 to 2,653 over

[12] Using alternative estimation periods to estimate abnormal returns do not change the overall results. Results have been checked based on an estimation period (-250, -11) following Bajaj and Vijh (1990) and (1995), and an estimation period (-131, 31) consistent with essay one. Results are qualitatively unchanged from those presented here.

the sample period (1,012 quarterly dividend decreases for low R^2 stocks, 888 quarterly dividend decreases for medium R^2 stocks, and 753 quarterly dividend decreases for high R^2 stocks).

The market model parameters, α_0 and β_q, are calculated by running OLS regression on Equation 2 over the estimation period of 80 trading days from t = -100 to t =-21. The estimated abnormal return, u_{it} is computed by using the actual return on day t minus the predicted return on day t in the market model:

$$u_{qt} = R_{qt} - (\alpha_0+\beta_q R_{mt}) \tag{3}$$

The daily estimated abnormal return, u_{qt} is used to measure the information content of quarterly dividend changes. The daily average estimated abnormal return ($AR_{i,j}$) for dividend changes category i (increase/decrease) and stock's return R^2 category j (low, medium, and high R^2) is calculated by averaging the daily estimated abnormal returns u_{qt} over all the N_{ij} events belonging to stock group ij during the sample period. The daily average cumulative abnormal returns (CAR) for each stock is also calculated over the event window period and then averaged for each stock group ij.

$$CAR_{i,j} = (\textstyle\sum_{t=t1}^{t2} u_{q,t})/N_{i,j} \tag{4}$$

To test if the mean abnormal return on day t of the low R^2 group is statistically different from the high R^2 group, the t-statistics are calculated for the low-minus-high differences in each dividend change group as follows:

$$t_{LH} = (AR_{i,L}-AR_{i,H})/(S_{i,L}/n_{i,L} + S_{i,H}/n_{i,H})^{1/2} \tag{5}$$

where t_{LH} is a t-statistic that tests the difference between the daily mean abnormal return on day t for the low R^2 dividend change group and the daily mean abnormal return on day t for the high R^2 dividend change group; $AR_{i,L}$, and AR_{iH} are the mean abnormal returns on day t for the low and high R^2 groups within a dividend change group i; and $S_{i,L}$, and $S_{i,H}$ are the residual standard deviations on day t for the low and high R^2 groups within a dividend change group i.

3.4.4 R^2 and abnormal returns of quarterly dividend change announcements: regression analysis

The robustness of the univariate relationship between R^2 and abnormal returns of quarterly dividend changes is tested by controlling for other firm-level control variables. The following regression model is performed separately for dividend increases and dividend decreases. Abnormal returns on the dividend announcement date 0 are used as the dependent variable. Since R^2 is bounded between 0 and 1, R^2 is converted to the *synchronicity* measure using log $(R^2/(1-R^2))$. The OLS regression model is specified as below:

$$Abnormal\ Return = a_0 + a_1\ synchronicity + a_2\ change\ in\ dividend + a_3 dividend\ yield + a_4\ cash\ flow + a_5 profitability + a_6\ growth\ opportunity + a_7 firm\ size \quad (6)$$

Denis, Denis, and Sarin (1994) document that dividend announcement period excess returns are positively related to the magnitude of standardized dividend change and dividend yield, and negatively related to cash flow. Fama and French (2001) suggest that dividend payers are particularly firms with large size, greater profitability, and less growth opportunities. To ensure results are not driven by these previously documented effects or typical firm characteristics, *Change in Dividend*, *Dividend Yield*, *Cash Flow*, *Profitability, Growth Opportunity*, and *Firm Size* are included as control variables. Specifically, *Change in Dividend* is measured as the dividend change scaled by the stock price two days prior to the dividend announcement date; *Dividend Yield* is the CRSP annual return from dividend payments; *Cash Flow* equals the operating income before depreciation minus interest expenses, taxes, preferred dividends, and common dividends, all divided by total assets; *Profitability* is estimated as the ratio of firm's earnings before interest to its total assets; *Growth Opportunities* are represented by *Market-to-Book Ratio*; and *Firm Size* is denoted as the log of total assets. Following Denis, Denis, and Sarin (1994), control variables *Dividend Yield, Cash Flow, Profitability*, and *Growth Opportunity* are measured as of the fiscal year ending just prior to the dividend announcement.

Previous literature has documented a strong correlation between price synchronicity and firm size. To ensure the results are not driven by the impact of size on synchronicity, the size effect on synchronicity is further purged out by using *Orthogonalized Synchronicity* to replace *Synchronicity* in Equation 6. As explained in essay one, this methodology allows synchronicity, which is strongly correlated with firm size and possibly with other control variables, to be converted into the portion of synchronicity that is independent to other effects. In this essay, *Orthogonalized Synchronicity* is estimated as the residual from the regression of synchronicity on all the remaining independent variables included in Equation 6.

3.4.5 The relationship between current dividends and future earnings conditional on R^2

The test of the second hypothesis is based on the comprehensive and conservative regression approach introduced by Grullon, Michaely, Benartzi, and Thaler (2005). Specifically, the regression for future earnings is estimated in the following equation:

$$\begin{aligned}\frac{(E_\tau - E_{\tau-1})}{B_{-1}} &= \beta_0 + \beta_{1P} DPC_0 \times R\Delta DIV_0 + \beta_{1N} DNC_0 \times R\Delta DIV_0 \\ &+(\gamma_1 + \gamma_2 NDFED_0 + \gamma_3 NDFED_0 \times DFE_0 + \gamma_4 PDFED_0 \times DFE_0) \times DFE_0 \\ &+(\lambda_1 + \gamma_2 NCED_0 + \gamma_3 NCED_0 \times CE_0 + \lambda_4 PCED_0 \times CE_0) \times CE_0 + \varepsilon_\tau \end{aligned} \tag{7}$$

where E_τ and $E_{\tau-1}$ are earnings before extraordinary items of firm *i* in year τ and year τ-1 accordingly; B_{-1} is book value of equity at the end of year -1; DPC_0 is the dividend increase dummy variable, which takes a value of 1 if the annual dividend payment in year 0 (event year) is higher than that in year *t*-1, and zero otherwise; DNC_0 is the dividend decrease dummy variable, which takes a value of 1 if the annual dividend payment in year 0 is lower than the previous year, and zero otherwise: *RΔDIV* is the annual percentage change in cash dividend payment in year 0 compared to that in the previous year; DFE_0 is the unexpected profitability in the contemporaneous year defined as the difference between realized return on equity of the firm in year 0 and the expected value (E(ROE)) or fitted value of $ROE_{i,0}$ derived from the regression: $ROE_0 = \alpha_0 + \alpha_1 lnTotalAssets_{t-1} + \alpha_2 lnMB_{t-1}$ +

$\alpha_2 ROE_{t-1}$ + ε; where $TotalAssets_{t-1}$, MB_{t-1} and ROE_{t-1} represent total assets, market-to-book ratio, and return on equity, respectively, of firm *i* in year *t*-1. $NDFED_0$ is a negative dummy variable which takes the value of 1 if DFE_0 is negative and zero otherwise; $PDFED_0$ is a positive dummy variable which takes the value of 1 if DFE_0 is positive and zero otherwise; and CE_0 is the shift in earnings of firm *i* in year 0 compared to the previous year, scaled by the book value of equity in the previous year. $NCED_0$ is a negative dummy variable, which takes the value of 1 if CE_0 is negative, and zero otherwise; and $PCED_0$ is a positive dummy variable, which takes the value of 1 if CE_0 is positive, and zero otherwise.

The above regression is the modified partial adjustment model in the spirit of Fama and French (2000). Grullon, Michaely, Benartzi, and Thaler (2005) utilize this approach to control for the non-linear relationship between changes in the firm's future prospects (i.e. shifts in earnings) and lagged earnings. This is important to acknowledge since asymmetric patterns in the earnings process (e.g., faster reversions in earnings for larger and negative changes) are documented by Brooks and Buckmater (1976), Elgers and Lo (1994), and Fama and French (2000). As Grullon, Michaely, Benartzi, and Thaler (2005) report no relationship between future earnings and current dividends, this method should provide a conservative model for use in investigating the research question of this study. This regression model also allows distinguishing between the different signals for dividend increases and dividend decreases. In accordance with the dividend signaling hypothesis, if changes in current dividends convey information about firms' future earnings, the estimated coefficients of β_{1P} and β_{1N} in Equation 7 should be significantly positive. To test the second hypothesis regarding whether changes in current dividends have a stronger correlation to future earnings for firms with lower levels of R^2 than for firms with higher levels of R^2, *Synchronicity* and two interaction terms, *Synchronicity*DPC*RDIV* and *Synchronicity*DNC*RDIV*, are introduced into Equation 7. The two interaction terms examine whether the effect of dividend increases (*DPC*RDIV)* or dividend decreases (*DNC*RDIV)* on future earnings changes varies with the magnitude of synchronicity. To purge out the size effect and other possible effects on synchronicity, *Synchronicity* is also converted into *Orthogonalized Synchronicity* and the regression model is replicated.

To deal with panel data regressions, the standard errors are adjusted for clustering at both the firm level and year level. The reason for this is to produce unbiased standard errors and to improve the efficiency of the coefficients as to whether the firm effect or time effect in both the independent variable and the residual is permanent or temporary.

3.5 Empirical results

3.5.1 Do prices of low R^2 stocks display stronger reaction to dividend change announcements?

Quarterly announcements of dividend increases and dividend decreases are used to examine whether price reaction is the strongest for stocks with low R^2. Table 3.3 reports the daily average abnormal returns and cumulative daily average abnormal returns for three R^2 groups for the dividend increase group and the dividend decrease group over the entire sample period from 1950 to 2012. Within the dividend increase group (Panel A), the average daily abnormal returns on the dividend announcement date (date 0) show a monotonic trend across all three R^2 groups: the average daily abnormal returns are 0.54%

for the low R^2 group, 0.46% for the medium R^2 group, and 0.38% for the high R^2 group. These average abnormal returns on the dividend announcement date are positive and highly significant at the 1% level, which supports the notion that dividend increases are associated with positive abnormal returns. The low-minus-high difference is positive and statistically significant at the 1% level, indicating that the low R^2 group has a greater price reaction in response to the dividend increase announcements than the high R^2 group. The monotonic relationship between the price reaction and R^2 is consistent with the first hypothesis that the signaling effect of dividend announcements is strongest for the low R^2 group. Also, within the dividend increase group, the average cumulative abnormal returns, CAR (-1, 1), CAR (-1, 0), CAR (0, 1), and CAR (-5, 5), are all found to decrease monotonically with the increase of R^2 levels. These average cumulative abnormal returns, as well as their low-minus-high differences, are all positive and significantly different from zero at the 1% level. This provides further supportive evidence of the validity of the first hypothesis.

Next, price reaction to the announcements of dividend decreases within different levels of R^2 is tested by using the market model, and it is expected that price reaction to dividend decreases on the dividend announcement day would be more markedly negative for the lower R^2 group. The results shown in Table 3.3 Panel B illustrate that within the dividend decrease group, the average abnormal returns decrease monotonically in magnitude with the increase of R^2 levels on announcement day (date 0); the average abnormal returns are -1.37%, -1.21%, and -1.13% for the low, medium, and high R^2 groups respectively, and are statistically significant at the level of 1%. Similar to the findings for the dividend increase group, the monotonic relationship between price reaction in response to the dividend decrease announcements and R^2 levels continues to hold for wider periods of time around the announcement date. Specifically, there is a monotonic trend of the average cumulative abnormal returns across the three R^2 groups for CAR (-1, 1), CAR (-1, 0), CAR (0, 1), and CAR (-5, 5), with statistical significance at the 1% level. The low-minus-high differences for CAR (-1, 1), CAR (0, 1), and CAR (-5, 5) are negative and significant at the 5% level, indicating that low R^2 stocks have more negative cumulative price responses to dividend decrease announcements than high R^2 stocks. This is in line with the first hypothesis.

It is also worth noting that the signaling effect is asymmetric between good news and bad news; the magnitude of price reaction conditional on different R^2 levels is greater in the dividend decrease group compared to the dividend increase group, not only on the announcement day, but also for wider periods of time around the announcement date. This finding implies that unfavourable news sends a stronger signal to investors and conveys a greater amount of information than favourable news; hence, unfavourable news is more informative.

Table 3.3 Dividend signaling effect among stocks with different R^2 levels

Tables below report the daily average abnormal returns and the cumulative daily average abnormal returns in three different R^2 groups for the quarterly dividend increase group (Panel A) and the quarterly dividend decrease group (Panel B) during the sample period of 1950 to 2012. Standardized cross-sectional Z scores are presented in parentheses. The Low-minus-High is defined as the difference of daily mean abnormal returns between low R^2 group and high R^2 group. The t statistics are calculated for testing whether the Low-minus-High differences are statistically different from 0. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, using a 2-tail test.

Panel A: Dividend increase announcements

	Dividend Increase			
R^2 Group	Low R^2	Medium R^2	High R^2	Low-High
Event day	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (T Value)
-5	0.01% (1.108)	0.01% (0.703)	0.02% (1.297)	-0.01% (-0.742)
-4	0.06% (2.339**)	0.03% -1.204	0.00% -0.501	0.06% (1.853*)
-3	0.02% (0.811)	0.05% (2.234**)	0.03% (2.435**)	-0.01% (-0.425)
-2	0.06% (2.987***)	0.05% (3.014***)	0.04% (2.101**)	0.02% -(0.818)
-1	0.04% (1.651*)	0.08% (4.189***)	0.07% (4.006***)	-0.03% (-1.003)
0	0.54% (20.115***)	0.46% (17.969***)	0.38% (17.703***)	0.16% (4.425***)
1	0.34% (13.440***)	0.29% (12.855***)	0.25% (12.609***)	0.09% (2.437**)
2	0.16% (7.625***)	0.13% (6.977***)	0.09% (5.720***)	0.07% (2.320**)
3	0.11% (5.971***)	0.08% (5.006***)	0.04% (2.441**)	0.07% (2.370**)
4	0.05% (3.006***)	0.03% (2.346**)	0.03% (2.591***)	0.02% (0.454)
5	0.02% (1.858*)	0.03% (2.695***)	0.02% (2.172**)	0.00% (0.023)
CAR (-1, 1)	0.92% (21.429***)	0.83% (21.208***)	0.70% (20.458***)	0.22% (3.660***)
CAR (-1, 0)	0.58% (16.979***)	0.54% (17.156***)	0.45% (16.449***)	0.13% (2.813***)
CAR (0, 1)	0.88% (23.078***)	0.75% (21.263***)	0.63% (20.986***)	0.25% (4.756***)
CAR (-5,5)	1.40% (19.879***)	1.24% (18.957***)	0.97% (17.089***)	0.43% (4.282***)
Obs	7380	7686	8256	

Panel B: Dividend decrease announcements

	Dividend Decrease			
R^2 Group	Low R^2	Medium R^2	High R^2	Low-High
Event day	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (T Value)
-5	-0.10% (-1.341)	-0.11% (-1.942*)	0.08% (-0.187)	-0.18% (-0.938)
-4	0.03% (0.000)	-0.04% (-0.782)	-0.13% (-1.106)	0.16% (1.436)
-3	-0.05% (-1.235)	-0.06% (-0.208)	0.11% (1.203)	-0.16% (-1.328)
-2	0.01% (0.240)	-0.17% (-1.620)	-0.09% (-0.416)	0.10% (0.803)
-1	-0.17% (-1.641*)	-0.14% (-1.757*)	-0.07% (-0.515)	-0.10% (-0.794)
0	-1.37% (-9.163***)	-1.21% (-7.344***)	-1.13% (-7.330***)	-0.24% (-1.095)
1	-1.07% (-7.099***)	-1.14% (-7.803***)	-0.70% (-4.770***)	-0.37% (-1.848*)
2	0.08% (-0.298)	0.02% (0.371)	0.11% (1.320)	-0.03% (-0.209)
3	-0.03% (-1.071)	0.05% (0.599)	0.10% (1.410)	-0.13% (-1.053)
4	-0.05% (-0.540)	0.13% (1.048)	0.12% (1.376)	-0.17% (-1.304)
5	-0.02% (-0.220)	0.09% (1.077)	0.08% (1.343)	-0.10% (-0.814)
CAR (-1, 1)	-2.61% (-11.036***)	-2.49% (-10.331***)	-1.90% (-7.921***)	-0.71% (-2.105**)
CAR (-1, 0)	-1.54% (-8.943***)	-1.35% (-7.312***)	-1.20% (-6.655***)	-0.34% (-1.333)
CAR (0, 1)	-2.44% (-11.240***)	-2.43% (-10.501***)	-1.83% (-8.209***)	-0.61% (-1.994**)
CAR (-5,5)	-2.73% (-8.971***)	-2.57% (-8.161***)	-1.52% (-4.691***)	-1.21% (-2.545**)
Obs	1012	888	753	

It has been well documented in previous literature that firm size has great impact on R^2. Firms with lower stock return R^2 tend to be smaller (see, e.g., Roll, 1988; Kelly, 2014). To ensure that the strongest signaling effect on stock price identified among low R^2 stocks (in Table 3.3) is not merely driven by the size effects, the full sample is divided into size terciles (large size, medium size, and small size). After first dividing the full sample into the size terciles, each tercile subsample is further divided into three R^2 subgroups (low R^2, medium R^2, and high R^2), and then the dividend signaling effect on stock price is re-examined in subgroups of each subsample. This grouping method allows sample events to be relatively evenly distributed across each R^2 subgroup within each size tercile, ensuring result comparability across each subgroup.

Table 3.4 reports the results of price response conditional on different R^2 levels in each size subsample. Overall, findings show that the previous results hold across all size subsamples. The magnitude of price reaction in response to both dividend increases and decreases diminishes monotonically throughout the three R^2 subgroups across all size subsamples on the announcement date 0. The only exception exists in the price reaction for dividend decreases in the small size subsample (shown in Panel C), in which there is a more negative daily average abnormal return for the high R^2 group than for the low R^2 group on event day 0. However, the high-minus-low difference is indistinguishable from 0 (the *t* statistics of the high-minus-low is shown to be insignificant at only 0.42).

Table 3.4 Dividend signaling effect among stocks with different R^2 levels: The size effect

Tables below report the average abnormal returns on the announcement date 0 and the cumulative daily average abnormal returns in three different R^2 groups for the quarterly dividend increase group and the quarterly dividend decrease group during the period of 1950 to 2012 across 3 size subsamples. Results for large size, medium size and small size subsamples are demonstrated in Panel A, B and C respectively. Standardized cross-sectional Z scores are presented in parentheses. The t statistics are calculated for testing whether the Low-minus-High differences are statistically different from 0. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, using a 2-tail test.

Panel A: Large Size Subsample

	Dividend Increase			
R^2 Group	Low R^2	Medium R^2	High R^2	Low-High
Event day	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (T Value)
0	0.30% (7.091***)	0.25% (5.419***)	0.18% (3.806***)	0.12% (1.811*)
CAR (-1, 1)	0.53% (7.919***)	0.48% (6.638***)	0.51% (6.438***)	0.02% (2.953***)
CAR (-1, 0)	0.33% (6.506***)	0.23% (4.689***)	0.31% (5.041***)	0.02% (0.319)
CAR (0, 1)	0.50% (8.024***)	0.49% (7.097***)	0.38% (5.499***)	0.12% (1.232)
CAR (-5,5)	0.88% (6.877***)	0.65% (6.210***)	0.74% (5.319***)	0.14% (0.703)
Obs	1393	1410	1395	

	Dividend Decrease			
R^2 Group	Low R^2	Medium R^2	High R^2	Low-High
Event day	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (T Value)
0	-1.41% (-1.745*)	-1.00% (-2.204**)	-0.11% (-0.490)	-1.30% (-1.530)
CAR (-1, 1)	-2.12% (-1.901*)	-1.46% (-1.995**)	-1.38% (-1.899*)	-0.74% (-0.523)
CAR (-1, 0)	-1.75% (-1.682*)	-0.95% (-1.989**)	-0.53% (-1.326)	-1.22% (-0.996)
CAR (0, 1)	-1.78% (-1.981**)	-1.51% (-2.092**)	-0.95% (-1.314)	-0.83% (-0.764)
CAR (-5,5)	-0.56% (-0.347)	-1.44% (-1.015)	-1.72% (-1.588)	1.16% (0.730)
Obs	117	125	109	

Panel B: Medium Size Subsample

	Dividend Increase			
R^2 Group	Low R^2	Medium R^2	High R^2	Low-High
Event day	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (T Value)
0	0.45% (9.187***)	0.42% (7.071***)	0.28% (5.669***)	0.17% (2.105**)
CAR (-1, 1)	0.57% (7.354***)	0.54% (6.284***)	0.58% (6.968***)	-0.01% (-0.121)
CAR (-1, 0)	0.35% (5.754***)	0.39% (5.679***)	0.38% (5.881***)	-0.03% (-0.342)
CAR (0, 1)	0.67% (9.639***)	0.57% (6.894***)	0.48% (6.676***)	0.19% (1.678*)
CAR (-5,5)	1.17% (8.162***)	0.88% (6.420***)	0.73% (5.665***)	0.44% (1.862*)
Obs	1385	1428	1385	

	Dividend Decrease			
R^2 Group	Low R^2	Medium R^2	High R^2	Low-High
Event day	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (T Value)
0	-1.87% (-4.668***)	-1.67% (-3.067***)	-1.18% (-2.608***)	-0.69% (-1.071)
CAR (-1, 1)	-3.47% (-4.760***)	-2.88% (-3.837***)	-1.43% (-2.624***)	-2.04% (-2.121**)
CAR (-1, 0)	-2.22% (-4.306***)	-1.62% (-2.812***)	-1.17% (-2.486**)	-1.05% (-1.438)
CAR (0, 1)	-3.12% (-4.662***)	-2.92% (-4.213***)	-1.44% (-2.751***)	-1.68% (-1.855*)
CAR (-5,5)	-3.22% (-4.005***)	-2.61% (-3.367***)	-1.68% (-2.534**)	-1.54% (-1.058)
Obs	105	130	117	

Panel C: Small Size Subsample

	Dividend Increase			
R^2 Group	Low R^2	Medium R^2	High R^2	Low-High
Event day	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (T Value)
0	0.71%	0.57%	0.52%	0.19%
	(9.931***)	(8.116***)	(7.808***)	(1.817*)
CAR	0.96%	1.06%	0.83%	0.13%
(-1, 1)	(8.536***)	(9.531***)	(7.903***)	(0.743)
CAR	0.64%	0.74%	0.52%	0.12%
(-1, 0)	(7.316***)	(8.113***)	(6.538***)	(0.940)
CAR	1.02%	0.90%	0.83%	0.19%
(0, 1)	(10.027***)	(9.249***)	(8.492***)	(1.264)
CAR	1.46%	1.71%	1.06%	0.40%
(-5,5)	(8.427***)	(9.335***)	(6.248***)	(1.417)
Obs	1383	1392	1396	

	Dividend Decrease			
R^2 Group	Low R^2	Medium R^2	High R^2	Low-High
Event day	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (StdCsect Z)	Mean AR (T Value)
0	-1.60%	-1.92%	-1.93%	0.33%
	(-2.997***)	(-4.505***)	(-3.833***)	(0.420)
CAR	-3.89%	-5.04%	-3.34%	-0.55%
(-1, 1)	(-5.213***)	(-6.262***)	(-4.626***)	(-0.536)
CAR	-2.36%	-2.56%	-1.96%	-0.40%
(-1, 0)	(-4.014***)	(-4.900***)	(-3.743**)	(-0.492)
CAR	-3.14%	-4.40%	-3.31%	0.17%
(0, 1)	(-4.526***)	(-6.028***)	(-4.815***)	(0.173)
CAR	-4.51%	-5.22%	-4.90%	0.39%
(-5,5)	(-4.502***)	(-4.496***)	(-4.946**)	(0.275)
Obs	112	126	111	

3.5.2 R^2 and price reaction to dividend change announcements: regression analysis

Before presenting the multivariate regression analysis, the correlation matrix of R^2 (using the *Synchronicity* measure) and other independent variables used in the multivariate regression analysis are presented. As shown in Table 3.5, the pairwise correlation results are generally consistent with the univariate results presented previously. Stock price synchronicity is shown to have a positive relation with *Firm Size*, *Stock Turnover*, *Payout Ratio*, *Earnings*, and *Profitability*, and a negative relation with *Debt Ratio*, *Dividend Change Frequency*, and *Dividend Yield*. All these correlations are shown to be statistically significant at the 5% level or lower, consistent with the notion that firms with high stock price synchronicity are less risky and are hence associated with a more efficient information environment.

Multivariate regression analysis is then performed to investigate the relation between stock price synchronicity and price reaction to dividend changes while controlling for other firm-level effects. The regression coefficients are reported in Table 3.6. Overall, the regression results confirm our previous findings that the magnitude of price reaction to dividend changes varies with price synchronicity. With respect to dividend increase announcements, the regression coefficient of synchronicity is -0.0003 and is statistically significant at 10% in Model 1. The negative correlation between *Synchronicity* and abnormal returns of dividend increase announcements further supports the event study findings and indicates that dividend increase announcements are associated with greater

Table 3.5 Correlation Matrix of Independent Variables

This table provides pairwise correlations between the firm characteristics reported in Table 3.2 and independent variables used in the multivariate regression analysis. Variable details are provided in the Appendix. * indicates significance at the 5% level or lower.

	Synchronicity	Firm Size	Debt Ratio	Stock Turnover	Return on Equity	Earnings	Dividend Change Frequency	Payout Ratio	Change in Dividend	Dividend Yield	Cash Flow	Profitability	Growth
Synchronicity	1												
Firm Size	0.3189*	1											
Debt Ratio	-0.0543*	-0.0201*	1										
Stock Turnover	0.0353*	0.0579*	-0.0248*	1									
Return on Equity	-0.0055	-0.0576*	0.0266*	0.0055	1								
Earnings	0.1611*	0.4336*	0.0317*	0.0279*	0.4087*	1							
Dividend Change Frequency	-0.0311*	0.0001	-0.0272*	-0.0188	-0.0011	0.0390*	1						
Payout Ratio	0.0189*	0.0319*	-0.0042	-0.0021	-0.0306*	-0.0118*	0.0049	1					
Change in Dividend	0.0095*	-0.0220*	-0.0005	-0.0016	0.0057	0.0015	0.0039	-0.0023	1				
Dividend Yield	-0.0154*	-0.0140*	0.0544*	0.0116	-0.0310*	-0.0508*	0.2179*	0.0416*	-0.0056	1			
Cash Flow	-0.0120*	-0.1540*	0.0392*	0.0059	0.3442*	0.1979*	-0.0719*	-0.0245*	0.0088*	-0.2422*	1		
Profitability	0.2123*	0.6169*	0.0654*	0.0384*	0.2391*	0.7718*	0.003	0.0205*	-0.0065	-0.0150*	0.2964*	1	
Growth	0.2113*	0.7115*	-0.0118*	0.0455*	0.0793*	0.6048*	0.0042	0.0388*	-0.0112*	-0.0913*	-0.0643*	0.6936*	1

positive price reaction among stocks with lower price synchronicity. *Change in Dividend* and *Dividend Yield* are positively correlated with abnormal returns, which is consistent with Denis, Denis, and Sarin (1994). The results also suggest that abnormal returns are negatively related to *Growth Opportunity* and *Firm Size*. With respect to dividend decrease announcements, *Synchronicity* is found to be positively correlated with abnormal returns with a regression coefficient of 0.0032 and statistical significance at 10%. This is also consistent with the event study results, suggesting that dividend decrease announcements have a greater negative impact on price (or there are more negative abnormal returns) among stocks with lower price synchronicity. *Profitability* and *Growth Opportunity* are also found to have statistically significant impact on abnormal returns. Specifically, abnormal returns have a positive relation with *Growth Opportunity* and a negative relation with *Profitability*.

To further purge out the size effect on *Synchronicity*, *Orthogonalized Synchronicity* is used to replace *Synchronicity* and replicate the regression models. The results are illustrated in Table 3.6 Model 2. Consistent with the results in Table 3.6 Model 1, *Orthogonalized Synchronicity* appears to have a significant negative relation with price reaction to dividend increases and a positive relation with price reaction to dividend decrease. In both Model 1 and Model 2, the regression coefficients of *Synchronicity* or *Orthogonalized Synchronicity* are considerably greater in magnitude for dividend decrease than dividend increase, indicating effects of price synchronicity are more evident in unfavourable market reaction than favourable market reaction.

Table 3.6 Relation between synchronicity and price reaction to dividend changes

This table presents estimated regression coefficients for the regression analysis on the relationship between synchronicity and abnormal returns to dividend increases and decreases by controlling for other effects. Since the price effects of dividend increases and decreases have opposite signs, the below regression model is estimated separately for increases and decreases using abnormal returns on the dividend announcement date 0 as the dependent variable. In Model 1, *Synchronicity* is the independent variable. In Model 2, *Orthogonalized Synchronicity* is the independent variable. Details of other independent variables are provided in Appendix. Standard errors are adjusted for clustering at firm-level and year-level. The *t*-statistics are presented in parentheses. The symbols *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dividend Increase		Dividend Decrease	
	Model 1	Model 2	Model 1	Model 2
Intercept	0.0046	0.0050	-0.0123	-0.0161
	(5.07***)	(5.58***)	(-2.36**)	(-3.21***)
Synchronicity	-0.0003		0.0032	
	(-1.70*)		(1.77*)	
Orthg. Synchronicity		-0.0007		0.0044
		(-2.63***)		(1.86*)
Change in Dividend	0.0077	0.0076	0.0212	0.0196
	(2.41**)	(2.42**)	(1.00)	(0.92)
Dividend Yield	0.0255	0.0233	-0.0126	-0.0162
	(2.24**)	(2.03**)	(-0.24)	(-0.30)
Cash Flow	-0.0149	-0.0148	0.0088	0.0070
	(-1.15)	(-1.14)	(0.28)	(0.23)
Profitability	0.0081	0.0088	-0.0391	-0.0373
	(1.10)	(1.19)	(-2.06**)	(-1.99**)
Growth Opportunity	-0.0005	-0.0005	0.004	0.0037
	(-1.81*)	(-1.77)	(1.70*)	(1.64*)
Firm Size	-0.0005	-0.0006	0.0014	0.0020
	(-5.19***)	(-5.63***)	(1.57)	(2.48**)
R^2	0.0106	0.0111	0.0211	0.0198
Obs	16053	16053	1170	1170

3.5.3 Do changes in current dividends of lower R^2 stocks provide better indication about the firms' future prospects?

The majority of previous studies concludes that real signals from current dividend changes about firms' future prospects are weak or even opposite to that suggested by the dividend signaling hypothesis. A study conducted by Nissim and Ziv (2001) finds a positive association between current dividend changes and future earnings changes, supporting the contention that dividend changes provide information content about future profitability in subsequent years. However, Nissim and Ziv's (2001) findings have been challenged as spurious because their assumption of linear mean reversion in earnings is considered to be inappropriate (Grullon, Michaely, Benartzi, & Thaler, 2005). After controlling for the non-linear patterns in the behaviour of earnings, Grullon, Grullon, Michaely, Benartzi, and Thaler (2005) find that the relationship between current dividend changes and future earnings changes as documented in Nissim and Ziv (2001) disappears.

In this essay, the modified non-linear model of earnings expectation proposed by Grullon, Michaely, Benartzi, and Thaler (2005) is used to examine whether changes in current dividends do convey more information about firms' future prospects (i.e. changes in earnings) for stocks with lower R^2. To establish a baseline, the regression model in Equation 7 is first estimated without adding the effect of price synchronicity. Table 3.7 Model 1 presents the estimated coefficient parameters. Although the regression coefficient of dividend increase changes (DPC*RDIV) appears to be insignificant, the regression coefficient of dividend decrease changes (DNC*RDIV) is positive and highly significant at 1%, indicating that dividend decreases carry signals about firms' future earnings in the 1950 to 2012 study period. To demonstrate how the relationship between dividend changes and future earnings varies with price synchronicity, Equation 7 is replicated with the inclusion of price synchronicity and two interaction terms of synchronicity and dividend changes. As shown in Table 3.7 Model 2, the interaction term of synchronicity and dividend increases (*Synchronicity*DPC*RDIV*) is shown to be insignificant, whereas the interaction term of synchronicity and dividend decreases (*Synchronicity*DNC*RDIV*) is found to be negative (-0.0118) and significant at 10% level. This result suggests that the relationship between dividend decreases and future earnings changes varies significantly with price synchronicity, and this positive relationship is stronger for firms with lower price synchronicity than firms with higher price synchronicity. These findings also imply that the synchronicity effect is asymmetric between favourable and unfavourable information. The predicting ability of dividend changes about earnings prospects is identified only for unfavourable news. To the extent that low synchronicity stocks are less informative and are associated with a poor information environment, any signals sent through dividend policy for these stocks should attract greater investor attention, resulting in a stronger market reaction. Therefore, corporate executives of such companies will be particularly cautious in making dividend changes and will require confidence about poorer future prospects before sending negative signals accordingly.

To control for the size effect, a *Size* variable and an interaction term of synchronicity and size (*Synchronicity*Size*) are introduced in Equation 7 as additional control. As shown in Model 3, while *Size* and the size interaction term (*Synchronicity*Size*) are both demonstrated to have a negative and highly significant relationship with future earnings changes, the interaction term of synchronicity and dividend decreases (*Synchronicity*DNC*RDIV*) remains negative

Table 3.7 Relation between changes in current dividends and firms' future prospects

This table presents the relationship between current dividend changes and future earnings changes. Model 1 shows the test of Grullon, Michaely, Benartzi, and Thaler's (2005) model as a baseline. In Model 2, *synchronicity* and two interaction terms, *synchronicity*dpctridiv* and *synchronicity*dnctrdiv*, are introduced to examine if the impact of current dividend increases or decreases on future earnings changes varies with the magnitude of synchronicity. To control for the size effect, *size* and an additional interaction term, *synchronicity*size* are included in Model 3. Finally in Model 4, size effect is further controlled by using *orthogonalized synchronicity* to replace *synchronicity*. The panel data regression employed in our study is the clustered standard errors by firms and years. All numbers are based on the τ=1 case. The t-statistics are in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.0262 (-13.24***)	-0.0323 (-13.89***)	0.0248 (3.22***)	-0.0261 (-13.21***)
Synchronicity		-0.0058 (-5.25***)	0.0304 (7.32***)	
Synchronicity*DPC*RDIV		-0.0002 (-1.15)	-0.0001 (-0.71)	
Synchronicity*DNC*RDIV		-0.0118 (-1.72*)	-0.0158 (-2.28**)	
Synchronicity*size			-0.0052 (-8.94***)	
Size			-0.0075 (-7.80***)	
Orthg. Synchronicity				0.0007 (0.52)
Orthg. Synchronicity * DPC*RDIV				-0.0002 (-1.13)
Orthg. Synchronicity *DNC*RDIV				-0.0170 (-2.12**)
DPC*RDIV	0.0000 (-0.19)	-0.0001 (-0.79)	-0.0001 (-0.45)	0.0000 (-0.16)
DNC*RDIV	0.0295 (3.97***)	0.0174 (1.79*)	0.0112 (1.14)	0.0289 (3.89***)
DFE	-0.1593 (-1.69*)	-0.1387 (-1.47)	-0.1251 (-1.31)	-0.1627 (-1.72*)
NDFED*DFE	0.1063 (0.66)	0.0913 (0.57)	0.0117 (0.07)	0.1104 (0.69)
NDFED*DFE*DFE	0.4140 (0.99)	0.4375 (1.04)	0.2377 (0.56)	0.4139 (0.99)
PDFED*DFE*DFE	-1.0913 (-2.20**)	-1.1758 (-2.37**)	-1.1733 (-2.36**)	-1.0707 (-2.16**)
CE	0.2432 (4.23***)	0.2227 (3.86***)	0.1831 (3.09***)	0.2435 (4.24***)
NCED*CE	-0.1988 (-1.76*)	-0.1674 (-1.48)	-0.0532 (-0.45)	-0.1970 (-1.74*)
NCED*CE*CE	0.8719 (2.43**)	0.8985 (2.51**)	1.0997 (3.04***)	0.8838 (2.47***)
PCED*CE*CE	-0.3569 (-2.34**)	-0.3188 (-2.09**)	-0.2475 (-1.60)	-0.3588 (-2.36**)
R^2	0.0195	0.0212	0.0259	0.0199
Obs	21449	21449	21449	21449

(-0.0158) and significant at the 5% level. Finally, in Model 4, the size effect on synchronicity is purged out further by using *Orthogonalized Synchronicity* to replace *Synchronicity*. Consistent with previous results, the interaction term of orthogonalized synchronicity and dividend decreases (*Orthg. Synchronicity* *DNC*RDIV) remains negative (-0.0170) and significant at the 5% level. Regression coefficients of other variables are generally as expected and consistent with previous models. Results from Model 3 and Model 4 corroborate the earlier findings that current dividend decrease changes have a greater positive relationship with future earnings changes among firms with lower price synchronicity and provide supportive evidence for *Hypothesis 2*.

The above reported results are based on future earnings one year ahead (τ =1). Consistent with previous studies, this essay finds that the ability of current dividends to predict future prospects dissipates when expanding the forecasting horizon (e.g., τ =2). These results are not reported but are available upon request. Overall, the findings differ from recent studies that report the overall disappearance of signals in dividend announcements (see, e.g., Benartzi, Michaely, & Thaler, 1997; and Grullon, Michaely, Benartzi, & Thaler, 2005). This essay provides counter-evidence that although dividend increases exhibit insignificant results, dividend decreases are both economically and statistically meaningful in their signals regarding firms' prospects. Importantly, the finer dynamics presented in this essay suggest that such signals are stronger among less synchronized stocks, as would be predicted by the dividend signaling hypothesis.

3.6 Conclusion

If investors perceive that dividend change announcements provide signals about a specific firm's future prospects, the magnitude of stock price reactions to dividend change announcements should vary with the relative importance of the firm-specific versus market-wide information in their return dynamics. As a proxy of how much stock price variations reflect firm-specific information, the firm's return R^2 (which can be calculated rather conveniently among practitioners) can improve the understanding of the complex dynamics of the corporate signaling effect. First, the signaling effect of dividend change announcements on stock prices conditional on different levels of R^2 is investigated. The results reveal that price reaction to both dividend increase announcements and decrease announcements is indeed stronger for stocks with lower R^2, and the magnitude of price reaction decreases monotonically with the increase of R^2 levels. The pattern is obvious on the announcement date and also holds to a wider period of time around the announcement date. Consistent findings are documented in the regression analysis by controlling for other firm-level effects. While these findings are generally stronger for dividend decrease announcements (e.g., unfavourable corporate signals), these results widely support the prediction of the theoretical model developed by Dasgupta, Gan, and Gao (2010) and imply that stocks with lower R^2 are associated with poorer information environment.

Second, this essay sheds further light on the ongoing debate regarding the real signals about firms' prospects from changes in their dividend payouts. The inverse relationship between R^2 and the magnitude of price reaction in response to dividend change announcements, together with the corporate managers' behavioural model, leads to the prediction that changes in dividend payments of less synchronized stocks should provide a more meaningful signal about firms' future earnings prospects. The results, based on the most conservative model, show that dividend decreases provide a credible signal, especially among stocks with lower price synchronicity (e.g., those of opaque or less transparent firms). The results from this essay lend support to the traditional view that dividend announcements can provide meaningful information and signals to the (imperfect) stock market. Finally, the analysis framework developed in this essay can be extended to other signaling effect topics, of which dynamics and credibility of announcement signals about specific firms' prospects are still ongoing debates.

Appendix: Description of Variables Used in the Study

Variable Name	**Description and Source**
Panel A: Variables Used in Comparative Analysis	
Assets	Total assets *Source:* Compustat
Market-to-book Ratio	Sum of book value of debt plus market value of equity scaled by total assets. *Source*: Compusat
Debt Ratio	Total debt divided by total assets. *Source:* Compustat
Stock Turnover	Daily trading volume divided by shares outstanding. *Source*: CRSP
Return on Equity	Net income divided by common shareholder equity. *Source*: Compustat
Earnings	Earnings before extraordinary items. *Source*: Compustat
Dividend Change Frequency	Count of how many time a firm changes its dividend policy within a year. *Source*: CRSP
Dividend Payout Ratio	Dividend divided by net income. *Source:* Compustat
Panel B: Additional Variables Used in Regression Analysis	
Change in Dividend	Dividend change scaled by the stock price two days prior to the dividend announcement date. *Source*: CRSP
Dividend Yield	The CRSP annual return from dividend payments, measured as of the fiscal year ending just before the dividend announcement. *Source*: CRSP
Cash Flow	The operating income before depreciation minus interest expenses, taxes, preferred dividends and common dividends, all divided by total assets, measured as of the fiscal year ending just before the dividend announcement. *Source*: Compustat
Profitability	The ratio of firm's earnings before interest to its total assets, measured as of the fiscal year ending just before the dividend announcement.. *Source*: Compustat
Growth Opportunity	Market-to-book ratio, measured as of the fiscal year ending just before the dividend announcement. *Source*: Compustat
Firm Size	Log of total assets, measured as of the fiscal year ending just before the dividend announcement. *Source:* Compustat

CHAPTER FOUR: ESSAY THREE

DOES R^2 MEAN MORE OR LESS INFORMATIVE STOCK PRICE? EVIDENCE FROM BOND MARKET

This chapter presents essay three, which studies R^2 in the context of the bond market. Section 4.1 presents an overview of this study and highlights the research motivation and contribution. Section 4.2 reviews the related literature on bond pricing, and Section 4.3 develops the hypotheses. Section 4.4 describes data collection and methodology. Section 4.5 discusses empirical results and findings. Section 4.6 demonstrates the results of the robustness check, and Section 4.7 outlines the essay's conclusions.

Abstract

Using stock price synchronicity as a proxy for the information environment surrounding a firm, this essay finds that stock price synchronicity has an explanatory role in bond valuation and bond structure. Lower stock price synchronicity is found to be associated with greater cost of corporate debt as indicated by higher yield spread and lower credit ratings. This relation is particularly more prominent among bonds with higher yield and shorter maturity. Further analysis demonstrates that lower stock price synchronicity is also related to a higher likelihood of callable bonds issuance and a higher incidence of bonds receiving split ratings from rating agencies. All these results corroborate the view that lower stock price synchronicity represents a less efficient information environment.

4.1 Introduction

The conventional interpretation of stock price synchronicity (or R^2) as a measurement of firm-specific information being incorporated into stock prices has been questioned in recent literature. Following Morck, Yeung, and Yu (2000), stock price synchronicity (or R^2) has been conventionally applied as an inverse proxy for price informativeness in extensive literature. The underlying rationale is that synchronicity refers to the comovement of stocks: the higher the synchronicity, the greater the stock returns comovement, and vice versa. As the information is reflected into stock prices via trading, the stock return comovements increase when stocks respond to market-wide information and decrease when stocks respond to firm-specific information. However, a number of recent studies document contradicting evidence and propose that synchronicity (or R^2) captures stock price noisiness and is inversely associated with information inefficiency (see, e.g., Kelly, 2014; Dasgupta, Gan, & Gao, 2010; Rajgopal & Venkatachalam, 2010; Teoh, Yang, & Zhang, 2009; Ashbaugh-Skaife et al., 2006).

This essay aims to address the question as to whether low stock price synchronicity represents greater information efficiency or information asymmetry using the pricing and structure of corporate bonds as the experimental setting. Previous literature examines the correlation between R^2 and price efficiency mainly based on the stock market, using measures of stock price informativeness. This study differentiates from previous literature by establishing a relation between stock price synchronicity and bond pricing as well as bond structure characteristics. Compared with the stock market, it has been established that the bond market is less subjective to noise, as common factors, namely default risk, liquidity risk, and information risk, have been documented to explain a substantial portion of corporate bond pricing. If default risk and liquidity risk are well controlled for, any significant incremental impact of stock price synchronicity on bond pricing should be attributed to information risk.

As stock price synchronicity has never been linked to the bond market in previous literature, the first question to address is whether stock price synchronicity is a measure relevant to the bond market. Despite that individual stocks and bonds issued by the same firm represent different claims, they are joint claims on the same underlying assets of the firm (Kwan, 1996). Therefore, any changes in the value of a firm's underlying assets or changes in a firm's asset return variance would cause changes in price for stocks and bonds of a firm. In other words, value relevant information as reflected by stock price movement should also have impact on that firm's bond price. Also, Downing, Underwood, and Xing (2009) and Hotchkiss and Ronen (2002) have investigated the dynamics of firm-specific information flow between the stock and bond markets and identified firm-specific information spillover from the equity market to the bond market. Their findings indicate that stock price efficiency (or inefficiency) should extend from the stock market to the bond market, and stock price related information measures should be relevant to the bond market.

Based on samples of corporate at-issue bonds and seasoned bonds, preliminary univariate results presented by this essay show that bonds issued by firms with low stock price synchronicity tend to have firm-level and bond-level characteristics consistent with greater information asymmetry and a lower quality information environment. Further multivariate analyses on bond pricing and bond structure corroborate this finding and suggest that low stock price synchronicity is actually a proxy for information asymmetry, rather than for information efficiency. This essay first investigates the impact of synchronicity on cost of debt measured using corporate bond yield spread and credit ratings. The documented negative relation between synchronicity and yield spread, and positive relation between synchronicity and credit ratings suggest that stock price synchronicity is a priced risk factor from the perspective of bondholders beyond existing default, liquidity, and information risk factors in the bond pricing model. By relating stock price related information measure to bond pricing, the findings of this research also support the view that stock and bond are claims on the same underlying assets of the firm, hence any information affecting a firm's fundamental value (such as the information reflected by the stock price movement) should have impact on a firm's stock price as well as on a firm's bond price.

Second, this essay investigates if synchronicity has an explanatory role in the structure of corporate bonds and identifies a negative relation between synchronicity and the likelihood of embedded call provisions for newly issued bonds. Less synchronous firms are more likely to issue callable bonds, this result is consistent with the view that the motivation of firms issuing callable bonds is to reduce information asymmetry and signal positive future prospects. Third, a direct test of the information asymmetry explanation of synchronicity is conducted by linking synchronicity to the incidence of split ratings. Findings show that firms with lower synchronicity are associated with greater probability of receiving split ratings from Moody and S&P, suggesting that lower synchronicity represents greater information asymmetry, even from the perspective of rating agencies outside the firm.

Finally, the multivariate regression analysis is replicated using orthogonalized synchronicity, from which other possible effects on the synchronicity variable are further purged out. The robust and consistent findings yielded using orthogonalized synchronicity confirm that synchronicity captures a dimension of information asymmetry that is distinct from the existing default, liquidity, and information risk variables included in the regression models.

This essay contributes to the ongoing debate regarding what R^2 really proxies for. As mentioned in the previous chapter of the thesis, conventional wisdom suggests that low R^2 reflects high price informativeness (see, e.g., Morck, Yeung, & Yu, 2000; Durnev, Morck, Yeung, & Zarowin, 2003; Durnev, Morck, & Yeung, 2004), while the opposing theory argues that low R^2 captures price noisiness and represents information inefficiency (see, e.g., Kelly, 2014; Dasgupta, Gan, & Gao. 2010; Rajgopal & Venkatachalam, 2010). A recent study by Gassen, LaFond, Skaife and Veenman (2014) proposes a liquidity explanation for R^2 and implies that R^2 proxies more for liquidity risk than for information risk. By linking stock price synchronicity to corporate bond yield spread and credit ratings, the initial evidence from this essay contradicts the conventional information-based explanation of R^2. The following analyses of synchronicity on a bond's callable feature and split ratings help to further distinguish between the liquidity and information asymmetry explanations of R^2. Since there is no liquidity-based explanation for such bond characteristics, the results provide supportive evidence to corroborate the information asymmetry interpretation of R^2 and suggest that low R^2 represents a less efficient information environment. This essay also adds to the literature by providing further evidence that information asymmetry plays a role in explaining yield spread changes (see, e.g., Han & Zhou, 2014; Lu, Chen, & Liao, 2010; Yu, 2005; Liao, Chen, & Lu, 2009). Findings from this essay confirm that information asymmetry provides incremental explanatory power to the cost of corporate debt beyond the existing default, liquidity, and other previously documented factors.

The remainder of this essay is organised as follows: Sections 4.2 and 4.3 review related literature and develop the hypotheses, respectively. Section 4.4 describes data and methodology. Section 4.5 presents the empirical results. Section 4.6 conducts the robustness check, and Section 4.7 outlines the conclusions.

4.2 Literature Review of bond pricing

This essay aims to answer the question of whether R^2 reflects price informativeness or price noisiness in the corporate bond pricing and bond structure setting. The analysis first tests how the information environment surrounding a firm, as represented by R^2, affects its cost of debt as measured by yield spread and credit ratings. Previous literature has established three main components of corporate bond yield spread, namely default risk component, liquidity risk component, and information risk component.

Literature on the default risk component builds on the seminal works of Black and Scholes (1973) and Merton (1974). Merton (1974) assumes that default trigger occurs on the maturity date if the firm's value falls below the bond's face value, and he introduces a structural model that incorporates default risk into corporate bond valuation based on the option pricing model developed by Black and Scholes (1973).

Merton's model has been further extended in many studies. For example, Anderson and Sundaresan (1996) incorporate insights of corporate finance literature into the bond valuation model and document that strategic debt service increases default risk and hence yield spread. Campbell and Taksler (2003) find equity volatility can explain as much yield spread changes as can credit ratings. Since debt claim can be valued as a short position in a put option (Merton, 1973), they suggest that the value of a put option increases with the equity volatility, which benefits equity holders at the expense of bond holders. Furthermore, Collin-Dufresne and Goldstein (2001) modify the structural model to incorporate a more complex capital structure, for which firms are allowed to adjust their capital structure to reflect changes in asset value.

However, the yield spread predicted by the traditional Merton's model is found to be far below the empirically observed corporate yield spread, and corporate yield spread cannot be solely explained by default risk. Collin-Dufresne, Goldstein, and Martin (2001) examine theoretical determinants of default risk proposed by the traditional structural model (e.g., changes in spot rate, changes in the slop of the yield curve, leverage, volatility, etc.) and find that these credit risk related variables have rather limited explanatory power to corporate yield spread. Similarly, Huang and Huang (2012) explore how much of historically observed yield spread can be explained by the credit risk and conclude that credit risk explains only a small portion of yield spread for bonds. Also, Elton, Gruber, Agrawal, and Mann (2001) find that corporate bonds paying higher coupon rates are subject to a higher tax burden; hence they are less attractive to investors. Even after taxes and default risk are both included in the corporate bond pricing model, Elton, Gruber, Agrawal, and Mann (2001) conclude that a large portion of yield spread still remains unexplained.

One of the important determinants of yield spread omitted in the traditional bond pricing model is liquidity. Longstaff, Mithal, and Neis (2005) decompose corporate yield spread into default and non-default components using credit default swap data. They find that default risk can explain a large portion of yield spread, but the remaining portion is strongly related to measures of liquidity. Confirming these findings, Chen, Lesmond, and Wei (2007) establish a negative relation between bond-specific liquidity and yield spread levels (as well as yield spread changes). Focusing on the aggregate level liquidity risk, Lin, Wang, and Wu (2011) document a positive relation between aggregate liquidity beta and corporate bond returns. Their findings suggest that bonds that are more sensitive to liquidity earn higher returns than those that are less sensitive. Huang, Huang, and Oxman (2015) further extend the structural bond pricing model by including stock market liquidity and exhibit consistent results that the deterioration of stock market liquidity increases bond yield spread.

More recent research identifies information risk as another important determinant in explaining corporate bond yield spread that has been omitted from the traditional model. Duffie and Lando (2001) posit that the incomplete accounting information could affect and shape the term structure of credit spread on corporate bonds. Confirming this notion, Yu (2005) finds that a firm's information environment has an impact on its credit spread. Firms with good information disclosure quality tend to have lower credit spread and such a negative relation between accounting transparency and yield spread is particularly stronger for short-term bonds. Similarly, Mansi, Maxwell, and Miller (2011) investigate the relation between analyst forecast characteristics and cost of debt. Given that analyst forecast activities contribute to a firm's information environment by reducing information asymmetry, Mansi, Maxwell, and Miller (2011) demonstrate that corporate bond yield spread is reduced with the increase of analyst activities. Moreover, Zhou (2010) directly incorporates liquidity and information risk into the corporate bond pricing model. Consistent with previous findings, he finds that liquidity affects yield spread of risky corporate bonds, and more importantly, he also finds that information asymmetry of individual bonds provides significant additional explanatory power to their yield spread. Using measures to differentiate information uncertainty (measured by accruals quality, firm age, analyst coverage, and forecast dispersion) and information asymmetry (measured by PIN, adjusted PIN, and order imbalances), Lu, Chen, and Liao (2010) show that corporate bond yield spread contains a significant risk premium for investors for bearing information risk. With respect to the term structure, their results indicate that information uncertainty and information asymmetry have stronger effects for short-maturity bonds than for long-maturity bonds. Focusing on informed bond trading, Han and Zhou (2014) confirm the effects of information asymmetry in explaining corporate bond yield, particularly for lower-rating bonds and short-term bonds. In addition, Liao, Chen, and Lu (2009) compare the credit risk evaluation estimated by the structural form models to the credit ratings estimated by rating agencies. They find that the deviation is caused by the effects of agency conflict between equity holders and management, between equity holders and debt holders, as well as by the information asymmetry among outsiders. Therefore, they suggest that both the agency conflict and information asymmetry need to be included in the credit risk modelling.

4.3 Hypotheses Development

Based on the discussions in previous literature, the information environment surrounding the bond issuer should have a direct impact on its bond pricing, given that bond investors observe available information to assess the firm's value. Within a poor information environment, bond investors only have access to limited and imprecise information about firm value and would therefore require higher returns as compensation for increased risk, resulting in a widened yield spread. By adding R^2 into the existing bond pricing model and controlling for the previously documented default risk and liquidity risk, any incremental impact of R^2 identified on the corporate yield spread should be left to be explained by information risk. If lower R^2 represents greater information asymmetry, firms with lower R^2 should be associated with greater cost of debt as indicated by greater corporate yield spread.

H1: Stock price synchronicity has a significant negative relation with corporate yield spread for both at-issue bonds and seasoned bonds.

The negative relation between R^2 and yield spread should be stronger for high yield bonds with great risk. As Kwan (1996) demonstrated, low rating bonds are more sensitive to firm-specific information, whereas AAA-rated bonds are insensitive to firm-specific information. Similarly, Mansi, Maxwell, and Miller (2011) find that the information contained in analysts' forecasts is most valuable when the uncertainty about firm value is the highest (i.e., firms with high idiosyncratic risk). Also, Han and Zhou (2014) exhibit that bonds that are closer to default are more sensitive to information asymmetry. Comparing to investment graded bonds, these previous findings suggest that investors holding high yield bonds should be more sensitive to the information risk and require even higher risk premiums, leading to a stronger relation between R^2 and yield spread.

H1a: The relation between stock price synchronicity and corporate yield spread should be stronger for high yield bonds than investment graded bonds.

The negative relation between R^2 and yield spread should also be stronger for bonds with short term maturity. Traditional structural models (such as those by Leland, 1994; and Longstaff & Schwartz, 1995) suggest that bond credit spread diminishes and eventually goes to zero as the maturity approaches to zero, regardless of the issuing firm's credit quality. However, Duffie and Lando (2001) indicate that this is not true under the imperfect information environment, especially for short-term maturity bonds. Consistent with Duffie and Lando (2001), Yu (2005); Lu, Chen, and Liao (2010); and Han and Zhou (2014) show that the impact of information asymmetry on yield spread intensifies with the decrease of bond maturity. Therefore, if lower R^2 represents greater information asymmetry, the negative relation between R^2 and yield spread should be more obvious for short-term maturity bonds than for long-term maturity bonds.

H1b: The relation between stock price synchronicity and corporate yield spread should be stronger for bonds with short-term maturity than long-term maturity.

In addition, a firm's credit rating is an indicator of its default risk, which can be used as an alternative measure of cost of debt. There is indication from previous literature that a firm's information environment should affect its credit rating. For example, analysing the relation between credit ratings and the level of adverse selection in the equity market, Odders-White and Ready (2006) find that the amount of private information captured by the equity adverse selection measures is significantly negatively related to credit ratings. Providing that adverse selection reflects an information imbalance between insiders and outsiders, their findings indicate that firms with higher information asymmetry are associated with lower credit ratings while controlling for other explanatory variables. Also, Yu (2005) suggests that rating agencies specifically include the quality of information disclosure as a determinant of corporate bonds' credit ratings, indicating information asymmetry affects the rating decisions made by the rating agencies. To the extent that corporate bonds' credit ratings inversely measure cost of debt, if lower R^2 represents greater information asymmetry, firms with lower R^2 should be associated with greater cost of debt as reflected by poorer credit ratings.

H2: Stock price synchronicity has a significant positive relation with corporate bonds' credit ratings for both at-issue bonds and seasoned bonds.

The information environment, as proxied by R^2, should also have an impact on how corporate bonds are structured. Previous studies find that firms with poor information environment are more likely to issue bonds with embedded callable features to reduce the information asymmetry problem. As callable bonds allow issuers to call back the bonds and to refinance at a later time when expected good news is announced in the market, firms with great information asymmetry problems can signal investors about their positive prospects by issuing callable bonds (see, e.g., Robbins & Schatzberg, 1986; Banko & Zhou, 2011). Therefore, if lower R^2 represents greater information asymmetry, firms with lower R^2 should be more likely to issue callable bonds.

H3: Stock price synchronicity is negatively related to the likelihood of embedded call options for newly issued bonds.

Bonds issued by firms with a poor information environment are more likely to receive split ratings between the two major rating agencies, Moody's and S&P. Split ratings refer to the disagreement among the rating analysts when assessing the creditworthiness of the issuing firm. Split ratings have been found to occur mostly for firms under great information opacity (see, e.g., Morgan, 2002; Livingston & Zhou, 2010). Therefore, if lower R^2 represents greater information asymmetry, bonds issued by lower R^2 firms should have a higher probability of receiving split ratings.

H4: Stock price synchronicity has a significant negative relation with the levels of split ratings for both at-issue bonds and seasoned bonds.

4.4 Data and Methodology

The empirical tests are performed based on two samples: a sample of U.S. at-issue bonds covering 1985–2013, and a sample of U.S. seasoned bonds covering 1994–2013. Data for at-issue bonds are collected from SDC Platinum and data for seasoned bonds are collected from TRACE (Trade Reporting and Compliance Engine) and FISD (Fixed Income Securities

Database)[13]. Other firm-level variables are obtained from IBES, Compustat, and CRSP. Table 4.1 summarises the numbers of bond observations for at-issue bonds and seasoned bonds collected from the databases for every five years over the sample period. As shown in the table, there are 9,785 bond observations for at-issue bonds collected from SDC and 37,453 observations for seasoned bonds collected from TRACE and FISD. Employing a sample of seasoned bonds in addition to at-issue bonds allows for checking the results robustness with a considerably larger sample of observations and also enables a more complete analysis in the corporate bond market.

Table 4.1 Sample Description

This table describes the numbers of bond observations every five years from 1985 to 2013. The U.S. at-issue bonds sample covers the 1985–2013 period. The U.S. seasoned bonds sample covers the 1994–2013 period. The total numbers of bond observations and total numbers of firm issuers are reported at the bottom.

Year	At-issue bond observations	Seasoned bond observations
1985-1990	934	n/a
1991-1995	1537	1996
1996-2000	2606	8086
2001-2005	1482	9838
2006-2010	1771	10195
2011-2013	1455	7338
Total bond observation	9785	37453
Total firm issuers	2021	1541

In each year, R^2 is estimated for each firm issuer based on the firm's daily stock return over the one-year period prior to the bond issuance year (for at-issue bonds) or the transaction year (for seasoned bonds). Consistent with essay one, R^2 is estimated based on the four-factor

[13] For transaction data of seasoned bonds, data are collected after year 2006 from TRACE and then combined with with other data collected from FISD.

model[14], which is defined as:

$$R_{jt} - R_{ft} = \alpha_j + \beta_j (R_{mt} - R_{ft}) + \delta_j SMB_t + h_j HML_t + m_j PMOM_t + \varepsilon_{jt} \ , \qquad (1)$$

where R_{jt} is the daily return of stock j and R_{ft} is the daily risk-free T-Bill return; $R_{mt}$is the return on the CRSP daily value-weighted index; SMB_t is the difference between returns of value-weighted portfolio of small stocks and large stocks on day *t*; HML_t is the difference between returns of value-weighted portfolio of high book-to-market stocks and low book-to-market stocks on day *t*, and $PMOM_t$ is the difference of average returns between a high prior return portfolio and low prior return portfolio on day *t*.[15] Given the bounded nature of R^2 (between 0 and 1), R^2 is converted into stock price synchronicity using log (R^2/(1- R^2)) when conducting the regression analysis.

To test *Hypotheses 1*, *1a*, and *1b*, the following OLS regression model is constructed to investigate the relation between stock price synchronicity and the cost of debt for both at-issue bonds and seasoned bonds. The strategy is to incorporate stock price synchronicity as the measure of information risk into the bond valuation model, while controlling for the default and liquidity components as well as the previously documented control variables. An affirmative result would support the contention that R^2 measures information asymmetry and affects corporate bond valuation. The cost of debt model for at-issue and seasoned bonds is specified as below:

[14] Estimating R^2 based on a market-industry model using weekly returns has no impact on the overall results. Final results generally remain consistent with those presented in this essay.
[15] The four factors' data are directly obtained from Kenneth French's data library, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$$Yield\ Spread = \alpha_0 + \alpha_1 Synchronicity + \alpha_2 OrthogonalCreditRating + \alpha_3 IssueSize + \alpha_4 BondAge + \alpha_5 NumberofTrade + \alpha_6 AnalystsCoverage + \alpha_7 MarketBookRatio + \alpha_8 SalesGrowth + \alpha_9 BidAskSpread + \alpha_{10} Duration + \alpha_{11} Callable + \alpha_{12} Putable + \alpha_{13} QualitySpread + \alpha_{14} FirmSize + \alpha_{15} Profitability + \alpha_{16} CashflowRisk + \alpha_{17}\ DebtRatio + \alpha_{18} Volatility + \alpha_{19} CapitalExpenditure + \alpha_{20}\ IndustryFixedEffects + \alpha_{21}\ YearFixedEffects \qquad (2)$$

where the dependent variable *Yield Spread* is calculated as the difference between the yield to maturity of sample corporate bond and the interpolated yield to maturity of Treasury bond corresponding to the same time to maturity as the sample corporate bond. To calculate the interpolated yield to maturity of Treasuries, data about constant-maturity Treasury bond indices is collected from the Federal Reserve of St. Louis Economic Data (FRED), which provides daily yield to maturity data for Treasury bond indices with constant maturities (e.g., 3-month, 6-month, 1-year, 2-year, 3-year, 5-year, 7-year, 10-year and 20-year). These indices are then interpolated to obtain a yield curve for maturity between 3 months and 20 years. For at-issue bonds, there is only one yield observation for each bond and this is merged with other yearly data by the year of that observation. For seasoned bonds, multiple buys and sells occurring on the same day are aggregated into aggregated value-weighted daily yield to maturity based on the par amounts of each transaction as weights. Then the yield observation of the closest transaction day to the fiscal year end date is used to merge with other yearly data. The control variables are listed as below:

Default Component

Credit Rating is used as a proxy for default risk, which is indicated by Moody's bond ratings. Since the information contained in other bond-related or firm-related variables is partially captured by firms' credit ratings (Mansi, Maxwell, & Miller, 2004; Klock, Mansi, &

Maxwell, 2005; Mansi, Maxwell, & Miller, 2011), there is therefore a need to purge out this information on ratings by creating *Orthogonalized Credit Rating. Orthogonalized Credit Rating* captures only the information provided by credit ratings and is independent to the remaining control variables. *Orthogonalized Credit Rating* is the residual from regressing *Credit Rating* on all other independent variables (including synchronicity) included in the regression model.

Liquidity Component

Three measures are adopted for liquidity risk: *Issue Size* is related to the depth of the secondary market, and the larger the issue size, the smaller the liquidity risk (Lu, Chen, & Liao, 2010; Huang, Huang, & Oxman, 2015). For the sample of seasoned bonds, *Bond Age* and *Number of Trades* are included as additional liquidity measures. Greater *Bond Age* represents higher liquidity risk, since older bonds trade less frequently than younger bonds (Lu, Chen, & Liao, 2010; Huang, Huang, & Oxman, 2015). Similarly, greater *Number of Trades* is expected to reduce the yield spread due to lower liquidity risk (Chuluun, Prevost, & Puthenpurackal, 2014).

Information Component

Information asymmetry is also a key determinant to the corporate yield spread model and is expected to provide significant explanatory power beyond default risk and liquidity risk. Measures for information asymmetry generally contains analyst based measures, growth opportunity based measures, and microstructure based measures. As each category has its strengths and weaknesses and there is no single best measure (Clarke & Shastri, 2000), the information asymmetry proxies are selected based on three different categories, including analyst based measure *Analyst Coverage* (Mansi, Maxwell, & Miller, 2011; Chuluun, Prevost, &

Puthenpurackal, 2014), growth opportunity based measures *Market-to-Book Ratio* and *Sales Growth* (Banko & Zhou, 2010), and microstructure based measure *Bid-Ask Spread* (Chuluun, Prevost, & Puthenpurackal, 2014).

Additional control variables

Following prior studies, other bond related and issuing firm related variables are included as additional control variables. At the bond level, *Duration* represents the effective maturity of a bond and is used to control for the term structure effects. *Callable Bond* and *Putable Bond* are dummy variables indicating whether the bond has a callable feature or putable feature. *Quality Spread* is defined as the yield difference between Baa and Aaa corporate bond indexes and is used to control for the economic risk and capture the changes of credit risk premiums over time (Mansi, Maxwell, & Miller, 2004; Klock, Mansi, & Maxwell, 2005). At the firm level, *Firm Size*, *Profitability*, *Cash Flow Risk*, *Debt Ratio*, *Volatility*, and *Capital Expenditure* are included as the additional control variables. *Year Fixed Effects* and *Industry Fixed* E*ffects* are also included. A description of each variable used in the multivariate analysis is detailed in the Appendix.

To test how stock price synchronicity affects cost of debt using credit rating as the alternative measure (*Hypothesis 2*), the specified model is as follows:

$$Credit\ Rating = \alpha_0 + \alpha_1 Synchronicity + \alpha_2 IssueSize + \alpha_3 BondAge + \alpha_4 NumberofTrade + \alpha_5 AnalystsCoverage + \alpha_6 MarketBookRatio + \alpha_7 SalesGrowth + \alpha_8 BidAskSpread + \alpha_9 Duration + \alpha_{10} Callable + \alpha_{11} Putable + \alpha_{12} QualitySpread + \alpha_{13} FirmSize + \alpha_{14} Profitability + \alpha_{15} CashflowRisk + \alpha_{16}\ DebtRatio + \alpha_{17} Volatility + \alpha_{18} CapitalExpenditure + \alpha_{19}\ IndustryFixedEffects +$$

$$\alpha_{20}\,YearFixedEffects \qquad (3)$$

where *Credit Rating* is indicated by Moody's bond ratings. The letter ratings are coded using numbers from 1 (rated as "*C*") to 21 (rated as "*Aaa*"). Since credit rating is an alternative measure of cost of debt, the same control variables as those used in Equation 2 are applied.

To test *Hypothesis 3*, the following logit regression is established to examine the relation between bonds' callable provisions and stock price synchronicity. Given that the callable provisions are embedded features for bonds at issuance, the relation between the likelihood of callable bonds and synchronicity is only examined for at-issue bonds as follows:

$$\begin{aligned} Callable\ Bonds &= \alpha_0 + \alpha_1 Synchronicity + \alpha_2 FirmSize + \alpha_3 FreeCashflow + \alpha_4 MarketBookRatio + \\ &\alpha_5 SalesGrowth + \alpha_6 LowRating + \alpha_7 ModRating + \alpha_8 DebtRatio + \alpha_9 Yield_{10year} + \\ &\alpha_{10} ChangeinYield_{10year} + \alpha_{11} YieldSlope + \alpha_{12} StdSlope + \alpha_{13} Profitability + \alpha_{14} Maturity + \\ &\alpha_{15} IssueSize + \alpha_{16} IndustryFixedEffects + \alpha_{17} YearFixedEffects \qquad (4)\end{aligned}$$

where *Callable Bonds* is indicated as 1 if the bond is issued with a call provision, and 0 otherwise. In addition to *Synchronicity*, which is used as an indication for information environment surrounding a firm, other explanatory variables are also included to control for other possible effects on *Callable Bonds*. Following Banko and Zhou (2010), *Firm Size* is included as additional proxy for information asymmetry; *Free Cash Flow* is used as proxy for risk-shifting: the more the free cash flow, the greater the discretionary assets the company should have to engage in risk shifting activities. *Market-to-Book Ratio* and *Sales Growth* are employed as proxies for firms' growth opportunities, and *Low Ratings*, *Moderate Rating*, and *Debt Ratio* are included as proxies for agency conflicts between bond holders and equity holders. Other variables, including a ten-year Treasury yield (*Yield_10year*), *Change in Yield_10year*, *Yield Slope*, Standard Deviation of Yield Slope (*Std Slope*), *Profitability*, *Maturity*, *Issue Size*, *Industry Fixed Effects*, and *Year Fixed Effects* are also included in this regression model as additional control following Banko and Zhou (2010).

To explore the relation between stock price synchronicity and the incidence of rating split, the following logit regression is employed to test *Hypothesis 4* for both at-issue bonds and seasoned bonds:

$$Split\ Rating = \alpha_0 + \alpha_1 Synchronicity + \alpha_2\ MarketBookRatio + \alpha_3 IntangibleAssests + \alpha_4 Accuracy + \alpha_5 AnalystsCoverage + \alpha_6 BidAskSpread + \alpha_7 FirmSize + \alpha_8 Maturity + \alpha_9 OrthogonalCreditRating + \alpha_{10} IssueSize + \alpha_{11} Callable + \alpha_{12} CapitalExpenditure + \alpha_{13} Dispersion + \alpha_{14} BondAge + \alpha_{15} NumberofTrade + \alpha_{16} IndustryFixedEffects + \alpha_{17} YearFixedEffects \quad (5)$$

where *Split Rating* captures the credit rating split between Moody's and S&P. Following Livingston, Naranjo, and Zhou (2007) and Livingston and Zhou (2010), the control variables include accounting based measures (*Book-Market-Ratio*, *Intangible Assets*), opinion based measures (*Analyst Forecast Accuracy*, *Analysts Coverage*, *Dispersion*), market microstructure measures (*Bid-Ask Spread*) and information asymmetry measures (*Firm Size* and *Maturity*), and other explanatory variables (*Orthogonal Credit Rating, Issue Size, Callable Bonds, Capital Expenditure*). For the sample of seasoned bonds, *Bond Age* and *Number of Trades* are included as additional liquidity measures. Consistent with previous regression models, *Industry Fixed Effects* and *Year Fixed Effects* are included as additional control.

4.5 Empirical Results

The analysis first demonstrates whether low R^2 bonds are associated with bond-level and firm-level characteristics that are consistent with good or poor information environment. To address this question, sample firms are sorted according to their R^2 levels within each year and divided into three groups: low R^2, medium R^2, and high R^2. The low R^2 group represents the bottom tercile, while the high R^2 group represents the top tercile. The mean values of each characteristic variable are calculated for the three groups. Results are illustrated in Table 4.2. The mean (and median) results are presented across the three R^2 groups, as well as the differences in means (and medians) between the low and high R^2 groups for at-issue bonds in Panel A, and for seasoned bonds in Panel B [16]. The findings show that mean values of all bond-level characteristics for both at-issue bonds and seasoned bonds demonstrate monotonic relations throughout three R^2 groups [17]. The differences in means between low and high R^2 groups are highly significant for all these characteristic variables. Specifically, bonds issued by firms with low R^2 tend to have wider *Yield Spread* and lower *Credit Ratings*, indicating low R^2 bonds are more risky bonds, for which investors require greater risk premiums. Moreover, bonds with low R^2 experience higher levels of *Credit Ratings Split*, suggesting that issuing firms may have a less transparent information environment, which impedes rating analysts in collecting accurate information and reaching consensus in assessing issuer credit quality. In addition, low R^2 bonds are also associated with lower *Duration* and higher probability of *Callable* provision, features that are consistent with a more asymmetric information environment. According to Flannery (1986), Diamond (1991), Robbins and Schatzberg (1986), and Banko and Zhou (2010), information asymmetry plays a role in explaining firms' debt maturity choices and embedded

[16] The preceding discussion will focus on the mean value of the variables.
[17] Except for Duration in Panel A, where no strict monotonic relation is identified

callable provisions. In the presence of information asymmetry, firms are more likely to issue short-term maturity bonds and callable bonds in order to reserve the option of refinancing with favourable future news and in order to signal investors about their positive future prospects.

Issuers' firm-level characteristics across the three R^2 groups provide further evidence that low R^2 issuers exhibit a noisier and less transparent information environment. For both at-issue bonds (Panel A) and seasoned bonds (Panel B), issuing firms with low R^2 are shown to be more information asymmetric, as indicated by higher *Bid-Ask Spread*, lower *Analyst Coverage* and *Forecast Accuracy*, and smaller *Firm Size*. Low R^2 issuers are also associated with greater uncertainty and risks, as reflected by higher *Cash Flow Risk*, higher *Debt Ratio* and *Volatility*, and lower levels of *Free Cash Flow* and *Profitability*. The differences in means between the low and high R^2 groups are highly significant for all these variables. Viewed collectively, the findings reported in Table 4.2 are in line with the notion that bond issuers with low R^2 are associated with a poor information environment and investors should demand higher yield premiums as compensation for adverse information risk. Note that *Market-to-Book Ratio* appears to be increasing with R^2 levels, which seems to be contradicting with the information asymmetry explanation of low R^2. However, as pointed out by Zhou (2010), using market-to-book ratio to measure information could generate controversial results, as it sometimes has insignificant or even negative relation with alternative information asymmetry measures.

Table 4.2 Bond-Level and Firm-Level Characteristics across R^2 Group

This table presents bond-level and firm-level characteristics associated with corporate at-issue bonds (Panel A) and seasoned bonds (Panel B) across three R^2 group. The mean (median) estimates for each R^2 group are reported in column 2-4. The differences in means (medians) between low- and high R^2 group are reported in column 5. The p-values for the differences in means are adjusted for clustering at the firm level, and the p-values for differences in medians are estimated using Wilcoxon test. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A: At-issue Bonds

	Low R^2	Medium R^2	High R^2	Low-High	*P*- value for Difference in Mean (Median)
Bond Characteristics					
Yield Spread	0.0305 (0.0259)	0.0209 (0.0144)	0.0177 (0.0121)	0.0128*** (0.0138) ***	<.0001 (<.0001)
Credit Rating	10.9297 (10.4439)	12.8376 (12.9255)	13.9977 (14.1233)	-3.0681*** (-3.6794) ***	<.0001 (<.0001)
Duration	6.5874 (6.2308)	7.1424 (6.7577)	6.9980 (6.8570)	-0.4106*** (-0.6262) ***	0.0023 (<.0001)
Issue Size	5.5743 (5.5202)	5.8250 (5.7026)	5.9110 (5.8538)	-0.3367*** -(0.3335)	<.0001 (<.0001)
Split Rating	0.6530 (0.0803)	0.6087 (0.0014)	0.5169 (0.0000)	0.1361*** (0.0803) ***	<.0001 (<.0001)
Callable Bond	0.7262 (0.3115)	0.6523 (0.2335)	0.6232 (0.1977)	0.1030*** (0.1138)***	<.0001 (<.0001)
Firm Characteristics					
Bid-Ask Spread	0.0124 (0.0051)	0.0071 (0.0028)	0.0053 (0.0021)	0.0071*** (0.0031) ***	<.0001 (<.0001)
Analyst Coverage	1.9931 (2.2209)	2.3843 (2.6533)	2.5138 (2.7602)	-0.5207*** (-0.5393) ***	<.0001 (<.0001)
Forecast Accuracy	-0.0615 (-0.0017)	-0.0070 (-0.0011)	-0.0056 (-0.0010)	-0.0559*** (-0.0007)***	0.0012 (<.0001)
Market-to-Book Ratio	1.6071 (1.3853)	1.7134 (1.4390)	1.7993 (1.5287)	-0.1923*** (-0.1434) ***	<.0001 (<.0001)
Cash Flow Risk	0.0508 (0.0255)	0.0386 (0.0220)	0.0318 (0.0194)	0.0190*** (0.0060) ***	<.0001 (<.0001)
Capital Expenditure	0.0910 (0.0517)	0.0827 (0.0545)	0.0761 (0.0563)	0.0149 (-0.0046) **	0.2434 (0.0450)
Volatility	0.0258 (0.0225)	0.0228 (0.0200)	0.0221 (0.0194)	0.0037*** (0.0031) ***	<.0001 (<.0001)
Firm Size	12.3637 (1.6969)	20.0834 (4.8499)	27.8611 (10.1163)	-15.4974*** (-8.4194) ***	<.0001 (<.0001)
Debt Ratio	0.4361 (0.3965)	0.3591 (0.3328)	0.3269 (0.3093)	0.1092*** (0.0873) ***	<.0001 (<.0001)
Free Cash Flow	1493.75 (277.30)	2337.21 (771.50)	3346.98 (1312.92)	-1853.23*** (-1035.61) ***	<.0001 (<.0001)
Intangible Assets	0.2463 (0.1383)	0.2122 (0.1177)	0.1763 (0.1080)	0.0700* (0.0303) ***	0.0669 (<.0001)
Sales Growth	0.1139 (0.0566)	0.0881 (0.0474)	0.0843 (0.0513)	0.0296*** (0.0053) ***	0.0008 (<.0001)
Profitability	0.1317 (0.1297)	0.1420 (0.1391)	0.1469 (0.1470)	-0.0152*** (-0.0173) ***	<.0001 (<.0001)
No. of Obs.	2876	2876	2869		

Panel B: Seasoned Bonds

	Low R^2	Medium R^2	High R^2	Low-High	*P*- value for Difference in Mean (Median)
Bond-Level Characteristics					
Yield Spread	0.0416 (0.0287)	0.0322 (0.0217)	0.0263 (0.0185)	0.0153*** (0.0101) ***	<.0001 (<.0001)
Bond Age	3.5548 (2.5088)	3.9983 (2.8783)	4.5134 (3.3507)	-0.9586*** (-0.8419) ***	<.0001 (<.0001)
Credit Rating	11.2297 (11.4490)	12.6649 (12.5970)	13.7226 (13.5255)	-2.4929*** (-2.0765) ***	<.0001 (<.0001)
Duration	5.6273 (5.0078)	6.0693 (5.3866)	6.2518 (5.6434)	-0.6246*** (-0.6356) ***	<.0001 (<.0001)
Issue Size	12.5260 (12.4292)	12.6024 (12.6115)	12.6181 (12.6115)	-0.0921** (-0.1823) ***	0.0128 (<.0001)
Number of Trades	19.0240 (11.9768)	19.8344 (12.6121)	21.1427 (12.9124)	-2.1188** (-0.9355) ***	0.0122 (<.0001)
Split Rating	0.6373 (0.0368)	0.5840 (0.0000)	0.4886 (0.0000)	0.1487*** (0.0368) ***	<.0001 (<.0001)
Callable Bond	0.7763 (0.3559)	0.7120 (0.2977)	0.6735 (0.2576)	0.1028*** (0.0983) ***	<.0001 (<.0001)
Firm-Level Characteristics					
Bid-Ask Spread	0.0097 (0.0019)	0.0049 (0.0012)	0.0038 (0.0011)	0.0059*** (0.0009) ***	<.0001 (<.0001)
Analyst Coverage	2.1883 (2.3197)	2.4143 (2.4951)	2.4947 (2.5720)	-0.3064*** (-0.2523) ***	<.0001 (<.0001)
Forecast Accuracy	-0.0467 (-0.0015)	-0.0082 (-0.0012)	-0.0034 (-0.0010)	-0.0433** (-0.0004) ***	0.0244 (<.0001)
Market-to-Book Ratio	1.6139 (1.3866)	1.6693 (1.4272)	1.7554 (1.5284)	-0.1415*** (-0.1417) ***	0.0017 (<.0001)
Cash Flow Risk	0.0467 (0.0257)	0.0394 (0.0223)	0.0316 (0.0209)	0.0151*** (0.0048) ***	<.0001 (<.0001)
Capital Expenditure	0.0627 (0.0462)	0.0648 (0.0453)	0.0606 (0.0429)	0.0021 (0.0033) ***	0.5193 (-0.0013)
Volatility	0.0261 (0.0226)	0.0234 (0.0205)	0.0223 (0.0200)	0.0038*** (0.0026) ***	<.0001 (<.0001)
Firm Size	21.3556 (7.2296)	30.3131 (10.2719)	28.8779 (15.6054)	-7.5223*** (-8.3758) ***	0.0072 (<.0001)
Debt Ratio	0.3868 (0.3486)	0.3334 (0.3084)	0.3028 (0.2800)	0.0840*** (0.0686) ***	<.0001 (<.0001)
Free Cash Flow	2157.68 (619.26)	3047.57 (1115.53)	3289.02 (1672.74)	-1131.35*** (-1053.48) ***	0.0017 (<.0001)
Intangible Assets	0.2092 (0.1454)	0.1872 (0.1178)	0.1746 (0.1237)	0.0346** (0.0217) ***	0.0207 (<.0001)
Sales Growth	0.0709 (0.0385)	0.0615 (0.0374)	0.0624 (0.0443)	0.008 (-0.0058)	0.1164 (-0.1106)
Profitability	0.1341 (0.1323)	0.1366 (0.1363)	0.1427 (0.1395)	-0.0086** (-0.0072) ***	0.029 (<.0001)
No. of Obs.	12197	12326	12320		

Table 4.3 illustrates the pairwise correlations between synchronicity and bond- and firm-specific variables. Overall, the pairwise correlations of synchronicity and characteristic variables are consistent with the findings from the univariate comparison as reported in Table 4.2. For both at-issue bonds and seasoned bonds, firms with lower *Synchronicity* are more likely to issue corporate bonds associated with greater *Yield Spread*, lower *Credit Rating*, lower *Duration*, smaller *Issue Size*, and higher likelihood of *Rating Split*. Also, lower *Synchronicity* issuers exhibit strong correlation with firm-specific characteristics that are consistent with poorer information environment and greater information asymmetry. For example, lower *Synchronicity* issuers are shown to have greater *Bid-Ask Spread*, lower *Analyst Coverage*, higher *Debt Ratio* and *Volatility*, smaller *Firm Size* and less *Free Cash Flow*. It is also worth noting that *Credit Rating* for both at-issue bonds and seasoned bonds is highly correlated with most of the characteristic variables, suggesting that the information contained in other bond-level and firm-level variables may be partially captured by *Credit Rating* (Mansi, Maxwell, & Miller, 2004; Klock, Mansi, & Maxwell, 2005; Mansi, Maxwell, & Miller, 2011). This finding confirms the importance of creating *Orthogonalized Credit Rating* in the multivariate regression analysis, which allows for purging out the information contained in the remaining control variables from the *Credit Rating* variable.

Table 4.4 presents the multivariate regression results for *Hypotheses 1, 1a,* and *1b*. In Panel A Model (1), the relation between synchronicity and bond yield spread among at-issue bonds is established. As indicated by the negative but insignificant coefficient (-0.0005), *Synchronicity* is found to have no statistically significant impact on yield spread for corporate bonds at issuance. However, the proxy of default risk, measured by *Orthogonal Credit Rating,* is found to be highly significantly related to yield spread (-0.0030), which confirms the role of default risk as an important determinant of corporate bond pricing. *Debt Ratio* and *Volatility*, which are viewed as alternative indicators for firms' default risk according to previous literature, are also found to be positively related to yield spread (0.0184 and 0.6446, respectively) and the coefficients are statistically significant at 1%. As an inverse proxy for information asymmetry, *Analyst Coverage* is found to have a negative correlation with yield spread (-0.0060) and is statistically significant at 1%. The likelihood of bonds issued with *Callable* options has a positive relation with yield spread (0.0045) and is significant at 1%, consistent with the view that corporate bonds issued with callable provisions are considered more risky (see, e.g., Banko & Zhou, 2010). As expected, yield spread is enlarged with greater risks such as *Cash Flow Risk* and economic risk (measured by *Quality Spread*), and yield spread is lowered with greater *Issue Size*, *Firm Size*, and *Profitability*. Regression coefficients of all these explanatory variables are shown to be statistically significant at 1%. It is noticeable that *Market-to-book Ratio* has a highly significant negative association with yield spread, which seems to contradict the growth opportunity explanation on yield spread. However, this result is consistent with the alternative view that higher market-to-book ratio indicates greater expected future cash flow, leading to a lowered bond yield spread (Chuluun, Prevost, & Puthenpurackal, 2014). *Capital Expenditure* is also found to reduce the bond yield spread, as it represents greater collateralization of bondholders (Chuluun, Prevost, & Puthenpurackal, 2014).

Table 4.3 Correlation Matrix

This table provides pairwise correlations between the independent variables used in the multivariate regression analysis. * indicates significance at the 5% level or lower.

Panel A: At-issue Bonds

	Synchronicity	Yield Spread	Credit Rating	Duration	Issue Size	Split Rating	Callable Bond	Bid-Ask Spread	Analysts Coverage	Forecast Accuracy	Market to Book	Cash Flow Risk	Capital Expenditure	Volatility	Firm Size
Synchronicity	1														
Yield Spread	-0.1088*	1													
Credit Rating	0.2659*	-0.7566*	1												
Duration	0.0904*	-0.1869*	0.1596*	1											
Issue Size	0.3726*	-0.0201	0.1231*	0.1956*	1										
Split Rating	-0.0525*	0.1263*	-0.1512*	-0.0229*	0.0229	1									
Callable Bond	0.1433*	0.3397*	-0.3497*	0.1230*	0.3327*	0.0314*	1								
Bid-Ask Spread	-0.5331*	0.1651*	-0.2268*	-0.1257*	-0.3689*	-0.021	-0.1296*	1							
Analysts Coverage	0.1977*	-0.2772*	0.3431*	0.1508*	0.3410*	-0.0681*	-0.1075*	-0.3835*	1						
Forecast Accuracy	0.0684*	-0.0823*	0.0566*	0.0249*	0.0166	0.0049	-0.0215	-0.1170*	0.0875*	1					
Market-to-Book	0.0619*	-0.1954*	0.2719*	0.0466*	0.0768*	-0.0333*	-0.0644*	-0.1184*	0.2167*	0.0264*	1				
Cash Flow Risk	-0.0771*	0.3240*	-0.2985*	-0.0701*	-0.0016	0.0780*	0.1139*	0.1026*	-0.1272*	-0.0941*	0.007	1			
Capital Expenditure	-0.0632*	-0.0026	-0.0148	-0.0463*	-0.0814*	-0.0256*	-0.0560*	0.0499*	0.0290*	-0.0123	0.0072	0.0316*	1		
Volatility	-0.1212*	0.5913*	-0.4990*	-0.1914*	-0.1116*	0.0443*	0.1729*	0.3948*	-0.3057*	-0.1339*	-0.1151*	0.3553*	0.0643*	1	
Firm Size	0.2413*	-0.2952*	0.4748*	0.0932*	0.4494*	-0.0842*	-0.0719*	-0.2122*	0.3263*	0.0193	0.2597*	-0.1124*	-0.0114	-0.2614*	1
Debt Ratio	-0.2969*	0.4088*	-0.5126*	-0.1433*	-0.1296*	0.0412*	0.0689*	0.3139*	-0.2129*	-0.0806*	-0.0088	0.2287*	0.0282*	0.3484*	-0.2375*
Free Cash Flow	0.2598*	-0.2550*	0.4190*	0.0969*	0.4354*	-0.0793*	-0.0562*	-0.2067*	0.3022*	0.0165	0.0704*	-0.1056*	-0.0006	-0.2337*	0.8703*
Intangible Assets	-0.0185	-0.0289*	0.016	-0.0342*	0.0441*	-0.0194	0.0007	-0.02	0.0511*	0.0043	0.0103	-0.0117	0.8560*	-0.0151	0.0620*
Sales Growth	-0.1152*	0.1590*	-0.2371*	-0.0318*	-0.0520*	0.0124	0.0649*	0.0919*	-0.1025*	-0.012	0.0960*	0.1333*	0.0635*	0.2454*	-0.0798*
Profitability	0.1156*	-0.3426*	0.3659*	0.0706*	0.0098	-0.0870*	-0.1032*	-0.1450*	0.1436*	0.0557*	0.4221*	-0.2121*	0.0032	-0.3425*	0.1999*

	Debt Ratio	Free Cash Flow	Intangible Assets	Sales Growth	Profitability
Debt Ratio	1				
Free Cash Flow	-0.2064*	1			
Intangible Assets	-0.0063	0.0584*	1		
Sales Growth	0.1500*	-0.0851*	-0.0131	1	
Profitability	-0.1639*	0.1655*	0.002	-0.1739*	1

Panel B: Seasoned Bonds

	Synchronicity	Yield Spread	Bond Age	Credit Rating	Duration	Issue Size	No. of Trades	Split Rating	Callable Bond	Bid-Ask Spread	Analysts Coverage	Forecast Accuracy	Market to Book	Cash Flow Risk	Capital Expenditure
Synchronicity	1														
Yield Spread	-0.1069*	1													
Bond Age	0.0728*	0.0738*	1												
Credit Rating	0.2142*	-0.5742*	0.0986*	1											
Duration	0.0601*	-0.3010*	-0.0240*	0.1888*	1										
Issue Size	0.2372*	-0.1652*	-0.3169*	0.2227*	0.0272*	1									
No. of Trades	0.1412*	-0.0813*	-0.2494*	0.1365*	-0.0423*	0.6578*	1								
Split Rating	-0.0597*	0.1441*	-0.0700*	-0.1718*	-0.0496*	0.0443*	0.0621*	1							
Callable Bond	0.1175*	0.0815*	-0.2852*	-0.1997*	0.0501*	0.3029*	0.2051*	0.0315*	1						
Bid-Ask Spread	-0.3783*	0.2210*	-0.0465*	-0.2434*	-0.0747*	-0.2704*	-0.2025*	0.0152	-0.0811*	1					
Analysts Coverage	0.2142*	-0.3312*	0.0595*	0.4888*	0.1631*	0.3421*	0.2054*	-0.1256*	0.0418*	-0.2982*	1				
Forecast Accuracy	0.0096	-0.1144*	0.0058	0.1016*	0.0313*	0.0023	0.0058	-0.0111	-0.0186	-0.1381*	0.1052*	1			
Market-to-Book	0.0358*	-0.2228*	-0.0425*	0.3696*	-0.0097	0.0445*	0.014	-0.0422*	-0.0891*	-0.0845*	0.1813*	0.0347*	1		
Cash Flow Risk	-0.0496*	0.2742*	-0.0360*	-0.3354*	-0.1173*	-0.0695*	-0.0197	0.1607*	0.0737*	0.1223*	-0.2357*	-0.0583*	0.0021	1	
Capital Expenditure	-0.1669*	0.0822*	-0.0643*	-0.1437*	-0.0481*	-0.1884*	-0.1559*	-0.0861*	0.017	0.1866*	-0.0911*	-0.0067	0.0001	0.1128*	1
Volatility	-0.0685*	0.5592*	-0.0383*	-0.5163*	-0.1327*	-0.1792*	-0.0985*	0.0911*	0.0546*	0.3388*	-0.2664*	-0.1063*	-0.1813*	0.3291*	0.1434*
Firm Size	0.1458*	-0.2767*	0.0173	0.5493*	0.0720*	0.4791*	0.3867*	-0.0877*	0.0695*	-0.1927*	0.3818*	0.0732*	0.3587*	-0.1176*	-0.1642*
Debt Ratio	-0.1884*	0.2211*	-0.0797*	-0.3862*	-0.0722*	-0.1136*	-0.0849*	0.0018	-0.0578*	0.2032*	-0.2708*	0.0134	-0.1312*	-0.012	0.1451*
Free Cash Flow	0.2172*	-0.2495*	0.0106	0.4982*	0.1092*	0.5291*	0.4628*	-0.0830*	0.0684*	-0.1860*	0.3624*	0.0045	0.1204*	-0.1129*	-0.0827*
Intangible Assets	0.1139*	-0.1034*	-0.1136*	0.0566*	-0.0665*	0.2959*	0.1936*	0.0204	0.2016*	-0.1534*	0.0626*	0.0369*	0.1152*	-0.1461*	-0.3492*
Sales Growth	-0.0784*	-0.0365*	-0.1076*	-0.0443*	0.0261*	-0.0312*	-0.023	-0.0306*	0.0531*	0.0327*	-0.0465*	0.0211	0.0104	0.0305*	0.1132*
Profitability	0.005	-0.2643*	-0.0982*	0.3809*	0.0193	0.0918*	0.0340*	-0.0994*	0.0002	-0.1099*	0.2170*	0.0455*	0.6258*	-0.0580*	0.1405*

	Volatility	Firm Size	Debt Ratio	Free Cash Flow	Intangible Assets	Sales Growth	Profitability
Volatility	1						
Firm Size	-0.3105*	1					
Debt Ratio	0.2031*	-0.2607*	1				
Free Cash Flow	-0.2459*	0.8790*	-0.2121*	1			
Intangible Assets	-0.2329*	0.2653*	-0.003	0.1415*	1		
Sales Growth	0.0292*	0.023	0.0700*	0.0022	0.0914*	1	
Profitability	-0.2580*	0.2988*	-0.1366*	0.2294*	0.0681*	0.0308*	1

Table 4.4 Synchronicity and Yield Spread

This table exhibits the regression results for testing Hypotheses 1, 1a, and 1b for at-issue bonds (Panel A) and seasoned bonds (Panel B). Regression coefficients reported in Model (1) – Model (5) are estimated based on Equation 2. Standard errors are clustered at two-dimensions (firm and year). *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A: At-Issue Bonds

	Model (1) All At-Issue Bonds	Model (2) High Yield Bonds	Model (3) Investment Graded Bonds	Model (4) Long-Term Bonds	Model (5) Short-Term Bonds
Dependent Variable	Yield Spread	Yield Spread	Yield Spread	Yield Spread	Yield Spread
Intercept	-0.009	0.0464***	-0.0117***	0.0319***	-0.0471***
	(-1.02)	(5.86)	(-5.12)	(4.89)	(-7.20)
Synchronicity	-0.0005	-0.0007*	0.0000	-0.0005	-0.0014**
	(-1.37)	(-1.94)	(0.09)	(-1.50)	(-2.21)
Orthg. Credit Rating	-0.0030***	-0.0039***	-0.0014***	-0.0028***	-0.0015***
	(-14.42)	(-13.90)	(-7.76)	(-13.35)	(-4.96)
Debt Ratio	0.0184***	0.0193***	0.0098***	0.0180***	0.0112***
	(10.94)	(14.67)	(4.30)	(13.27)	(3.06)
Volatility	0.6446***	0.5275***	0.4157***	0.5659***	0.4421***
	(9.70)	(17.02)	(3.12)	(11.83)	(4.02)
Issue Size	-0.0016***	-0.0012**	-0.0004**	-0.0012***	-0.0009***
	(-5.62)	(-2.76)	(-2.18)	(-5.81)	(-2.82)
Analyst Coverage	-0.0060***	-0.0072***	-0.0026***	-0.0056***	-0.0050***
	(-11.56)	(-16.24)	(-6.79)	(-12.83)	(-3.20)
Market-to-Book	-0.0016***	-0.0041***	-0.0010***	-0.0018***	0.0001
	(-3.83)	(-5.91)	(-3.02)	(-5.06)	(0.07)
Sales Growth	0.0012	0.0048***	-0.0029	0.0019	0.0007
	(0.75)	(3.61)	(-0.89)	(1.07)	(0.19)
Bid-Ask Spread	-0.0465	0.0285	-0.09*	-0.0475	-0.1537**
	(-0.81)	(0.81)	(-1.68)	(-0.94)	(-2.21)
Duration	-0.0003***	-0.0037***	0.0002**	-0.0007***	0.0003
	(-3.10)	(-5.25)	(2.53)	(-6.49)	(0.57)
Firm Size	-0.0000***	-0.0001	-0.0000***	-0.0000***	0.0000
	(-4.42)	(-0.86)	(-6.74)	(-3.90)	(1.18)
Profitability	-0.0161***	-0.0194***	-0.0130**	-0.0148***	-0.0223**
	(-4.15)	(-5.29)	(-2.20)	(-4.03)	(-2.27)
Cash Flow Risk	0.0225***	0.0140***	0.0191*	0.0203***	0.0153***
	(6.06)	(4.88)	(1.87)	(5.57)	(2.90)
Capital Expenditure	-0.0016***	-0.0026	-0.0014***	-0.0013	-0.0013***
	(-3.97)	(-1.00)	(-5.85)	(-1.24)	(-8.73)
Callable Bonds	0.0045***	0.0065***	0.0030***	0.0038***	0.0030***
	(6.63)	(8.56)	(4.57)	(7.00)	(2.91)
Putable Bonds	-0.0029***	0.0052*	-0.0058***	-0.0024***	0.0019
	(-4.03)	(1.94)	(-5.66)	(-4.07)	(0.42)
Quality Spread	1.2467***	1.2510***	1.3314***	1.1408***	0.9666***
	(13.14)	(4.03)	(17.74)	(8.94)	(8.24)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
No. of Obs	6013	1982	4031	4460	559
adj. R-sq	0.791	0.75	0.666	0.794	0.883

Panel B: Seasoned Bonds

	Model (1) All Seasoned Bonds	Model (2) High Yield Bonds	Model (3) Investment Graded Bonds	Model (4) Long-Term Bonds	Model (5) Short-Term Bonds
Dependent Variable	Yield Spread	Yield Spread	Yield Spread	Yield Spread	Yield Spread
Intercept	0.0760***	0.0781***	0.0387	0.0342***	0.1071
	(7.44)	(3.41)	(0.01)	(5.96)	(0.00)
Synchronicity	-0.0024***	-0.0045***	-0.0001	-0.0021***	-0.0022***
	(-5.82)	(-7.72)	(-0.47)	(-5.87)	(-3.54)
Orthg. Credit Rating	-0.0029***	-0.0035***	-0.0015***	-0.0026***	-0.0030***
	(-14.09)	(-7.19)	(-6.64)	(-18.61)	(-8.05)
Debt Ratio	0.0213***	0.0199***	0.0093***	0.0179***	0.0228***
	(7.87)	(5.52)	(3.65)	(7.61)	(5.91)
Volatility	1.1109***	1.0524***	0.5546***	0.9796***	1.2087***
	(11.97)	(11.74)	(6.67)	(13.13)	(10.59)
Issue Size	-0.0035***	-0.0041**	-0.0013***	-0.0024***	-0.0044***
	(-3.63)	(-2.38)	(-2.94)	(-4.55)	(-3.94)
Bond Age	0.0008***	0.0009***	0.0007***	0.0006***	0.0004**
	(5.86)	(3.15)	(8.46)	(5.19)	(2.35)
Number of Trade	0.0000*	0.0000***	0.0000	0.0000**	0.0000**
	(1.67)	(3.06)	(0.30)	(2.44)	(2.08)
Analyst Coverage	-0.0031***	-0.0027**	-0.0017***	-0.0026***	-0.0046***
	(-4.55)	(-2.28)	(-3.01)	(-6.26)	(-4.30)
Market-to-Book	-0.0008*	-0.0024	-0.0012***	-0.0007*	-0.0002
	(-1.76)	(-1.51)	(-3.70)	(-1.71)	(-0.36)
Sales Growth	-0.0017	0.0053*	-0.0064**	0.0020	-0.0081
	(-0.62)	(1.85)	(-2.44)	(0.79)	(-1.53)
Bid-Ask Spread	0.1119**	0.1389**	0.1365**	0.1017***	0.4398***
	(2.01)	(2.53)	(2.37)	(2.62)	(2.70)
Duration	-0.0012***	-0.0031***	-0.0009***	-0.0009***	-0.0093***
	(-8.36)	(-5.71)	(-6.97)	(-5.68)	(-15.71)
Firm Size	-0.0000	-0.0001	-0.0000***	-0.0000*	-0.0000**
	(-1.55)	(-1.09)	(-4.32)	(-1.74)	(-2.31)
Profitability	-0.0432***	-0.0540***	-0.0158**	-0.0407***	-0.0407***
	(-6.56)	(-8.19)	(-2.28)	(-7.00)	(-5.16)
Cash Flow Risk	0.0181***	0.0105	0.0190	0.0145**	0.0298*
	(2.90)	(1.47)	(1.39)	(2.21)	(1.72)
Capital Expenditure	-0.0058	-0.0096	-0.0041	0.0004	-0.0018
	(-0.83)	(-1.16)	(-0.83)	(0.07)	(-0.12)
Callable Bonds	0.0016**	0.0026	0.0007	0.0026***	0.0027**
	(2.35)	(1.51)	(0.94)	(3.48)	(2.30)
Putable Bonds	-0.0063***	-0.0081*	-0.0042***	-0.0066***	0.0058
	(-3.67)	(-1.64)	(-4.37)	(-4.48)	(0.76)
Quality Spread	0.0046***	0.0127***	0.0062***	0.0058***	0.0028
	(3.09)	(4.09)	(4.45)	(4.73)	(1.09)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
No. of Obs.	24818	6366	18452	14107	7148
adj. R-sq	0.578	0.604	0.322	0.669	0.524

In Panel A Models (2) and (3), the full sample of at-issue bonds is divided into high yield bonds and investment graded bonds, according to their credit ratings. Equation 2 is then replicated in each subsample. Bonds are classified into the high yield subsample if their ordinal number coded credit ratings are less than 12 and into the investment graded subsample if their ordinal number coded credit ratings are more than 12. The findings show that *Synchronicity* exhibits a negative coefficient (-0.0007) on yield spread with statistical significance at 10% among high yield bonds, but an insignificant coefficient (-0.0000) among investment graded bonds. Other control variables generally demonstrate similar results as in Model 1. These findings support *Hypothesis 1a* and indicate that information asymmetry is a risk factor that is particularly more important to investors when investing in high risk bonds.

Next, the full sample of at-issue bonds is divided into long-term and short-term subsamples according to their maturity. Bonds are grouped into the long-term subsample if the time to maturity (converted in years) is greater than 7 years, and into the short-term subsample if the time to maturity (converted in years) is less than (or equal to) 5 years[1]. As shown in Models (4) and (5), there is a significant negative relation between synchronicity and yield spread among short-term bonds with a coefficient of -0.0014 and statistical significance at 5%, but an insignificant relation between synchronicity and yield spread among long-term bonds. Other explanatory variables are largely as expected and consistent with the results in Model (1). These results provide supportive evidence to

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[1] We follow Lu, Chen and Liao (2010) and Goyal and Wang (2013) to define short-term and long-term maturity. For both at-issue bonds and seasoned bonds, we also tried to divide bonds into short-term and long-term sub-sample using different maturity definitions, e.g., we define short-term bonds with maturity less than 3 years and long-term bonds with maturity greater than 10 years, the number of observations in each sub-sample is reduced largely, but the results remain consistent.

Hypothesis 1b. To the extent that firms with great information asymmetry are more likely to issue bonds with short maturity (Flannery, 1986; Diamond, 1991; Berger, Espinosa-Vega, Frame, & Miller, 2005), these findings suggest that investors place greater weight on exposure to information asymmetry risk when investing in short-term bonds.

In Table 4.4 Panel B, Equation 2 is re-examined in the sample of seasoned bonds. As shown in Panel B Model (1), after controlling for default, liquidity, economic risk, and other firm-level and bond-level factors, the coefficient of information asymmetry measure *Synchronicity* is found to be negative (-0.0024) and statistically significant at 1%. As information is incorporated into prices via trading activities, the transaction prices of seasoned bonds are more likely to reflect information opacity than prices of at-issue bonds, resulting in a stronger negative impact of synchronicity on yield spread for seasoned bonds. Also consistent with the findings in Panel A, *Synchronicity* is shown to have a considerably stronger impact on yield spread among high yield seasoned bonds and short-term seasoned bonds. The regression coefficients of *Synchronicity* are: 0.0045, significant at 1% for high yield bonds; -0.0001, insignificant, for investment graded bonds; -0.0022, significant at 1% for short-term bonds; and -0.0021, significant at 1% for long-term bonds. The control variables are largely as expected and consistent with previous findings. Among others, the liquidity measure *Bond Age* is found to be significantly and positively related to yield spread across all models. This is consistent with the view that older bonds are subject to higher liquidity risk as they trade less frequently than younger bonds (Lu, Chen, & Liao, 2010; Huang, Huang, & Oxman, 2015).

Overall, the findings in Table 4.4 shed further light on the notion that low synchronicity reflects a poor information environment in which bond investors require higher risk premiums as compensation for bearing additional information risk, resulting in increased yield spread.

In Table 4.5, the relation between synchronicity and cost of debt is explored using an alternative measure – *Credit Rating*. The relation between synchronicity and credit ratings is reported for at-issue bonds in Panel A, and for seasoned bonds in Panel B. As expected, *Synchronicity* is found to have a highly significant positive relation with *Credit Rating.* Specifically, the regression coefficient is 0.4167 for at-issue bonds and 0.3370 for seasoned bonds, suggesting that *Credit Rating* improves with the increase of issuers' *Synchronicity.* These results are consistent with *Hypothesis 2* and indicate that rating analysts consider a firm's information environment to be an important determinant of a firm's credit quality. Firms with lower synchronicity are considered to have a greater information asymmetry problem and are therefore assigned with lower credit ratings. For both at-issue bonds and seasoned bonds, firm characteristics associated with high probability of default also reduce bond credit ratings. Consistent with Adams, Burton, and Hardwick (2003), Bhojraj and Sengupta (2003), and Alali, Anandarajan, and Jiang (2012), results from Table 4.5 show that *Credit Rating* has a strong positive relation with *Firm Size* and *Profitability* and a negative relation with *Debt Ratio, Volatility*, and *Sales Growth*. Moreover, an issuer's debt structure also has impact on its credit rating. Inclusion of *Callable Bonds* in debt structure increases an issuer's default risk and hence lowers its *Credit Rating*.

Table 4.5 Synchronicity and Credit Rating

This table exhibits the regression results for testing Hypothesis 2 for at-issue bonds (Panel A) and seasoned bonds (Panel B). Regression coefficients reported are estimated based on Equation (3). Standard errors are clustered at two-dimensions (firm and year). *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Panel A: At-Issue Bonds	**Panel B:** Seasoned Bonds
	Credit Rating	Credit Rating
Intercept	14.5097***	6.5304***
	(18.20)	(7.10)
Synchronicity	0.4167***	0.3370***
	(4.94)	(5.52)
Debt Ratio	-4.5964***	-4.4962***
	(-13.00)	(-10.46)
Volatility	-83.1887***	-94.4530***
	(-6.72)	(-7.99)
Issue Size	0.2027**	0.0968
	(2.35)	(1.37)
Bond Age		0.0125
		(0.85)
Number of Trades		-0.0001
		(-0.67)
Analyst Coverage	1.0455***	0.9347***
	(11.13)	(6.15)
Market-to-Book	0.3140***	0.2719**
	(2.58)	(2.03)
Sales Growth	-1.3113***	-1.2828***
	(-3.91)	(-3.47)
Bid-Ask Spread	5.8360	-3.2369
	(0.80)	(-0.46)
Duration	0.0967***	0.0619***
	(6.61)	(5.5)
Firm Size	0.0215***	0.0222***
	(9.47)	(11.97)
Profitability	3.9603***	5.0650***
	(3.36)	(4.17)
Cash Flow Risk	-1.3246	-5.0869***
	(-1.46)	(-4.18)
Capital Expenditure	0.0993	0.3697
	(0.78)	(0.28)
Callable Bonds	-0.9635***	-0.4331***
	(-7.24)	(-3.39)
Putable Bonds	-0.2658	-0.3967**
	(-0.68)	(-2.04)
Quality Spread	29.9092***	1.0107***
	(3.75)	(9.19)
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
No. of Obs	6013	24818
adj. R-sq	0.747	0.727

Table 4.6 Synchronicity and Callable Provision

This table exhibits the logit regression results for testing Hypothesis 3 for at-issue bonds. Regression coefficients reported are estimated based on Equation (4). Standard errors are clustered at two-dimensions (firm and year). *, **, and *** indicate significance at 10%, 5%, and 1%, levels, respectively.

	At-Issue Bonds
Dependent Variable	Callable Bond
Intercept	-1.3199**
	(-2.00)
Synchronicity	-0.1189*
	(-1.84)
Market-to-Book	0.0164
	(0.23)
Sales Growth	0.0326
	(0.14)
Profitability	0.9225
	(1.15)
Firm Size	-0.0098***
	(-3.23)
Free Cash Flow	-0.0000
	(-0.84)
Low Rating	2.0595***
	(7.31)
Mod Rating	0.5059**
	(2.07)
Debt Ratio	-0.5087
	(-1.62)
YTM-10year	-0.0995
	(-0.75)
Change in YTM-10year	-0.0937
	(-0.74)
Yield Slope	-0.1538
	(-0.98)
Std Slope	0.4404
	(0.89)
Maturity	0.0464***
	(7.73)
Issue Size	0.5003***
	(8.77)
Industry Fixed Effects	Yes
Year Fixed Effects	Yes
No. of Obs	6527
Pseudo R-sq	0.3924

Table 4.6 exhibits the regression results for testing *Hypothesis 3* for newly issued bonds. As indicated by the negative coefficient (-0.1189), *Synchronicity* is found to reduce the possibility of firms issuing bonds with embedded callable provisions. Based on the premise that lower synchronicity proxies for a less transparent information environment and greater information asymmetry, firms with lower synchronicity are more likely to issue bonds with callable features in order to convey a positive signal to the market about their future performance. Also, *Firm Size*, which can be used as an alternative information asymmetry indicator, is also found to have a negative relation with the probability of callable bond issuance. While the indicator variables of *Low Rating* and *Moderate Rating* are both found to be positively related to callable bond issuance, the motivation of issuing callable bonds is different for firms with low credit ratings and moderate credit ratings. According to Banko and Zhou (2011), below-investment-grade firms issue callable bonds mainly to alleviate the agency conflict arising from the asymmetric information environment, while the investment-grade firms issue callable bonds primarily to hedge interest rate risk. Indeed, as shown in Table 4.6, the regression coefficient of *Low Rating* is considerably stronger than the regression coefficient of *Moderate Rating* in both magnitude and significance level, implying that the callable bond market is dominated by below-investment-grade bonds (Banko & Zhou, 2011).

Next, the relation between synchronicity and split of credit ratings for at-issue bonds and seasoned bonds is investigated. Results are shown in Table 4.7. Consistent with *Hypothesis 4*, a significant negative relation between *Synchronicity* and *Split Rating* for both at-issue bonds and seasoned bonds is documented; the regression coefficients of *Synchronicity* are -0.1405, significant at 10% for at-issue bonds, as shown in Panel A; and -0.1064, significant at 10% for seasoned bonds, as shown in Panel B. To the extent that credit rating split is an indication of information opacity, the findings further support the view that low synchronicity represents a less transparent information environment. Also, consistent with the information opacity hypothesis, results from Table 4.7 show that alternative information risk measures, such as *Analysts Coverage* and *Dispersion* demonstrate significant negative correlations with *Split Rating* for both at-issue and seasoned bonds.

Viewed collectively, the multivariate regression results are consistent with the univariate results and pairwise correlation reported in Tables 4.2 and 4.3, and they further corroborate the view that low synchronicity is an indication of information inefficiency and asymmetry. Findings show that firms with low stock price synchronicity are associated with higher cost of debt, indicating synchronicity is a priced risk factor from the perspective of bondholders. In subsequent tests, synchronicity is also found to have an explanatory role in the likelihood of callable bond issuance and the incidence of credit rating splits. These empirical findings provide further evidence to the information asymmetry explanation of synchronicity.

Table 4.7 Synchronicity and Split Rating

This table exhibits the regression results for testing Hypothesis 4 for at-issue bonds (Panel A) and seasoned bonds (Panel B). Regression coefficients reported are estimated based on Equation (5). Standard errors are clustered at two-dimensions (firm and year). *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Panel A: At-Issue Bonds	**Panel B:** Seasoned Bonds
Dependent Variable	Split Rating	Split Rating
Intercept	0.7349	4.1339
	(0.54)	(1.17)
Synchronicity	-0.1405*	-0.1064*
	(-1.88)	(-1.88)
Issue Size	0.2840	-1.0882
	(1.05)	(-0.76)
Analysts Coverage	-0.4989***	-0.4346***
	(-3.68)	(-3.94)
Market-to-Book	-0.1055	-0.1562**
	(-1.26)	(-2.19)
Bid-Ask Spread	-3.9942***	-7.5487
	(-3.48)	(-1.38)
Firm Size	-0.0679	-0.0338
	(-1.01)	(-0.59)
Callable Bond	0.0708	0.2336**
	(0.75)	(2.27)
Orthg. Credit Rating	-0.1032***	-0.1546***
	(-3.85)	(-6.50)
Intangible Assets	0.3478	0.0919
	(0.94)	(0.49)
Forecast Accuracy	-1.1123*	0.0207
	(-1.92)	(0.99)
Maturity	-0.0381	-0.0202
	(-0.63)	(-0.92)
Capital Expenditure	0.8058	1.8380**
	(1.18)	(2.56)
Dispersion	3.2897**	2.1451**
	(2.09)	(2.18)
Bond Age		-0.0188
		(-0.88)
Number of Trades		-0.0096
		(-0.31)
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
No. of Obs	5179	29795
pseudo R-sq	0.097	0.085

4.6 Robustness Check

Recent literature has documented a strong relation between stock price synchronicity and liquidity. Chan, Hameed, and Kang (2013) find that illiquidity measures decrease with synchronicity and conclude that the degree of stock price synchronicity has a significant impact on asset liquidity. Gassen, LaFond, Skaife, and Veenman (2014) further explore the relation between illiquidity and synchronicity, and argue that illiquidity is a first order determinant of the variation in synchronicity. They re-examine the association of synchronicity with analyst coverage and with firm-level transparency and identify that after controlling for illiquidity, the relations appear to either disappear or significantly weaken. The findings mentioned above imply a possibility that synchronicity effects documented in this essay may be comingled with liquidity effects, since synchronicity may represent (or partially represent) liquidity risk rather than the hypothesized information risk.

Indeed, as shown by the pairwise correlation reported in Table 4.3, synchronicity has a strong correlation with liquidity indicators such as *Bid-Ask Spread, Issue Size, Number of Trades*, and *Bond Age.* In addition to the liquidity factors, synchronicity also appears to be highly correlated with *Credit Rating*, *Analyst Coverage,* and *Firm Size*, implying the possibility that synchronicity and other independent variables included in the regression models may be overlapping in what they proxy for. Therefore, the same methodology that is introduced in essay one and essay two is adopted to further purge out the effects of the remaining independent variables included in each regression model from *Synchronicity* by creating *Orthogonalized Synchronicity.* All the regression models

Table 4.8 Orthogonalized Synchronicity and Yield Spread

This table checks the regression results presented in Table 4.4 using *Orthogonalized Synchronicity* to replace *Synchronicity*. Results for at-issue bonds are presented in Panel A and results for seasoned bonds are presented in Panel B. Regression coefficients reported in Model (1) – Model (5) are estimated based on Equation (2). Standard errors are clustered at two-dimensions (firm and year). *, ** and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel A: At-Issue Bonds

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	All At-Issue Bonds	High Yield Bonds	Investment Graded Bonds	Long-Term Bonds	Short-Term Bonds
Dependent Variable	Yield Spread	Yield Spread	Yield Spread	Yield Spread	Yield Spread
Intercept	-0.0087	0.0483***	-0.0117***	0.0328***	-0.0462***
	(-0.98)	(6.02)	(-5.07)	(4.98)	(-7.02)
Orthg. Synchronicity	-0.0005	-0.0007*	-0.0000	-0.0005	-0.0014**
	(-1.37)	(-1.94)	(-0.09)	(-1.50)	(-2.21)
Orthg. Credit Rating	-0.0030***	-0.0039***	-0.0014***	-0.0028***	-0.0015***
	(-14.42)	(-13.90)	(-7.76)	(-13.35)	(-4.96)
Debt Ratio	0.0187***	0.0197***	0.0098***	0.0182***	0.0119***
	(10.88)	(15.18)	(4.35)	(13.28)	(3.34)
Volatility	0.6425***	0.5246***	0.4156***	0.5638***	0.4362***
	(9.68)	(16.79)	(3.11)	(11.78)	(3.96)
Issue Size	-0.0016***	-0.0012**	-0.0004**	-0.0012***	-0.0010***
	(-5.54)	(-2.80)	(-2.18)	(-5.81)	(-3.01)
Analyst Coverage	-0.0061***	-0.0073***	-0.0026***	-0.0057***	-0.0053***
	(-11.13)	(-16.44)	(-6.80)	(-12.33)	(-3.27)
Market-to-Book	-0.0016***	-0.0042***	-0.0010***	-0.0018***	-0.0001
	(-3.85)	(-5.99)	(-2.95)	(-5.14)	(-0.10)
Sales Growth	0.0013	0.0049***	-0.0029	0.0019	0.0008
	(0.78)	(3.67)	(-0.89)	(1.10)	(0.23)
Bid-Ask Spread	-0.0376	0.0407	-0.0895*	-0.0386	-0.1284*
	(-0.68)	(1.20)	(-1.65)	(-0.79)	(-1.79)
Duration	-0.0003***	-0.0037***	0.0002**	-0.0007***	0.0003
	(-3.10)	(-5.25)	(2.53)	(-6.49)	(0.56)
Firm Size	-0.0000***	-0.0001	-0.0000***	-0.0000***	-0.0000
	(-4.53)	(-0.87)	(-6.83)	(-3.95)	(-1.43)
Profitability	-0.0161***	-0.0193***	-0.0130**	-0.0148***	-0.0223**
	(-4.15)	(-5.29)	(-2.20)	(-4.03)	(-2.27)
Cash Flow Risk	0.0229***	0.0145***	0.0191*	0.0206***	0.0163***
	(6.22)	(5.25)	(1.89)	(5.80)	(3.20)
Capital Expenditure	-0.0015***	-0.0025	-0.0014***	-0.0013	-0.0011***
	(-3.97)	(-0.97)	(-6.09)	(-1.20)	(-7.66)
Callable Bonds	0.0045***	0.0065***	0.0030***	0.0038***	0.0030***
	(6.63)	(8.56)	(4.57)	(7.00)	(2.91)
Putable Bonds	-0.0029***	0.0052	-0.0058***	-0.0024***	0.0019
	(-4.03)	(1.94)	(-5.66)	(-4.07)	(0.42)
Quality Spread	1.2564***	1.2643***	1.3320***	1.1506***	0.9943***
	(13.01)	(4.06)	(17.68)	(8.93)	(8.43)
Industry Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
No. of Obs	6013	1982	4031	4460	559
adj. R-sq	0.791	0.75	0.666	0.794	0.883

Panel B: Seasoned Bonds

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	All Seasoned Bonds	High Yield Bonds	Investment Graded Bonds	Long-Term Bonds	Short-Term Bonds
Dependent Variable	Yield Spread	Yield Spread	Yield Spread	Yield Spread	Yield Spread
Intercept	0.0802***	0.0935***	0.0388	0.0403***	0.1106
	(7.57)	(4.00)	(0.00)	(6.65)	(0.01)
Orthg. Synchronicity	-0.0021***	-0.0043***	0.0000	-0.0018***	-0.0020**
	(-5.30)	(-7.31)	(0.15)	(-5.29)	(-3.14)
Orthg. Credit Rating	-0.0029***	-0.0035***	-0.0014***	-0.0026***	-0.0030***
	(-14.06)	(-7.18)	(-6.57)	(-18.55)	(-8.06)
Debt Ratio	0.0231***	0.0234***	0.0093***	0.0197***	0.0244***
	(8.19)	(6.32)	(3.68)	(8.24)	(6.12)
Volatility	1.1134***	1.0557***	0.5525***	0.9813***	1.2112***
	(11.96)	(11.76)	(6.65)	(13.12)	(10.60)
Issue Size	-0.0037***	-0.0045***	-0.0013**	-0.0026***	-0.0046***
	(-3.78)	(-2.60)	(-2.95)	(-4.84)	(-4.06)
Bond Age	0.0008***	0.0008***	0.0007***	0.0006***	0.0004**
	(5.77)	(3.01)	(8.48)	(5.06)	(2.27)
Number of Trade	0.0000**	0.0000***	0.0000	0.0000***	0.0000**
	(2.10)	(3.52)	(0.32)	(3.02)	(2.32)
Analyst Coverage	-0.0034***	-0.0033***	-0.0017***	-0.0029***	-0.0048***
	(-4.97)	(-2.75)	(-3.00)	(-6.99)	(-4.48)
Market-to-Book	-0.0010**	-0.0028	-0.0012***	-0.0010**	-0.0004
	(-2.28)	(-1.78)	(-3.74)	(-2.22)	(-0.67)
Sales Growth	-0.0018	0.0051	-0.0064**	0.0019	-0.0082
	(-0.66)	(1.77)	(-2.41)	(0.75)	(-1.54)
Bid-Ask Spread	0.1590***	0.2281***	0.1401**	0.1453***	0.4852***
	(2.84)	(4.27)	(2.37)	(3.75)	(2.97)
Duration	-0.0012***	-0.0031***	-0.0009***	-0.0009***	-0.0093***
	(-8.37)	(-5.76)	(-6.98)	(-5.69)	(-15.74)
Firm Size	-0.0000	-0.0002	-0.0000***	-0.0000**	-0.0000***
	(-1.82)	(-1.15)	(-4.29)	(-2.03)	(-2.58)
Profitability	-0.0429***	-0.0536***	-0.0157**	-0.0405***	-0.0404***
	(-6.53)	(-8.17)	(-2.26)	(-6.96)	(-5.13)
Cash Flow Risk	0.0192***	0.0123*	0.0192	0.0155**	0.0309*
	(3.07)	(1.70)	(1.41)	(2.34)	(1.78)
Capital Expenditure	-0.0064	-0.0109	-0.0041	-0.0002	-0.0022
	(-0.91)	(-1.32)	(-0.81)	(-0.03)	(-0.14)
Callable Bonds	0.0016**	0.0027	0.0007	0.0026***	0.0027**
	(2.36)	(1.53)	(0.94)	(3.48)	(2.29)
Putable Bonds	-0.0063***	-0.0082*	-0.0042***	-0.0066***	0.0058
	(-3.67)	(-1.64)	(-4.37)	(-4.48)	(0.76)
Quality Spread	0.0051***	0.0137***	0.0063***	0.0063***	0.0032
	(3.46)	(4.47)	(4.47)	(5.18)	(1.28)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
No. of Obs.	24818	6366	18452	14107	7148
adj. R-sq	0.578	0.604	0.322	0.669	0.524

Table 4.9 Orthogonalized Synchronicity and Credit Rating

This table checks the regression results presented in Table 4.5 using *Orthogonalized Synchronicity* to replace *Synchronicity*. Results for at-issue bonds are presented in Panel A and results for seasoned bonds are presented in Panel B. Regression coefficients reported are estimated based on Equation (3). Standard errors are clustered at two-dimensions (firm and year). *, ** and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Panel A: At-Issue Bonds	**Panel B:** Seasoned Bonds
	Credit Rating	Credit Rating
Intercept	14.2596***	5.9351***
	(17.98)	(6.52)
Orthg. Synchronicity	0.4167***	0.3009***
	(4.94)	(4.90)
Debt Ratio	-4.8197***	-4.7590***
	(-13.58)	(-11.04)
Volatility	-81.3763***	-94.8012***
	(-6.53)	(-8.00)
Issue Size	0.2244***	0.1278*
	(2.63)	(1.83)
Bond Age		0.0150
		(1.02)
Number of Trades		-0.0003
		(-1.27)
Analyst Coverage	1.1186***	0.9764***
	(11.82)	(6.31)
Market-to-Book	0.3505***	0.3047**
	(2.85)	(2.28)
Sales Growth	-1.3573***	-1.2684***
	(-4.02)	(-3.43)
Bid-Ask Spread	-1.8774	-9.9939
	(-0.26)	(-1.37)
Duration	0.0968***	0.0624***
	(6.62)	(5.50)
Firm Size	0.0221***	0.0226***
	(9.73)	(11.98)
Profitability	3.9488***	5.0294***
	(3.35)	(4.14)
Cash Flow Risk	-1.6439*	-5.2382***
	(-1.83)	(-4.29)
Capital Expenditure	0.0607	0.4601
	(0.47)	(0.34)
Callable Bonds	-0.9635***	-0.4341***
	(-7.24)	(-3.39)
Putable Bonds	-0.2658	-0.3905**
	(-0.68)	(-2.00)
Quality Spread	21.4841**	0.9342***
	(3.02)	(8.51)
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
No. of Obs	6013	24818
adj. R-sq	0.747	0.727

Table 4.10 Orthogonalized Synchronicity and Callable Provision

This table checks the logit regression results presented in Table 4.6 using *Orthogonalized Synchronicity* to replace *Synchronicity* for at-issue bonds. Regression coefficients reported are estimated based on Equation (4). Standard errors are clustered at two-dimensions (firm and year). *, ** and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	At-Issue Bonds
Dependent Variable	Callable Bond
Intercept	-1.1767*
	(-1.76)
Orthg. Synchronicity	-0.1189*
	(-1.84)
Market-to-Book	-0.0036
	(-0.05)
Sales Growth	0.0425
	(0.18)
Profitability	0.9619
	(1.20)
Firm Size	-0.0095***
	(-3.16)
Free Cash Flow	-0.0000
	(-0.93)
Low Rating	2.1218***
	(7.63)
Mod Rating	0.5331**
	(2.18)
Debt Ratio	-0.4202
	(-1.34)
YTM-10year	-0.1066
	(-0.80)
Change in YTM-10year	-0.0930
	(-0.74)
Yield Slope	-0.1652
	(-1.05)
Std Slope	0.4804
	(0.97)
Maturity	0.0466***
	(7.76)
Issue Size	0.4924***
	(8.57)
Industry Fixed Effects	Yes
Year Fixed Effects	Yes
No. of Obs	6527
Pseudo R-sq	0.3924

Table 4.11 Orthogonalized Synchronicity and Split Rating

This table checks the regression results presented in Table 4.7 using *Orthogonalized Synchronicity* to replace *Synchronicity*. Results for at-issue bonds are presented in Panel A and results for seasoned bonds are presented in Panel B. Regression coefficients reported are estimated based on Equation (5). Standard errors are clustered at two-dimensions (firm and year). *, ** and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	Panel A: At-Issue Bonds	**Panel B:** Seasoned Bonds
Dependent Variable	Split Rating	Split Rating
Intercept	1.0316	4.2431
	(0.76)	(1.21)
Orthg. Synchronicity	-0.1405*	-0.1064*
	(-1.88)	(-1.88)
Issue Size	0.3232	-1.0315
	(1.21)	(-0.72)
Analysts Coverage	-0.5022***	-0.4321***
	(-3.70)	(-3.92)
Market-to-Book	-0.0919	-0.1547**
	(-1.10)	(-2.17)
Bid-Ask Spread	-2.5391***	-5.8773
	(-3.25)	(-1.08)
Firm Size	-0.1001	-0.0558
	(-1.54)	(-1.00)
Callable Bond	0.0734	0.2295**
	(0.78)	(2.23)
Orthg. Credit Rating	-0.0972***	-0.1502***
	(-3.75)	(-6.53)
Intangible Assets	0.4041	0.0938
	(1.09)	(0.50)
Forecast Accuracy	-1.1386**	0.0231
	(-1.96)	(1.10)
Maturity	-0.0397	-0.0199
	(-0.66)	(-0.91)
Capital Expenditure	0.7206	1.8131**
	(1.07)	(2.52)
Dispersion	3.3780**	2.1691**
	(2.15)	(2.20)
Bond Age		-0.0186
		(-0.87)
Number of Trades		-0.0074
		(-0.24)
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
No. of Obs	5179	29795
pseudo R-sq	0.097	0.085

(Equations 2 to 5) are replicated using *Orthogonalized Synchronicity*. The results are reported in Tables 4.8–4.11. According to the results, this methodology is found to have no impact on the explanatory power of synchronicity. The regression coefficients of *Orthogonalized Synchronicity* throughout Tables 4.8–4.11 are consistent with the regression coefficients of *Synchronicity* presented in Tables 4.4-4.7. All other independent variables are generally consistent with previously documented results. To sum up, the robustness check confirms that synchronicity explains a dimension of information asymmetry that is not directly captured by other factors such as liquidity, firm size, and others.

4.7 Conclusion

Motivated by the ongoing debate of the interpretation of stock price synchronicity (R^2) as a measure of price informativeness, this essay aims to address the question of whether low stock price synchronicity represents an efficient information environment or an asymmetric information environment from another new angle. Using pricing and structural characteristics of corporate bonds, this essay provides empirical evidence to the information asymmetry interpretation of synchronicity. Based on the premise that stock price synchronicity reflects the information environment surrounding the bond, results show that synchronicity has a negative relation with yield spread, indicating that investors demand greater yield premiums as compensation for adverse information risk when holding bonds issued by low synchronicity firms. This negative relation is found to be particularly more evident among high yield bonds and short-term maturity bonds, suggesting that bondholders consider price synchronicity as a more important risk factor when investing in bonds with higher risk and greater uncertainty. Using credit ratings as the alternative measure of cost of debt, results consistently show that low synchronicity is related to low credit ratings. This result suggests that firms with low synchronicity are considered more risky, even from the perspective of rating agencies.

Further analysis shows that firms with low synchronicity are more likely to issue bonds with embedded callable features. To the extent that firms under an environment with great information asymmetry issue callable bonds to reduce the asymmetric information problem, this result offers further support to the notion that lower synchronized firms are subject to greater information asymmetry. A direct examination of the information asymmetry explanation of synchronicity is then carried out by linking synchronicity to the levels of credit rating split. The negative relation between synchronicity and rating split confirms the view that firms with low synchronicity are associated with a poor information environment in which rating agencies experience more difficulties in reaching consensus when assigning credit ratings. Overall, these findings contradict conventional wisdom and suggest that low synchronicity actually represents high information risk and a low quality information environment.

Appendix: Description of Variables Used in the Study

Variable Name	Description and Source
Panel A: Bond Related Variables	
10-Year Treasury Yield	Yield of 10-year Treasury bonds. *Source*: St. Louis Federal Reserve
Bond Age	The difference in years between the issue date and the transaction date. *Source*: TRACE & FISD
Callable Bonds	A dummy variable which equals to 1 if the bonds are issued with callable provision, 0 otherwise. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Change in 10-Year Treasury Yield	Change in the 10-year Treasury yield measured over 100 days prior to the date of bond issuance. *Source*: St. Louis Federal Reserve
Credit Rating	Moody's bond ratings, where the letter ratings are coded using numbers from 1 (rated as "C") to 21 (rated as "AAA"). *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Duration	Calculated using the DURP call function in SAS (using time to maturity, coupon, yield to maturity). *Source:* SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Issue Size	Log of total USD proceeds of the issue. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Maturity	Log of number of years to final maturity. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Moderate Rating	Indicated by dummy variable, equal to one for bonds rated A or BBB by Moody's and zero otherwise. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Low Rating	Indicated by dummy variable, equal to one for BB or lower rated bonds and zero Otherwise. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Number of Trades	Number of trades over the calendar year relevant to the bond transaction date. *Source*: TRACE & FISD
Orthogonalized Credit Rating	The residual from regressing *Credit Rating* on all other independent variables included in Equation (5). *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Putable Bonds	A dummy variable which equals to 1 if the bonds are issued with putable provision, 0 otherwise. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Quality Spread	The yield difference between Baa and Aaa corporate bond indexes. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Split Rating	Dummy variable equals to 0 if the S&P and Moody's ratings are the same, 1 if the S&P and Moody's ratings differ by at least one notch. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Standard Deviation of Yield Slope	Standard deviation of yield slope. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Yield Slope	The yield difference between the 10 year Treasury bonds and 1 year Treasury bonds on the bond issuance date. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds)
Yield Spread	The difference between the yield to maturity between corporate bond and the interpolated yield to Treasury bond yield. Winsorized at the 1% level. *Source*: SDC (at-issue bonds), TRACE & FISD (seasoned bonds), St. Louis Federal Reserve (T-Bond yields).
Panel B: Firm Related Variables	
Analysts Coverage	Number of analysts posting forecasts for the sample firm over the prior year. *Source*: IBES
Bid-Ask Spread	Mean of the daily bid-ask spread (ASK-BID/((ASK+BID)/2) over the year prior to the bond issuance year or transaction year. *Source:* CRSP
Market-to-book Ratio	Sum of book value of debt plus market value of equity scaled by total assets, measured over the year prior to the bond issuance or transaction year. *Source:* Compustat
Cash Flow Risk	Standard deviation of ROA over 5 years prior to the bond issuance or transaction year.

	Source: Compustat
Capital Expenditure	Capital expenditure (CAPEX) divided by total assets, estimated over the year prior to the bond issuance or transaction year. *Source*: Compustat
Debt Ratio	Total debts divided by total assets (LC + DLTT/AT), measured over the year prior to the bond issuance or transaction year. *Source:* Compustat
Dispersion	Standard deviation of the inter-analyst forecast divided by the fiscal-year-end stock price. *Source:* IBES
Firm size	Market value of equity, measured over the year prior to the bond issuance or transaction year. *Source:* Compustat
Forecast Accuracy	Negative absolute value of the analyst forecast error (the actual EPS minus the median forecast divided by the stock price). *Source*: IBES
Free Cash Flow	Firm's operating free cash flow over the year prior to the bond issuance or transaction year. *Source:* Compustat
Intangible Assets	Intangible assets scaled by total assets, measured over the year prior to the bond issuance or transaction year. *Source:* Compustat
Profitability	Represented by ROA and is defined as earnings before interest and taxes divided by total assets, measured over the year prior to the bond issuance or transaction year. *Source:* Compustat
Sales Growth	Growth rate in sales for the 3 years ending the bond issuance year or bond transaction year. *Source:* Compustat
Synchronicity	log (R^2/(1-R^2)), where R^2 is the regression statistics obtained based on the four factors model. *Source:* CRSP (stock prices), Kenneth French's data library (four factors data)
Volatility	Standard deviation of daily stock returns over the year preceding the bond issuance or transaction year. *Source:* CRSP
Panel C: Other Variables	
Industry Fixed Effects	Indicated by dummy variable which equals to 1 if the company falls into a specific industry and 0 otherwise. Industry classification is defined based on Fama French 49 industry definitions. *Source*: Kenneth R French Data Library
Year Fixed Effects	Indicated by dummy variable which equals to 1 if the bond issuance or bond transaction falls into a specific sample year and 0 otherwise

CHAPTER FIVE: CONCLUSION

This chapter presents a conclusion of the thesis. It presents the main findings of each essay along with a discussion of the implications of the results. Section 5.1 demonstrates the findings of essay one. Section 5.2 presents the main findings of essay two. Finally, the findings of essay three are summarised in Section 5.3.

5.1 Essay One: R^2 and market response to analyst recommendation revisions

Essay one relates R^2 to the market response to informational events and highlights the role of analyst recommendation revisions. After employing event study methodology in the preliminary test, findings of essay one show that the immediate return, volume, volatility, and bid-ask spread reactions, in response to upgrade and downgrade recommendation revisions, are all shown to be stronger in magnitude among lower R^2 stocks compared to higher R^2 stocks. Further multivariate regression analysis documents consistent and robust results with the inclusion of control variables, including firm size. These results are consistent with the view that lower R^2 stocks are less informative with less firm-specific information being previously anticipated and incorporated into their prices (Dasgupta, Gan, & Gao, 2010). Accordingly, lower R^2 stocks experience stronger price reaction as a result of new information incorporation. Lower R^2 stocks also benefit more from this new information with greater improvement in the information-based trading, as indicated by stronger changes in trading volume and return volatility. Lower R^2 stocks also benefit from greater improvement in the information environment, as indicated by greater reduction in bid-ask spread. All these findings confirm the informational role of analysts in dispersing firm-specific information and facilitating the stock price formation process. This value added role of stock analysts is particularly important for firms with less informative and noisier trading environments.

5.2 Essay Two: R^2 and the corporate signaling effect

Essay two examines R^2 in the corporate context by focusing on dividend change announcements. With similar to essay one, an event study methodology is adopted and the analysis begins with an examination of the immediate price reaction to dividend increase and decrease announcements. Findings show that the magnitude of stock price reaction in response to dividend change announcements decreases monotonically with the increase of R^2 levels. The price reaction is demonstrated to be asymmetric between dividend increases and decreases. Specifically, dividend decrease announcements are accompanied by stronger price changes, indicating investors place greater weight on bad news. These results also hold while controlling for other explanatory variables in the multivariate regression analysis.

This essay also investigates if the predicting ability of current dividend changes to future earnings changes varies with stocks' R^2 levels, based on the conservative model introduced by Grullon, Michaely, Benartzi, and Thaler (2005). While current dividend increases are found to provide no statistically significant signal to future profitability, current dividend decreases are found to provide a creditable signal to future earnings changes. In particular, dividend decreases convey more information about future earnings when stock price synchronicity is lower.

5.3 Essay Three: Does R^2 mean more or less informative stock price? Evidence from bond market

This essay further investigates the interpretation debate on R^2 by relating stock price synchronicity to cost of corporate debt and bond features. It demonstrates that the synchronicity measure of information environment is a relevant determinant for bond valuation. Consistent with the information asymmetry explanation of R^2, stock price synchronicity is found to have a negative association with corporate bond yield spread and a positive association with credit ratings, indicating that, from the perspective of bondholders, synchronicity is a priced risk factor. To provide additional evidence on the information asymmetry explanation, stock price synchronicity is linked to the probability of callable bonds issuance and the likelihood of split ratings, the presence and occurrence of which are indicators of greater information asymmetry and poor information environment. The affirmative results further confirm the role of low R^2 in explaining information inefficiency. With careful control for other firm-level and bond-level variables, results of this study imply that stock price synchronicity (or R^2) explains a dimension of information asymmetry beyond existing risk factors (such as default, liquidity, and information risk components) in the corporate bond pricing model and bond structure model.

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