An Investigation on Stock Market Calendar Month Anomalies

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Dedicated to my partner Benjamin Liu,
my parents and my friend Lynn Ye

Abstract

Calendar anomalies are one of the earliest identified challenges against market efficiency theory, but to a large extent yet remain unsolved today. This raises the question of whether the anomalies are real, or simply products of data snooping. This dissertation comprises three independent studies investigating stock market seasonal anomalies.

Using extended long time series data of over 300 years of UK market index returns, the first study reveals that many well-known monthly seasonals are sample specific. For instance, the January effect only emerges around 1830. Most months have had their 50 years of fame, showing the importance of long time series to safeguard against sample selection bias, noise and data snooping. The overall conclusion is that monthly seasonals might simply be in the eye of the beholder.

The second study examines the 'Halloween indicator' or 'Sell in May'-effect using all 108 available stock market indices over all time periods. In total 55,425 monthly observations over 319 years show winter returns – November through April - are 4.52% significantly higher than summer returns. The effect is increasing in strength: The average difference between November-April and May-October returns is 6.25% over the past 50 years. A Sell-in-May trading strategy beats the market more than 80% of the time over 5 year horizons. The study also addresses a number of (methodological) issues that have been raised with respect to the effect.

The third study examines the seasonal behaviour of vacation activity as a possible explanation for the seasonal pattern in stock market returns using 34 countries' outbound travel data as a proxy for vacation behaviour. It shows that vacation activity

has a negative impact on stock market returns, and significant lower summer returns are attributable to the seasonal behaviour in vacation activities, however, the well known Halloween effect may only be partially related to seasonal behaviour of vacations. The evidence is especially strong in the European markets. The findings offer support to vacation induced change in exogenous liquidity demand and risk aversion hypothesis proposed in Bouman and Jacosen (2002), but cast doubt on the vacation induced lack of trading hypothesis argued in Hong and Yu (2009).

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Chapter 1 Introduction

1.1 Introduction

Research into calendar anomalies is one of the oldest strands in finance literature that challenges the foundation of modern financial theory: The efficient market hypothesis. Starting with Wachtel's study in 1942 on the January effect, and followed by many other, now classic, studies including Rozeff and Kinney (1976), French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Roll (1983), Keim (1983), Reinganum (1983), and Ariel (1987). Ever since 1942, old and new calendar anomalies (like the other January effect (Cooper, McConnell, & Ovtchinnikov, 2006) and seasonal effects in the cross-section of stock returns (Heston & Sadka, 2007)) keep practitioners and academics intrigued.

While many papers now assume that there are seasonal anomalies and try to explain them, another strand of studies casts doubt and raises the question whether the anomalies are real, or are products of data snooping, noise and selection bias (For example, Lakonishok & Smidt, 1988; Sullivan, Timmermann & White, 2001). In their seminal study, Lakonishok and Smidt (1988) prescribe long and new data series as the best 'medicine' against data snooping, noise and 'boredom' (selection bias). With 90-years of the Dow Jones market index, they were able to confirm the robustness of many daily anomalies, however, as they point out, at the monthly level, even with a 90-year sample, it offers no remedy to the problem. While new data sets of long time series of stock returns are becoming available, no paper has used these data to verify whether monthly seasonals are real, or are chimeras.

This dissertation focuses on seasonal anomalies at a monthly frequency. Essay one extends Lakonishok and Smidt (1988)'s work and investigates all previously documented calendar month effects with long historical time series of over 300 years of UK stock market returns data. Essay two provides the most comprehensive re-examination to date of the Halloween effect (or the Sell-in-May effect) that considers all stock markets worldwide using the full history of stock market indices available for each market. Essay three tests whether a lower summer return effect and Halloween effect can be attributed to seasonal behaviour in vacation activities using 34 countries monthly outbound travel data. While all three essays are related to seasonal anomalies, each individual study is self contained. The following section summarises the main findings and contributions of each study.

1.2 Main findings and contribution to the literature

1.2.1 Are monthly seasonals real? A three century perspective

Using sub-period analysis and rolling window regressions, the study shows whether the seasonal monthly anomalies are present, depends strongly on the sample period and sample length considered. Significant results fluctuate over time, many months significantly under- or outperform over the full period and in sub-periods, but few have done so persistently throughout the full data period. For almost every month, one can find 50 years of fame. Conclusions vary strongly based on the selected sample period even over 100-year intervals. For example, the January effect switches from significantly negative to significantly positive based on the 100-year samples. If I only consider the full sample over 300 years, 4 monthly anomalies (significantly positive January and December effects and significantly negative July and October effect) and the Halloween effect are robust across different estimation methods. In that case, however, one should be aware that in extremely long sub periods, the effect may be reversed and that this reversal may be significant. Thus, the overall conclusion is that monthly seasonals might simply be in the eye of the beholder.

This evidence confirms the potential problems caused by data snooping, noise and sample selection bias, and highlights the importance of studying long time series to safeguard against these issues. While many studies now take seasonal anomalies as a fact and try to explain them, this study contributes to the literature by taking a step back and asking the question – using these new historical data – of whether or not these monthly seasonal anomalies exist and, if so, when they emerge. For instance, the new evidence suggests that explanations for a January effect should allow for a valid explanation as to why the January effect changed from being a relatively negative month before 1830 to a positive month thereafter. Thus, understanding whether, and if so which, calendar anomalies persist assists our understanding of the working of financial markets and the behaviour of investors.

1.2.2 The Halloween indicator: Everywhere and all the time

This study provides the most rigorous robustness tests for the Halloween effect, which has been shown to be a relatively robust anomaly in the first study in this dissertation. To this purpose, I consider all 108 stock markets worldwide using the full history of stock market indices available for each market. The results reveal that, unlike other seasonal anomalies, the Halloween effect has strengthened rather than weakened in recent years. It is prevailing around the world to the extent that the mean returns are higher for the period of November-April than for May-October in 81 out of 108 countries, with difference being statistically significant in 35 countries, compared to only 2 countries having significantly higher May-October returns. In addition, the strength of the effect is stronger in developed and emerging markets than in frontier and rarely studied markets, as well as being more prevalent in countries located in Europe, North America and Asia than in other regions. Moreover, the Halloween trading strategy still beats a buy and hold strategy out-of-sample in 36 of the 37 countries originally studied. The UK evidence reveals that investors with a long horizon would have remarkable odds of beating the market.

While the author is not aware of any study which has considered all stock markets with all time period data available, this is probably the best safeguard against data mining and sample selection bias. As my first essay shows that, even with an extremely large sample, for just one country it is hard to determine the presence of monthly anomalies, this study contributes to the literature by answering the sceptics regarding whether or not the Halloween effect exists based on all of the empirical evidence available, rather than relying on a limited selection of one or more countries.

In addition, a full analysis of the effect may contribute to discovering what causes this anomaly by answering the following questions: Is the effect present in all countries? All regions? All the time? Is it constant over time? While it might be difficult to rely on cross sectional evidence to find a definite answer to the Halloween effect, the finding that the effect has been strengthening over the past 50 years implies that any feasible explanation should allow for time variation in the effect and should be able to explain why the effect has increased so strongly in the last fifty years.

Last, but not least, this study not only considers whether the effect is present, but also whether, as an investor, it would make sense to assume it is by considering trading strategies and comparing these with buy and hold strategies.

1.2.3 Vacation behaviour and seasonal patterns of stock market returns

This study takes a closer look at the association between seasonal patterns of stock market returns and vacation activities with 34 countries' monthly outbound travel data as a more direct proxy for vacation behaviour. It shows that the strength of lower summer returns and the negative impact outbound travel has on stock market returns are stronger in the portfolios with higher vacation importance rankings and significant summer peaks in outbound travel. The evidence is especially strong for the European countries, the lower summer return effect in the markets located in other regions, however, might be a by-product of market integration. The size of the Halloween effects seems unrelated to the vacation activity. While given that the 6-month period of the Halloween effect comprises the summer months in most of the countries in the sample, the Halloween effect may, at best, be partially affected by vacation activities.

With respect to what might be the sources that connect the vacation activities to stock return seasonals, the findings offer support to a liquidity demand induced change in risk aversion hypothesis proposed in Bouman and Jacobsen (2002), while the analysis of the trading activities provide evidence inconsistent with the lack of trading activities induced lower return hypothesis, as argued in Hong and Yu (2009).

Using a summer dummy variable, Hong and Yu (2009) link lower summer trading volume to lower stock market returns, assuming that the low summer trading volume is caused by investors "Gone fishin'". This study contributes to the literature by providing the missing link, as the data shows exactly when and how many investors went fishin'. In addition, the study makes the vacation explanation more distinguishable from other seasonal variables that attempt to explain the effects through both cross-sectional and time series analysis with outbound travel measures.

Chapter 2 Are monthly seasonals real? A three century perspective

2.1 Introduction

Had stock markets been a field of academic study early in the nineteenth century, our predecessors would have wondered about the significantly positive August and December effects and asked themselves why stocks performed so poorly in October. Researchers in the early 1900s pondering a century of stock market returns might have tried to explain the significantly negative July and August effects.

To what extent are seasonal stock market anomalies real? In their seminal study Lakonishok and Smidt (1988) prescribe long and new data series as the best medicine against data snooping, noise and 'boredom' (selection bias). They confirm many daily anomalies, like the Turn of the Month effect and the Turn of the Week effect, in their extended sample of 90 years of the Dow Jones market index. As they point out at a monthly level, however, they add little new data and even a 90-year sample offers no remedy using monthly frequency data[1]:

"Monthly data provides a good illustration of Black's (1986) point about the difficulty of testing hypotheses with noisy data. It is quite possible that some month is indeed unique, but even with 90 years of data the standard deviation of the mean monthly return is very high (around 0.5 percent). Therefore, unless the unique month

[1] Increasing the interval of observation does not answer this question either, as Merton (1980, p.365) points out: "Accuracy of the (expected return) estimator…depends only upon the total length of the observation period… nothing is gained in term of accuracy of the expected return estimate by choosing finer observations intervals for the returns…"

outperforms other months by more than 1 percent, it would not be identified as a special month."(Lakonishok & Smidt, 1988, p.422)

While new data sets of long time series of stock returns are becoming available, no paper has used these data to verify whether monthly seasonals are real, or are chimeras. This paper fills that gap by looking at over 300 years of monthly data on the UK stock market, starting in 1693. I use these UK data as it is the longest time series available and also provides me with a relatively fresh new data set, as they have been less mined than have data from the United States.

Contrary to the Lakonishok and Smidt (1988) results, where their longer sample period confirmed well-known daily effects, the longer series sheds new light on many monthly calendar anomalies. Many months significantly under- or outperform over the full period and in sub periods, but few have done so persistently throughout the ages. This suggests that monthly calendar anomalies change over time, or that these anomalies do not exist. Whether or not anomalies exist seems to depend strongly on the chosen sample period and sample length. I illustrate this using the full sample but also sample lengths of a hundred years (close to the ninety years suggested in the quote above) and fifty years (as proxy for the smaller sample sizes used by most other studies).

Whether or not these anomalies exist also depends on how one weighs the statistical evidence. If one requires an anomaly to be statistically significant and with consistent signs in all sub-periods of reasonable length and across different estimation methods (OLS, GARCH and robust regressions), there may be no monthly anomalies. If one feels that Lakonishok and Smidt's argument above has some merit - that we needs at least ninety years or more to establish reasonable confidence bounds – we should rely on the longer samples or full sample evidence only. Based on the full sample only the evidence points to seasonal effects in four months (significantly positive in January and December and negative in July and October) and a significant Halloween or Sell in May effect. These effects are significant and robust across estimation methods in the full sample. Changing the weights one uses to evaluate the statistical evidence leads to a different combination of anomalies. In short it seems safe to say that whether or not these anomalies do exist, is in the eye of the beholder, and depends strongly on the sample used and which criteria are applied.

No month – including January - significantly outperforms the market persistently in all the 50- and 100-year subsamples, although December comes close, only exhibiting below average returns in the first half of the twentieth century. In the first 150 years, instead of being the best performing month, January is significantly worse than average. Before 1830 there is a strong positive December effect, which weakens as the January effect emerges. Only July almost consistently underperforms in the full sample and in all of the 50- and 100-year subsamples. However, not even in subsamples of a hundred years does it always underperform significantly. Moreover, if I use fifty year rolling window regressions I find periods with positive July returns as well. The fifty year rolling regressions nicely illustrate the point of Lakonishok and Smidt (1988) that these sample sizes are too small for reasonable statistical inference. Unfortunately even the 100-year subsamples do not seem to provide unambiguous evidence either.

This long monthly series also allows me to test the persistence of the Sell-in-May effect, or the Halloween effect (Bouman & Jacobsen, 2002), which is the notion that winter returns (November through April) are substantially higher than summer returns

(May through October). Bouman and Jacobsen (2002) find this anomaly present in 36 out of 37 countries. Many studies have confirmed the existence of this Halloween effect in stock returns.[2] Bouman and Jacobsen (2002) also present evidence of the effect in the same UK data as I use over the full three hundred year period starting from 1693. Nonetheless, they leave open the possibility that this anomaly may also have varied over time. This study considers that possibility here. The evidence confirms their result for the full sample. But it cannot confirm the effect has always been significantly present in subsamples as well. Measured over hundred year intervals it is always positive but not always significant. Measured over fifty years the effect tends not to be significant in the first 100 years and in the beginning of the 20th century it is sometimes negative (although not significantly so). Again, the anomaly may be in the eye of the beholder. However, if one believes it does exist it has dramatically increased in strength since the 1950s.

This study's focus on the long-term history of UK data is especially interesting, as the United Kingdom is the home of the market wisdom *Sell in May and go away*. Popular wisdom suggests that the effect originated from the English upper class spending winter months in London, but spending summer away from the stock market on their estates in the country: An extended version of summer vacations as we know

[2] For instance, Swinkels and Van Vliet (2010) find a US equity premium over the sample period of 1963-2008 of 7.2% if there is a Halloween effect and a Turn of the Month effect, and a negative risk premium of -2.8% in all other cases. We discuss more studies in section 2.

them today.[3] Thus, if the Sell in May anomaly should be significantly present in one country over a long period, one would expect it to be the United Kingdom.

A number of studies have made profound contributions in making high quality historical time series data available, allowing others to test and revisit current findings in the literature. For instance, Goetzmann et al. (2001) construct monthly stock price and total return indices from over 600 individual stocks on the NYSE starting from 1815 and running to 1925. Wilson and Jones (2002) improve the monthly S&P stock price index from 1871 to 1999 making it a more consistent broad index. For the UK, Grossman (2002) provides an annual price index with broader coverage of the market to the standard index for the period from 1870 to 1913 and Acheson et al. (2009) present a monthly index of total returns for the UK stock market for 1825 to 1870.

Historical data are used to examine the robustness of current empirical findings and economic theories. For instance, Goetzmann and Ibbotson (2005) document the historical equity premium of the US market back to 1792 and find a relatively stable real rate of returns over the past two centuries. Using stock prices of three big companies traded in both the London and Amsterdam stock markets, Neal (1987) shows that both markets are informationally efficient, with high levels of integration between them. Harrison (1998) examines the distribution and higher moments of Amsterdam and London stock returns in the eighteenth century. Brown and Easton (1989) test whether weak form efficiency holds for the 3% Consols in the London market for the period

[3] To give an example: "Historically, the summer fall was caused by farmers selling and sowing their crops and rich investors swanning off to enjoy Ascot, The Derby, Wimbledon, Henley and Cowes. Modern investors jet off to the Med, where they cannot find copies of their pink papers and senior fund managers soak up the sun on Caribbean cruises leaving their nervous second-in-commands in charge" (The Evening Standard, May 26, 1999).

from 1821 to 1860. Brown Jr. et al. (2006) study the volatility of 3% Consols in the London market from 1792 to 1959 and infer that political stability might be an important explanation for the dramatic decline in volatility during the Pax Britanica period. Jorion and Goetzmann (1999) report the equity premia for 39 countries and the potential diversification benefits of the countries over the period from 1921 to 1996. Goetzmann et al. (2005) investigate the benefits of international diversification from 1850 onwards and find that the benefit of global investing varies over time. Grossman and Shore (2006) reveal that size and long term reversal anomalies are not present in the UK market from 1870 to 1913, and that the period only exhibits weak evidence of a value effect. With a 90 year daily time series index from 1897 to 1986, Lakonishok and Smidt (1988) confirm the persistence of many daily anomalies including the turn of the week, turn of the month, turn of the year and the holiday effect in the US market. Using data back to 1871, Jones et al. (1987) show that the January effect is present long before income taxes in the US, which goes against the tax loss selling hypothesis. Similarly, Choudhry (2001) also reports evidence of the January effect in both the US and the UK in the period from 1870 to 1913.

Others study long time series data to increase the power of the test where small sample inference could potentially bias the results of empirical findings. For example, Shiller (1989) examines the co-movements of stock prices and dividends between the UK and US markets from 1919 to 1987. Goetzmann (1993b) finds evidence of mean reversion of long term stock returns using 300 years of UK data and 200 years of US data. Goetzmann (1993a) shows a strong positive relation between art demand and the stock market over the period of 1715 to 1986. Lundblad (2007) confirms the positive relation between the market risk premium and expected volatility using US equity market return data from 1836 to 2003 and argues the insignificant relation between risk and return documented in the previous literature could be due to small sample problems. Using monthly data for the US and annual data for the UK from 1871, Goetzmann and Jorion (1995) find only weak evidence of dividend yield predictability on long horizon returns, while Goetzmann et al. (2001) reach a similar conclusion using a new dataset of the US market for the period of 1815 to 1925. In addition, they test for time varying volatility using GARCH estimation and confirm earlier empirical evidence that positive shocks and negative shocks have different predictability for future volatility. Using a sample size of over 300 years should allow me to examine the robustness of calendar anomalies with a strong increase in the power of the tests.

Research into calendar anomalies, which I discuss more extensively below, is one of the oldest strands in the finance literature, starting with Wachtel's study in 1942 on the January effect, and followed by many other, now classic, studies including Rozeff and Kinney (1976), French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Roll (1983), Keim (1983), Reinganum (1983) and Ariel (1987). Ever since 1942, old and new calendar anomalies (like the other January effect (Cooper et al., 2006) and seasonal effects in the cross-section of stock returns (Heston and Sadka, 2007)) keep practitioners and academics intrigued. Swinkels and Van Vliet (2010) try to disentangle the different calendar anomalies. Ogden (2003) relates equity return patterns to the seasonality of macroeconomic variables and a recent paper by Ogden and Fitzpatrick (2010) shows that many other anomalies, like the failure-risk anomaly, earnings momentum and the book-to-market anomaly, may also be seasonal. Many papers now assume that there are seasonal anomalies, like the January effect, and try to explain them. I feel that this paper contributes to the literature, as it takes a step back and asks the question – using these new historical data – of whether or not these monthly seasonal anomalies exist and, if so, when they emerge. For instance, explanations for a January effect should allow for a valid explanation as to why the January effect changed from being a relatively negative month before 1830 to a positive month thereafter. Thus, understanding whether, and if so which, calendar anomalies persist helps our understanding of the working of financial markets and the behaviour of investors.

2.2 A short literature review on monthly calendar anomalies

The main findings of seasonality studies are summarised in Table 2.1. Given the data I use, I focus on the UK market. Panel A reports sample periods, data sources, weighting methods and index types used in all the seasonality studies for the UK stock market. the key statistical findings at the market index level of each study are also quoted to facilitate the comparison with the results produced here. The last column reports the main reasons given by the studies for the observed seasonality. For the US market in Panel B, I report the studies that are either the first to document a particular calendar effect, or are the first investigation of a particular sample period. Panel C summarises the empirical findings available for other countries. The positive (negative) sign indicates a significant positive (negative) effect.

Calendar Month Seasonals

Wachtel (1942) uncovers the January effect in the US stock market as early as 1942. Interestingly, at least from a modern perspective he documents it in a short sample from 1928 to 1940. However, as studies on seasonal behaviour of stock market returns do not receive much academic attention at the time, it takes until 1976 before studies on the January effect become popular. In 1976 Rozeff and Kinney investigate the presence of seasonality in the US. Their study made the January effect popular among academics using a relatively long sample of 70 years of NYSE index data from 1904 to 1974. Subsequently many other studies document a January effect all over the world, albeit in generally relatively small samples, as Table 2.1shows.

To date there is no conclusive evidence on what causes this January effect. In Wachtel's original study, he proposes five possible causes for the January effect: 1) tax loss selling; 2) unusual cash demand around Christmas; 3) a pre-Christmas holiday effect; 4) the anticipation of better business in Spring; and 5) a positive feeling about the coming new year. The tax-loss selling explanation[4] subsequently becomes the most widely investigated hypothesis, especially after Keim (1983) shows the January effect in the US market to be size related and concentrated in the small firms. The US evidence generally supports the tax loss selling hypothesis (see, for instance, Reinganum, 1983; Roll, 1983; Schultz, 1985; Jones et al., 1991; Poterba and Weisbenner, 2001; Starks, Yong and Zheng, 2006). At the same time these studies cannot rule out the validity of other alternative explanations, like window dressing, the information hypothesis, the liquidity hypothesis and optimistic expectations.[5]

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4 The tax loss selling hypothesis states that downward pressure on stock prices might be induced at year end by investors selling the losing stocks with the intention of realising capital losses against their taxable incomes. The abnormally high January return is the effect of the stock price rebounding to its equilibrium level when the selling pressure stops at the beginning of the year.

5 The window dressing hypothesis is supported by Haugen and Lakonishok (1987), Lakonishok et al. (1991), and Ng and Wang (2004). It refers to the phenomenon when fund managers sell losing stocks prior to the disclosure of their portfolio holdings, typically at year end to impress investors, and buy the stocks back after the disclosure. The information hypothesis, discussed in Rozeff and Kinney (1976), Keim (1983) and Barry and Brown (1984), suggests that the January effect is caused by inappropriate modelling of risk: The market fails to account for the increased uncertainty in January due to the impending release of important information for the firms with a December fiscal year end. A related study, Kim (2006), constructs an earning information uncertainty risk factor that explains the

Meanwhile, earlier seasonality studies outside the US, primarily investigated as robustness checks for the tax loss selling hypothesis and the January effect, suggest that the January effect is prevalent. However, these studies also find that tax loss selling may only partially account for the January effect. In particular, Brown et al. (1982) find that Australian stocks during the period from 1958 to 1981 exhibit higher returns not only in July (in line with the tax loss selling as the fiscal year ends in June), but also in December, January and August. Using monthly data of value weighted stock market indices of 17 industrialised countries from 1959 to 1979, Gultekin and Gultekin (1983) show the presence of the January effect in all 17 countries and an April effect for the UK market.[6] With the only exception of Australia, their finding is in support of the tax loss selling hypothesis. Berges et al. (1984) show, however, that the January effect in the Canadian stock market is present both before and after the introduction of capital gain tax in 1973 using 30 years data from the 1950s on. In addition, Tinic et al. (1987) find no seasonality in stocks traded by foreign investors and Canadians who were subjected to taxation before 1972, indicating that tax loss selling cannot fully explain the January effect. In the Netherlands, Van den Bergh and Wessels (1985) find a January effect in the Dutch stock market for the period 1966 to 1982 even though capital gains are not taxed. Although individual investors are not subject to capital gain taxes in Japan and the corporate fiscal year end varies among firms, Kato and

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January effect in the US market. The liquidity hypothesis proposed by Ogden (1990) argues that the January effect stems from the increased demand for stocks caused by liquid cash injection from year end salaries, bonuses and dividend payments. The optimistic expectation hypothesis suggested by Ciccone (2011) claims that the turn of the year is a time of renewed optimism that bids up the stock price in January. In addition, Anderson et al. (2007) finds behaviourally related explanations are supported by laboratory tests.

6 As the tax year ends on 5 April in the UK, an April effect is consistent with the tax loss hypothesis.

Schallheim (1985) report both a January and a June effect for the Japanese stock market from 1952 to 1980. Their study inclines to support the alternative liquidity and information hypothesis.

For this study the UK evidence is interesting. Reinganum and Shapiro (1987) using monthly data from 1955 to 1980, find support for the tax loss selling hypothesis. They document both a January[7] and an April effect after the introduction of capital gain taxes in April 1965, while they detect no seasonality in the pre-tax period. In addition to the higher January and April returns, a later study by Clare et al. (1995) also reports high December returns and low September returns in the UK stock market during the period of 1955 to 1990. With the benefit of cross sectional data, studies show that the January effect in the UK (Dimson and Marsh, 2001) and Australia (Brown et al., 1982) is a market wide phenomenon, unlike in the US, the anomaly in these countries is not related to firm size.

For emerging markets, Ho (1990) confirms the presence of the January effect in 7 out of 10 Asia Pacific markets. Fountas and Segredakis (2002) investigate monthly seasonality in 18 emerging markets and find a significant January effect in Chile, Greece and Turkey, relatively high December returns in Colombia and Malaysia, and low October returns in Greece. A recent study (Darrat et al., 2011) updates the monthly seasonalities in 34 equity markets including the US and the UK. Using a more recent sample period from 1988 to 2010, they find an absence of the January effect in all

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7 A January effect might be caused by international stock market integration; see Gultekin and Gultekin (1983) for evidence of the January effect in capital markets around the world. In addition, Reinganum and Shapiro (1987) suggest that the January effect in the UK stock market is driven by corporations that have a tax year ending at the end of December.

Table 2.1 Summary of empirical findings

The table summarises the empirical studies for the calendar month seasonals. PW, VW, and EW refer to price weighted index, value weighted
The statistics are reported at percentage value, bold numbers in Panel A & B, and + (-) sign in Panel C denote statistically significant effects repor

Referred studies in Panel C: (A) Brown et al. (1982); (B) Gultekin and Gultekin (1983); (C) Berges et al. (1984); (D) Kato and Schallheim (19
Tinic et al. (1987); (G) Ho (1990); (H) Bouman and Jacobsen (2002); (I) Fountas and Segredakis (2002); (J) Zarour (2007); (K) Hong and Yu (20

Notes: (1) Summer refers to the deviation of mean returns during summer months (July through September for Northern Hemisphere countries, J
countries) from the rest of the year. (2) Hal refers to the difference in mean returns between November through April and May through October.
returns from the annual average modelled from a detrended index using first-order differencing. (4) Mean returns for 12 calendar months, d
October returns for Hal. (5) Statistics are not provided in the study. (6) Value weighted Cowles price index for the period 1910-1925, equally wei
The two 6-month periods are October through March and April through September.

Empirical Studies	Data Period Used	Country/Data source	Weighting	Index Type	Statistic Type	Monthly Seasonals												Sum
						Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
Panel A. UK Evidence																		
Gultekin and Gultekin (1983)	1959-1979	Capital International Perspective Indices	VW	Price Return	Mean	3.41	0.69	1.25	3.13	-1.21	-1.69	-1.11	1.88	-0.24	0.80	-0.61	2.06	
Reinganum and Shapiro (1987)	1956-1965	London Share Price Data Base	EW	Total Return	Mean	1.15	0.94	1.24	3.05	0.39	-0.79	-0.04	2.84	0.33	2.00	0.46	1.93	
	1966-1980					**5.38**	1.10	0.51	**3.91**	-0.21	-1.01	0.33	0.53	0.74	0.51	-1.01	1.32	
Corhay et al. (1987)	1969-1983	London Stock Price Data Base	EW	Total Return	Mean	**5.49**	2.21	0.73	**4.19**	-0.48	-1.39	1.22	1.13	-1.04	-0.07	-0.06	1.62	
Clare et al. (1995)	1955-1990	FTSE A All Share Index	VW	Price Return	Deviation (3)	**2.00**	-0.33	-0.44	**2.21**	**-1.34**	-0.85	-0.90	0.76	**-1.64**	-1.34	-0.69	**1.68**	
Dimson and Marsh (2001)	1955-1999	London Business School's Share Price Database	VW	Total Return	Mean	**2.83**	0.64	1.05	**2.67**	-0.46	-0.71	-0.24	0.91	-0.65	-0.10	0.08	**1.86**	

Table 2.1 Continued

Empirical Studies	**Data Period Used**	**Country/Data source**	**Weighting**	**Index Type**	**Statistic Type**	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Summ**
						Monthly Seasonals												
Choudhry (2001)	1870-1913	NBER website	VW	Price Return	Mean	**1.13**	-0.09	**-0.69**	0.08	-0.18	-0.25	**-0.39**	0.11	0.16	-0.20	-0.06	0.06	
Bouman and Jacobsen (2002)	1970-1998	MSCI Reinvestment Indices	VW	Total Return	Mean/Deviation [4]	3.10	0.80	-0.30	1.90	-1.40	-1.50	-0.10	0.00	-1.60	-0.80	1.30	1.20	
	1697-1969	Global Financial Data																
Hong and Yu (2009)	1965-2005	Datastream	VW	Total Return	Deviation													**-1**
Darrat et al. (2011)	1988-2010	MSCI Country Indices	VW	Total Return	Deviation	-1.01	-0.21	0.19	**1.60**	-0.50	**-1.88**	0.78	-0.29	-1.81	0.45	0.50	**2.17**	
Panel B. US Evidence																		
Wachtel (1942)[5]	1928-1940	DJIA	PW	Price Return		+												-
Rozeff and Kinney (1976)	1904-1974	NYSE	EW [6]	Total Return	Mean	**3.48**	0.26	-0.16	0.63	-0.37	0.18	1.90	1.46	-0.52	0.07	0.71	0.47	
Jones et al. (1987)	1871-1917	Cowles Industrial Index	VW	Price Return	Mean	**1.44**	0.36	0.33	1.04	-0.55	-0.28	-0.52	1.12	0.35	-0.01	0.54	-0.35	
	1918-1938					**2.61**	0.89	0.33	-0.33	0.28	-0.61	3.22	2.39	1.05	-2.52	-0.13	-0.61	
Bouman and Jacobsen (2002)	1970-1998	MSCI Reinvestment Indices	VW	Total Return	Mean/Deviation [4]	1.20	0.00	0.00	0.10	-0.20	0.10	-0.20	-0.70	-1.30	-0.60	0.60	0.90	
Ogden (2002)	1947-2000	NYSE Stocks	EW	Total Return	Mean	**3.37**	0.56	**1.18**	0.35	0.09	-0.36	0.79	0.19	-0.56	-0.90	**1.29**	**1.51**	
			VW		Excess Return	**1.26**	0.28	**0.95**	0.62	0.26	0.17	0.62	0.21	-0.68	0.09	**1.41**	**1.72**	
Hong and Yu (2009)	1962-2005	Datastream	VW	Total Return	Deviation													**-1**
Darrat et al. (2011)	1988-2010	MSCI Country Indices	VW	Total Return	Deviation	-0.35	-1.18	0.47	1.32	0.82	**-1.22**	0.32	-1.79	-0.94	0.27	0.86	**1.42**	

Table 2.1 Continued

Panel C. International Evidence														
(L)	Argentina										-	-	+	
(J)	Abu Dhabi													
(A), (B), (L)	Australia	+			+			+	+				+	
(H), (L)	Austria									-			+	
(J)	Bahrain													
(B), (H), (L)	Belgium	+			+					-			+	
(H)	Brazil													-
(B), (C), (F), (H), (K),	Canada	+				+				-			+	
(L)														
(I)	Chile	+												
(M)	China													
(I)	Colombia												+	
(B), (L)	Denmark	+								-			+	
(J)	Egypt													
(K), (L)	Finland						-							
(H), (K), (L)	France				+		-			-			+	
(K), (L)	Finland						-							
(H), (K), (L)	France				+		-			-			+	
(B), (H), (K), (L)	Germany	+							-	-			+	
(H), (I), (L)	Greece	+			+			+			-			
(G), (K), (L)	Hong Kong	+							-					
(L)	Indonesia									-			+	
(M)	India													
(H), (L)	Ireland	+		+	+		-			-			+	
(H), (K), (L)	Italy				+					-			+	
(B), (D), (G), (H), (M)	Japan	+			+		+						+	
(L), (J)	Jordan	+	-						-					
(G), (L)	Korea	+	-											
(J)	Kuwait													
(G), (H), (I), (L), (M)	Malaysia	+		-					-				+	
(B), (E), (H), (K)	Netherlands	+			+					-			+	
(L)	New Zealand		-		+			+		-				
(K)	Nigeria													
(B), (K), (L)	Norway	+								-			+	
(J)	Oman													
(J)	Palestine													
(G), (H), (K), (L)	Philippines	+							-					
(L)	Portugal						-							
(K)	Russia													
(G), (H), (L), (M)	Singapore	+							-				+	
(B), (H), (K), (L)	Spain	+			+					-				
(B), (H), (L)	Sweden	+							-	-				
(B), (H), (K), (L)	Switzerland	+								-			+	
(G), (H)	Taiwan	+												
(K)	Thailand												+	
(I), (L)	Turkey	+		-		-			-				+	

except 3 countries in the sample (Denmark, Ireland and Jordan). Moreover, many stock markets reveal significantly higher returns in April and December, while lower returns in June, August and September.

Halloween Effect

The Halloween effect, or Sell-in-May effect, refers to the notion that stock market returns tend to be higher from November through April than from May through October. It originates from an old European market wisdom first investigated empirically by Bouman and Jacobsen (2002) using 37 countries' monthly return indices. They show that the Halloween effect is present in 36 stock markets, and statistically significant in twenty of those markets. Andrade et al. (2012) find that in an out-of-sample (1998-2012) period all 37 of these countries in the original study have performed better in November through April than during the remainder of the year and fourteen have done so significantly. In addition, Jacobsen et al. (2005) show that the Halloween effect is a market wide phenomenon, which is not related to the common anomalies such as size or Book to Market ratios and/or dividend yields. Jacobsen and Visaltanachoti (2009) investigate the Halloween effect among US stock market sectors and find substantial differences across sectors.

Zarour (2007) studies the Halloween effect in Arabic stock markets and Lean (2011) considers markets in Asia. Zarour (2007) finds that the Halloween effect is present in 7 of the 9 Arabic markets in the sample period from 1991 to 2004. Lean (2011) investigates 6 Asian countries for the period 1991 to 2008, and shows that the Halloween effect is only significant in Malaysia and Singapore if modelled with OLS, but that 3 additional countries (China, India and Japan) become statistically significant when modelled allowing for time varying variance.

There are a number of explanations doing the rounds for what may cause this effect. Bouman and Jacobsen (2002) examine a large number of possible explanations. However, they can rule out many and their findings incline to support the vacation induced change in risk aversion or liquidity hypothesis as a likely candidate. Interestingly, Hong and Yu (2009) report a similar seasonal trading pattern that turnovers are significantly lower over a 3-month period (July-September for Northern Hemisphere countries and January-March for Southern Hemisphere countries), which they attribute to investors taking summer vacations away from the stock market. In addition, they document significantly reduced summer returns in 15 out of 51 stock markets studied in their sample.

However, there are many other possible explanations. Ogden (2003) reports a similar seasonal pattern in the US stock returns. He finds that the mean excess return during October through March is significantly higher than the return from April through September and suggests an annual cycle view of economic activities and risk conditions. Gerlach (2007) attributes the significantly higher 3-month returns from October through December in the US market to higher macroeconomic news announcements during the period. Gugten (2010) finds, however, that macroeconomic news announcements have no effect on the Halloween anomaly.

A number of studies also document a similar seasonal pattern in various stock markets, however, based on alternative mood related theories. For example, the Seasonal Affective Disorder (SAD) effect in Kamstra et al. (2003), and the temperature effect in Cao and Wei (2005), are highly correlated with the Halloween effect, as shown by Jacobsen and Marquering (2008). However, as Jacobsen and Marquering (2008) point out correlation is not causation therefore it is hard to distinguish between these explanations. Moreover, the validity of particularly the SAD paper by Kamstra et al. (2003) has been strongly criticised by a number of studies. For instance, Kelly and Meschke (2010) show the model used in Kamstra et al. (2003) is misspecified, due to a misreading of the evidence in the psychological literature regarding the timing of changes in mood. Kelly and Meschke (2010) then show that this misspecification drives the findings in Kamstra et al. (2003).

2.3 Data

I obtain a 317-year index of monthly UK stock prices compiled by Global Financial Data from several different sources. Starting from 1693, the index basically covers the entire trading history of the UK equity market.[8] Table 2.2 summarises the sources.

The index consists of stocks of the East India Company, the Bank of England and the South Sea Company for the first 110 years. From a 21st century perspective this may seem strange, but in the 18th century these three stocks essentially *were* the market.[9]

8 Great Britain switched from the Julian calendar to the Gregorian calendar in September 1752. This change results in an omission of 11 days. Wednesday, 2 September 1752 was followed by Thursday 14 September 1752. Since our data is at monthly frequency, 11 days change within September should not have any effect on our results.

9 Of course a three stock index might have a higher variance than more diversified indices of later periods and make estimates noisier, however, we show in our robustness tests that this hardly seems to affect our overall conclusions.

Table 2.2 Sources and descriptive statistics of sub-indices used to contruct the Global Financial Data index

Dates	Source	No. Of Stocks	Companies/Types	Weighting Method	Mean (%)	Std. Dev. (%)
1693	Thorold Roger, A history of prices in England (1693-1697); Larry Neal, The rise of financial capitalism (1698-Jan 1811)	1	East Indies Stock	--	-0.32	5.94
1694 –08/1711		2	Bank of England & East Indies Stock	Equally Weighted		
09/1711 –01/1811		3	Bank of England, East Indies Stock, & South Sea Stock	Equally Weighted	0.03	3.88
02/1811-12/1850	Rostow's Total Index (Gayer, Rostow & Schwartz, 1975)	63	Canals, Docks, Waterworks, Insurance, Gas-light and Coke, Mines, Railways, & Banks	Value Weighted	-0.05	4.19
01/1851 –06/1867	Hayek's Index (Gayer, Rostow & Schwartz, 1975)	Unknown	Canals, Docks, Waterworks, Gas-light and Coke, British Mines, Railways, & miscellaneous companies	Equally Weighted	0.13	1.94
07/1867-12/1906	London and Cambridge Economic Service Index	25-75	Broad-based, but does not include Bank, Discount Companies, Insurance & Railways	Equally Weighted	0.1	1.52
01/1907 –05/1933	Banker's Magazine	287	Broad-based, virtually all stocks quoted on the exchange	Value Weighted	-0.13	2.51
06/1933 –03/1962	Actuaries General Index	30 industrials	Blue-Chip index represents several industries, including Financial Stocks, Commodities & Utilities, but excluded Debentures & Preferred Shares	Value Weighted	0.4	3.98
04/1962 –12/2009	Financial Times-Actuaries All-Share Index	500 industrial companies	Broad-based, represents 98-99% of capital value of all UK companies	Value Weighted	0.58	5.48

These were the only stocks which traded on a daily, or at least weekly, basis before 1800. Other stocks could go an entire year without a price change.[10] Shea (2000) documents the total observable value of equity in the 18^{th} century in relation to these three big companies. This confirms their relative importance at the time. Before 1810 the market share measured in market value of the three companies ranges between 98.50% at the beginning of the 18^{th} century to 92.10% towards 1810. Mirowski (1981) examines surviving financial reports of some investing companies, indicating that their major investments were unanimously in these particular companies. He notes:

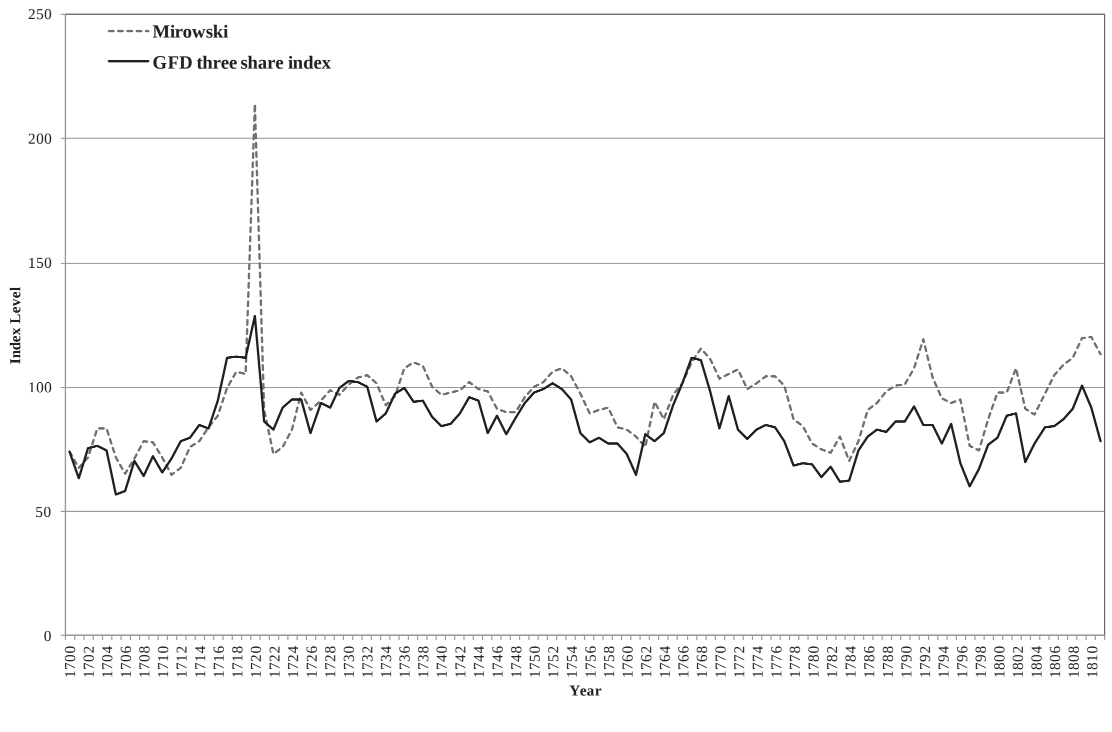
"The relative insignificance of securities not linked to the government or the three big companies (Bank of England, East Indies and South Sea) in the eighteenth century

10 Private correspondence with Bryan Taylor of Global Financial Data.

is also supported by surviving evidence from much smaller balance sheets. The Scotch Mines Company's balance sheet shows that in 1773 the main assets were Bank of England securities (58 percent), East India Company annuities (31 percent), and bills of exchange (2 percent). No other company's shares were included.”

Mirowski also constructs an annual index consisting of up to eight stocks[11] for the eighteenth century. If I compare this with the index this allows me to evaluate to what extent the big three were a good reflection of total market activity during this century. Figure 2.1 shows that, on an annual basis, the index based on these three big stocks seems well in line with the broader market index calculated by Mirowski (1981).

Figure 2.1 The Global Financial Data (GFD) three share index compared with Mirowski (1981) annual share price index (1700-1811)



11 Among the eight stocks, only the three companies included in our index have a continuous record for the whole of the eighteenth century.

For the first half of nineteenth century, the index adopts Rostow's total index (1811-1850) and Hayek's index (1851-1867), which are sourced from Gayer et al. (1975). Both indices are broad based and favour large and frequently traded companies. The Rostow's total index represents one-third of the companies officially listed in the market. For the second half of the nineteenth century, the index uses the London and Cambridge Economic Service index constructed by Smith and G.F. Horne, which is the most widely studied index for the pre-World War I period. The Banker's Magazine index applies for the period from 1907 to 1933. It is the broadest index of London shares for the period. The stock market ceased trading for five months from August 1914 to December 1914. The data for this period is treated as missing. The index consists of the Actuaries General Index from 1933 to 1962, and the Financial Times-Actuaries All-Share index, which covers about 98%-99% of the capital value of all UK companies from April 1962 onwards.

Some of these sub-indices are equally weighted, while others are value weighted. This might affect the estimation results, as the equally weighted indices will put relatively more weight in smaller companies. In the robustness section I show that the results are not affected if I replace all series by value weighted indices wherever possible.

Most of these sub-indices are frequently used in other empirical studies; for example, Shiller (1989), Goetzmann (1993b) and Goetzmann and Jorion (1995). While the series does not include dividends, I show in the robustness tests that this does not seem to affect the overall results.[12]

2.4 Monthly seasonality

Are stock returns in different months significantly different from each other? To study the potential effects of sample sizes on monthly stock returns, as discussed in Lakonishok and Smidt (1988), I first consider the full sample and also divide it into three (roughly) one-hundred-year sub-periods and six sub-periods of around fifty years. This allows me to examine the monthly stock return seasonality with relatively large sample sizes, while still being able to detect any trends and persistent patterns over time. Table 2.3 reports the results for the general seasonality tests, as well as basic statistical characteristics of the returns for each calendar month. I also report basic characteristics for winter months (November through April) and summer months (May through October) defined by the Halloween effect and for the entire year over the various sample periods.

The latest hundred-year and fifty-year subsamples enable me to confirm the findings of most earlier studies[13], and the other two (and a half) centuries data can be safely treated

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12 Global Financial Data does not have a reliable long series including dividends before 1929. The only series available relies on the Bank of England stock mostly before 1922 and assumes a dividend yield for the next seven years, however, even with that series the main conclusions in our paper remain unaffected.

13 Seasonality studies for the US market include earlier periods (i.e. the sample period in Wachtel (1942) starts from 1927, in Rozeff and Kinney (1976) from 1904, in Schultz (1985) from 1900, and in Jones et al. (1987) from 1871). Sample periods in seasonality studies of the UK market focus on the latest 50-year sub-period of the sample. For example, Gultekin and Gultekin (1983) examine UK data from 1959 to 1979, Corhay et al. (1987) consider the period 1969 to 1983, and Reinganum and Shapiro (1987) use the period 1955 to 1980 A recent study by Dimson and Marsh (2001) investigates the period from 1955 to 1999, and Darrat et al. (2001) tests for the period 1988 to 2010.

as fresh data for out of sample tests over a longer time period, as they have not been studied before in relation to seasonal anomalies.

Table 2.3 Seasonality tests and descriptive statistics of seasonal returns

The table reports average return (percentage), standard deviation (percentage), skewness and kurtosis for each calendar month, winter months (November through April), summer months (May through October) and entire year. The sample is sub-divided into three sub-periods of around 100-year intervals and six sub-periods of 50-year intervals. Seasonality is tested using a Kruskal and Wallis (K-W test) rank-based non-parametric equality test and parametric joint significance test. The F-stat reports the joint significance of the regression parameter α_2 to α_{12} from the regression $R_t = \alpha_1 + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \cdots + \alpha_{12} D_{12t} + \varepsilon_t$, where α_1 is the average return of January, and α_2 to α_{12} represent the differences between January returns and the returns of the other months. ***denotes significance at the 1% level; **denotes significance at 5% level; * denotes significance at 10% level

	January				February				March			
Sample Period	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**
1693-2009	0.69	5.10	4.90	51.28	0.09	3.21	0.46	9.49	-0.03	3.73	0.63	21.56
100-year Interval												
1693-1800	-0.60	3.74	-2.01	13.97	0.20	3.04	-0.48	8.91	0.11	4.46	2.11	24.34
1801-1900	1.34	5.79	7.53	67.79	-0.05	2.47	-2.07	11.08	-0.33	2.14	0.03	0.95
1901-2009	1.35	5.37	3.99	31.38	0.10	3.92	1.43	7.59	0.11	4.07	-1.50	9.60
50-year Interval												
1693-1750	-0.48	4.72	-2.12	10.06	0.10	3.71	-0.52	7.04	-0.28	5.72	2.15	17.34
1751-1800	-0.73	2.18	1.59	6.50	0.32	2.05	0.44	2.71	0.56	2.24	-1.15	4.14
1801-1850	1.55	7.98	5.83	38.39	-0.25	3.03	-2.29	9.13	-0.50	2.53	-0.29	-0.66
1851-1900	1.12	2.00	1.75	5.52	0.14	1.75	0.54	0.63	-0.16	1.68	1.52	5.44
1901-1950	0.86	1.35	-0.23	0.54	-0.50	2.32	-1.59	5.82	-0.49	2.50	0.60	2.79
1951-2009	1.75	7.19	2.97	16.98	0.60	4.85	1.32	4.59	0.62	5.00	-1.83	8.15

	April				May				June			
Sample Period	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**
1693-2009	0.49	3.39	-0.25	6.33	0.02	4.11	3.03	42.74	-0.12	3.78	3.44	42.94
100-year Interval												
1693-1800	0.31	3.01	-0.33	6.66	0.48	5.41	4.24	40.62	0.31	4.58	6.35	56.17
1801-1900	-0.40	2.65	-3.44	22.87	-0.22	2.59	-1.85	6.50	0.20	2.05	0.28	3.52
1901-2009	1.50	4.05	0.16	2.02	-0.21	3.74	-0.71	1.26	-0.85	4.05	-0.74	1.85
50-year Interval												
1693-1750	0.61	3.70	-0.57	5.17	1.09	7.11	3.35	24.33	0.61	6.00	5.21	35.18
1751-1800	-0.04	1.92	0.30	1.78	-0.23	2.02	-1.58	3.95	-0.04	1.90	1.21	4.85
1801-1850	-0.60	3.48	-3.00	14.77	-0.25	3.30	-1.63	3.99	0.47	2.36	0.78	1.54
1851-1900	-0.21	1.42	0.10	0.74	-0.19	1.64	-1.61	6.92	-0.07	1.65	-1.72	7.05
1901-1950	0.11	2.79	-0.98	2.93	0.12	2.76	-1.01	3.13	-0.94	3.68	-1.46	5.21
1951-2009	2.67	4.57	-0.09	1.49	-0.49	4.40	-0.50	0.33	-0.77	4.37	-0.40	0.41

	July				August				September			
Sample Period	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**
1693-2009	-0.31	3.31	-1.10	8.81	0.44	3.25	-0.09	2.78	-0.49	5.62	-7.07	91.72
100-year Interval												
1693-1800	-0.45	3.04	0.13	2.97	0.73	2.77	0.46	1.98	-0.93	8.15	-6.52	60.47
1801-1900	-0.49	1.90	-0.24	0.85	-0.32	1.94	-0.49	2.27	-0.27	2.19	-1.20	5.15
1901-2009	0.00	4.41	-1.55	7.27	0.86	4.36	-0.46	1.34	-0.26	4.68	-1.36	2.71
50-year Interval												
1693-1750	-0.34	3.71	0.02	1.93	0.71	3.05	0.26	1.75	-1.81	10.95	-4.89	33.67
1751-1800	-0.57	2.03	0.39	0.29	0.74	2.42	0.93	2.24	0.08	1.95	-0.81	1.56
1801-1850	-0.94	2.11	-0.13	0.19	-0.78	2.48	-0.02	0.77	-0.86	2.64	-0.95	3.66
1851-1900	-0.05	1.55	0.17	1.94	0.14	1.02	0.27	-0.62	0.32	1.44	0.13	-0.20
1901-1950	-0.18	4.55	-2.91	15.18	0.44	3.25	-0.14	2.45	0.40	2.51	-1.47	4.11
1951-2009	0.16	4.32	-0.26	-0.49	1.21	5.11	-0.63	0.76	-0.82	5.90	-0.95	0.71

Table 2.3 Continued

Sample Period	October Mean	October Std. Dev.	October Skew.	October Kurt.	November Mean	November Std. Dev.	November Skew.	November Kurt.	December Mean	December Std. Dev.	December Skew.	December Kurt.
1693-2009	-0.50	4.37	-2.55	19.22	0.35	3.86	0.25	9.35	0.81	3.22	1.53	10.91
100-year Interval												
1693-1800	-1.38	4.99	-2.75	18.56	0.17	3.48	-0.49	6.76	0.61	2.51	0.55	2.02
1801-1900	-0.12	2.37	0.74	6.01	0.36	3.70	3.01	24.89	1.00	3.56	2.76	19.33
1901-2009	0.02	4.99	-2.26	13.49	0.51	4.35	-0.99	2.83	0.82	3.53	0.58	3.24
50-year Interval												
1693-1750	-1.95	6.56	-2.09	10.24	0.45	3.78	-0.37	7.23	0.80	2.97	0.48	1.08
1751-1800	-0.73	1.87	1.30	4.81	-0.16	3.10	-0.93	5.78	0.39	1.83	0.13	2.39
1801-1850	-0.28	2.81	0.74	5.39	0.55	4.88	2.54	16.18	1.67	4.55	2.23	12.97
1851-1900	0.04	1.83	0.99	4.07	0.17	1.96	1.12	3.97	0.33	2.01	1.58	8.26
1901-1950	-0.03	3.08	0.47	4.32	0.82	3.27	0.47	2.35	-0.43	2.43	-0.88	3.29
1951-2009	0.06	6.19	-2.30	10.17	0.24	5.11	-1.16	1.84	1.89	3.97	0.43	2.43

Sample Period	Winter Mean	Winter Std. Dev.	Winter Skew.	Winter Kurt.	Summer Mean	Summer Std. Dev.	Summer Skew.	Summer Kurt.	Annual Mean	Annual Std. Dev.	Annual Skew.	Annual Kurt.
1693-2009	0.40	3.81	2.27	34.85	-0.16	4.16	-2.62	67.89	0.12	4.00	-0.51	54.70
100-year Interval												
1693-1800	0.13	3.44	0.14	17.42	-0.21	5.18	-3.18	79.30	-0.04	4.40	-2.60	79.95
1801-1900	0.32	3.64	5.87	84.12	-0.20	2.19	-0.57	5.06	0.06	3.01	5.18	92.37
1901-2009	0.73	4.27	1.21	16.41	-0.07	4.40	-1.28	5.78	0.33	4.36	-0.10	11.02
50-year Interval												
1693-1750	0.20	4.19	0.15	13.80	-0.28	6.80	-2.60	48.80	-0.04	5.65	-2.29	53.78
1751-1800	0.06	2.28	-0.29	4.88	-0.13	2.08	0.36	2.57	-0.03	2.18	0.00	3.89
1801-1850	0.40	4.81	5.01	54.48	-0.44	2.67	-0.39	3.35	-0.02	3.91	4.76	65.01
1851-1900	0.23	1.86	1.26	4.78	0.03	1.54	-0.36	4.61	0.13	1.71	0.71	5.13
1901-1950	0.06	2.56	-0.25	3.60	-0.03	3.38	-1.66	10.51	0.02	2.99	-1.27	9.63
1951-2009	1.30	5.25	0.99	12.06	-0.11	5.12	-1.09	3.77	0.59	5.23	0.00	8.31

Sample Period	Seasonality Test K-W		Seasonality Test F-Stat	
1693-2009	55.07	***	3.84	***
100-year Interval				
1693-1800	59.75	***	3.06	***
1801-1900	41.21	***	1.84	**
1901-2009	35.20	***	2.76	***
50-year Interval				
1693-1750	36.06	***	1.42	
1751-1800	50.59	***	3.87	***
1801-1850	36.90	***	2.34	***
1851-1900	23.81	***	1.93	**
1901-1950	31.31	***	2.88	***
1951-2009	30.09	***	2.90	***

Overall, the average monthly return over the entire sample is only 0.12% (1.44% per year), which is relatively low, but this is due to the negative average returns during the first 150 years.[14] The table reveals an increasing trend in average price returns over

14 Negative capital gains in the long run may seem surprising nowadays, however, during the eighteenth and nineteenth centuries dividends were relatively more important. Relatively high dividend payments (around 5% annually) are observed in the first two centuries of the sample: The series including dividends (not reported in the table) has monthly returns of 0.53% and 0.40% in the first two centuries, respectively.

time, with the latest 50 years showing the highest average return. While the standard deviations of different sample periods do not have a clear pattern, the market in the nineteenth century seems to be less volatile than it does in the eighteenth and twentieth centuries.

The last two columns report the results of the calendar month seasonality tests. I use both parametric and non-parametric tests. The latter is the Kruskal and Wallis rank-based test of equality. The null hypothesis is that all of the calendar months have the same continuous distribution and that the test statistic is approximately distributed as a χ^2 with 11 degrees of freedom. The alternative hypothesis is that at least one month has a different distribution. The parametric test examines the joint significance of parameters α_2 to α_{12} from the following regression Equation (2.1):

$$\boldsymbol{r_t = \alpha_1 + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \cdots + \alpha_{12} D_{12t} + \varepsilon_t} \tag{2.1}$$

where r_t is the monthly continuously compounded index returns, and $D_{2t} \ldots D_{12t}$ denote dummy variables for February to December. The constant parameter α_1 is the average return for January, and the coefficient estimates α_2 to α_{12} represent the differences between January returns and the returns in other months. If returns for each month of the year are the same, the parameters α_2 to α_{12} should be jointly insignificant. Both tests reveal strong calendar month seasonality over all of the examined sample periods.

While the tests statistics indicate significant differences between months, these tests do not clarify which month contributes to this seasonality and whether it is the same month in different samples. Based on the literature, we expect to see higher returns in January, April and December, while lower returns in September (Reinganum and Shapiro, 1987; Clare et al. 1995; Dimson and Marsh, 2001). Note that the results confirm these findings. For the subsample period 1951 to 2009, April, December and

January have the highest returns, while the average September return is the lowest during the period. The interesting question is whether we will find similar results in earlier sub-periods.

The evidence in Table 2.3 suggests that these patterns do not persist over time. January returns are negative and lower than for the other months in the first 100 years, with the best month over the 300 years being December rather than January. The overall performance for October seems similar to September (-0.50% versus -0.49% return per month), but the average October return is higher than September in the most recent 50 years. In Table 2.4 I test the statistical significance of the individual months in more detail, using the standard random walk regression with a dummy variable:

$$r_t = \alpha + \beta_m D_{mt} + \varepsilon_t \qquad (2.2)$$

where r_t is the continuously compounded monthly index return, D_{mt} is the dummy variable for a particular month (or a Halloween dummy that equals 1 if month t falls in the period from November through April and 0 otherwise), α is the constant and ε_t is the error term. β_m shows the magnitude of the difference between the mean return of the month(s) of interest and the mean return during the rest of the year.

Table 2.4 contains the coefficient estimates and t-statistics based on Newey-West standard errors for each calendar month and the Halloween effect. As before, I consider the full sample results and the 100 and 50 year subsamples. To ensure that the results do not depend on the choice of the specific 50 year subsamples and to detect possible structural breaks[15] I plot 50 year rolling window estimates for each of the 12 calendar month effects and the Halloween effect with their corresponding confidence bounds over the full sample in Figure 2.2.[16] These plots also illustrate how these monthly patterns vary over time and how - as Lakonishok and Smidt (1988) point out – the relatively large standard errors even with a sample size as long as fifty years make it difficult to infer statistical significance.

Over the entire sample period (Table 2.4), the December, January, April and August returns are significantly higher than the returns for the rest of the year. Despite this, however, none of these months persistently outperform the market. December comes close, with negative coefficient estimates only in the sub-period 1901 to 1950. Even the well-known January effect appears only in the second half of the sample. Intriguingly, on average, the January returns are significantly lower, rather than higher, during the eighteenth century. Before 1850, a strong positive December effect dominates the market, which disappears as the January effect emerges in the nineteenth century.

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15 I also performed formal structural break tests. While these confirm the results I find, they tend, however, to be sensitive to data trimming assumptions and, more importantly, did not provide the insight and detail these rolling regressions provide.

16 I use 50 years to reduce the effect of outliers and to make our results comparable with the GARCH estimates used in the robustness tests. Jacobsen and Dannenburg (2003) show that for reliable GARCH estimates in monthly data one needs around 50 years of monthly observations.

Table 2.4 Calendar month effects and the Halloween effect: OLS regressions

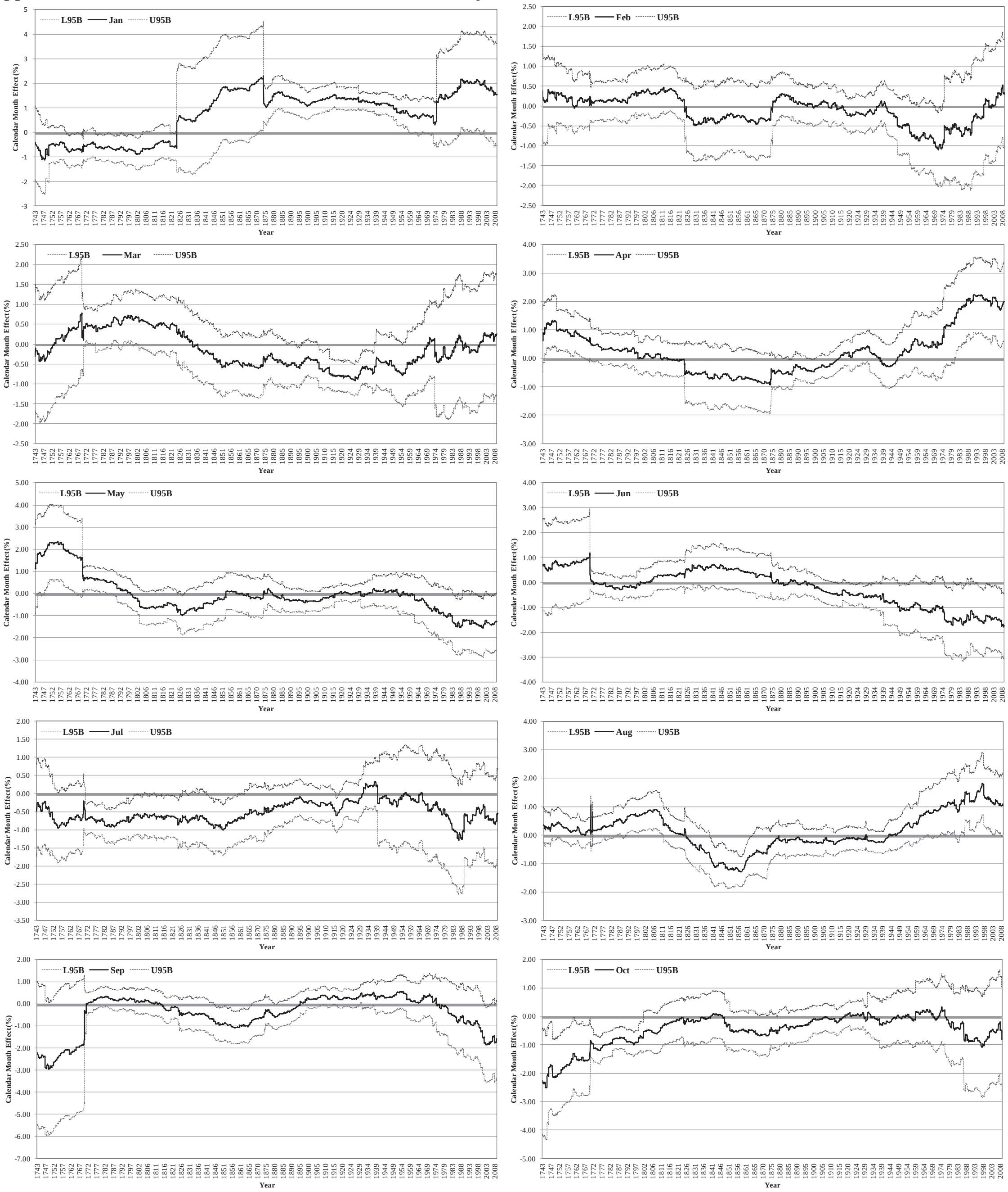
The table presents the coefficients estimates (percentage) and the t-statistics of the regression in a form of $r_t = \alpha + \beta_m D_{mt} + \varepsilon_t$, where r_t is D_{mt} is the dummy variable of the calendar month m (or the Halloween dummy that equals 1 if the month falls on the period November throug regression), α is the constant and ε_t is the error term. T-statistics are calculated based on Newey-West standard errors. The sample is sub-divid year intervals and six sub-periods of 50-year intervals. ***denotes significance at the 1% level; **denotes significance at 5% level; * denotes sig

Sample Period	January		February		March		April		May		June	
	β	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*
1693-2009	0.62	2.14 **	-0.04	-0.19	-0.16	-0.76	0.41	2.03 **	-0.11	-0.46	-0.26	-1.18
100-year Interval												
1693-1800	-0.61	-1.82 *	0.26	0.90	0.16	0.55	0.38	1.02	0.56	0.98	0.38	0.84
1801-1900	1.40	2.52 **	-0.12	-0.40	-0.42	-1.67 *	-0.50	-1.77 *	-0.31	-1.16	0.16	0.74
1901-2009	1.11	2.09 **	-0.25	-0.65	-0.24	-0.57	1.28	2.72 ***	-0.59	-1.87 *	-1.28	-3.27 ***
50-year Interval												
1693-1750	-0.48	-0.83	0.15	0.31	-0.26	-0.57	0.71	1.10	1.23	1.23	0.71	0.91
1751-1800	-0.76	-2.72 ***	0.39	1.43	0.65	2.36 **	-0.01	-0.04	-0.21	-0.80	-0.01	-0.02
1801-1850	1.72	1.60	-0.25	-0.46	-0.53	-1.30	-0.63	-1.21	-0.26	-0.56	0.53	1.54
1851-1900	1.08	3.51 ***	0.01	0.06	-0.32	-1.03	-0.37	-1.70 *	-0.36	-1.39	-0.22	-0.99
1901-1950	0.93	4.08 ***	-0.56	-1.48	-0.55	-1.75 *	0.10	0.20	0.11	0.32	-1.04	-2.81 ***
1951-2009	1.26	1.34	0.01	0.01	0.03	0.04	2.27	3.98 ***	-1.18	-2.43 **	-1.49	-2.29 **

Sample Period	July		August		September		October		November		December	
	β	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*
1693-2009	-0.46	-2.35 **	0.35	1.85 *	-0.67	-2.08 **	-0.68	-2.74 ***	0.25	1.11	0.75	3.99 ***
100-year Interval												
1693-1800	-0.45	-1.56	0.83	2.73 ***	-0.98	-1.06	-1.47	-3.67 ***	0.23	0.79	0.71	2.43 **
1801-1900	-0.60	-3.00 ***	-0.42	-1.92 *	-0.35	-1.33	-0.19	-0.77	0.33	1.13	1.03	3.14 ***
1901-2009	-0.36	-0.94	0.58	1.47	-0.64	-1.53	-0.34	-0.81	0.19	0.44	0.54	1.34
50-year Interval												
1693-1750	-0.33	-0.72	0.82	1.66 *	-1.93	-1.17	-2.08	-3.14 ***	0.53	1.28	0.92	1.86 *
1751-1800	-0.59	-1.81 *	0.84	2.61 ***	0.12	0.42	-0.76	-2.78 ***	-0.13	-0.37	0.46	1.91 *
1801-1850	-1.00	-3.31 ***	-0.83	-2.38 **	-0.92	-2.28 **	-0.29	-0.68	0.62	1.14	1.84	3.40 ***
1851-1900	-0.20	-1.03	0.00	0.03	0.21	0.89	-0.10	-0.38	0.04	0.22	0.21	0.87
1901-1950	-0.22	-0.38	0.47	1.16	0.42	1.48	-0.05	-0.15	0.88	1.41	-0.49	-1.20
1951-2009	-0.47	-0.96	0.68	1.09	-1.54	-2.27 **	-0.59	-0.81	-0.39	-0.62	1.41	2.97 ***

Figure 2.2 50-year rolling woindow OLS regressions of estimates for the 12 calendar month effects and the Halloween effect

The figure plots 50-year rolling window OLS regressions of estimates for the 12 calendar month effects and the Halloween effect, the dark solid line indicates the coefficient estimates of the effect, the light dotted lines indicate the upper and lower 95% bounds calculated based on Newey-West standard errors.



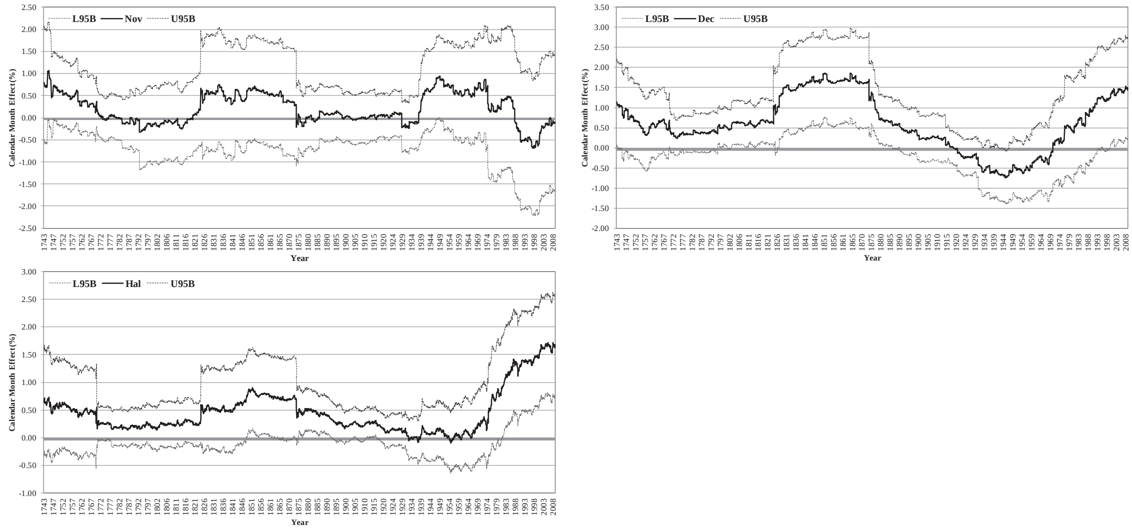


Figure 2.2 shows this shift in January returns more clearly. January returns are rarely higher than the average months until the 1820s to 1830s. (Note that the extremely high January returns exhibited in the 1820s are partially caused by the Panic of 1825[17] leading to an upward shift and, subsequently, to a strong downward shift in the rolling regression estimates. In the robustness tests I perform an outlier robust regression and find that these outliers do not tend to influence the overall findings.) Only around 1830 do January returns become higher than those of other months and these higher returns continue to the end of the twentieth century. The higher January returns start from the mid-1830s if I exclude the extreme price behaviour in 1825. It is, however, not clear what causes this January effect, as a tax loss selling explanation does not seem feasible.

[17] During the period, the index shows that the price level started to rise dramatically, by more than 20% per month, from November 1824, and had the largest increase of 54% in January 1825. Price levels remained high for three months and then sharply dropped back to the original level within a year. This price behaviour is consistent with the description in Glasner (1997, p.511), "…a speculative fever which seems to have begun in late 1824. They included a widespread feeling of optimism at the time, a general shortage of investment vehicles resulting from the decrease in the interests on bonds, an excess demand for several commodities, and the opening up of investment opportunities in South America…At the beginning of 1824, there were 154 joint stock companies with capital of £48 million. An additional 624 such companies were either started or proposed during the next two years, 127 of which survived the crisis and were still in operation in 1927. The crash in the real sector followed that of the financial sector, with the bottom being reached in 1826."

In particular, the UK capital gains tax was not imposed until 1965 with a tax year end of April, and income tax was first introduced in 1799, but repealed in 1816 and not reintroduced until 1842, however, neither of these periods coincide with the emergence of the January effect in the 1830s. Thus, tax loss selling by individual investors with an April tax year end, or corporations and traders with a December tax year end, cannot explain the effect. In addition, income tax was not prevalent in other countries during the nineteenth century. For example, the US introduced the War Revenue Act in 1917. Therefore, the emerging January effect cannot have been carried over from the US. Tax-loss selling by foreign traders is also unable to explain the emergence of the January effect in the 1830s. An alternative explanation would be that the January effect is imported from the US market for a different reason, however, January returns in the US are significantly below average up to 1870 and change thereafter.[18] The emerging January effect around this time in both the UK and the US might offer some support for the Christmas hypothesis introduced by Wachtel (1942) as an explanation for the January effect, as the United Kingdom started officially celebrating Christmas in 1835 or 1837[19] and in the US Christmas was declared a legal holiday in 1870 by President

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[18] Estimations based on extended S&P 500 composite price index data obtained from Global Financial Data over the period 1791 to 2009. The results are not reported here but available on request from the authors.

19 Christmas becomes a national holiday in 1835 according to the website http://www.johnowensmith.co.uk/histdate/, but other sources (http://www.historic-uk.com/HistoryUK/England-History/VictorianChristmas.htm) suggest that the Christmas holiday is introduced later, in 1837: "Before Victoria's reign started in 1837 nobody in Britain had heard of Santa Claus or Christmas Crackers. No Christmas cards were sent and most people did not have holidays from work. The wealth and technologies generated by the industrial revolution of the Victorian era changed the face of Christmas forever…the wealth generated by the new factories and industries of the Victorian age allowed middle class families in England and Wales to take time off work and celebrate over two days, Christmas Day and Boxing Day. Boxing Day, December 26th, earned its name as the day servants and working people opened the boxes in which they had collected gifts of money from the "rich folk". Those new fangled inventions, the railways allowed the country folk who had moved into the towns and cities in search of work to return home for a family Christmas. "

Ulysses S. Grant. Clearly, the evidence reported here is speculative, but suggests that the Christmas hypothesis put forward by Wachtel in 1942 may deserve more attention.

In the UK a capital gains tax was introduced on April 6, 1965. The results of, for instance, Reinganum and Shapiro (1987) suggest that this leads to the introduction of higher April returns from that point on. They find no seasonality in monthly UK returns in the 10 years prior to the introduction of capital gains tax. Having the benefit of a longer sample, I can revisit their evidence. The plot based on a rolling window of fifty years in Figure 2.2 suggests that around this time average April returns indeed do become higher. The evidence is, however, less conclusive if I plot annual April returns minus the average returns of the other 11 months (Figure 2.3), and a 10-year moving average of April returns minus the average returns of the other months (Figure 2.4) for the period 1900 to 2009 when April effect becomes positive.

Figure 2.3 Stock market return difference between April and the average of the 11 other months (Global Financial Data index)

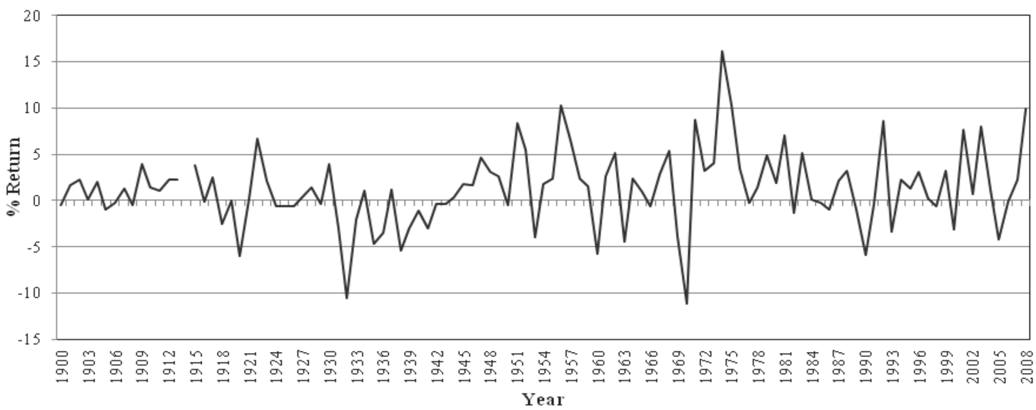
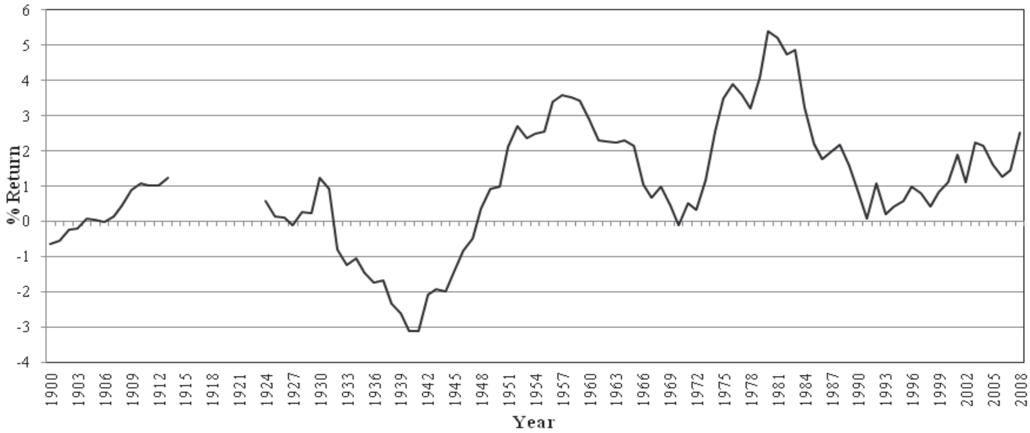


Figure 2.4 Global Financial Data stock market return difference between April and average of the other 11 months (10-year moving average)



Positive April returns occur frequently, however, it is not definite that the outperformance occurs only in the period after the imposition of the capital gains tax in 1965. In fact, the smoothed graph using a 10-year moving average reveals that the rising trend starts from the 1940s onwards. This suggests that it may not necessarily be the capital gains tax that causes these higher April returns to emerge.

Table 2.3 shows that the average returns for October, September, and July are frequently negative. Table 2.4 reveals that the relatively worst months are October and July, which significantly underperform the other calendar months over the whole sample period. They also persistently underperform in all sub-periods. Although the results are not statistically significant for all subsamples, the coefficient estimates are unanimously negative. The average return for October over the whole sample period is 0.68% lower than the other months' averages. For July this is 0.46%. However, the statistical significance weakens after the 1850s. The plots confirm that this is not a result of the specific sample periods used. Based on a 50-year window one rarely sees positive estimates for both July and October, however, for September things are different.

The evidence confirms the low September returns reported by Clare et al. (1995) for the period of 1955 to 1990. With the benefit of a longer sample period, however, I am able to show that the pattern is not persistent and that the September mean returns are actually higher than the returns during the other months for three out of the six fifty-year sub-periods, although the difference is not statistically significant. Also the September plot in Figure 2.2 shows that over three-hundred years it is hard to conclude that stock returns show a negative September effect.

The Halloween effect seems relatively robust over time. Six monthly winter returns tend to be on average 3.4% higher than six monthly summer returns measured over three hundred years. In the first half of the twentieth century this drops to around half a percent to later increase to 8.4% in the last sixty years of the sample. However, there are long periods when the effect does not show up significantly. And the point estimates even indicate a reversed effect in the early 20th century, although not significantly so.

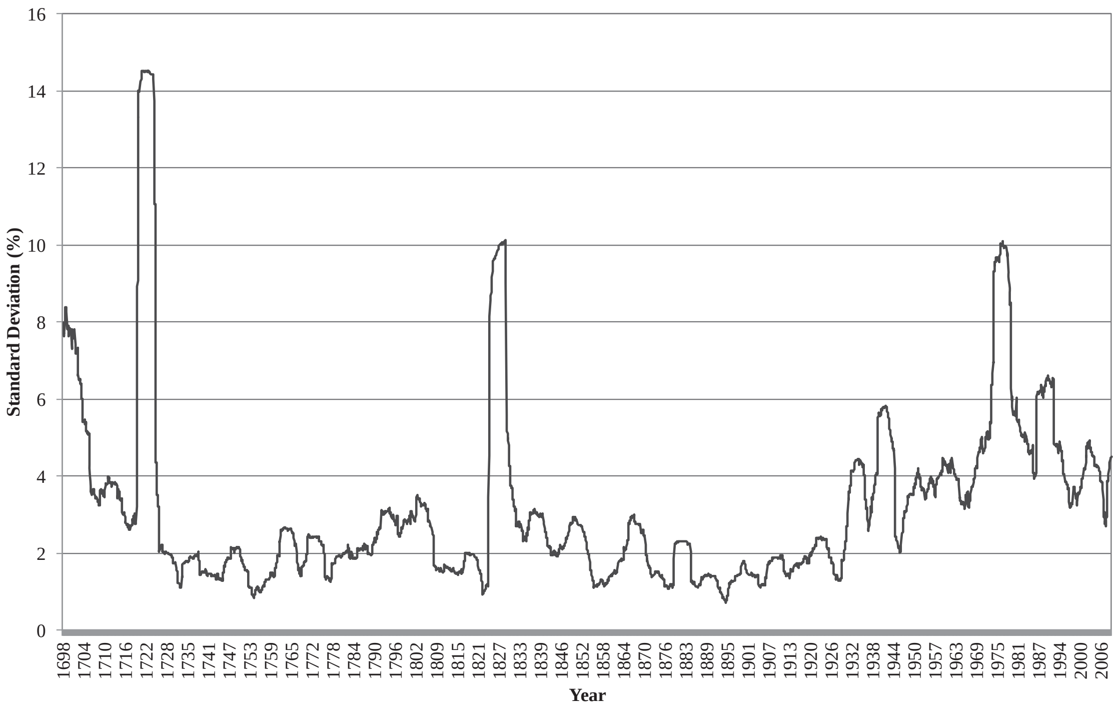
All-in-all the evidence suggests that findings regarding many monthly anomalies may be less robust and very time dependent. This might either mean that there are no monthly seasonal effects, or alternatively that these monthly seasonals are themselves time varying. Unfortunately, in the latter case the evidence from the past 300 years suggests that the monthly seasonals are varying over time with a speed that we might never be able to estimate whether they are real, or not, at least not with current estimation methods. If we require that coefficients need to be persistently negative, or positive, almost all of the time and be significant over the full sample, the only exceptions may be the negative July and October effects, and the Halloween effect. It is hard to find 50-year periods when these effects change signs. But based on the fifty year samples it is difficult to conclude these effects are significantly present. I now check the robustness of these results against alternative specifications.

2.5 Robustness checks

2.5.1 Volatility clustering and possible outliners

In the first part of the sample I use an index of only three stocks. This may increase volatility and reduce the power of the test statistics. Moreover, as monthly stock returns may also exhibit volatility clustering when I use Newey West standard errors that are heteroscedasticity and autocorrelation consistent, this may reduce the power of the tests. To verify the impact volatility might have I first plot an annualised five-year moving average standard deviation (Figure 2.5).

Figure 2.5 5-year moving standard deviation from the Global Financial Data stock market index



This shows a couple of things. Indeed volatility is higher at the start of the sample although it decreases to a low level even in the case of the three stocks. It also tends to spike, for instance, during the South Sea Bubble. This also seems to show up as wider confidence bounds in the rolling window regressions. Interestingly, volatility also seems to have increased on average in the twentieth century. Overall, because volatility is time varying and spikes occasionally, it may be good to verify robustness of the results controlling for both conditional heteroscedasticity and outliers using GARCH models and OLS robust regressions. Of course, the price to pay is that I have to impose a specific structure on the conditional heteroscedasticity and may accidentally exclude observations that were not outliers. As a robustness check, however, it may be good to make these assumptions.

For the GARCH model I use a GARCH(1,1) model, as this simple parsimonious representation generally captures volatility clustering well in monthly data if a window of around fifty years or more is used (see, for instance, Jacobsen and Dannenburg, 2003). I estimate both assuming a normal distribution and t-distributed standard errors, but as the results are similar only the former is reported. I use the same mean equation with a dummy for the different months as used in the main regressions and re-estimate the seasonal effects from Equation (2.3).

$$r_t = \mu + \beta_m D_{mt} + \varepsilon_t,$$

$$\varepsilon_t | \Phi_{t-1} \sim N(0, \sigma_t^2),$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{2.3}$$

For the robust regression, the M-estimation introduced by Huber (1973) is adopted, as it is considered appropriate when the dependent variable may contain outliers.

Table 2.5 Calendar month effects and the Halloween effect: GARCH (1,1) models

This table presents the coefficients estimates (percentage) and the t-statistics of the calendar month effect and the Halloween $r_t = \mu + \beta_m D_{mt} + \varepsilon_t, \varepsilon_t|\Phi_{t-1} \sim N(0, \sigma_t^2), \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2$, where r_t is the continuously compounded monthly returns, $D_{mt}$is the Halloween dummy that equals 1 if the month falls on the period November through April and 0 otherwise). The sample is sub-divided into three and six sub-periods of 50-year intervals. ***denotes significance at the 1% level; **denotes significance at 5% level; * denotes significance at 10%

Sample Period	January		February		March		April		May		June	
	β	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*
1693-2009	0.23	1.74 *	-0.05	-0.39	-0.05	-0.38	0.11	0.89	0.02	0.15	-0.28	-2.09 **
100-year Interval												
1693-1800	-0.74	-3.33 ***	0.08	0.33	0.54	2.65 ***	0.26	1.35	0.37	1.97 **	-0.18	-0.71
1801-1900	0.71	3.24 ***	-0.02	-0.11	-0.22	-1.12	-0.38	-1.74 *	-0.18	-0.84	-0.07	-0.30
1901-2009	0.85	2.37 **	-0.30	-1.06	-0.53	-2.33 **	0.76	2.99 ***	-0.17	-0.67	-0.85	-2.94 ***
50-year Interval												
1693-1750	-0.60	-1.63	-0.28	-0.82	0.28	0.91	0.53	2.04 **	1.29	3.79 ***	-0.27	-0.67
1751-1800	-0.82	-2.68 ***	0.33	0.95	0.67	2.04 **	0.00	0.01	-0.21	-0.79	-0.14	-0.41
1801-1850	0.54	1.23	0.25	0.44	-0.09	-0.21	-0.22	-0.45	-0.06	-0.12	0.34	0.70
1851-1900	0.82	3.64 ***	-0.13	-0.62	-0.31	-1.47	-0.41	-1.93 *	-0.19	-0.85	-0.13	-0.55
1901-1950	1.04	2.19 **	-0.24	-0.78	-0.84	-3.23 ***	0.63	2.24 **	0.31	1.08	-0.70	-2.24 **
1951-2009	0.52	0.81	-0.48	-0.75	0.39	0.61	1.42	2.31 **	-1.52	-2.91 ***	-1.31	-2.08 **

Sample Period	July		August		September		October		November		December		Ha
	β	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*	*t-value*	*β*
1693-2009	-0.56	-4.35 ***	0.01	0.09	-0.01	-0.05	-0.24	-1.88 *	0.28	2.39 **	0.45	3.31 ***	0.32
100-year Interval													
1693-1800	-0.83	-4.00 ***	0.55	2.91 ***	0.08	0.37	-0.86	-3.77 ***	0.24	1.21	0.51	2.23 **	0.26
1801-1900	-0.39	-1.56	-0.61	-3.34 ***	-0.06	-0.28	0.12	0.61	0.39	1.94 *	0.53	2.64 ***	0.38
1901-2009	-0.45	-1.89 *	0.41	1.65 *	-0.07	-0.23	0.11	0.45	0.10	0.42	0.18	0.53	0.31
50-year Interval													
1693-1750	-0.49	-1.27	0.25	0.91	-0.21	-0.62	-1.12	-3.57 ***	0.34	0.90	0.35	1.02	0.21
1751-1800	-0.94	-3.81 ***	0.76	2.60 ***	0.33	1.02	-0.65	-1.86 *	0.12	0.51	0.63	2.04 **	0.27
1801-1850	-1.04	-1.91 *	-1.21	-3.59 ***	-1.26	-2.82 ***	0.05	0.11	0.79	1.69 *	1.19	2.44 **	0.92
1851-1900	-0.12	-0.50	-0.24	-1.02	0.42	2.19 **	-0.02	-0.13	0.10	0.48	0.19	0.93	0.09
1901-1950	-0.60	-2.27 **	0.16	0.55	0.31	0.73	0.16	0.59	0.12	0.42	-0.23	-0.57	0.11
1951-2009	-0.01	-0.02	1.18	2.46 **	-1.38	-2.79 ***	-0.34	-0.58	0.03	0.05	1.53	1.94 *	1.05

Table 2.6 Calendar month effects and the Halloween effect: Robust regressions

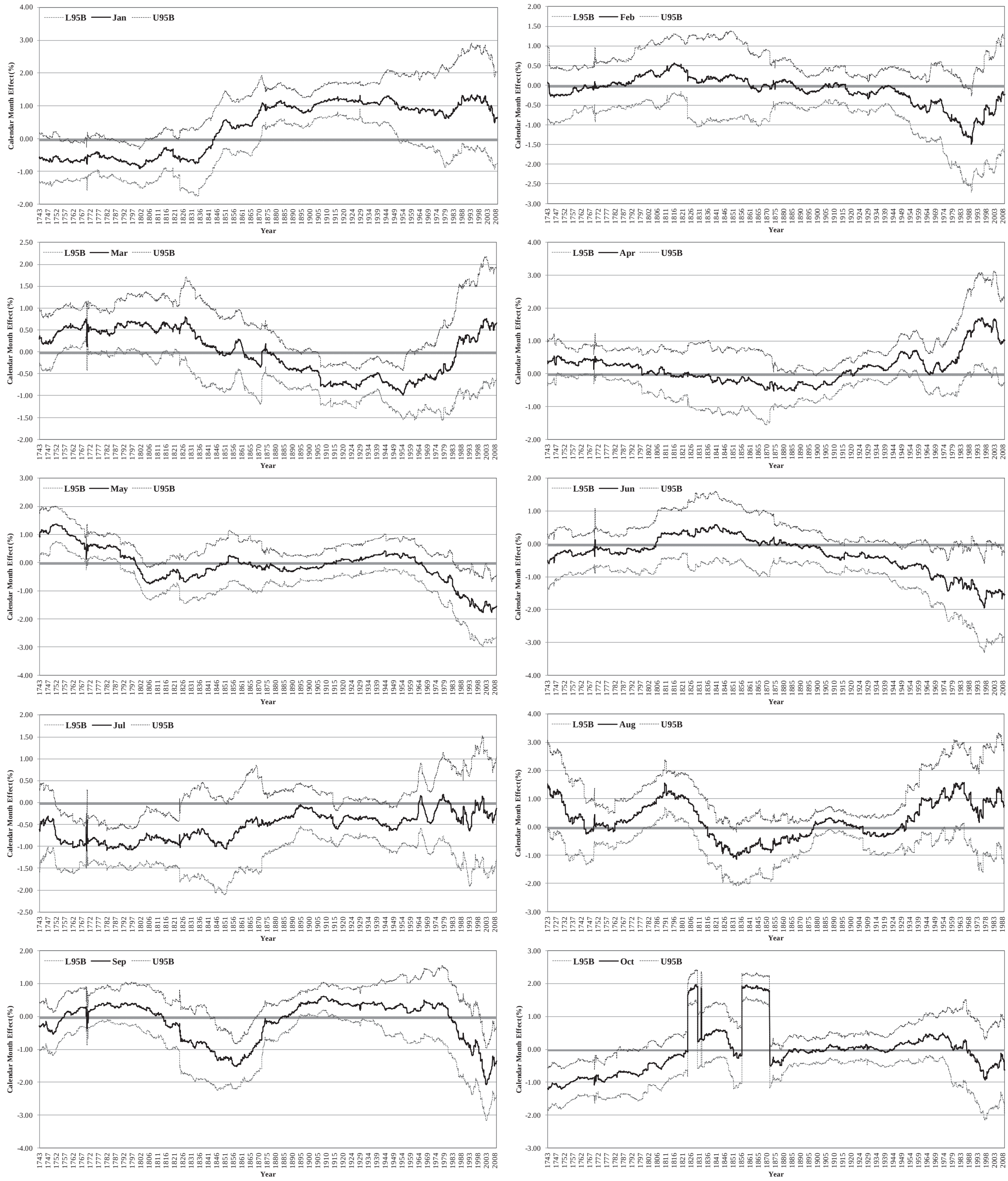
This table presents the coefficients estimates (percentage) and the Chi-square of the calendar month effect and the Halloween effect from t
$\beta_m D_{mt} + \varepsilon_t$, where r_t is the continuously compounded monthly returns, D_{mt} is the dummy variable of the calendar month m (or the Hallowee
period November through April and 0 otherwise for the Halloween effect regression). The robust regressions are based on M-estimation introdu
into three sub-periods of approximately 100-year intervals and six sub-periods of 50-year intervals. *** denotes significance at the 1% level
significance at 10% level.

Sample Period	January		February		March		April		May		June	
	β	X^2	β	X^2	β	X^2	β	X^2	β	X^2	β	X^2
1693-2009	0.26	3.34 *	-0.15	1.11	-0.18	1.62	0.25	3.18 *	0.16	1.40	-0.22	2.48
100-year Interval												
1693-1800	-0.56	7.52 ***	0.01	0.00	0.33	2.56	0.32	2.44	0.55	7.19 ***	-0.04	0.04
1801-1900	0.66	12.40 ***	0.13	0.47	-0.36	3.77 *	-0.20	1.18	0.17	0.78	0.11	0.36
1901-2009	0.63	3.37 *	-0.75	4.74 **	-0.39	1.28	0.99	8.33 ***	-0.43	1.57	-1.10	10.33 ***
50-year Interval												
1693-1750	-0.14	0.17	-0.18	0.31	-0.40	1.48	0.73	4.83 **	0.93	8.00 ***	0.04	0.02
1751-1800	-0.92	13.20 ***	0.24	0.90	0.96	14.50 ***	-0.02	0.01	0.23	0.80	-0.13	0.26
1801-1850	0.48	1.90	0.27	0.60	-0.37	1.17	-0.10	0.08	0.52	2.30	0.34	0.96
1851-1900	0.80	15.45 ***	-0.12	0.37	-0.41	4.06 **	-0.31	2.22	-0.13	0.40	0.06	0.08
1901-1950	0.75	5.72 **	-0.50	2.48	-0.94	9.06 ***	0.33	1.08	0.16	0.27	-0.60	3.64 *
1951-2009	0.46	0.56	-0.73	1.46	0.22	0.13	2.02	11.23 ***	-1.22	4.02 **	-1.58	6.82 ***

Sample Period	July		August		September		October		November		December		H
	β	X^2	β	X^2	β	X^2	β	X^2	β	X^2	β	X^2	β
1693-2009	-0.53	14.32 ***	0.26	3.48 *	-0.08	0.36	-0.46	11.01 ***	0.25	3.19 *	0.41	8.76 ***	0.26
100-year Interval													
1693-1800	-0.57	7.71 ***	0.56	7.57 ***	-0.21	1.04	-1.00	24.64 ***	0.12	0.33	0.48	5.41 **	0.22
1801-1900	-0.51	7.55 ***	-0.25	1.73	-0.15	0.62	-0.18	0.91	0.15	0.67	0.50	7.18 ***	0.25
1901-2009	-0.26	0.56	0.68	3.97 **	0.17	0.25	-0.09	0.07	0.44	1.63	0.18	0.27	0.32
50-year Interval													
1693-1750	-0.48	2.15	0.54	2.74 *	-1.02	9.41 ***	-1.16	12.65 ***	0.41	1.54	0.49	2.26	0.29
1751-1800	-0.68	7.09 ***	0.58	5.18 **	0.38	2.17	-0.91	12.96 ***	-0.21	0.66	0.51	3.93 **	0.18
1801-1850	-0.95	7.73 ***	-0.78	5.09 **	-0.67	3.82 *	-0.26	0.57	0.50	2.14	1.15	11.27 ***	0.58
1851-1900	-0.17	0.71	0.07	0.10	0.26	1.62	-0.14	0.45	-0.07	0.10	0.20	0.99	0.01
1901-1950	0.05	0.03	0.44	1.97	0.60	3.64 *	-0.20	0.38	0.24	0.56	-0.47	2.26	-0.16
1951-2009	-0.65	1.13	0.90	2.20	-0.66	1.16	0.03	0.00	0.13	0.05	1.02	2.84 *	0.98

Figure 2.6 Estimates of 50-year rolling window regression for the 12 calendar month effects and the Halloween effect - GARCH (1,1) models

The figure plots estimates of the 50-year rolling window regressions for the 12 calendar month effects and the Halloween effect estimated from time varying volatility GARCH (1,1) models, the dark solid line indicates the coefficient estimates of the effect, the light dotted lines indicate the upper and lower 95% bounds based on the Global Financial Data index.



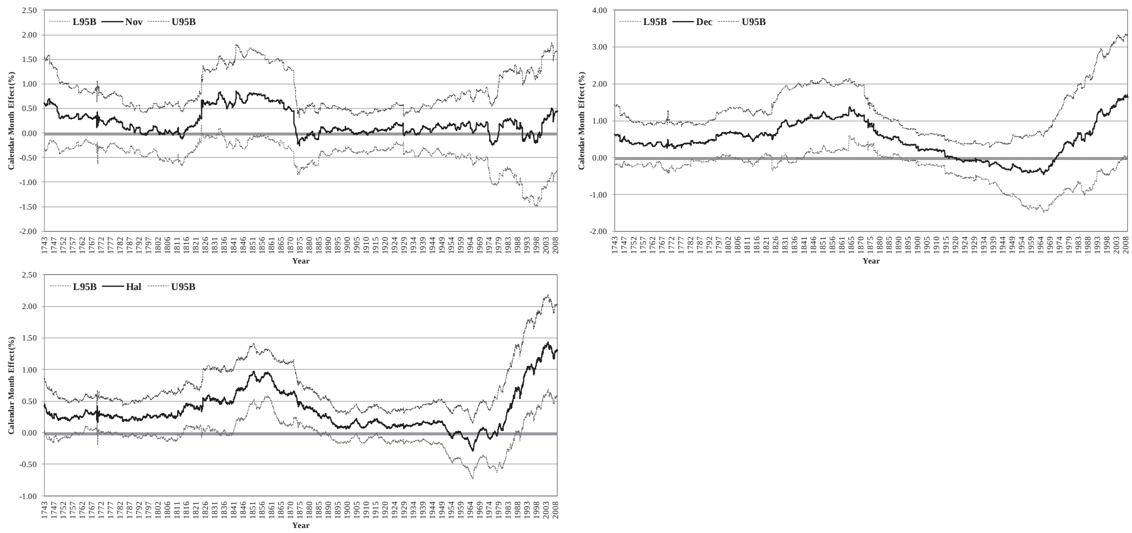


Table 2.5and Table 2.6 contain the estimation results for these regressions and Figure 2.6 and Figure 2.7 contain the plots for the rolling window regressions.[20]

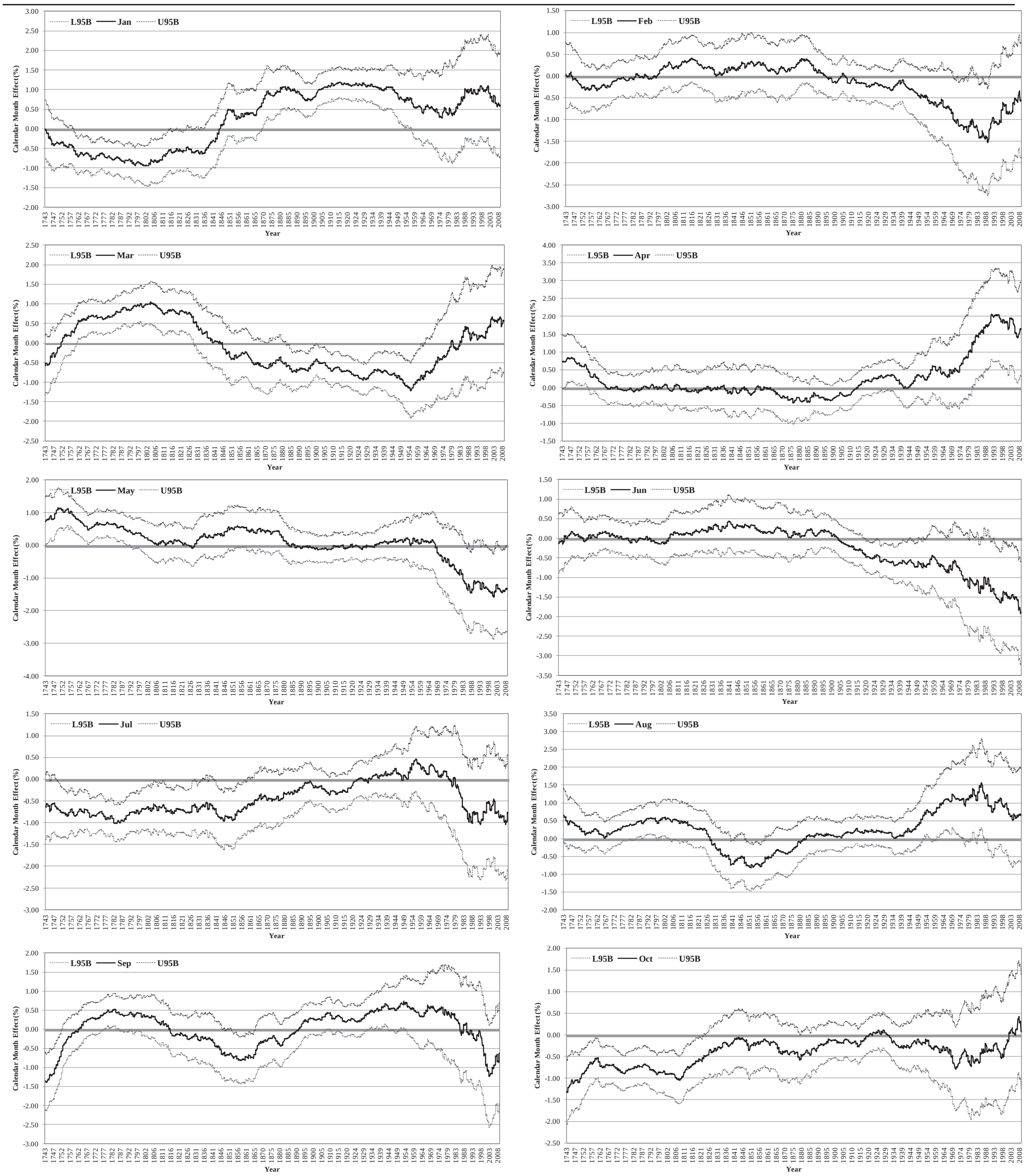
First, it may be good to note from the GARCH rolling windows and the OLS robust regressions that the widening of the confidence bounds seem to have disappeared and these tend to be the same size over time, suggesting that loss of power due to time varying volatility is no longer an issue.

How far does this affect the results? If I use the same criteria, an overall significant effect and coefficients that must be of the correct sign for almost the full sample when using rolling windows of fifty years, I find based on the GARCH models, that October drops out and positive November and December effects may resurface. Using OLS Robust regressions, I would probably reverse that conclusion and include October while again dropping November and December. The robustness tests seem to increase the

[20] The sudden shifts in the October GARCH plot seem to be caused by three subsequent months with high returns (November 1824-January 1825, with returns of 26.2%, 24.18% and 53.53%, respectively). Once we remove these three observations the shifts disappear. The GARCH model with t-distributed errors does not show the shifts.

Figure 2.7 Estimates of 50-year rolling window regression for the 12 calendar month effects and the Halloween effect - Robust Regressions

The figure plots estimates of the 50-year rolling window regressions for the12 calendar month effects and the Halloween effect estimated from robust regressions based on M-estimation introduced in Huber (1973), the dark solid line indicates the coefficient estimates of the effect, the light dotted lines indicate the upper and lower 95% bounds. Results are based on the Global Financial Data market index.



strength for a July effect and a Halloween effect. The July effect is now significantly present in two out of 100-year sub-periods. The Halloween effect is significant in all three 100-year subsamples. While both effects seem to be a bit stronger after I control for outliers and GARCH effects there are still many fifty year periods when the effects are not significant.

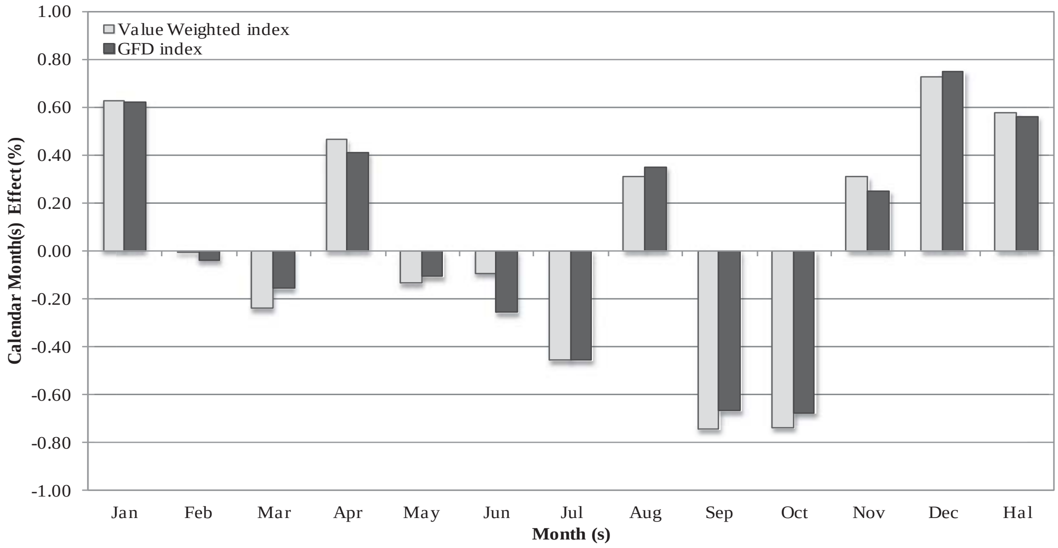
2.5.2 Value weighted and equally weighted indices

As Table 2.1 shows some indices are value weighted and others equally weighted. To determine whether this might affect the results, I try to construct a value weighted index throughout. First, I construct a market value weighted index for the three companies based on the individual price series for these three shares and calculate a value weighted index assuming that there are no changes in the number of shares outstanding (de facto a price index). While there is some evidence (see, for instance, Shea, 2000) that these companies have issued shares and repurchased shares, these actions are infrequent and I have no exact details. So this is the closest I can get to a value weighted index for this period. The other time period that uses an equally weighted index is from 1851 to 1906. Here I was able to extend the Banker's magazine index backwards to August 1887. For the period 1851 to 1870 I use the value weighted index constructed by Acheson et al. (2009). This leaves only a period of 16 years (1871-1887) equally weighted.

If I replace the equally weighted parts with the value weighted parts (apart from 1851-1887) and re-estimate the results, these are hardly affected (Figure 2.8).

This is not surprising as the three stocks value weighted index give almost similar results to the GFD index, because the market shares of these stocks were, with the exception of the South Sea Bubble in 1720, relatively stable over time.

Figure 2.8 Calendar month(s) effect in Global Financial Data index and the constructed value weighted index

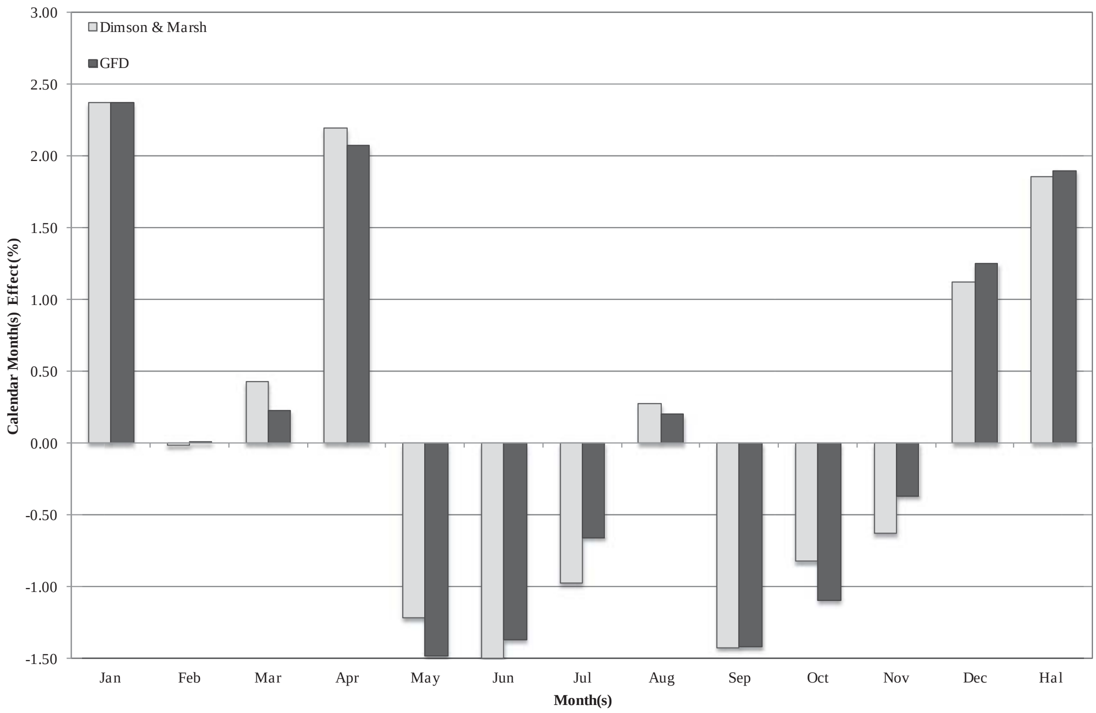


2.5.3 Dividends

Dividends may influence these results if large dividend payments cluster in specific months. In that case by using a price index I could overestimate the significance of a negative effect, or underestimate a positive effect, in those months.

It is hard to conclusively determine whether there might be an effect over the full sample, but for two subsamples I find little evidence that dividend clustering can explain the result. Thanks to a very thorough study of UK market returns and dividend payments by Dimson and Marsh (2001) I can conclude that in more recent periods the impact seems marginal and dominated by other differences in index construction. Dimson and Marsh (2001) construct an index including dividends and report monthly UK equity premia from 1955 to 1999. In Figure 2.9 I compare their monthly excess returns (in deviation from the average of the other 11 months) with my data. To be consistent with Dimson and Marsh (2001), I also subtract 3-month UK Treasury bill yields from the returns of the GFD index.

Figure 2.9 Calendar month(s) effect in Global Financial Data index and the Dimson and Marsh (2001) index (1955-1999)

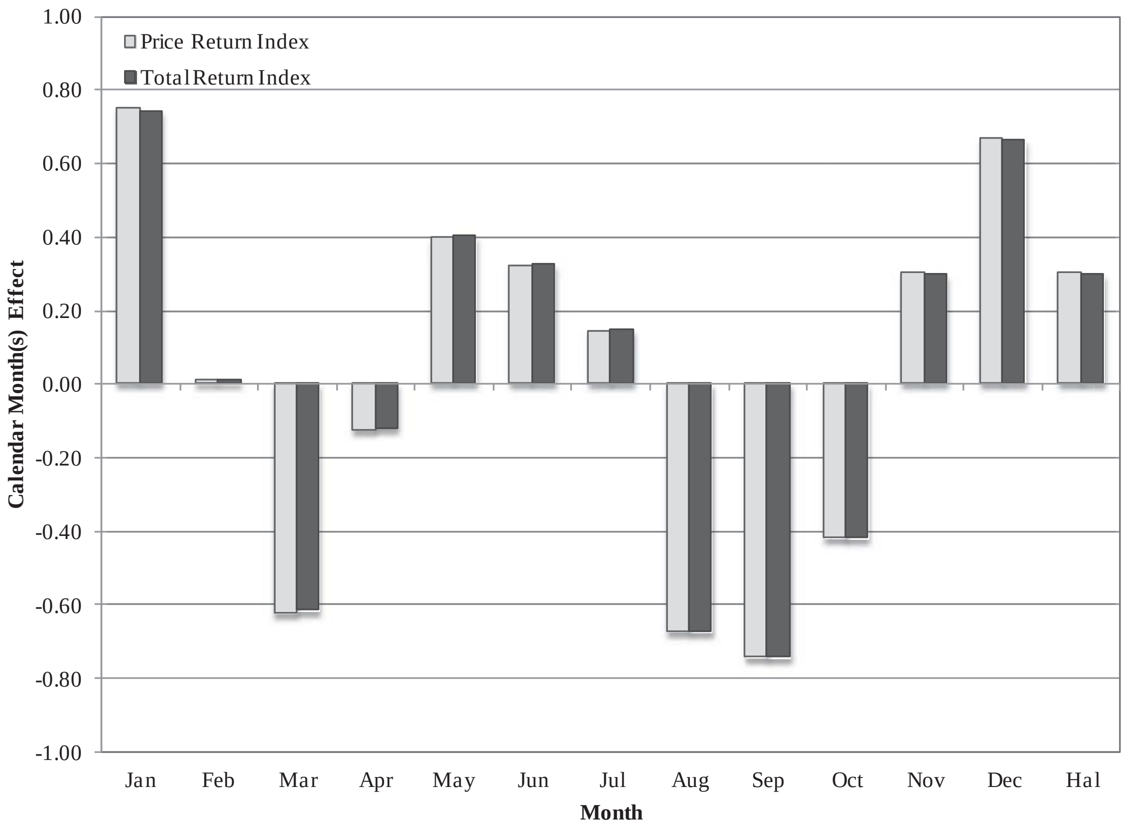


These results are similar and do not seem to change the main findings. This may not come as a surprise, because Dimson and Marsh (2001) also document that the largest difference between high and low dividend months is, at most, 9% of total dividends.

Thanks to the extensive work of Acheson et al. (2009) I can make a more direct comparison over the 1825 to 1870 period. They report monthly dividend yields. In Figure 2.10 I compare monthly seasonals based on both their value weighted price index and their total return index, which includes dividends.

As the figure shows, annual dividends of 4.5% are almost equally distributed over the different months. A formal test also reveals no significant seasonalities in these dividend payments.

Figure 2.10 Calendar month(s) effect in UK price index and total return index data of Acheson et al. (2009) (1825-1870)



Unfortunately, for the other periods exact evidence on the timing and size of dividend payments is not available. Shea (2000) reports annual returns including dividends for the big three companies. If I combine these with the price information for these individual shares I can extract the annual dividend yields. These are, on average, 6% up to 1719, and then ranging between 4 and 5%. This suggests annual dividends up to 1834 of around 5%. In the concern of this study the distribution of these dividend payments over the months is more important. Neal (1987) documents that, just as in more recent history, UK dividends were paid semi-annually and different stocks would go ex-dividend in different months. For instance, The South Sea Company paid dividends in May and November, while the Bank of England paid dividends in March and September, as did the East Indies Company.[21]

Semi-annual dividend payments, at least, will not have an impact on the Halloween effect and, while the evidence suggests that the influence of dividends in the past should not be large, I cannot completely rule out that it may have an impact on the estimates over time. As, however, for most of the sample July and October have not been the dominant dividend months, this suggests that other months may have done relatively better than documented and, thus, that I underestimate the negative effects.

2.5.4 Interaction between seasonals

With both July and October as consistently negative months, another question that might be raised is – that if one is willing to accept a Halloween effect exists - as to whether the negative returns in these two months may be the cause of the Halloween effect. Both months with negative returns on average fall in the summer period, which is the poor performance period in the Halloween effect. To verify this, I re-estimate the Halloween indicator regression controlling for both October and July. This reduces the Halloween effect marginally. Average monthly winter returns are 0.56% higher than the

[21] Private Correspondence with Bryan Taylor of Global Financial Data

summer months without the two control variables (t-value of 4.04). If I include the dummies then monthly winter returns are 0.44% higher (t-value of 3.16). The same conclusion holds if I include the overall significantly positive months (January, April and December) jointly with a Halloween dummy. Halloween returns remain a significant 0.30% per month higher (t-value 2.05). The monthly July and October anomalies also remain significant if I control for the overall significantly positive months. If I include January, April and December dummies, the July and October effect still remains significantly negative, with -0.34% and -0.54% lower average returns on average (t-values -1.69 and -2.15, respectively).

2.6 Conclusion

This study finds that what should be a relatively simple question: whether or not there are seasonal monthly anomalies, strongly depends on the sample period considered. I show that many calendar months significantly outperform, or underperform, the market in the sample, but that few have done so persistently over the 300 years. This result confirms the potential problems caused by data snooping, noise and selection bias, and highlights the importance of studying long time series and suggests that many if not all calendar month anomalies may be spurious. Based on fifty year samples it is hard to detect any persistent statistically significant anomalies. The rolling window regressions show significant results fluctuate over time. For almost every month I can find fifty years of fame. Conclusions vary strongly based on the selected sample size even over 100 year intervals. For example, the January effect switches from significantly negative to significantly positive based on 100 year samples. If only considering the full sample, I find four monthly anomalies robust across different estimation methods (significantly positive returns for January and December and significantly below average returns for

July and October) and also a positive Halloween or Sell in May effect. However, in that case one should be aware that in extremely long sub-periods the effect may be reversed and significantly so. Again the January effect is a clear example: significantly positive over the full sample but significantly negative in the first one hundred years. Therefore, whether or not, and which of these monthly anomalies exist, seems to depend strongly on sample periods and criteria applied. Or in other words, these monthly anomalies may be in the eye of the beholder.

Chapter 3 The Halloween indicator: Everywhere and all the time

3.1 Introduction

Since 2002 when Bouman and Jacobsen published their study on the Halloween Indicator, also known as the 'Sell in May and go away' effect, in the American Economic Review their study has attracted a lot of attention in both the academic and popular press. Bouman and Jacobsen (2002) find that returns during winter (November through April) are significantly higher than during summer (April-October) in 36 out of the 37 countries in their study. What makes the Halloween or Sell in May effect particularly interesting is that it challenges traditional economic theory, as it suggests predictably negative excess returns during summer.[22]

Recently, a number of papers have appeared that show the effect is also present out of sample in many of these countries (for instance, Andrade, Chhaochharia, & Fuerst, 2012; Grimbacher, Swinkels, & van Vliet, 2010; Jacobsen & Visaltanachoti, 2009). This is another reason why the effect is interesting. The anomaly does not suffer from Murphy's law as documented by Dimson and Marsh (1999). It does not seem to disappear or reverse itself after discovery, but continues to exist even though investors may have become aware of it.

As with other calendar anomalies, a number of studies have remained sceptical and raise a number of issues emphasising the possibility of data mining, sample selection bias, statistical problems, or economic significance (Maberly & Pierce, 2003; Maberly

22 For instance, Grimbacher, Swinkels and van Vliet (2010) find a US equity premium over the sample period 1963-2008 of 7.2% if there is a Halloween effect and a Turn of the Month effect, and a negative risk premium of -2.8% in all other cases.

& Pierce, 2004; Lucey & Zhao, 2007; Zhang & Jacobsen, 2012; Powell, Shi, Smith, & Whaley, 2009). Moreover, we still lack a proper explanation on what causes the effect (see for instance, Jacobsen & Marquering, 2008).

The purpose of this paper is to rigorously re-examine the Halloween effect. To this purpose, I first consider all stock markets worldwide using the full history of stock market indices available for each market. While I am not aware of any study which has considered all available stock market data for all countries that have a stock market, this is probably the best safeguard against data mining and sample selection bias. The data consists of all 108 stock markets in the world. For each market it covers all historical data available for that market. As the sample covers all stock market returns available it also comprise all 37 stock markets examined in Bouman and Jacobsen (2002) with extended sample periods. The two main reasons for this rigorous examination are: Firstly, to answer the skeptics regarding whether or not a Halloween effect exists based on all empirical evidence available, rather than relying on a limited selection of one or more countries. For instance, Zhang and Jacobsen (2012) show that even with an extremely large sample for just one country (the same UK data set I use here) it is hard to determine whether monthly anomalies exist. The problem is the same as put forward by Lakonishok and Schmidt (1988): To detect monthly anomalies one needs samples of at least ninety years, or longer, to get any reliable estimates. Looking at all data across countries seems the best we can do. Secondly, I hope that a full analysis of the effect may contribute to finding what causes this anomaly. Is the effect present in all countries? All regions? All the time? Is it constant over time? Last but not least, this study not only considers whether the effect is present, but whether as an investor it would make sense to assume it is by considering trading strategies and comparing these with buy and hold strategies.

Overall, the 55,425 monthly observations over 319 years show a strong Halloween effect. Winter returns – November through April - are 4.52% (t-value 9.69) higher than summer returns. The Halloween effect is prevailing around the world to the extent that the mean returns are higher for the period of November-April than for May-October in 81 out of 108 countries, and the difference is statistically significant in 35 countries, compared to only 2 countries having significantly higher May-October returns. The evidence also reveals that the size of the Halloween effect does vary cross-nation. It is stronger in developed and emerging markets than in frontier and rarely studied markets. Geographically, the Halloween effect is more prevalent in countries located in Europe, North America and Asia than in other areas. As it shows, however, this may also be due to the small sample sizes yet available for many of these newly emerged markets.

As a general indication for the strength of the effect over time, I pool all market indices together and use time series subsample period analysis. I find over 31 ten-year sub-periods 24 have November-April returns higher than the May-October returns. However, this difference only becomes statistically significant over the past 50 years starting from the 1960s. The difference in these two 6-month period returns is very persistent and economically large ranging from 5.08% to 8.91% for the most recent five 10-year sub-periods. The world index from Global Financial Data reveals a similar trend. Subsample period analysis of 28 individual countries with data available for over 60 years also confirms this strengthening trend of the Halloween effect. More specifically, I show that the Halloween effect starts emerging around the 1960s, with 27 out of the 28 countries revealing positive coefficient estimates in the 10 year sub-period of 1961-1970. Both the magnitude and statistical significance of the Halloween effect keeps increasing over time, with the sub-period 1991 to 2000 showing the strongest Halloween effect among countries. Consistent with country by country whole sample period results, the Halloween effect is stronger in Western European countries

I examine the economic significance of the Halloween effect by investigating the out-of-sample performance of the trading strategy in the 37 countries used in Bouman and Jacobsen (2002). The Halloween effect is present in all 37 countries for the out-of-sample period September 1998 to April 2011. The out-of-sample gains from the Halloween strategy are still higher than the buy and hold strategy in 31 of the 37 countries; after taking risk into account, the Halloween strategy outperforms the buy and hold strategy in 36 of the 37 countries. In addition, given that the United Kingdom is the home of the old 'Sell in May' market wisdom, I investigate the performance consistency of the trading strategy using long time series of over 300 years of UK data. The result shows that investors with a longer horizon would have had remarkable odds beating the market using this trading strategy: Over 80% for investment horizons over 5 years; and over 90% for horizons over 10 years, with returns on average around 3 times higher than the market.

The study addresses a number of methodological issues concerning the sample size, impact of time varying volatility, outliners and problems with statistical inference using UK long time series data of over 300 year. In particular, extending the evidence in Zhang and Jacobsen (2012), I revisit the UK evidence and provide rolling regressions for the Halloween effect with a large sample size of 100-year time intervals. The results show that the Halloween effect is often significant if measured this way, but even within this long sample there are subsamples where the effect is not always significant. In addition, while point estimates are always positive based on traditional regressions and estimates taking GARCH effects into account, outlier robust regressions occasionally show negative point estimates halfway through the previous century. Using this large sample size, however, the effect is more often than not statistically significant. Moreover, if I consider trading strategies assuming different investment horizons, investors would have been better off if they had assumed that the effect was present. This dataset also allows me to test an argument put forward by Powell et al. (2009). They question the accuracy of the statistical inference drawn from standard OLS estimation with Newey and West (1987) standard errors when the regressor is persistent, or has a highly autocorrelated dummy variable and the dependent variable is positively autocorrelated. They suggest that this may affect the statistical significance of the Halloween effect. This argument has been echoed in Ferson (2007). With the benefit of long time series data, however, I address this concern by regressions using 6 monthly, rather than monthly, returns. The bias if any seems marginal, I find almost similar standard errors regardless of whether I use the 6-month intervals, or the monthly data, to estimate the effect.

In short the results provided here suggest that, based on all country evidence, there is a Halloween or Sell in May effect. While it may not be present in all countries, all the time, it most often is. The effect holds out-of-sample and cannot be explained by outliers, or the frequency used (monthly or six monthly) to measure it. The effect is economically large and seems to be increasing in the last fifty years, even when in doubt of the statistical evidence, it seems that investors may want to give this effect the benefit of the doubt, as trading strategies suggest a high chance of outperforming the market for investors with a horizon of five years or more. Of course, just as with in-sample results, past out-of-sample data do not guarantee future out-of-sample performance.

With respect to what may cause the effect, it seems that given all the statistical issues it might be difficult to rely on cross sectional evidence to find a definite answer. What can be said is that any plausible explanation should allow for time variation in the effect and should be able to explain why the effect has increased so strongly in the last fifty years.

3.2 A short background on the Sell in May or Halloween effect

Bouman and Jacobsen (2002) test for the existence of a seasonal effect based on the old market wisdom 'Sell in May and go away' so named because investors should sell their stocks in May because markets tend to go down during summer. While many people in the US are unfamiliar with this saying there is a similar indicator known as the Halloween indicator, which suggests leaving the market in May and coming back after Halloween (31 October). Bouman and Jacobsen (2002) find that summer returns (May through October) are substantially lower than winter returns (November through April) in 36 of the 37 countries over the period from January 1970 through to August 1998. They find no evidence that the effect can be explained by factors like risk, cross correlation between markets, or – except for the US - the January effect. Jacobsen, Mamun and Visaltanachoti (2005) show that the Halloween effect is a market wide phenomenon, which is not related to the common anomalies such as size, Book to Market ratios and dividend yield. Jacobsen and Visaltanachoti (2009) investigate the Halloween effect among US stock market sectors. The Halloween effect is also studied in Arabic stock markets by Zarour (2007) and in Asian stock markets by Lean (2011).

Zarour (2007) finds that the Halloween effect is present in 7 of the 9 Arabic markets in the sample period from 1991 to 2004. Lean (2011) investigates 6 Asian countries for the period 1991 to 2008, and shows that the Halloween effect is only significant in Malaysia and Singapore if modelled with OLS, but that 3 additional countries (China, India and Japan) become statistically significant when time varying volatility is modelled explicitly using GARCH models.

While Bouman and Jacobsen (2002) cannot trace the origin of this market wisdom, they are able to find a quote from the Financial Times dating back to 1964 before the start of their sample. This makes the anomaly particularly interesting. Contrary to, for instance, the January effect (Wachtel, 1942), the Halloween effect is not data driven inference, but based on an old market wisdom that investors should have been aware of. This reduces the likelihood of data mining.[23] Bouman and Jacobsen investigate several possible explanations, but find none, although they cannot reject that the Halloween effects might be caused by summer vacations, which would also explain why the effect is predominantly European.

This study's focus on the long-term history of UK data is especially interesting, as the United Kingdom is the home of the market wisdom "Sell in May and go away". Popular wisdom suggests that the effect originated from the English upper class spending winter months in London, but spending summer away from the stock market on their estates in the country: An extended version of summer vacations as we know them today. Jacobsen and Bouman (2002) report a quote from 1964 in the Financial

[23] For instance, an implication is that Bouman and Jacobsen (2002) need not consider all possible combinations of six month periods.

Times as the oldest reference they could find at the time. With more and more information becoming accessible online I can now report a written mention of the market wisdom “Sell in May” in the Financial Times of Friday 10 of May 1935. It states: “A shrewd North Country correspondent who likes stock exchange flutter now and again writes me that he and his friends are at present drawing in their horns on the strength of the old adage ‘Sell in May and go away.’” The suggestion is that, at that time, it is already an old market saying. This is confirmed by a more recent article in the Telegraph in 2005.[24] In the article “Should you ‘Sell in May and buy another day?’” the journalist George Trefgarne refers to Douglas Eaton, who in that year was 88 and was still working as a broker at Walker, Cripps, Weddle & Beck. “He says he remembers old brokers using the adage when he first worked on the floor of the exchange as a Blue Button, or messenger, in 1934. ‘It was always sell in May,’ he says. ‘I think it came about because that is when so many of those who originate the business in the market start to take their holidays, go to Lord’s, [Lord’s cricket ground] and all that sort of thing.’” Thus, if the Sell-in-May anomaly should be significantly present in one country over a long period, one would expect it to be the United Kingdom.

Gerlach (2007) attributes the significantly higher 3-month returns from October through December in the US market to higher macroeconomic news announcements during the period. Gugten (2010) finds, however, that macroeconomic news announcements have no effect on the Halloween anomaly.

Bouman and Jacobsen (2002) find that only summer vacations as a possible explanation survive closer scrutiny, this might either be caused by changing risk

24 http://www.telegraph.co.uk/finance/2914779/Should-you-sell-in-May-and-buy-another-day.html

aversion, or liquidity constraints. They report that the size of the effect is significantly related to both length and timing of vacations and also to the impact of vacations on trading activity in different countries. Hong and Yu (2009) show that trading activity is lower during the three summer holiday months in many countries. The evidence in these papers supports the popular wisdom, but probably the most convincing evidence to date comes from a recent study by Kaustia and Rantapuska (2012) using Finish data. They consider actual trading decisions of investors and find these trades to be consistent with the vacation hypothesis. They also report evidence which is inconsistent with the Seasonal Affective Disorder (SAD) hypothesis put forward by Kamstra, Kramer and Levi (2003). Kamstra, Kramer and Levi (2003) document a similar pattern in stock returns, but attribute it to mood changes of investors caused by a Seasonal Affective Disorder. Not only, however, does the new evidence in Kaustia and Rantapuska (2012) not support the SAD hypothesis, but the Kamstra, Kramer and Levy (2003) study itself has been critisiced in a number of papers for its methodological flaws (for instance, Kelly & Meschke, 2010; Keef & Khaled, 2011; Jacobsen & Marquering, 2008, 2009). By itself this does not mean, however, that the SAD effect could not play a role in financial markets, but the evidence of the absence of such an effect in some periods, coupled with a strong increase in the prevalence of this effect in the last fifty years seems hard to reconcile with a SAD effect. If it was a mood effect one would expect it to be relatively constant over time. The same argument also applies for a mood effect caused by temperature changes, as suggested by Cao and Wei (2005), who find a high correlation with temperature and stock market returns.

The long time series data used here allows me to address a number of methodological issues that have emerged regarding testing for the Halloween effect. In particular, there has been a debate on the robustness of the Halloween effect under alternative model specifications. For example, Maberly and Pierce (2004) re-examine the Halloween effect in the US market for the period to 1998 and argue that the Halloween effect in the US is caused by two extreme negative returns in October 1987 and August 1998. Using a similar methodology, Maberly and Pierce (2003) claim that the Halloween effect is only present in the Japanese market before 1986. Haggard and Witte (2010) show, however, that the identification of the two extreme outliers lacks an objective basis. Using a robust regression technique that limits the influence of outliers, they find that the Halloween effect is robust from outliers and significant for the period of 1954 to 2008.

Using 20-year sub-period analysis over the period of 1926 to 2002, Lucey and Zhao (2007) reconfirm the finding of Bouman and Jacobsen (2002) that the Halloween effect in the US may be related to the January effect. Haggard and Witte (2010) show, however, that the insignificant Halloween effect may be attributed to the small sample size used, which reduces the power of the test. With long time series data of 17 countries for over 90 years, I am able to reduce the impact of outliers, as well as increase the sample size in examining the out of sample robustness and persistence of the Halloween effect in these countries. As I noted earlier, Powell et al. (2009) question the accuracy of the statistical inference drawn from standard OLS estimation with Newey and West (1987) standard errors when the regressor is persistent, or has a highly autocorrelated dummy variable, and the dependent variable is positively autocorrelated. This argument by itself may seem strange as a regression with a dummy variable is nothing else than a difference in mean test. Still, it may be worthwhile to explicitly address the issue.

3.3 Data and methodology

I collect monthly price index data from Global Financial Data (GFD) and Datastream for all the countries in the world with stock market indices available. This provides me with a total of 108 countries in the sample, consisting of all 24 developed markets, 21 emerging markets, 31 frontier markets classified by the MSCI market classification framework and an additional 32 countries that are not included in the MSCI market classification. I denote them as *rarely studied markets*[25]. The sample has of course a considerable geographical coverage: there are 16 African countries, 20 countries in Asia, 12 countries from the Middle East, 39 countries located in Western and Eastern Europe, 3 countries from North America and 16 from Central/South America and the Caribbean area, as well as 2 countries in Oceania. Table 3.1 presents the source of the data and summary statistics for each country grouped on the basis of their MSCI market classification and geographic region. The world index used is the GFD world price index that goes back to 1919[26], the information for the index is provided in the last row.

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25 Our market classification is based on "MSCI Global Investable Market Indices Methodology" published in August 2011. MSCI classifies markets based on economic development, size and liquidity, as well as market accessibility. In addition to the developed market and emerging markets, MSCI launched frontier market indices in 2007; they define the frontier markets as "all equity markets not included in the MSCI Emerging Market Index that (1) demonstrate a relative openness and accessibility for foreign investors, (2) are generally not considered as part of the developed market universe, (3) do not belong to countries undergoing a period of extreme economic or political instability, (4) a minimum of two companies with securities eligible for the Standard Index" (p.58). The countries classified as rarely studied markets in our sample are not necessarily the countries that are less developed than the frontier markets; they can be countries that are considered part of the developed markets' universe with relatively small size; for example, Luxembourg and Iceland; which are excluded from the developed market category by MSCI.

26 The index is capitalisation weighted starting from 1970 and using the same countries that are included in the MSCI indices. Prior to 1970, the index consists of North America 44% (USA 41%, Canada 3%), Europe 44% (United Kingdom 12%, Germany 8%, France 8%, Italy 4%, Switzerland 2.5%, the Netherlands 2.5%, Belgium 2%, Spain 2%, Denmark 1%, Norway 1% and Sweden 1%), Asia and the Far East 12% (Japan 6%, India 2%, Australia 2%, South Africa Gold 1%, South Africa Industrials 1%), weighted in January 1919. The country weights were

Columns 4 to 6 report the starting date, ending date and the sample size for each index. For many of the countries, the time series almost cover the entire trading history of their stock market. In particular, I have over 310 years of monthly market index prices for the United Kingdom, more than 210 years for the United States and over 100 years data for another 7 countries. There are 28 countries in total having data available for over 60 years. This long time series data allows me to examine the emergence and persistence of the Halloween effect by conducting sub-period analysis. Although the countries with long time series data in this sample are primarily developed European and North American countries, it does have over 100 years data for Australia, South Africa and Japan, and over 90 years data for India. I also have countries with very small sample size; for example, there are 10 countries with data for less than 10 years. I calculate the continuously compounded monthly returns for each country. Columns 7 to 12 provide some basic descriptive statistics over the whole sample period. In general, the table reveals lower mean returns with relatively smaller standard deviations for countries in developed markets than the other markets, and the emerging market tends to have the highest average returns with the largest volatility. For example, the average annualised mean returns for all developed markets in the sample is 6.55%, which is only two-third of the average return of the emerging markets (10.59%) and about half the size of the frontier markets (11.62%) and the rarely studied markets (11.20%). Meanwhile, the volatility for the emerging markets is among the highest, with an annualised standard deviation of 36.70% comparing to 20.18% for the developed markets, and 28.57% and

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assumed unchanged until 1970. The local index values were converted into a dollar index by dividing the local index by the exchange rate.

Table 3.1 Summary statistics for 108 countres' market indices and the world index returns

The table presents the source, starting date, ending date and number of observations, as well as some basic descriptive statistics, for 108 market i
deviation of monthly index returns expressed as percentage are annualised by multiplying by 12 and $\sqrt{12}$. Maximum and minimum monthl
grouped based on the MSCI market classification and geographical regions.

Status	Region	Country	Start	End	Obs	Mean	StDev	Skew	Kurt	Max	Min	
Developed	**Asia**	Hong Kong	08/1964	07/2011	564	11.52	32.42	-0.78	6.89	51.44	-57.14	Hong Kon
		Japan	08/1914	07/2011	1154	6.30	21.77	0.25	7.39	50.87	-31.84	Nikkei 225
		Singapore	08/1965	07/2011	552	7.04	23.32	-0.53	3.68	27.16	-35.22	Singapore I
	Mid East	Israel	02/1949	05/2011	748	23.66	23.12	0.08	3.64	34.12	-37.08	Tel Aviv A
	North America	Canada	12/1917	07/2011	1124	5.03	16.12	-1.07	5.66	20.59	-33.46	Canada S&
		UnitedStates	09/1791	07/2011	2639	2.81	15.06	-0.58	10.18	35.24	-35.63	S&P 500 C
	Oceania	Australia	02/1875	07/2011	1638	4.99	13.51	-1.89	28.37	21.70	-55.25	Australia A
		New Zealand	01/1931	07/2011	967	4.33	14.22	-0.62	8.12	22.19	-33.88	New Zeala
	Western Europe	Austria	02/1922	07/2011	1018	9.04	27.52	4.30	54.87	114.75	-39.72	Austria Wi
		Belgium	02/1897	07/2011	1302	3.91	17.90	0.09	4.08	30.51	-26.03	Brussels A
		Denmark	01/1921	07/2011	1086	4.31	12.87	-0.34	4.28	17.24	-20.98	OMX Cop
		Finland	11/1912	07/2011	1179	8.30	20.51	0.36	5.22	36.50	-31.32	OMX Hels
		France	01/1898	07/2011	1348	6.67	18.82	1.05	14.15	63.16	-27.61	France CA
		Germany	01/1870	07/2011	1692	2.55	25.03	-4.75	111.68	68.87	-146.00	Germany C
		Greece	01/1954	07/2011	690	9.51	26.33	1.02	5.44	40.97	-32.67	Athens SE
		Ireland	02/1934	07/2011	930	5.67	16.29	-0.70	6.07	24.73	-32.09	Ireland ISE
		Italy	10/1905	07/2011	1264	5.44	23.95	0.94	6.49	46.81	-30.76	Banca Com
		Netherlands	02/1919	07/2011	1086	3.65	16.97	-0.55	2.79	22.51	-26.59	Netherland
		Norway	01/1970	07/2011	499	10.81	24.37	-0.73	2.27	23.19	-32.05	Oslo SE A
		Portugal	01/1934	07/2011	897	6.09	30.93	-5.78	132.51	62.91	-163.11	Oporto PS
		Spain	01/1915	07/2011	1116	5.35	17.31	0.30	8.88	45.87	-33.48	Madrid SE
		Sweden	01/1906	07/2011	1265	5.50	16.86	-0.66	5.45	24.30	-38.75	Sweden OM
		Switzerland	01/1914	07/2011	1155	3.19	15.24	-0.55	5.17	28.78	-28.22	Switzerlan
		United Kingdom	02/1693	07/2011	3817	1.44	13.86	-0.51	54.38	53.53	-73.55	UK FTSE

Table 3.1 Continued

Status	Region	Country	Start	End	Obs	Mean	StDev	Skew	Kurt	Max	Min	
Emerging	**Africa**	Egypt	01/1993	07/2011	222	-7.37	112.88	-13.27	189.99	29.75	-465.73	Cairo SE E
		Morocco	01/1988	07/2011	279	13.49	14.93	-0.17	2.91	17.88	-17.92	Casablanca
		South Africa	02/1910	07/2011	1218	7.67	16.76	-0.60	4.35	21.64	-35.14	FTSE/JSE
	Asia	China	01/1991	07/2011	247	14.83	48.14	2.33	16.32	101.97	-37.33	Shanghai S
		India	08/1920	07/2011	1080	5.88	19.26	0.41	4.69	35.06	-27.30	Bombay S
		Indonesia	04/1983	07/2011	340	13.13	31.02	0.82	12.53	69.37	-37.86	Jakarta SE
		Korea	02/1962	07/2011	592	13.47	39.03	1.42	26.89	112.93	-81.49	Korea SE S
		Malaysia	01/1974	07/2011	451	7.29	27.19	-0.46	3.39	29.44	-42.90	Malaysia K
		Philippines	01/1953	07/2011	703	2.87	28.93	0.23	2.73	40.94	-33.21	Manila SE
		Taiwan	02/1967	07/2011	534	10.16	33.21	-0.29	3.90	40.64	-49.34	Taiwan SE
		Thailand	05/1975	07/2011	435	6.70	29.14	-0.41	2.88	28.43	-35.92	Thailand S
	Central/South America & the Caribbean	Brazil	01/1990	07/2011	258	67.65	56.46	1.05	5.56	69.32	-69.32	MSCI Braz
		Chile	01/1927	07/2011	1015	27.36	29.53	2.80	19.66	82.39	-37.56	Santiago S
		Colombia	02/1927	07/2011	1014	9.74	19.94	2.06	19.45	64.08	-24.68	Colombia I
		Mexico	02/1930	07/2011	978	16.21	25.66	-0.32	10.03	36.23	-56.55	Mexico SE
		Peru	01/1933	07/2011	943	31.15	39.15	3.64	24.05	115.41	-46.65	Lima SE G
	Eastern Europe	Czech Republic	10/1993	07/2011	214	7.07	30.06	0.37	4.93	45.34	-31.65	Prague SE
		Hungary	01/1995	07/2011	199	16.01	30.99	-0.55	4.62	37.54	-44.76	Vienna OE
		Poland	05/1994	07/2011	207	5.28	33.44	-0.44	3.93	34.12	-44.98	Warsaw SE
		Russian	10/1993	07/2011	213	41.72	51.37	0.16	5.30	79.92	-64.95	Russia AK
		Turkey	02/1986	07/2011	306	43.29	53.65	0.70	3.05	81.94	-49.49	Istanbul S
Frontier	**Africa**	Botswana	06/1989	07/2011	266	19.29	14.70	1.53	8.02	26.59	-10.70	Botswana
		Ghana	01/1996	07/2011	187	11.62	18.49	0.76	3.55	25.12	-15.78	Standard a
		Kenya	02/1990	07/2011	258	7.11	23.94	0.96	6.64	41.29	-25.67	Kenya Nai
		Mauritius	08/1989	07/2011	264	13.16	16.42	-0.14	2.74	15.52	-20.77	Securities
		Nigeria	01/1988	07/2011	280	20.69	21.61	-0.81	8.16	32.41	-36.59	Nigeria SE
		Tunisia	01/1996	07/2011	187	3.44	16.62	0.10	3.23	21.89	-16.06	Standard a
		Zimbabwe	12/2010	07/2011	8	18.25	19.26	1.02	-0.69	10.37	-3.61	MSCI Zim

Table 3.1 Continued

Status	Region	Country	Start	End	Obs	Mean	StDev	Skew	Kurt	Max	Min	
Frontier	**Asia**	Bangladesh	02/1990	07/2011	258	11.39	33.37	0.67	6.90	56.92	-36.16	Bangladesh
		Kazakhstan	08/2000	07/2011	132	24.53	38.13	-0.08	4.33	43.67	-38.36	Kazakhstan
		Pakistan	08/1960	07/2011	608	9.61	23.34	-0.60	8.05	29.69	-44.88	Pakistan K
		Sri Lanka	01/1985	07/2011	319	15.90	25.81	0.37	1.04	30.97	-18.42	Colombo S
		Viet Nam	01/2001	07/2011	127	6.66	41.63	-0.04	0.54	32.58	-35.50	Viet Nam S
	Central/South America & the Caribbean	Argentina	01/1967	07/2011	535	63.70	62.03	2.34	10.86	129.94	-43.89	Buenos Ai
		Jamaica	07/1969	01/2011	499	16.21	25.60	1.00	3.64	36.94	-26.03	Jamaica Sto
		Trinidad And Tobago	01/1996	07/2011	187	12.67	14.40	0.67	2.48	15.35	-13.01	Standard ar
	Eastern Europe	Bosnia And Herzegowina	11/2004	07/2011	81	-8.45	32.26	0.57	0.94	27.57	-22.54	Sarajevo SE
		Bulgaria	11/2000	07/2011	129	12.34	35.83	-0.73	4.68	35.04	-47.63	Bulgaria SE
		Croatia	02/1997	07/2011	174	4.91	32.44	-1.46	7.48	29.68	-53.98	Croatia Bo
		Estonia	07/1996	07/2011	181	13.10	37.48	-0.68	3.87	37.03	-44.98	OMX Tall
		Lithuania	01/1996	07/2011	187	4.65	28.57	-0.60	6.76	32.55	-43.63	Standard ar
		Romania	10/1997	07/2011	166	12.44	38.79	-0.70	2.62	29.95	-44.05	Bucharest
		Serbia	08/2008	07/2011	36	-18.94	60.86	-1.08	2.60	35.52	-54.95	MSCI Serb
		Slovenia	01/1996	07/2011	187	6.66	25.32	0.94	5.30	41.53	-19.46	HSBC Slov
		Ukraine	02/1998	07/2011	162	19.19	44.43	-0.30	1.45	40.21	-40.33	Ukraine PF
	Mid East	Jordan	02/1978	07/2011	402	6.46	22.76	-0.03	3.70	27.17	-27.81	Jordan AF
		Kuwait	01/1995	07/2011	199	10.96	19.53	-0.67	3.54	18.47	-27.12	Kuwait SE
		Lebanon	02/1996	07/2011	186	2.45	28.23	1.03	4.32	39.01	-23.54	Beirut Stoc
		Oman	12/1992	07/2011	224	8.54	20.56	-0.51	3.88	18.46	-31.32	Muscat Sto
		Qatar	10/1999	07/2011	142	15.41	30.03	-0.46	1.67	25.96	-29.60	Qatar SE In
		United Arab Emirates	01/1988	09/2008	236	12.73	19.65	0.52	5.46	29.28	-21.38	United Ara
	Western Europe	Bahrain	07/1990	07/2011	253	3.48	13.57	-0.25	0.75	12.47	-13.02	Bahrain BS
Rarely Studied	**Africa**	Cote D`Ivoire	07/1997	07/2011	169	2.99	17.38	0.12	2.08	15.74	-17.53	Cote d'Ivoi
		Malawi	04/2001	01/2011	114	22.63	38.02	-0.96	13.50	49.32	-55.28	Malawi SE
		Namibia	03/1993	07/2011	218	11.59	24.88	-1.31	6.28	20.28	-42.20	Namibia St
		Swaziland	01/2000	04/2007	88	2.39	15.18	3.85	24.91	27.71	-14.18	Swaziland
		Tanzania	12/2006	07/2011	56	5.11	7.66	1.89	7.96	9.28	-6.13	Dar-Es-Sal
		Zambia	02/1997	07/2011	174	25.52	25.27	0.65	2.50	32.43	-17.98	Zambia Lu

Table 3.1 Continued

Status	Region	Country	Start	End	Obs	Mean	StDev	Skew	Kurt	Max	Min	
	Asia	Georgia	11/2008	07/2011	33	32.74	68.50	-1.06	3.84	51.08	-56.42	Standard ar
		Kyrgyzstan	01/2000	05/2011	137	6.68	42.52	0.14	3.41	45.53	-49.35	Kyrgyz St
		Mongolia	09/1995	05/2011	189	29.33	48.16	0.50	2.87	61.12	-43.38	Mongolia S
		Nepal	01/1996	07/2011	186	3.56	23.03	-0.07	1.09	18.01	-20.30	Nepal NEP
	Central/South America & the Caribbean	Barbados	04/1989	02/2011	263	4.24	13.99	2.09	18.67	31.35	-20.71	Barbados S
		Costa Rica	10/1997	02/2011	161	13.90	21.48	-0.70	5.92	22.19	-32.91	BCT Corp
		Ecuador	02/1994	07/2011	210	1.80	23.17	0.78	7.99	39.64	-25.91	Ecuador Bo
		El Salvador	01/2004	07/2011	91	7.41	8.07	0.60	4.70	10.16	-7.71	El Salvador
		Panama	01/1993	07/2011	223	14.08	11.18	1.13	4.77	14.91	-10.76	Panama Sto
		Paraguay	11/1993	09/2008	176	11.15	10.52	3.37	22.91	21.01	-11.81	Asuncion S
		Uruguay	02/1925	12/1995	848	13.10	41.57	3.56	35.72	143.90	-49.60	Uruguay St
		Venezuela	01/1937	07/2011	891	13.51	23.59	0.72	10.21	43.41	-51.25	Caracas SE
	Eastern Europe	Cyprus	01/1984	07/2011	331	2.98	34.04	0.79	6.38	57.54	-32.55	Cyprus CS
		Latvia	02/1996	07/2011	186	9.89	35.18	-0.72	6.12	35.78	-54.74	Nomura La
		Macedonia	11/2001	07/2011	117	12.50	37.87	0.31	2.80	37.99	-39.33	Macedonia
		Montenegro	04/2003	07/2011	100	29.25	44.42	0.66	1.97	46.55	-32.19	Montenegr
		Slovak Republic	10/1993	07/2011	214	4.54	32.33	2.93	24.50	75.83	-37.76	Bratislava
	Mid East	Iran	04/1990	06/2011	255	25.90	18.77	1.22	3.88	31.53	-12.85	Tehran SE
		Iraq	11/2004	07/2011	79	10.88	59.11	0.05	9.37	70.98	-79.31	Iraq SE ISX
		Palestine	08/1997	07/2011	166	11.48	40.51	-1.32	17.87	52.05	-82.67	Palestine A
		Saudi Arabia	01/1993	07/2011	222	6.59	23.43	-0.84	2.78	17.90	-29.78	Saudi Arab
		Syrian Arab Republic	01/2010	07/2011	19	2.70	28.18	-1.31	0.88	9.22	-17.92	Damascus
	North America	Bermuda	09/1996	10/2010	170	1.78	20.48	-0.70	3.93	16.45	-28.99	Bermuda R
	Western Europe	Iceland	01/1993	07/2011	223	2.47	36.53	-8.08	92.42	17.17	-125.58	OMX Icela
		Luxembourg	01/1954	07/2011	691	8.17	16.79	-0.91	7.20	17.91	-31.20	Luxembour
		Malta	01/1996	07/2011	187	7.51	18.89	1.00	2.03	22.17	-11.03	Malta SE I
		World	02/1919	07/2011	1110	4.17	13.23	-0.83	3.61	13.93	-21.06	GFD Worl

28.46% for the frontier and rarely studied markets, respectively. The highest increase in monthly index returns is 143.90% in Uruguay in January 1986 and the largest plunge in index prices in a single month is 465.73% in Egypt in July 2008 (Note that because I use log returns, drops of more than 100% are possible). The unequal sample size among the countries does, however, make direct comparison across nations difficult. I address this by applying sub-period analysis in the later sections of the study. The last column shows the index used for each country. All price indices are quoted at local currency, except Georgia where the only index data available is in USD.

As is common in the literature I investigate the statistical significance of the Halloween effect using the Halloween dummy regression model:

$$r_t = \alpha + \beta Hal_t + \varepsilon_t \qquad (3.1)$$

where r_t is the continuously compounded monthly index returns and Hal_t is the Halloween dummy, which equals one if the month falls in the period of November through April and is zero otherwise. If a Halloween effect is present I expect the coefficient estimate β to be significantly positive, as it represents the difference between the mean returns for the two 6-month periods of November-April and May-October.

3.4 Results

3.4.1 Out of sample performance

To be relevant it is necessary to insure that the Halloween effect still exists beyond the original Bouman and Jacobsen (2002) study. Their analysis ends in August 1998. Campbell (2000) and Schwert (2002) suggest that if an anomaly is truly anomalous, it should be quickly arbitraged away by rational investors. (Note that this argument also should have applied to the Bouman and Jacobsen (2002) study itself, as the market wisdom was known before their sample period.) To show whether the Halloween effect has weakened, I start with an out of sample test of the Halloween effect in the 37 countries examined in Bouman and Jacobsen (2002).

Table 3.4 compares in-sample performance for the period 1970 to August 1998[27] with out-of-sample performance for the period of September 1998 to November 2011. The in-sample test using a different dataset presents similar results to Bouman and Jacobsen (2002), with stock market returns from November through April being higher than from May through October in 34 of the 37 countries, and the difference being statistically significant in 20 of the countries. Although a small sample size may reduce the power of the test, the out of sample performance is still very impressive. All 37 countries show positive point estimates of the Halloween effect. For 15 countries the effect is statistically significant out of sample. The Halloween effect seems not to have weakened in the recent years. Moreover, the point estimates in the out-of-sample test of 18 countries are even higher than for the in-sample test. The average coefficient estimate in the out-of-sample test is 8.87%, compared to 8.16% in the in-sample test. Columns 4 and 7 show the percentage of years that November-April returns beats May-October returns in the sample for each country. Most of the countries have a value greater than 50%, suggesting that the positive Halloween effect is not due to outliers.

27 In their study, they have 18 countries' data starting from January 1970, 1 country starting in 1973 and 18 countries starting from 1988. Our in-sample test begins from 1970 for those countries with data available in our sample prior to 1970. We use the earliest data available in our dataset (refer to Table 1 for the starting data of each country) for the 7 countries for which data starts later than 1970.

Table 3.2 In-sample and Out-of-sample comparison of the Halloween effect

The table shows the coefficient estimates and t-statistics for the regression $r_t = \alpha + \beta Hal_t + \varepsilon_t$, as well as the percentage of times that November-April returns beat May-October returns for the in-sample period and out of sample period of 37 countries. The in-sample period refers to the sample period examined in Bouman and Jacobsen (2002) and runs from January 1970 (or the earliest date in the sample depending on data availability) to August 1998. The out-of-sample period is from September 1998 to July 2011. The coefficient β represents the 6-month return difference between November-April and May-October. T-values are adjusted using Newey-West standard errors. *** denotes significance at 1% level; **denotes significance at 5% level; *denotes significance at 10% level.

	IN SAMPLE				OUT OF SAMPLE			
Country	**β**	**t-value**		**%+**	**β**	**t-value**		**%+**
Argentina	0.61	0.28		0.66	2.54	1.51		0.57
Australia	0.90	1.49		0.59	0.49	0.89		0.50
Austria	1.46	2.72	***	0.69	2.35	2.84	***	0.71
Belgium	2.07	5.21	***	0.90	1.16	1.48		0.71
Brazil	6.24	1.72	*	0.67	1.60	1.29		0.50
Canada	1.29	2.57	**	0.69	1.00	1.54		0.50
Chile	-1.24	-0.7		0.45	0.24	0.37		0.57
Denmark	0.64	1.55		0.66	0.82	1.19		0.71
Finland	1.55	3.01	***	0.76	2.07	1.74	*	0.64
France	2.37	3.99	***	0.79	1.60	2.32	**	0.64
Germany	1.39	2.91	***	0.69	1.94	2.35	**	0.79
Greece	1.83	1.94	*	0.62	0.67	0.55		0.50
Hong Kong	0.86	0.75		0.66	0.02	0.01		0.43
Indonesia	2.10	1.5		0.56	2.43	1.89	*	0.57
Ireland	1.40	2.17	**	0.62	2.30	2.70	***	0.79
Italy	2.50	3.59	***	0.76	2.36	2.85	***	0.71
Japan	1.29	2.41	**	0.76	1.97	2.14	**	0.64
Jordan	0.75	1.08		0.52	0.51	0.72		0.43
Korea	0.28	0.43		0.55	2.14	1.70	*	0.71
Malaysia	2.14	1.9	*	0.68	0.97	1.04		0.57
Mexico	0.84	0.82		0.59	1.36	1.36		0.50
Netherlands	1.98	4.1	***	0.86	1.73	1.93	*	0.64
New Zealand	0.52	0.83		0.52	0.72	1.41		0.64
Norway	1.06	1.38		0.52	1.73	1.69	*	0.57
Philippines	2.17	1.96	*	0.62	0.43	0.36		0.43
Portugal	0.60	0.34		0.67	1.40	1.67	*	0.79
Russia	-1.06	-0.15		0.50	4.44	2.41	**	0.79
Singapore	1.30	1.52		0.62	0.79	0.78		0.50
South Africa	1.03	1.18		0.59	0.33	0.35		0.50
Spain	1.99	3.31	***	0.76	1.01	1.26		0.71
Sweden	1.95	3.44	***	0.76	2.30	2.95	***	0.79
Switzerland	1.05	2.2	**	0.72	0.84	1.30		0.71
Taiwan	3.35	3.44	***	0.72	2.50	1.69	*	0.79
Thailand	-0.05	-0.04		0.42	0.94	0.66		0.50
Turkey	0.12	0.05		0.46	3.12	1.48		0.50
UnitedKingdom	2.06	2.89	***	0.59	1.09	1.85	*	0.64
UnitedStates	0.97	2.45	**	0.72	0.82	1.57		0.57

3.4.2 Overall results

Using all 55,425 monthly observations for all 108 countries over 319 years, the first row of Table 3.3 gives a general impression of how strong the Halloween effect is. The average 6-month winter return (November through April) is 6.93%, compared to the summer return (May through October) of 2.41%. The overall Halloween effect that measures the difference between winter and summer returns is 4.52%, with a t-value of 9.69. Despite the possibility that the statistical significance might be overstated due to cross correlations between markets, these results do provide an overall feeling of the strength of the Halloween effect. The Halloween effect from the world index returns in the second row reveals a similar result. The average 6-month winter return is 4.53% (t-value 3.31) higher than the 6-month summer return.

3.4.3 Country by country analysis

Many explanations suggest cross-country variations of the strength of the Halloween effect. This section conducts the most comprehensive cross-nation Halloween effect analysis on all 108 countries with stock market indices available. The evidence shows that the Halloween effect is prevalent around the world to the extent that the mean returns are higher for the period of November-April than for May-October in 81 out of 108 countries and that the difference is statistically significant in 35 countries, compared to only 2 countries having significantly higher May-October returns.

Table 3.3 Country by country analysis

This table provides two 6-month (November-April and May-October) mean returns and standard deviations at percentage, the coefficient estimates and t-statistics for the regression $r_t = \alpha + \beta Hal_t + \varepsilon_t$, as well as percentage of times that November-April return beats May-October return for 108 countries' market index and the world index. β represents the 6-month mean returns difference between November-April and May-October. T-values are adjusted using Newey-West standard errors. The 6-month mean returns (standard deviations) are calculated by multiplying monthly returns (standard deviations) by 6 ($\sqrt{6}$).

*** denotes significance at 1% level; **denotes significance at 5% level; *denotes significance at 10% level. Countries are grouped based on the MSCI market classification and geographical regions.

Status	Region	Start Date	End Date	Country	November-April		May-October		Halloween		
					Mean	St Dev	Mean	St Dev	β	t-value	% +
	Pooled 108 countries	02/1693	07/2011	-	6.93	17.47	2.41	19.51	4.52	9.69***	58%
	World	02/1919	07/2011	-	4.35	8.75	-0.18	9.84	4.53	3.31***	67%
Developed	Asia	08/1964	07/2011	Hong Kong	7.08	22.48	4.44	23.39	2.64	0.56	58%
		08/1914	07/2011	Japan	7.31	16.05	-1.00	14.52	8.31	3.60***	66%
		08/1965	07/2011	Singapore	6.91	15.79	0.13	17.08	6.78	1.84*	60%
	Mid East	02/1949	05/2011	Israel	13.56	16.74	10.09	15.93	3.46	1.09	62%
	North America	12/1917	07/2011	Canada	5.29	9.94	-0.28	12.61	5.57	3.34***	61%
		09/1791	07/2011	United States	2.24	9.98	0.57	11.27	1.67	1.66*	57%
	Oceania	02/1875	07/2011	Australia	3.11	8.59	1.88	10.43	1.22	1.06	53%
		01/1931	07/2011	New Zealand	2.69	9.71	1.63	10.39	1.06	0.66	51%
	Western Europe	02/1922	07/2011	Austria	5.35	17.31	3.69	21.41	1.66	0.44	56%
		02/1897	07/2011	Belgium	3.99	12.03	-0.10	13.22	4.09	2.47***	62%
		01/1921	07/2011	Denmark	3.74	9.15	0.56	9.01	3.18	2.20**	64%
		11/1912	07/2011	Finland	4.08	14.14	4.22	14.87	-0.14	-0.06	50%
		01/1898	07/2011	France	7.05	13.50	-0.39	12.95	7.45	3.87***	66%
		01/1870	07/2011	Germany	4.09	14.36	-1.53	20.44	5.63	2.44***	59%
		01/1954	07/2011	Greece	8.65	18.50	0.84	18.63	7.81	2.00**	55%
		02/1934	07/2011	Ireland	6.14	10.85	-0.48	12.01	6.62	3.35***	69%
		10/1905	07/2011	Italy	6.11	16.89	-0.69	16.88	6.80	2.67***	60%
		02/1919	07/2011	Netherlands	5.62	10.90	-1.97	12.83	7.59	4.05***	67%
		01/1970	07/2011	Norway	9.19	16.18	1.60	18.13	7.58	1.97**	55%
		01/1934	07/2011	Portugal	4.87	26.91	1.21	15.20	3.66	0.94	62%
		01/1915	07/2011	Spain	6.26	12.47	-0.91	11.83	7.16	3.75***	69%
		01/1906	07/2011	Sweden	5.52	12.32	-0.03	11.41	5.56	3.14***	63%
		01/1914	07/2011	Switzerland	3.91	9.41	-0.73	11.92	4.64	2.94***	66%
		02/1693	07/2011	United Kingdom	2.40	9.34	-0.96	10.19	3.37	4.06***	59%
Emerging	Africa	01/1993	07/2011	Egypt	14.89	22.01	-22.26	110.45	37.15	1.32	58%
		01/1988	07/2011	Morocco	12.40	10.92	1.05	9.67	11.35	3.22***	71%
		02/1910	07/2011	South Africa	4.78	11.59	2.89	12.10	1.88	0.97	53%
	Asia	01/1991	07/2011	China	12.75	26.86	2.04	39.99	10.72	1.01	67%
		08/1920	07/2011	India	3.52	13.63	2.35	13.61	1.17	0.52	45%
		04/1983	07/2011	Indonesia	13.40	21.29	-0.18	22.27	13.58	2.14**	55%
		02/1962	07/2011	Korea	12.25	28.77	1.26	26.24	11.00	1.64*	62%
		01/1974	07/2011	Malaysia	8.86	18.56	-1.59	19.69	10.46	2.36**	63%
		01/1953	07/2011	Philippines	6.23	19.59	-3.37	21.13	9.60	2.26**	58%
		02/1967	07/2011	Taiwan	13.74	21.48	-3.58	24.87	17.31	3.70***	76%
		05/1975	07/2011	Thailand	4.29	17.99	2.42	22.93	1.87	0.38	46%
	Central/South America & the Caribbean	01/1990	07/2011	Brazil	43.92	39.80	23.72	39.77	20.20	1.28	59%
		01/1927	07/2011	Chile	11.70	17.01	15.66	24.13	-3.97	-0.94	52%
		02/1927	07/2011	Colombia	6.29	14.43	3.45	13.76	2.85	1.20	56%
		02/1930	07/2011	Mexico	9.76	17.74	6.45	18.53	3.30	1.13	56%
		01/1933	07/2011	Peru	13.72	23.77	17.43	31.13	-3.72	-0.68	49%

Table 3.3 Continued

Status	Region	Start Date	End Date	Country	November-April Mean	November-April St Dev	May-October Mean	May-October St Dev	Halloween β	Halloween t-value	Halloween % +
Emerging	Eastern Europe	10/1993	07/2011	Czech Republic	9.00	22.27	-2.03	20.01	11.03	1.73*	68%
		01/1995	07/2011	Hungary	14.69	21.23	1.26	22.35	13.42	1.91*	71%
		05/1994	07/2011	Poland	11.27	21.29	-5.75	25.35	17.02	2.43**	72%
		10/1993	07/2011	Russia	29.49	29.42	11.99	42.11	17.50	1.21	68%
		02/1986	07/2011	Turkey	26.51	39.78	16.78	36.02	9.73	0.90	46%
Frontier	Africa	06/1989	07/2011	Botswana	6.90	9.16	12.35	11.41	-5.45	-1.47	48%
		01/1996	07/2011	Ghana	8.46	14.12	3.13	11.91	5.33	1.00	63%
		02/1990	07/2011	Kenya	5.65	20.36	1.46	12.63	4.19	0.75	59%
		08/1989	07/2011	Mauritius	6.32	11.80	6.84	11.46	-0.52	-0.15	57%
		01/1988	07/2011	Nigeria	11.18	13.88	9.48	16.65	1.69	0.33	58%
		01/1996	07/2011	Tunisia	3.89	12.58	-0.47	10.84	4.35	1.01	81%
		12/2010	07/2011	Zimbabwe	22.33	14.88	-12.88	3.59	35.20	4.24***	50%
	Asia	02/1990	07/2011	Bangladesh	-5.45	24.43	16.84	21.89	-22.29	-2.46***	23%
		08/2000	07/2011	Kazakhstan	23.30	26.90	1.23	26.47	22.07	1.45	67%
		08/1960	07/2011	Pakistan	8.56	16.61	1.04	16.28	7.52	2.36**	62%
		01/1985	07/2011	Sri Lanka	6.22	18.72	9.69	17.81	-3.46	-0.63	52%
		01/2001	07/2011	Viet Nam	11.88	29.98	-5.36	28.67	17.23	1.17	64%
	Central/South America & the Caribbean	01/1967	07/2011	Argentina	35.90	38.66	27.78	48.55	8.12	0.76	64%
		07/1969	01/2011	Jamaica	11.48	18.34	4.74	17.79	6.74	1.49	56%
		01/1996	07/2011	Trinidad And Tobago	8.73	10.65	3.91	9.65	4.82	1.06	63%
	Eastern Europe	11/2004	07/2011	Bosnia And Herzegowina	-0.84	26.83	-7.87	17.73	7.03	0.46	50%
		11/2000	07/2011	Bulgaria	1.91	23.63	10.64	27.07	-8.73	-0.75	33%
		02/1997	07/2011	Croatia	9.33	20.74	-4.42	24.74	13.76	1.82*	60%
		07/1996	07/2011	Estonia	17.59	25.93	-4.38	26.45	21.97	2.28**	81%
		01/1996	07/2011	Lithuania	5.92	17.94	-1.31	22.26	7.22	0.84	56%
		10/1997	07/2011	Romania	9.56	27.50	2.81	27.46	6.75	0.55	47%
		08/2008	07/2011	Serbia	-3.70	37.88	-15.23	48.65	11.53	0.29	75%
		01/1996	07/2011	Slovenia	1.79	19.62	4.88	16.08	-3.09	-0.55	31%
		02/1998	07/2011	Ukraine	29.22	29.26	-10.03	31.63	39.25	2.74***	79%
	Mid East	02/1978	07/2011	Jordan	5.21	15.66	1.25	16.51	3.96	1.10	50%
		01/1995	07/2011	Kuwait	4.31	13.80	6.67	13.88	-2.36	-0.45	41%
		02/1996	07/2011	Lebanon	-3.57	19.44	6.02	20.39	-9.60	-1.27	63%
		12/1992	07/2011	Oman	5.16	13.89	3.36	15.22	1.80	0.34	45%
		10/1999	07/2011	Qatar	8.13	23.11	7.27	19.28	0.86	0.09	46%
		01/1988	09/2008	United Arab Emirates	6.51	13.34	6.22	14.48	0.29	0.05	48%
	Western Europe	07/1990	07/2011	Bahrain	-0.79	9.05	4.25	10.05	-5.04	-1.50	41%
Rarely Studied	Africa	07/1997	07/2011	Cote D`Ivoire	3.66	11.87	-0.65	12.69	4.31	0.92	80%
		04/2001	01/2011	Malawi	11.87	26.66	10.82	27.31	1.05	0.10	18%
		03/1993	07/2011	Namibia	10.93	15.14	0.66	19.60	10.26	1.71*	68%
		01/2000	04/2007	Swaziland	2.15	14.14	0.15	4.96	2.00	0.37	13%
		12/2006	07/2011	Tanzania	1.30	2.95	3.91	7.22	-2.62	-0.61	17%
		02/1997	07/2011	Zambia	7.34	15.70	18.18	19.64	-10.84	-1.54	47%
	Asia	11/2008	07/2011	Georgia	2.50	59.57	33.02	31.03	-30.52	-0.83	50%
		01/2000	05/2011	Kyrgyzstan	13.05	32.15	-6.80	27.34	19.84	1.80*	75%
		09/1995	05/2011	Mongolia	13.33	31.09	16.04	37.03	-2.71	-0.21	41%
		01/1996	07/2011	Nepal	-4.54	16.90	8.11	15.30	-12.65	-2.09**	31%

Table 3.3 Continued

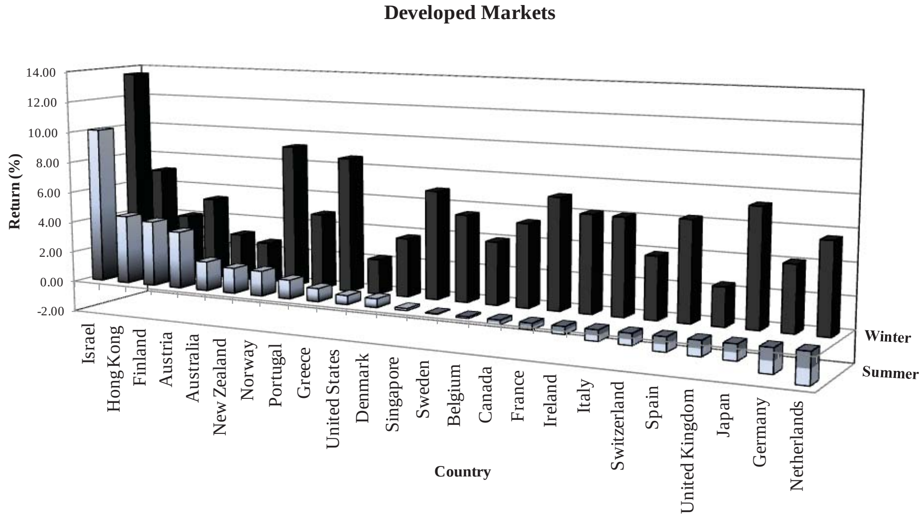
Status	Region	Start Date	End Date	Country	November-April		May-October		Halloween		
					Mean	St Dev	Mean	St Dev	β	t-value	% +
Rarely Studied	Central/South America & the Caribbean	04/1989	02/2011	Barbados	0.37	8.52	3.85	11.08	-3.48	-1.08	43%
		10/1997	02/2011	Costa Rica	7.42	17.57	6.46	12.36	0.96	0.15	47%
		02/1994	07/2011	Ecuador	-1.95	15.05	3.74	17.61	-5.69	-0.96	56%
		01/2004	07/2011	El Salvador	2.82	7.17	4.61	3.70	-1.78	-0.52	13%
		01/1993	07/2011	Panama	7.09	8.15	6.99	7.68	0.10	0.03	53%
		11/1993	09/2008	Paraguay	3.40	7.24	7.85	7.58	-4.45	-1.44	19%
		02/1925	12/1995	Uruguay	14.86	34.28	-1.80	23.03	16.66	3.52***	62%
		01/1937	07/2011	Venezuela	6.70	16.52	6.81	16.85	-0.10	-0.04	53%
	Eastern Europe	01/1984	07/2011	Cyprus	1.07	22.59	1.91	25.53	-0.84	-0.12	61%
		02/1996	07/2011	Latvia	8.32	23.17	1.56	26.53	6.76	0.65	69%
		11/2001	07/2011	Macedonia	4.39	27.27	8.21	26.47	-3.82	-0.27	55%
		04/2003	07/2011	Montenegro	13.08	29.86	16.11	33.11	-3.02	-0.16	56%
		10/1993	07/2011	Slovak Republic	6.74	28.41	-2.29	15.19	9.03	1.14	68%
	Mid East	04/1990	06/2011	Iran	11.43	10.97	14.46	15.24	-3.03	-0.62	55%
		11/2004	07/2011	Iraq	15.88	40.08	-6.41	43.71	22.29	0.73	50%
		08/1997	07/2011	Palestine	10.42	35.87	1.06	18.90	9.36	0.97	73%
		01/1993	07/2011	Saudi Arabia	3.87	16.52	2.72	16.68	1.15	0.22	53%
		01/2010	07/2011	Syrian Arab Republic	-7.26	21.16	10.92	18.89	-18.18	-0.84	0%
	North America	09/1996	10/2010	Bermuda	1.23	15.28	0.55	13.75	0.68	0.09	60%
	Western	01/1993	07/2011	Iceland	4.52	17.91	-2.08	31.93	6.60	0.74	58%
		01/1954	07/2011	Luxembourg	8.72	10.63	-0.56	12.74	9.28	3.71***	71%
		01/1996	07/2011	Malta	6.39	15.09	1.09	11.33	5.30	0.96	69%

3.4.3.1 Market development status, geographical location and the Halloween effect

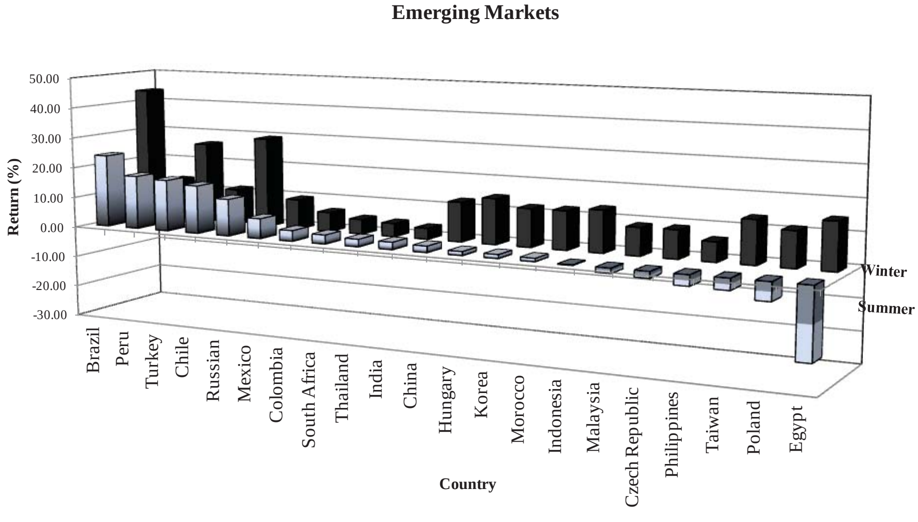
Figure 3.1(A-D) plots the November-April returns and the May-October returns for all the individual countries in four charts grouped by market classification, each chart is ordered by descending summer returns. An overall picture is that the Halloween effect is more pronounced in developed and emerging markets than in the frontier and rarely studied markets. Figure 3.1-A compares the two 6-month period returns for the 24 developed markets; with Finland being the only exception, 23 countries exhibit higher average November-April returns than May-October returns. The differences are quite large for many countries primarily due to the low returns during May-October, with 12 countries even having negative average returns for the period May-October. The chart for emerging markets (Figure 3.1-B) shows a similar pattern; 19 of the 21 countries have November-April returns that exceed the May-October returns, and 7 countries have negative mean returns for May-October. As we move to the frontier and rarely studied markets, this pattern becomes less distinctive. Figure 3.1-C and 1-D reveal that 22 out of 31 (71%) countries in the frontier markets and 17 out of 32 (53%) countries in the rarely studied markets have November-April returns greater than their May-October returns.

Figure 3.1 Two 6-month sub-period (November-April and October-May) returns comparision for the developed markets, emerging markets, frontier markets and rarely studied markets

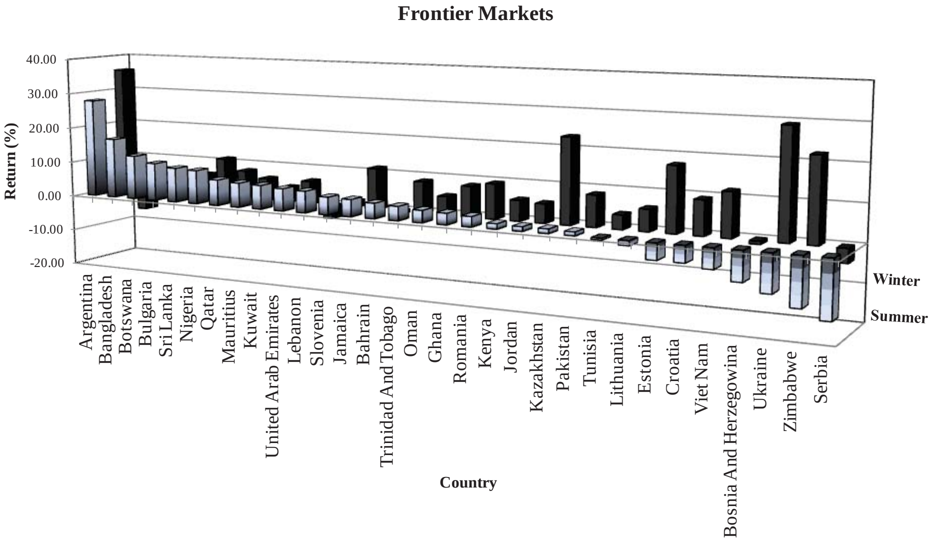
(A)



(B)



(C)



(D)

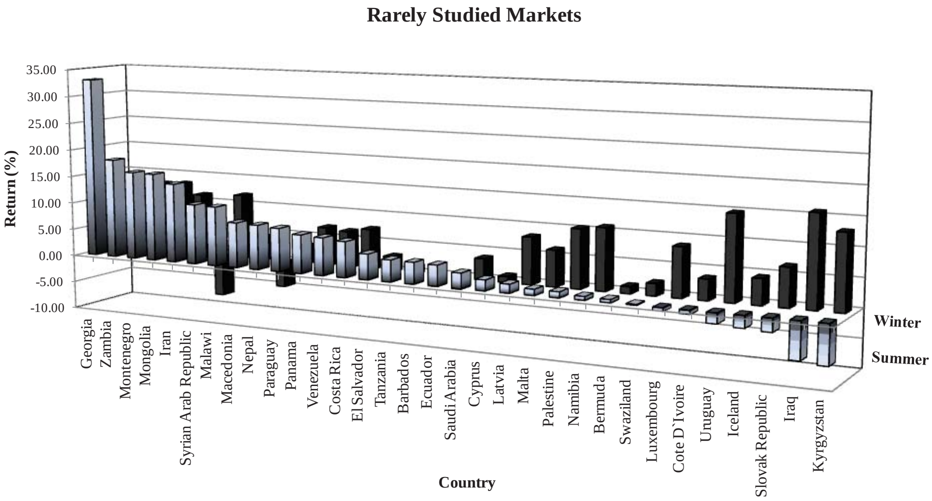


Table 3.3 provides statistical support for the Halloween effect across countries. The table reports average returns and standard deviations for the two 6-month periods, the coefficient estimates and t-statistics for the Halloween regression Equation (1), as well as the percentage of years that the November-April returns beat the May-October returns for each country. The countries are grouped based on market classifications and geographical regions. For the developed markets, a statistically significant Halloween effect is prevalent not only among the Western European countries, but also among the countries located in Asia and North America. In fact, the strongest Halloween effect in the sample is in Japan, which has a difference in returns of 8.31% with a t-statistic of 3.60. The Halloween effect is statistically significant in 17 out of 24 (71%) developed markets. The Middle East and Oceania are the only two continents where none of the countries exhibit a significant Halloween effect. This difference in the two 6-month returns cannot be justified by risk measured with standard deviations, since the table reveals similar or even lower standard deviations in the November-April returns. The number of countries with a statistically significant Halloween effect reduces as it moves to less developed markets. Among 21 emerging countries, 9 countries have November-April returns reliably higher than their May-October returns. The Halloween effect is more prevalent in Asian and Eastern European countries than in other regions. None of the countries in Central and South America and the Caribbean area show significant slope estimates. For the frontier markets, although over 70% (22/31) of the countries show higher average returns during November-April than during May-October, only 5 countries have significant t-statistics. For the rarely studied markets, the countries with a significant Halloween effect drops to 4 out of 32. At this stage the evidence is still not able to identify the root of this seasonal anomaly, nonetheless, over the total 108 countries, only 2 countries (Bangladesh and Nepal from the frontier and rarely studied markets groups) reveal a statistically significant negative Halloween effect; the overall picture, so far at least, suggests that the Halloween effect is a puzzling anomaly that prevails around the world. Another interesting observation that might be noted from the table is that, among the countries with a significant Halloween effect, the difference between 2 6-month period returns is much larger for the countries in the emerging, frontier and rarely studied markets groups than for the countries in the developed markets groups. The average difference in 6-month returns among countries with significant Halloween effect in the developed markets is 5.87%, comparing to 12.75% in the emerging markets, 23.54% in the frontier markets and 14.01% in the rarely studied markets. Readers need to be careful before making any judgement on the finding, however, since the sample size tends to be smaller in emerging, frontier and rarely studied markets. In addition, the observations in those newly emerged markets tend to be more recent. If the overall strength of the Halloween effect is stronger in recent samples than in earlier samples, higher point estimates may be present in the countries with shorter sample periods. I will address this issue by conducting cross sectional comparison within the same time interval using sub-period analysis in Section 3.4.4.

3.4.3.2 Sample size and the Halloween effect

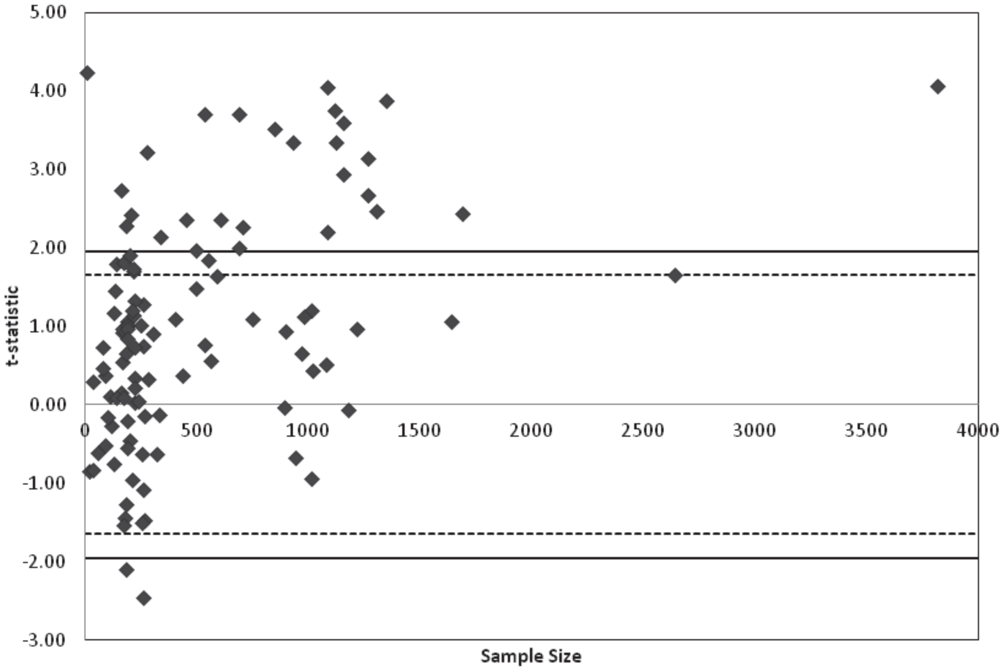
As shown in Table 3.3, the Halloween effect is stronger in the developed markets than in the other markets. The sample size for the developed market tends, however, to be considerably larger than the sample size for the emerging, frontier, or rarely studied, markets. For example, the country with the smallest sample size in among developed markets is Norway, which has 40 years data starting from 1970, while the sample starting date for many less developed countries is around the 1990s, or even after 2000. The difference in the strength of the Halloween effect between developed markets with large sized samples and other markets with small sized samples may not have any meaningful implication, as it may just be caused by noise. The importance of a large sample size to cope with noisy data is emphasized in Lakonishok and Smidt (1988), in that:

"Monthly data provides a good illustration of Black's (1986) point about the difficulty of testing hypotheses with noisy data. It is quite possible that some month is indeed unique, but even with 90 years of data the standard deviation of the mean monthly return is very high (around 0.5 percent). Therefore, unless the unique month outperforms other months by more than 1 percent, it would not be identified as a special month."

I examine whether there is a possible linkage between the Halloween effect and the sample size among countries. Figure 2 plots each country's number of observations against its Halloween regression t-statistics. Two solid lines at $y = \pm 1.96$ indicate 5% significance level, and two dotted lines at $y = \pm 1.65$ indicate a 10% significance level. The graph reveals that a small sample size seems to have some adverse effects on detecting a significant Halloween effect. In particular, a large proportion of countries with an insignificant Halloween effect is concentrated in the area of below 500 (around 40 years) observations, with most of the negative coefficient estimates from those countries with less than 360 (30 years) observations. As the sample size increases, the proportion of countries with a significant Halloween effect increases as well.

If I follow the advice of Lakonishok and Schmidt (1988) to the letter and only consider countries for which I have stock market data for more than ninety years, I find strong evidence of a Halloween effect. It is significantly present in 14 out of these 17 countries and the world market index. Two countries (Australia and South Africa have positive coefficients that are not significant and only for Finland I find a negative but not significant Halloween effect.)

Figure 3.2 Halloween effect and sample size



3.4.4 The evolution of Halloween effect over time

3.4.4.1 Pooled sub-sample period regression analysis

This section provides an overview of how the Halloween effect has evolved over time using time series analysis by pooling all countries in the sample together to form a long time series data from 1693 to 2011. I divide the entire sample into thirty-one 10-year sub-periods[28] and compare the two 6-month period returns in Table 3.4. These sub-period estimates allow me to detect whether, in general, there is any trend over time. The second column reports the number of countries in each sub-period. There is only one country in the sample during the entire eighteenth century, increasing to 6 countries by the end of 1900. The number of countries expands rapidly in the late twentieth

28 To be precise, the first sub-period is 8 years from 1693-1710 and the last sub-period is about 11 years from 2001 to July 2011.

century and reaches 107 in the most recent subsample period. Columns 4 to 7 report the mean returns and standard deviations for the two 6-month periods. The average 6-month return over the entire sample during November-April is 6.93%, compared to only 2.41%

Table 3.4 Pooled 10-year sub-period analysis

This table provides mean 6-month returns and standard deviations for two periods (November-April and May-October), the coefficient estimates and t-statistics for the regression $r_t = \alpha + \beta Hal_t + \varepsilon_t$, as well as the percentage of times that the November-April return beats the May-October return for 31 ten-year subsample periods. β represents 6-month mean returns differences between November-April and May-October. T-values are adjusted using Newey-West standard errors. The 6-month mean returns (standard deviations) are calculated by multiplying monthly returns (standard deviations) by 6 ($\sqrt{6}$).

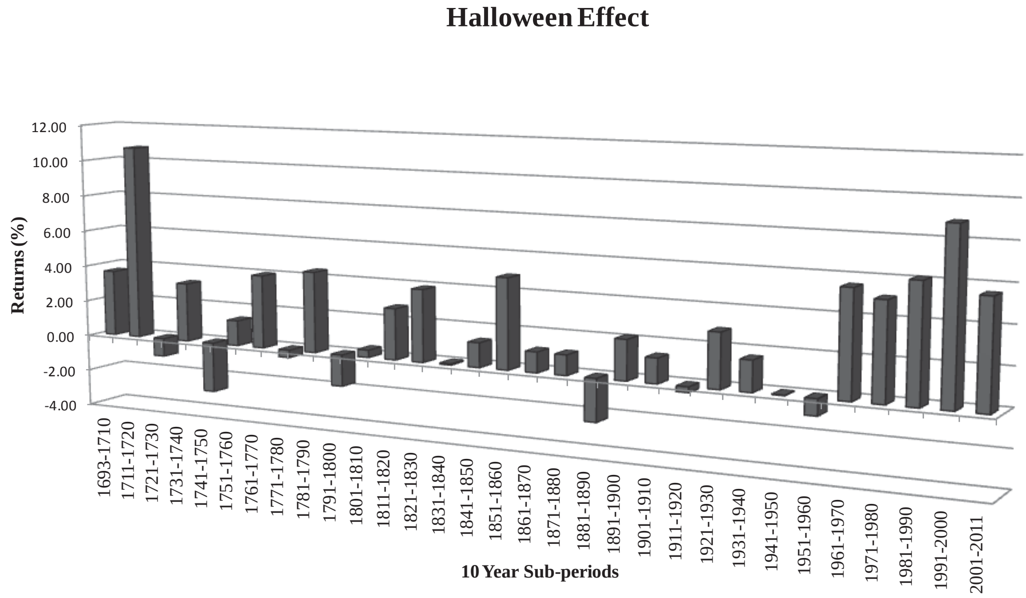
*** denotes significance at 1% level; **denotes significance at 5% level; *denotes significance at 10% level.

Period	No of Countries	Sample Size	Winter		Summer		Halloween		Percent of Positive Halloween
			Mean	Std Dev	Mean	Std Dev	β	t-value	
1693-2011	108	55425	1.16	7.13	0.40	7.96	0.75	9.69***	58%
1693-1710	1	215	-0.01	5.77	-0.62	6.29	0.61	0.73	61%
1711-1720	1	120	1.45	5.05	-0.34	13.45	1.79	0.97	60%
1721-1730	1	120	-0.27	3.23	-0.11	3.50	-0.17	-0.29	50%
1731-1740	1	120	0.11	1.20	-0.43	2.03	0.54	1.70*	80%
1741-1750	1	120	-0.11	1.93	0.35	1.50	-0.46	-1.58	20%
1751-1760	1	120	-0.12	1.27	-0.36	1.20	0.23	1.14	80%
1761-1770	1	120	0.44	2.21	-0.23	2.49	0.67	1.41	70%
1771-1780	1	120	-0.19	2.28	-0.12	1.54	-0.07	-0.15	60%
1781-1790	1	120	0.55	2.25	-0.18	2.12	0.74	2.01**	70%
1791-1800	2	232	-0.13	2.99	0.16	2.88	-0.29	-0.89	50%
1801-1810	2	240	0.07	1.89	0.01	2.19	0.07	0.24	30%
1811-1820	2	240	0.10	1.58	-0.36	1.76	0.46	1.89*	70%
1821-1830	2	240	0.40	6.94	-0.25	2.65	0.65	0.81	70%
1831-1840	2	240	-0.13	3.12	-0.14	2.88	0.01	0.03	55%
1841-1850	2	240	0.19	3.55	-0.03	2.89	0.22	0.47	60%
1851-1860	2	240	0.23	4.14	-0.58	4.15	0.81	1.26	75%
1861-1870	3	252	0.60	3.07	0.42	3.80	0.18	0.38	52%
1871-1880	4	431	0.18	3.66	0.00	3.77	0.18	0.44	53%
1881-1890	4	480	-0.07	2.29	0.31	2.41	-0.38	-1.63	43%
1891-1900	6	563	0.37	2.84	0.02	3.00	0.36	1.28	62%
1901-1910	9	854	0.31	2.51	0.08	2.74	0.22	1.00	51%
1911-1920	16	1383	-0.15	4.78	-0.10	4.44	-0.05	-0.18	55%
1921-1930	22	2313	0.42	5.53	-0.06	7.66	0.48	1.51	63%
1931-1940	27	2977	0.31	5.55	0.04	6.06	0.27	1.00	54%
1941-1950	28	3182	0.52	6.06	0.52	6.48	0.00	0.02	45%
1951-1960	32	3628	0.68	4.09	0.82	4.13	-0.14	-0.91	46%
1961-1970	39	4211	0.80	5.54	-0.13	5.51	0.93	5.15***	64%
1971-1980	42	4831	1.51	8.19	0.67	7.53	0.85	3.34***	60%
1981-1990	57	5558	2.48	9.38	1.46	10.81	1.02	3.29***	64%
1991-2000	96	9151	1.93	8.62	0.44	8.74	1.48	6.87***	63%
2001-2011	107	12764	1.18	7.61	0.25	9.77	0.93	4.57***	57%

for the period of May-October. Figure 3.3 graphically plots the 6-month return differences of 31 10-year sub-periods; 24 of the 31 10-year sub-periods have November-April returns higher than their May-October returns. In addition, there is not much difference between the volatilities in the two 6-month periods; if anything, the standard deviation in November-April tends to be even lower than in May-October. For example, the 6-month standard deviation over the entire sample is 17.47% for November-April and 19.51% for May-October, indicating that the higher return is not due to higher risk, at least measured by the second moment. Columns 8 and 9 show the Halloween coefficients in Equation (3.1) and the corresponding t-statistics corrected with Newey-West standard errors. Although the November-April returns are frequently higher than the May-October returns, the t-statistics are not consistently significant until the 1960s. For the most recent 50 years, the Halloween effect is very persistent and economically large. The November-April returns are over 5% higher than the May-October returns in all of the sub-periods, and this difference is strongly significant at the 1% level.[29] I report the percentage of times that November-April returns beat May-October returns in the last column. This non-parametric test provides consistent evidence with the parametric regression test; 24 of the 31 sub-periods have greater returns for the period of November-April than for May-October for over 50% of the years.

29 We acknowledge that there are many problems with this simple pooled OLS regression technique. Our intention here is, however, only to provide the reader with a general indication on the trend of the Halloween effect over time. The panel data analysis using a random effects model also gives a similar conclusion that the Halloween effect becomes significant since the 1960s.

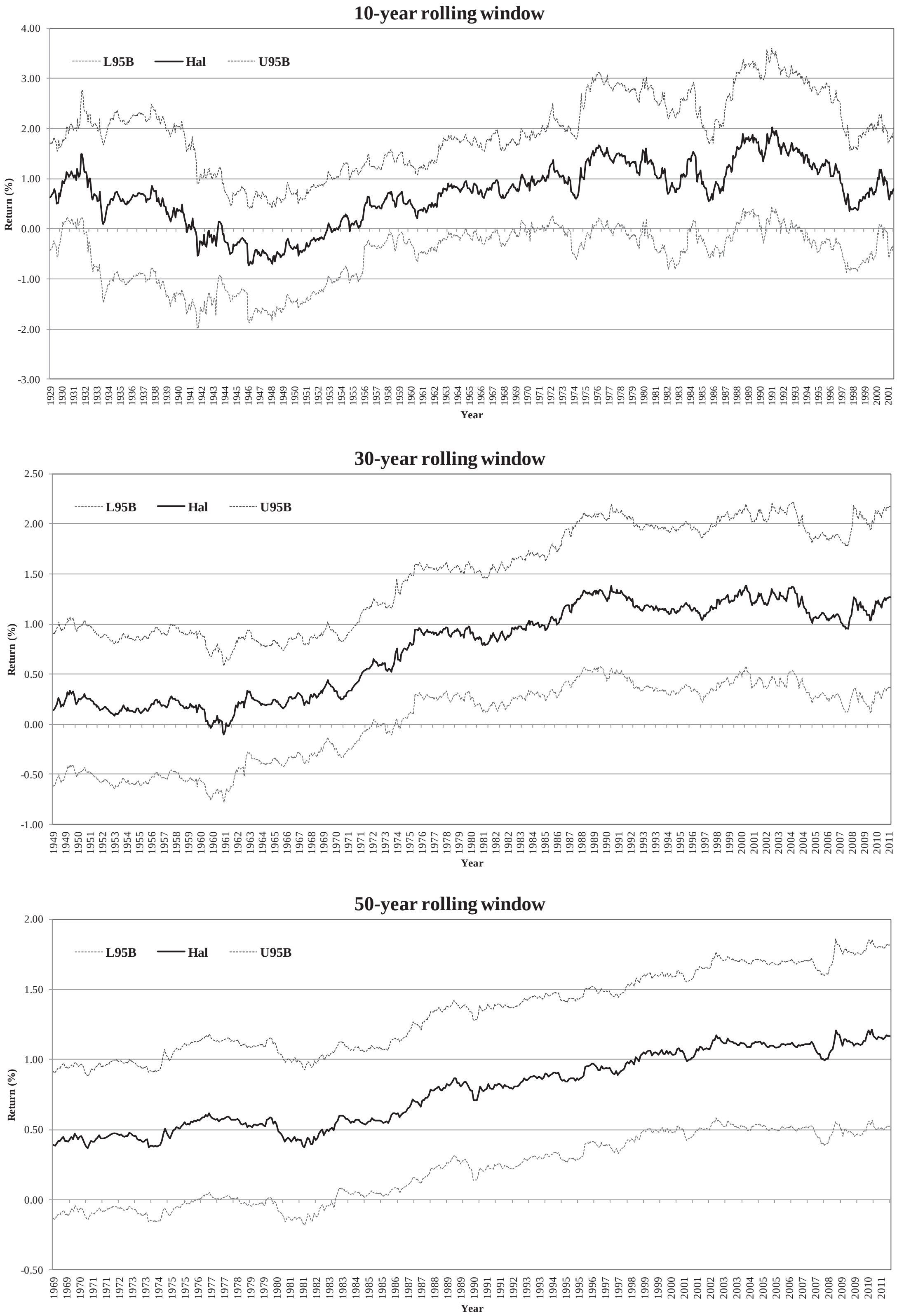
Figure 3.3 Size of the Halloween effect (difference between 6-month returns November-April and May-October) for 31 ten-year sub-periods from 108 pooled countries over the period 1693-2011



The standard errors estimated from pooled OLS regressions may be biased due to cross-sectional correlations between countries. Thus, I also reveal the trend of the Halloween effect in the Global Financial Data's world index returns from 1919 to 2011. Figure 3.4 plots the Halloween effects using 10-year, 30-year and 50-year rolling window regressions. The dark solid line shows the coefficient estimates of the effect, the upper and lower 95% confidence intervels for the estimates are indicated with lighter dotted lines. The plots reveal that the Halloween effect is quite prevelant over the previous century. For example, with a 50-year rolling window, the Halloween effect is almost always significantly positive. Even with a 10-year rolling window, which is a considerably small sample size, the coefficient estimates only appears negative in the 1940s around the World War II period. In addition, all of the plots exhibit an increasing trend of the Halloween effect starting from around the 1950s and 1960s. The point estimates have become quite stable since the 1960s.

Figure 3.4 Rolling window regressions of the Halloween effect in the GFD world index returns (1919-2011)

The figure plots Halloween effects in the GFD world index returns from 1919 to 2011 using a 10-year rolling window, a 30-year rolling window and a 50-year rolling window. The dark solid line indicates the coefficient estimates of the effect, the light dotted lines indicates the upper and lower 95% confidence interval based on Newey-West standard errors



3.4.4.2 Country by country subsample period analysis

Understanding how persistent the Halloween effect is and when it emerged and became prevalent among countries is important since it may help to validate some explanations, while ruling out others. To be specific, if the Halloween effect is related to some fundamental factors that do not change over time, one would expect a very persistent Halloween effect in the markets. If the Halloween effect is triggered by some fundamental changes of institutional factors in the economy, the emergence of the Halloween effect are expected to be around the same period. Alternatively, if the Halloween effect is simply a fluke or a market mistake, one would expect arbitragers to take the riskless profit away, with a weakening Halloween effect following its discovery. Longer time series data is essential for the subsample period analysis. In this section, I divide countries with over 60 years' data into several 10-year subsample periods to test whether or not there is any persistence of the Halloween effect in the markets. Table 3.5 presents the sub-period results for 28 countries that meet the sample size criterion, grouped according to market classification and regions. It consists of 20 countries from the developed markets, 6 from the emerging markets and 2 from the rarely studied markets. Geographically, the sample covers 14 countries in Western Europe, 2 countries in Oceania, 2 countries in Asia, 1 African country, 2 North American countries, and 6 countries from Central/South America and the Caribbean area. The table reports coefficient estimates and t-statistics of the Halloween effect regression for the whole sample period and 11 sub-sample periods. The sub-period analysis not only enables me to investigate the persistence of the effect for each individual country, but it also allows a direct comparison of the size of the anomaly between countries within the same time frame. The Halloween effect seems to be a phenomenon that emerges from the 1960s and has become stronger over time, especially among the Western European countries. The coefficient estimates become positive in 27 of the 28 countries, of which only 4 are statistically significant during the 10 year period from 1961 to 1970. The number of countries with statistically significant Halloween effect keeps growing with time. Sub-period 1991-2000 shows the strongest Halloween effect especially for the Western European countries. Of 27 countries, 25 have lower May-October returns than the rest of the year, being statistically significant in 14 countries. In addition, the sizes of the Halloween effects are much stronger in European countries than in other areas. Although the most recent 10 year period reveals a weaker Halloween effect, the higher November-April returns are present in all the markets except Chile. For the five 10-year sub-periods since 1960, the point estimates are persistently positive in Japan, Canada, the United States, Australia, New Zealand, South Africa and almost all western European countries except Denmark, Finland and Portugal. Countries like Austria, Finland, Portugal and South Africa that do not have a Halloween effect over the whole sample also exhibit a significant Halloween effect in the recent sub-periods. The sizes of the Halloween effect in recent subsample periods are also considerably larger compared to the earlier sub-periods and whole sample periods. Since the data for most of the emerging/frontier/rarely studied markets that have a Halloween effect starts within the past 30 years, if I focus the comparison to the most recent 30 year sub-periods, the difference in size of the Halloween effect between the developed markets and less developed markets noted in the previous section in Table 3.3 is reduced substantially. The average sizes of the coefficient estimates for the countries with significant Halloween effect in developed markets are 12.70% for the period of 2000-2011, 14.97% for 1991-2000, and 16.49% for 1981-1990. The Halloween effect does not appear in Israel, India, and all the countries located in the Central/South American area.

Table 3.5 Country by country sub-periods analysis

This table provide the coefficient estimates and t-statistics for the regression $r_t = \alpha + \beta Hal_t + \varepsilon_t$, for 28 countries that have data available over 60 years and the world market over the whole sample period and several 10-year sub-periods. The coefficient estimate β represents 6-month mean returns differences between November-April and May-October. T-values are adjusted using Newey-West standard errors. *** denotes significance at 1% level; **denotes significance at 5% level; *denotes significance at 10% level.

Status	Region	Country	Start Date	End Date	Whole Sample		Prior to 1911		1911-1920		1921-1930		1931-1940		1941-1950	
					β_{Hal}	t-value	β_{Hal}	t-value	β_{Hal}	t-value	β_{Hal}	t-value	β_{Hal}	t-value	β_{Hal}	t-value
Developed	Asia	Japan	08/1914	07/2011	8.31	3.60 ***	-	-	-3.26	-0.37	6.27	1.52	9.67	1.77 *	24.64	1.77 *
	Mid East	Israel	02/1949	05/2011	3.46	1.09	-	-	-	-	-	-	-	-	4.71	0.84
	North America	Canada	12/1917	07/2011	5.57	3.34 ***	-	-	-3.47	-0.86	4.58	1.01	3.81	0.50	-1.09	-0.27
		UnitedStates	09/1791	07/2011	1.67	1.66 *	0.85	0.70	-0.68	-0.15	6.70	1.31	-10.19	-1.08	-3.31	-0.68
	Oceania	Australia	02/1875	07/2011	1.22	1.07	-1.29	-0.92	6.64	2.28 **	-1.17	-0.31	-2.67	-0.72	-2.75	-0.98
		New Zealand	01/1931	07/2011	1.06	0.66	-	-	-	-	-	-	-1.62	-0.47	-1.09	-0.54
	Western Europe	Austria	02/1922	07/2011	1.66	0.44	-	-	-	-	-29.99	-1.26	9.31	1.09	-9.11	-0.44
		Belgium	02/1897	07/2011	4.09	2.47 **	0.43	0.11	-1.27	-0.21	-3.18	-0.42	1.88	0.23	-2.93	-0.56
		Denmark	01/1921	07/2011	3.18	2.20 **	-	-	-	-	1.08	0.27	-1.58	-0.49	0.53	0.20
		Finland	11/1912	07/2011	-0.14	-0.06	-	-	-19.35	-2.00 **	-0.77	-0.16	-6.42	-1.62	-18.20	-1.93 *
		France	01/1898	07/2011	7.45	3.87 ***	2.62	1.35	4.34	0.82	2.95	0.54	16.90	2.47 **	-8.86	-0.85
		Germany	01/1870	07/2011	5.63	2.44 **	-0.65	-0.41	-3.07	-0.39	22.54	1.05	11.54	1.98 *	12.31	0.82
		Ireland	02/1934	07/2011	6.62	3.35 ***	-	-	-	-	-	-	4.66	1.72 *	1.84	1.05
		Italy	10/1905	07/2011	6.80	2.67 ***	6.77	2.19 **	3.96	0.63	3.77	0.58	-4.06	-0.73	6.77	0.40
		Netherlands	02/1919	07/2011	7.59	4.05 ***	-	-	-13.92	-1.19	6.31	1.18	-2.04	-0.30	7.62	1.37
		Portugal	01/1934	07/2011	3.66	0.94	-	-	-	-	-	-	5.52	0.96	1.18	0.26
		Spain	01/1915	07/2011	7.16	3.75 ***	-	-	5.80	1.51	8.58	2.06 **	10.85	1.18	0.39	0.07
		Sweden	01/1906	07/2011	5.56	3.14 ***	0.47	0.09	5.11	1.23	6.81	1.52	-4.74	-0.56	1.27	0.45
		Switzerland	01/1914	07/2011	4.64	2.94 ***	-	-	9.03	1.61	0.67	0.19	4.19	0.66	-2.92	-1.10
		United Kingdom	02/1693	07/2011	3.37	4.06 ***	2.54	2.75 ***	-1.39	-0.62	1.68	0.66	1.22	0.21	-0.70	-0.20
Emerging	Africa	South Africa	02/1910	07/2011	1.88	0.97	4.29	0.80	-5.07	-1.57	-2.62	-0.97	5.57	0.97	-1.87	-0.48
	Asia	India	08/1920	07/2011	1.17	0.52	-	-	-	-	1.64	0.46	-2.33	-0.54	-3.28	-0.71
	Central/South America &the Caribbean	Chile	01/1927	07/2011	-3.97	-0.94	-	-	-	-	6.80	0.80	4.39	0.53	-5.85	-1.69 *
		Colombia	02/1927	07/2011	2.85	1.20	-	-	-	-	-3.52	-0.79	-2.66	-0.47	-5.31	-1.21
		Mexico	02/1930	07/2011	3.30	1.13	-	-	-	-	6.37	0.64	-4.37	-0.90	0.58	0.18
		Peru	01/1933	07/2011	-3.72	-0.68	-	-	-	-	-	-	-2.09	-0.61	-1.25	-0.33
Rarely Studied	Central/ South America & the Caribbean	Uruguay	02/1925	12/1995	16.66	3.52 ***	-	-	-	-	25.42	1.44	4.92	0.40	9.85	1.31
		Venezuela	01/1937	07/2011	-0.10	-0.04	-	-	-	-	-	-	1.97	0.33	1.54	0.62
		World	02/1919	07/2011	4.53	3.31 ***	-	-	-7.89	-1.47	6.60	2.25 **	0.50	0.10	-2.58	-0.81

Table 3.5 Continued

Status	Region	Country	Start Date	End Date	1951-1960 β_{Hal}	1951-1960 t-value	1961-1970 β_{Hal}	1961-1970 t-value	1971-1980 β_{Hal}	1971-1980 t-value	1981-1990 β_{Hal}	1981-1990 t-value	1991-2000 β_{Hal}	1991-2000 t-value	2001-2011 β_{Hal}	2001-2011 t-value
Developed	Asia	Japan	08/1914	07/2011	-4.32	-0.72	8.66	1.53	10.74	1.99 **	10.53	1.91 *	6.06	0.99	11.27	1.53
	Mid East	Israel	02/1949	05/2011	-0.78	-0.10	5.30	1.20	-2.07	-0.25	3.90	0.40	6.41	0.85	7.85	1.30 *
	North America	Canada	12/1917	07/2011	6.56	1.50	9.61	2.98 ***	9.27	1.66 *	8.82	1.53	5.21	1.19	6.20	1.20
		UnitedStates	09/1791	07/2011	5.02	1.40	5.54	1.47	6.66	1.50	6.62	1.42	4.20	1.38	5.65	1.17
	Oceania	Australia	02/1875	07/2011	-3.35	-0.97	4.03	0.96	5.52	0.80	6.11	0.85	7.02	1.63	1.87	0.40
		New Zealand	01/1931	07/2011	-6.51	-2.17 **	3.25	1.16	8.41	1.69 *	0.79	0.10	2.26	0.44	2.87	0.73
	Western Europe	Austria	02/1922	07/2011	-10.52	-2.11 **	6.17	1.15	4.16	1.67 *	10.91	1.56	13.40	2.25 **	14.88	1.96
		Belgium	02/1897	07/2011	-3.22	-1.09	7.50	2.54 **	10.92	2.73 ***	12.85	2.30 **	12.01	2.95 ***	8.10	1.27
		Denmark	01/1921	07/2011	3.45	1.77 *	8.96	3.07 ***	-1.85	-0.43	5.44	0.94	6.41	1.24	6.05	0.99
		Finland	11/1912	07/2011	-2.43	-0.49	-1.28	-0.39	7.88	1.50	8.38	1.56	21.11	2.52 **	5.21	0.58
		France	01/1898	07/2011	1.30	0.26	11.78	2.53 **	7.12	1.03	20.45	3.47 ***	16.77	3.65 ***	8.54	1.40
		Germany	01/1870	07/2011	-5.19	-0.97	5.17	1.10	9.80	2.04 **	5.31	0.93	13.88	2.67 ***	9.94	1.45 *
		Ireland	02/1934	07/2011	-0.88	-0.31	3.68	1.17	4.56	0.64	8.81	1.27	16.27	2.83 ***	13.08	1.77
		Italy	10/1905	07/2011	-7.44	-1.58	5.49	1.02	1.02	0.12	22.48	2.54 **	23.97	3.67 ***	11.71	1.93 *
		Netherlands	02/1919	07/2011	3.19	0.75	7.50	1.58	16.04	3.07 ***	11.72	2.54 **	12.39	2.67 ***	9.28	1.26
		Portugal	01/1934	07/2011	1.39	0.56	2.22	0.74	-2.90	-0.09	-1.63	-0.12	14.01	1.98 **	8.11	1.21
		Spain	01/1915	07/2011	3.20	0.80	1.65	0.47	10.36	1.76 *	9.88	1.19	16.95	2.86 ***	4.87	0.77
		Sweden	01/1906	07/2011	-4.33	-1.36	2.85	0.68	14.37	3.61 ***	8.79	1.26	16.76	2.37 **	11.12	1.65
		Switzerland	01/1914	07/2011	3.39	0.78	7.74	1.40	8.08	1.49	3.54	0.79	9.74	2.20 **	4.86	0.89
		UnitedKingdom	02/1693	07/2011	-2.19	-0.49	7.09	1.54	17.13	1.71 *	14.93	2.90 ***	7.34	1.99 **	6.30	1.24
Emerging	Africa	South Africa	02/1910	07/2011	-6.08	-1.66 *	9.37	1.22	2.25	0.25	0.27	0.03	14.12	2.10 **	2.69	0.40
	Asia	India	08/1920	07/2011	-1.42	-0.46	1.96	0.70	6.78	1.59	-4.52	-0.63	11.67	0.94	0.16	0.02
	Central/South America & the Caribbean	Chile	01/1927	07/2011	-11.77	-1.32	2.87	0.33	-40.24	-1.68 *	13.29	1.74 *	2.79	0.36	-1.55	-0.33
		Colombia	02/1927	07/2011	1.73	0.87	3.13	1.40	7.31	1.46	-3.35	-0.37	12.83	1.14	10.83	1.25
		Mexico	02/1930	07/2011	2.35	0.93	2.40	1.28	21.87	2.50 **	-14.49	-1.00	7.86	0.86	9.19	1.39
		Peru	01/1933	07/2011	-2.50	-1.29	0.24	0.23	-8.22	-0.92	-29.37	-0.91	-0.83	-0.06	13.63	1.29
Rarely Studied	Central/South America & the Caribbean	Uruguay	02/1925	12/1995	1.56	0.28	0.51	0.04	9.26	0.88	55.39	2.95 ***	-	-	-	-
		Venezuela	01/1937	07/2011	-1.97	-0.50	1.99	0.97	-3.85	-0.82	1.75	0.18	-1.30	-0.11	0.03	0.00
		World	02/1919	07/2011	2.34	0.89	5.77	1.98 **	7.27	1.58	10.66	2.16 **	5.77	1.84 *	6.49	1.18

3.5 Economic significance

3.5.1 Out-of-sample performance in 37 countries examined in Bouman and Jacobsen (2002)

Bouman and Jacobsen (2002) develop a simple trading strategy based on the Halloween indicator and the Sell-in-May effect, which invests in a market portfolio at the end of October for six months and sells the portfolio at the beginning of May, using the proceeds to purchase risk free short term Treasury bills and hold these from the beginning of May to the end of October. They find that the Halloween strategy outperforms a buy and hold strategy even after taking transaction costs into account. I investigate the out-of-sample performance of this trading strategy in this section.

Table 3.6 Out-of-sample performance of Buy & Hold strategy versus Halloween strategy

The table presents the annualised average returns, standard deviations in percentages, and Sharpe ratios of the buy and hold strategy and the Halloween strategy, as well as the percentage of years that the Halloween strategy outperforms the Buy & Hold strategy for the sample period from October 1998 to April 2011.

Country	Buy & Hold Strategy			Halloween Strategy			Percentage of Winning
	Return	St Dev	Sharpe	Return	St Dev	Sharpe	
Argentina	18.67	32.19	0.58	21.53	24.15	0.89	38%
Australia	4.92	13.29	0.37	6.42	8.56	0.75	46%
Austria	6.68	20.59	0.32	11.43	12.15	0.94	46%
Belgium	0.46	17.78	0.03	4.50	12.09	0.37	38%
Brazil	17.25	26.54	0.65	21.52	19.37	1.11	54%
Canada	6.47	16.03	0.40	7.96	10.61	0.75	31%
Chile	15.23	14.34	1.06	10.66	10.89	0.98	38%
Denmark	6.78	18.58	0.36	6.47	12.71	0.51	23%
Finland	4.14	30.05	0.14	9.14	23.26	0.39	38%
France	2.29	19.05	0.12	6.85	12.86	0.53	38%
Germany	1.78	22.20	0.08	7.66	15.16	0.51	46%
Greece	-3.28	28.81	-0.11	1.81	19.10	0.09	54%
Hong Kong	6.79	23.59	0.29	5.74	16.42	0.35	38%
Indonesia	20.33	27.92	0.73	19.03	18.34	1.04	23%
Ireland	-2.87	22.17	-0.13	6.74	13.85	0.49	46%
Italy	-0.51	20.54	-0.02	7.30	15.09	0.48	46%
Japan	-2.56	20.73	-0.12	4.74	13.58	0.35	62%
Jordan	8.96	20.47	0.44	7.70	14.86	0.52	46%
Korea	13.54	28.44	0.48	15.90	20.99	0.76	46%
Malaysia	10.65	20.92	0.51	10.94	16.14	0.68	23%
Mexico	17.64	22.10	0.80	18.60	16.09	1.16	38%
Netherlands	-0.95	20.91	-0.05	5.59	13.36	0.42	46%
New Zealand	1.60	13.13	0.12	5.78	8.61	0.67	62%
Norway	10.71	22.97	0.47	12.50	14.69	0.85	38%
Philippines	7.21	23.57	0.31	9.59	16.05	0.60	38%
Portugal	-2.47	19.46	-0.13	3.83	13.44	0.29	46%
Russia	33.89	38.71	0.88	36.05	28.23	1.28	38%
Singapore	6.94	22.86	0.30	7.67	14.37	0.53	31%
South Africa	14.35	19.31	0.74	13.11	13.36	0.98	31%
Spain	2.90	19.69	0.15	5.57	13.64	0.41	38%
Sweden	5.90	21.57	0.27	10.74	15.46	0.69	38%
Switzerland	0.86	14.53	0.06	3.02	10.25	0.29	54%
Taiwan	1.83	26.92	0.07	9.75	18.53	0.53	54%
Thailand	9.55	27.84	0.34	10.80	18.53	0.58	54%
Turkey	27.61	45.88	0.60	38.98	38.52	1.01	46%
UnitedKingdom	1.85	15.15	0.12	6.23	9.79	0.64	46%
UnitedStates	1.73	16.28	0.11	5.02	11.32	0.44	46%

The approach is to see how investors might profit from the Halloween effect if they follow the Halloween trading strategies from November 1998 to April 2011. Table 3.6

shows the out-of-sample performance of the Halloween trading strategy relative to the Buy and Hold strategy of the 37 countries originally tested in Bouman and Jacobsen (2002). 3-month Treasury Bill Yields in the local currency of each country are used as the risk free rate. The annualised average returns reported in the second and the fifth columns reveal that the Halloween strategy frequently beats a buy and hold strategy. The Halloween strategy returns are higher than the buy and hold strategy in 31 of the 37 markets. The standard deviations of the Halloween strategy are always lower than the buy and hold strategy, this leads the Sharpe ratios of the Halloween strategy to be higher than the buy and hold strategy in all 37 markets except Chile. The finding indicates that after the publication of Bouman and Jacobsen (2002), investors using the Halloween strategy are still able to make higher risk adjusted returns than using the buy and hold strategy.

3.5.2 Longer term performance of the Halloween strategy in the UK data

With the availability of long time series data for UK stock market returns, I am able to examine the performance of this Halloween strategy over 300 years. Investigating the long term performance of the strategy in the UK market is especially interesting, since the United Kingdom is the origin of the market adage "Sell in May and go away". This has been referred to as an old market saying as early as 1935, indicating that UK investors are aware of the trading strategy over a long time period.

Table 3.7 presents the performance of the Halloween strategy relative to the buy and hold strategy over different subsample periods. The average annual returns reported in the second and the fifth columns reveal that the Halloween strategy consistently beats a buy and hold strategy over the whole sample period, and in all 100-year and 50-year subsamples. It only underperforms the buy and hold strategy in one out of ten of the 30-

year subsamples (1941-1970). The magnitude with which the Halloween strategy outperforms the market is also considerable. For example, the returns of the Halloween strategy are almost three times as large as the market returns over the whole sample. In addition, the risk of the Halloween strategy, as measured by the standard deviation of the annual returns is, in general, smaller than for the buy and hold strategy. This is evident in all of the sample periods I examine. Sharpe ratios for each strategy are shown in the fourth and seventh columns. Sharpe ratios for the Halloween strategy are unanimously higher than those for the buy and hold strategy.

Table 3.7 Annual performance of Buy & Hold strategy versus Halloween strategy of the UK market

The table presents the average annual returns, standard deviations in percentages, and Sharpe ratios of the buy and hold strategy and the Halloween strategy, as well as the number of years, and the percentage of times that the Halloween strategy outperforms the Buy & Hold strategy for the whole sample period from 1693-2009 of the UK market index returns, three subsamples of around 100 years, six 50-year subsamples, and ten 30-year subsamples.

Sample Period	Buy & Hold Strategy			Halloween Strategy			Obs.	NO. of Winnin	% Winning
	Mean	Std. Dev.	Sharp	Mean	Std. Dev.	Sharp			
1693-2009	1.38	14.58	0.09	4.52	10.71	0.42	316	200	63.29%
100-year interval									
1693-1800	-0.52	11.54	-0.05	2.95	8.92	0.33	107	70	65.42%
1801-1900	0.68	11.90	0.06	3.86	8.20	0.47	100	69	69.00%
1901-2009	3.91	18.71	0.21	6.69	13.68	0.49	109	61	55.96%
50-year interval									
1693-1750	-0.49	13.16	-0.04	3.19	10.82	0.29	57	32	56.14%
1751-1800	-0.56	9.45	-0.06	2.66	6.14	0.43	50	38	76.00%
1801-1850	-0.21	14.81	-0.01	4.62	10.46	0.44	50	38	76.00%
1851-1900	1.58	8.07	0.20	3.10	5.01	0.62	50	31	62.00%
1901-1950	0.20	11.07	0.02	1.59	6.00	0.26	50	28	56.00%
1950-2009	7.05	22.95	0.31	11.01	16.64	0.66	59	33	55.93%
30-year interval									
1693-1730	-0.62	15.52	-0.04	3.83	13.16	0.29	37	22	59.46%
1731-1760	-1.12	6.60	-0.17	1.71	3.50	0.49	30	20	66.67%
1761-1790	0.28	9.77	0.03	4.00	6.60	0.61	30	22	73.33%
1791-1820	-0.22	11.48	-0.02	3.04	5.75	0.53	30	21	70.00%
1821-1850	-0.39	16.82	-0.02	4.69	12.93	0.36	30	23	76.67%
1851-1880	1.45	9.03	0.16	3.45	5.57	0.62	30	18	60.00%
1881-1910	0.84	6.73	0.13	2.31	3.59	0.64	30	20	66.67%
1911-1940	-1.19	11.86	-0.10	1.12	7.01	0.16	30	17	56.67%
1941-1970	5.84	14.89	0.39	5.21	9.30	0.56	30	13	43.33%
1971-2009	7.61	25.75	0.30	13.36	18.68	0.72	39	24	61.54%

Table 3.7 also reveals the persistence of the outperformance of the Halloween strategy within each of the subsample periods by indicating the percentage of years that

the Halloween strategy beats the buy and hold strategy. Over the whole sample period, the Halloween strategy outperforms the buy and hold strategy 63.09% (200/317) of the time. All of the 100-year and 50-year subsample periods have a winning rate higher than 50%. Only one of the 30-year subsamples has a winning rate below 50% (1941-1970, 43.33%).

Most investors will, however, have shorter investment horizons than the subsample periods used above. Using this large sample of observations allows a realistic indication of the strategy over different short term investment horizons.

Table 3.8 contains the results. It compares the descriptive statistics of both strategies over incremental investment horizons, ranging from one year to twenty years. Returns, standard deviations, and maximum and minimum values are annualised to make the statistics of different holding periods comparable. The upper panel shows the results calculated from overlapping samples and the lower panel contains the results for non-overlapping samples.

The two sampling methods produce similar results. For every horizon, average returns are significantly higher for the Halloween strategy: Roughly three times as high as for the buy and hold strategy. For shorter horizons the standard deviation is lower for the Halloween strategy than for the buy and hold strategy. For longer investment horizons, however, the standard deviation is higher. This seems to be the result of positive skewness, indicating that we observe more extreme positive returns for the Halloween strategy than for the buy and hold strategy. The frequency distribution plots in Figure 5 confirm this. The graphs reveal that the returns of the Halloween strategy produce less extreme negative values, and more extreme positive values, than the buy and hold strategy.

Table 3.8 Strategy performance over different trading horizons of the UK market

The table shows average returns, standard deviations, skewness, and the maximum and minimum values of the buy and hold strategy and the Halloween strategy for different holding horizons from one year to twenty years of the UN market index returns from 1693-2009. The average returns and the standard deviations are annualised by dividing the total returns (standard deviations) by n ($\sqrt{n}$). The No. of Winning and the % of Winning are the number of times and the percentage of times that the Halloween strategy beats the Buy & Hold strategy, respectively. The upper panel presents the results calculated using the overlapping sample, and the lower panel are the results from the non-overlapping sample.

Holding Horizon	Overlapping Sample												
	Buy & Hold Strategy					Halloween Strategy					Obs.	No. of Win	% Win
	Return	St. Dev.	Skew	Max	Min	Return	St. Dev.	Skew	Max	Min			
1-Year	1.38	14.58	0.12	86.01	-80.60	4.52	10.71	2.06	83.59	-30.96	317	200	63.09%
2-Year	1.42	14.50	-0.39	41.03	-59.11	4.56	11.16	1.60	59.91	-28.78	316	223	70.57%
3-Year	1.50	14.00	0.10	38.85	-35.39	4.61	11.09	1.75	46.05	-11.12	315	236	74.92%
4-Year	1.55	13.50	0.31	29.79	-25.50	4.63	11.40	1.58	35.02	-7.86	314	250	79.62%
5-Year	1.59	13.12	0.58	24.68	-16.06	4.64	11.92	1.59	33.33	-6.28	313	257	82.11%
6-Year	1.60	12.96	0.77	24.56	-15.91	4.65	12.34	1.66	29.53	-3.66	312	258	82.69%
7-Year	1.60	12.75	1.01	22.05	-12.75	4.65	12.76	1.76	29.35	-4.07	311	267	85.85%
8-Year	1.59	12.67	1.27	21.79	-10.89	4.66	13.21	1.81	27.33	-2.46	310	271	87.42%
9-Year	1.59	12.78	1.35	21.67	-7.98	4.66	13.73	1.87	27.15	-2.83	309	281	90.94%
10-Year	1.61	13.00	1.43	21.82	-8.16	4.67	14.23	1.91	27.06	-2.89	308	282	91.56%
15-Year	1.63	13.98	1.56	19.27	-6.52	4.67	16.27	2.04	24.81	-0.20	303	282	93.07%
20-Year	1.61	14.75	1.72	15.62	-3.56	4.64	17.82	2.04	20.57	0.18	298	281	94.30%

	Non-Overlapping Sample												
	Buy & Hold Strategy					Halloween Strategy					Obs.	No. of Win	% Win
	Return	St. Dev.	Skew	Max	Min	Return	St. Dev.	Skew	Max	Min			
1-Year	-	-	-	-	-	-	-	-	-	-	-	-	-
2-Year	1.33	16.35	-0.59	41.03	-59.11	4.53	12.50	1.66	59.91	-28.78	158	110	69.62%
3-Year	1.46	16.12	0.15	38.85	-35.39	4.55	12.51	2.22	46.05	-11.12	105	80	76.19%
4-Year	1.33	15.87	-0.14	21.70	-25.50	4.53	11.63	1.01	23.35	-7.86	79	60	75.95%
5-Year	1.46	13.36	-0.01	16.46	-16.06	4.55	11.49	1.01	22.53	-6.28	63	51	80.95%
6-Year	1.37	16.41	0.72	24.56	-15.91	4.52	14.23	2.23	29.53	-3.01	52	42	80.77%
7-Year	1.46	13.39	0.79	18.44	-8.76	4.55	13.55	1.15	20.27	-4.07	45	41	91.11%
8-Year	1.37	11.73	1.13	14.43	-6.98	4.52	12.58	1.64	20.17	-1.70	39	36	92.31%
9-Year	1.46	13.15	0.99	15.75	-7.98	4.55	14.06	1.85	21.66	-2.40	35	32	91.43%
10-Year	1.30	11.82	1.19	12.72	-5.45	4.51	13.80	1.73	18.57	-1.51	31	29	93.55%
15-Year	1.46	15.36	0.88	12.33	-4.08	4.55	16.47	1.77	17.75	0.38	21	20	95.24%
20-Year	1.24	15.36	1.53	9.16	-2.51	4.36	18.77	2.39	17.34	0.18	15	14	93.33%

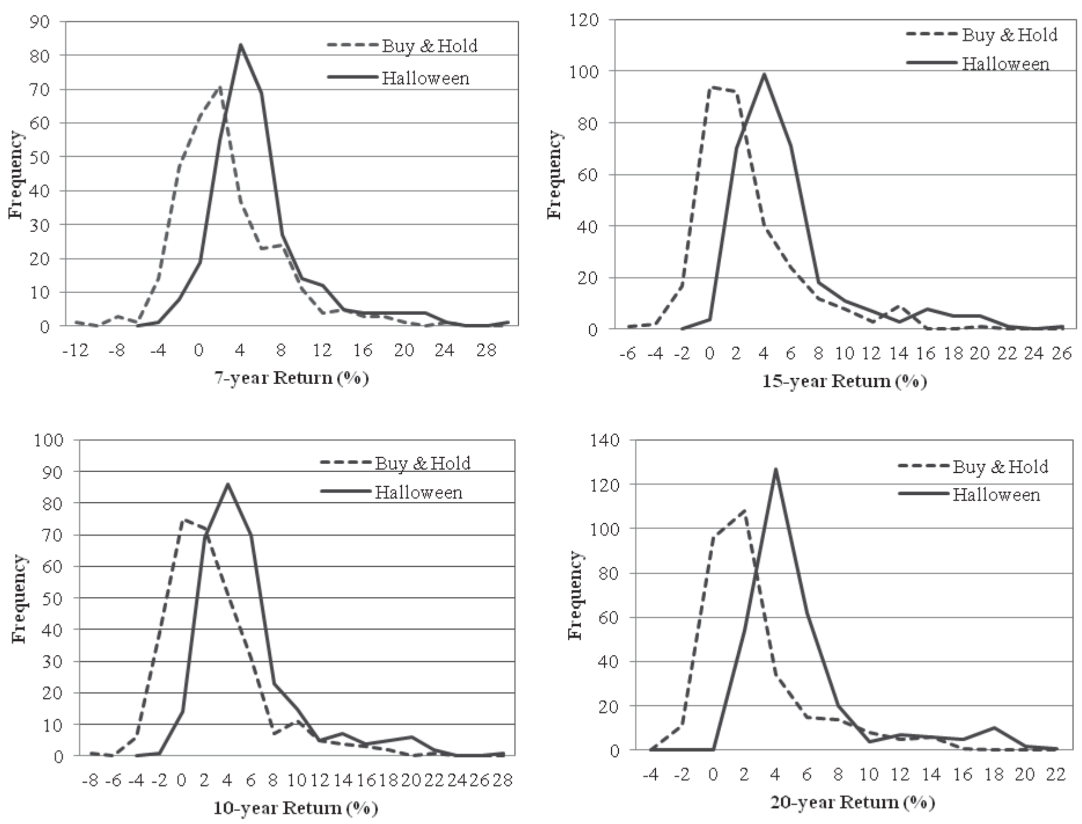
This is also confirmed if I consider the maximum and minimum returns of the strategies shown in

Table 3.8 Except for the one-year holding horizon, the maximum returns for the Halloween strategy of different investment horizons are always higher than for the buy and hold strategy, whereas the minimum returns are always lower for the buy and hold strategy. The last column of

Table 3.8 presents the percentage of times that the Halloween strategy outperforms the buy and hold strategy. The results calculated from the overlapping sample indicate that, for example, when investing in the Halloween strategy for any two-year horizon over the 317 years, an investor would have a 70.57% chance of beating the market. The percentage of winnings computed from the non-overlapping sample, shown in the lower panel, yield similar results. Once I expand the holding period for the Halloween trading strategy, the possibility of beating the market increases dramatically. If an investor uses a Halloween strategy with an investment horizon of five years, the chances of beating the market rises to 82.11%. As the horizon expands to ten years this probability increases to a striking 91.56%.

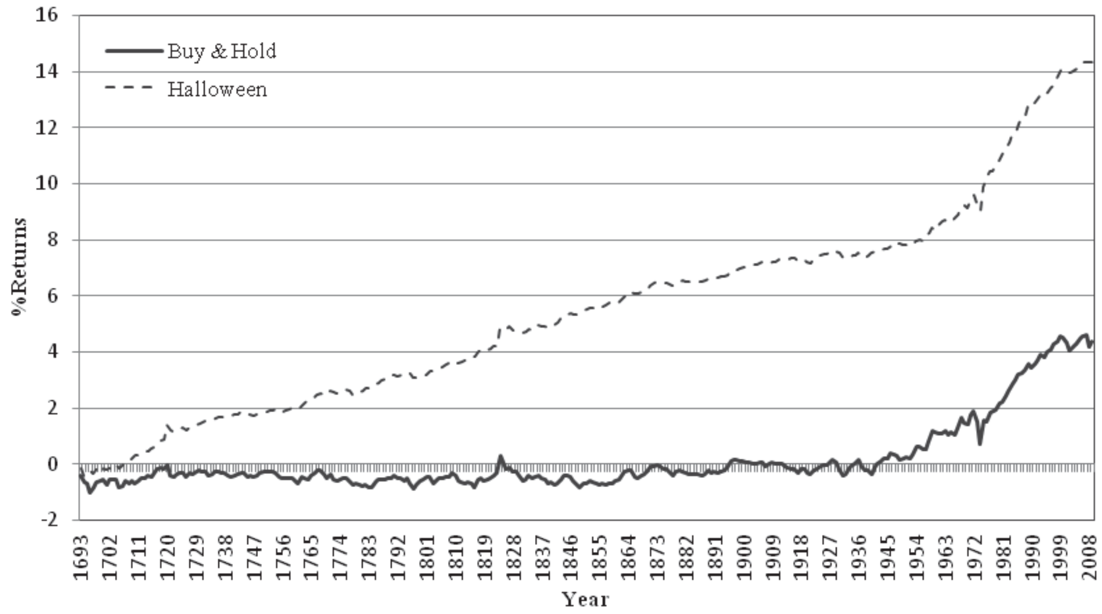
Figure 3.5 Return frequency distribution of Buy & Hold strategy and Halloween strategy

The figure shows the return frequencies of the Buy & Hold strategy and the Halloween strategy for the holding periods of seven years, ten years, fifteen years and twenty years. The returns are annualised and expressed in percentages.



As a last indication of the persistency of the Halloween strategy in the UK market over time, Figure 3.6 compares the cumulative annual return over the three centuries. The buy and hold strategy hardly shows any increase in wealth until 1950 (note that this is a price index and the series do not include dividends). The cumulative wealth of the Halloween strategy increases gradually over time and at an even faster rate since 1950.

Figure 3.6 End of period weath for the Buy and Hold strategy and the Halloween strategy (1693-2009)



3.6 Methodological issues

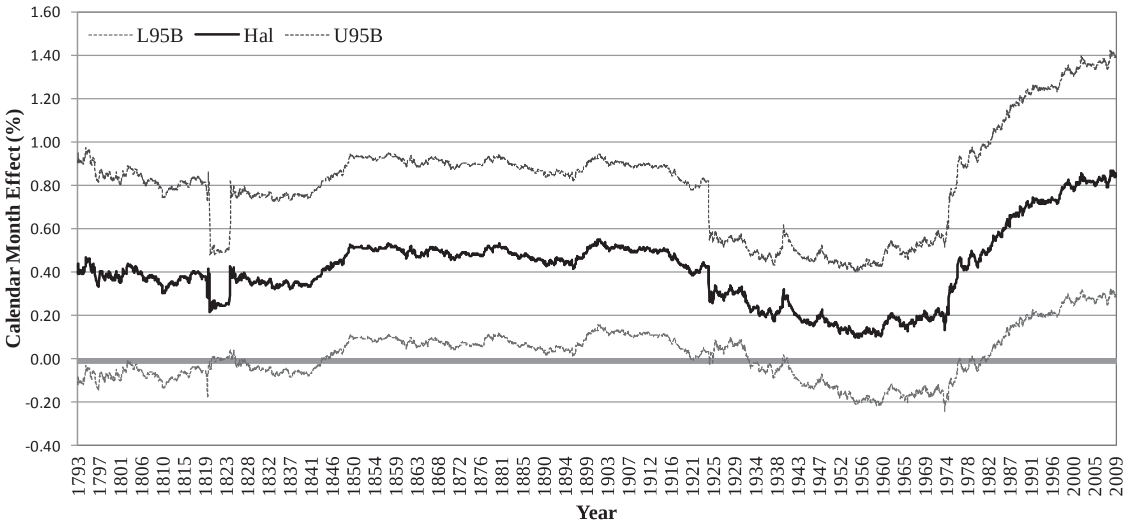
The long time series of over 300 years UK monthly stock market index returns allows me to address a number of methodological issues highlighted in the literature.

3.6.1 Sample size

Small sample size has always been an issue when testing monthly seasonal anomalies. As emphasised by Lakonishok and Schmidt (1988), even with 90 years data, monthly seasonals are difficult to identify due to the noise in the monthly return data. The long time series data provides me with a sufficiently large sample size to overcome the problem. Figure 3.7 extends the evidence in Zhang and Jacobsen (2012) and shows the Halloween effect of the UK market over 100-year rolling window regressions. The dark solid line indicates the estimates of the Halloween effect, and the light dotted lines show the 95% confidence interval calculated based on Newey-West standard errors. The Halloween effect seems to be persistently present in the UK market for a long time period. Point estimates for the effect are always positive, and the size of the effect is quite stable in the eighteenth and nineteenth centuries. Even with this large sample size, however, the effect is not always statistically significant. The first half of the twentieth century shows a weakening Halloween effect. Consistent with the results of the world index in Figure 3.4 and the sub-sample period analysis in Table 3.5, the Halloween effect keeps increasing in strength starting from the second half of the twentieth century.

Figure 3.7 UK Halloween effect 100-year rolling window OLS regressions

The figure plots 100-year rolling window estimates of the Halloween effect for the UK monthly stock market index returns over the period 1693 to 2010. The dark solid line indicates the coefficient estimates of the effect, the light dotted lines show the upper and lower 95% bounds calculated based on Newey-West standard errors.



3.6.2 Time varying volatility and outliers

To verify the impact of volatility clustering and outliers in the monthly index return I also show the rolling window estimates controlling for conditional heteroscedasticity using a GARCH model (Figure 3.8) and outliers using OLS robust regressions (Figure 3.9). I use a GARCH (1, 1) model, since this simple parsimonious representation generally captures volatility clustering well in monthly data with a window of 50 years or more (Jacobsen & Dannenburg, 2003). The model is given by:

$$r_t = \mu + \beta_{Hal} Hal_t + \varepsilon_t,$$

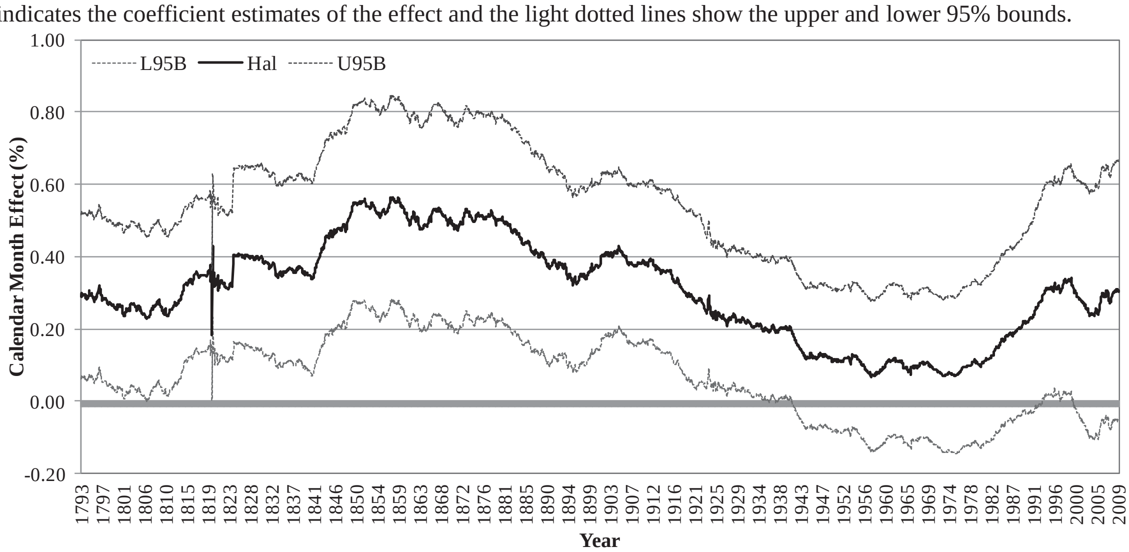
$$\varepsilon_t | \Phi_{t-1} \sim N(0, \sigma_t^2),$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \quad (3.2)$$

For the robust regression, I use the M-estimation introduced by Huber (1973), which is considered appropriate when the dependent variable may contain outliers.

Figure 3.8 UK Halloween effect 100-year rolling window regressions estimated with GARCH (1,1)

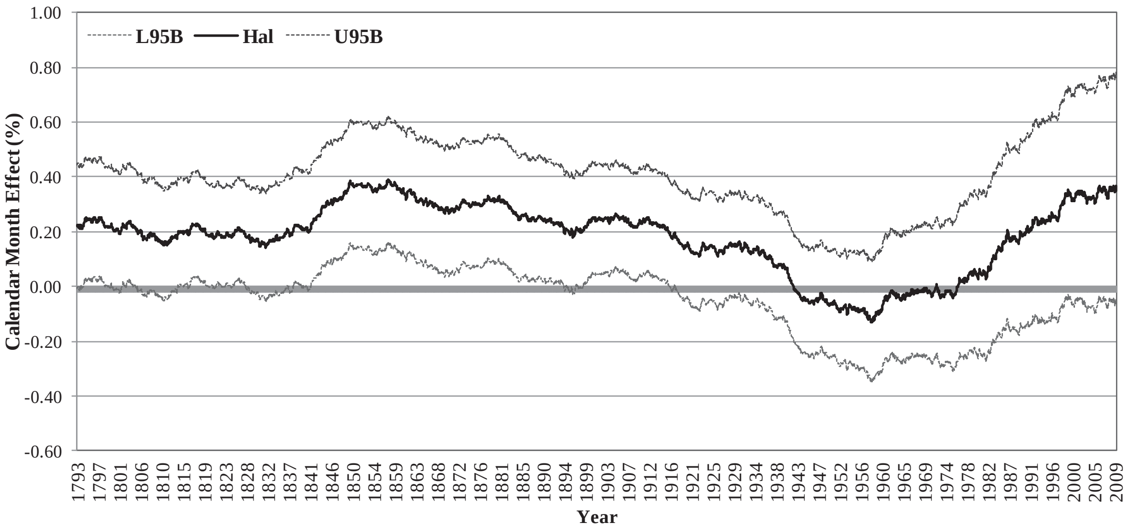
The figure plots 100-year rolling window estimates of the Halloween effect based on time varying volatility GARCH (1,1) model for the UK monthly stock market index returns over the period 1693 to 2010. The dark solid line indicates the coefficient estimates of the effect and the light dotted lines show the upper and lower 95% bounds.



The results from the GARCH rolling window are consistent with the OLS regressions. The estimates of the Halloween effect are always positive over the three centuries, and the strength of the effect reduces during the first half of the twentieth century, while it increases in the second half of the century. Although the result from the robust regressions reveals a similar trend, the point estimates become negative during the 1940s and 1950s.

Figure 3.9 UK Halloween effect 100-year rolling window regressions estimated with Robust Regressions

The figure plots 100-year rolling window estimates of the Halloween effect from robust regressions based on M-estimation introduced in Huber (1973) for the UK monthly stock market index returns over the period 1693 to 2010. The dark solid line indicates the coefficient estimates of the effect and the light dotted lines show the upper and lower 95% bounds.



3.6.3 Measuring the effect with a six month dummy

Powell et al. (2009) question the accuracy of the statistical inference drawn from standard OLS estimation with Newey and West (1987) standard errors when the regressor is persistent, or has a highly autocorrelated dummy variable and the dependent variable is positively autocorrelated. They suggest that this may affect the statistical significance of the Halloween effect. This argument has been echoed in Ferson (2007). However, it is easy to show that this is not a concern here. I find that statistical significance is not affected if the statistical significance of the Halloween effect is examined using 6-month summer and winter returns. By construction, this half-yearly Halloween dummy is negatively autocorrelated. Powell et al. (2009) show that the confidence intervals actually narrow relative to conventional confidence intervals when the regressor's autocorrelation is negative. This causes the standard t-statistics to under-reject, rather than over-reject, the null hypothesis of no effect. Thus, as a robustness check, it seems safe to test the Halloween effect using standard t-statistics adjusted with Newey and West (1987) standard errors from semi-annual return data. Table 3.9 presents the coefficient estimates and t-statistics.

Table 3.9 Halloween effect semi-annual data versus monthly data

The table compares the regression results of the Halloween effect using semi-annual data and monthly data. Coefficient estimates are in percentage terms. T-statistics are calculated based on Newey-West standard errors. The sample is sub-divided into three sub-periods of approximately 100-year intervals and six sub-periods of 50-year intervals. ***denotes significance at the 1% level; **denotes significance at 5% level; * denotes significance at 10% level

Sample Period	Half-year data		Monthly data	
	β	t-value	β	t-value
1693-2009	3.36	4.39***	0.56	4.26***
100-year Interval				
1693-1800	2.03	1.71*	0.34	1.6
1801-1900	3.14	3.03***	0.52	2.71***
1901-2009	4.87	3.04***	0.80	3.03***
50-year Interval				
1693-1750	2.83	1.47	0.48	1.29
1751-1800	1.10	0.88	0.18	0.93
1801-1850	5.06	2.88***	0.84	2.29**
1851-1900	1.22	1.33	0.20	1.46
1901-1950	0.67	0.4	0.08	0.31
1951-2009	8.43	3.59***	1.40	3.33***

The results drawn from semi-annual data do not change the earlier conclusion based on monthly returns. If anything, these results show an even stronger Halloween effect. The periods with significant Halloween effects in the earlier tests remain statistically significant, with t-values based on semi-annual data. The first hundred years (1693-1800) period was not statistically significant using the monthly data, but now becomes significant at the 10% level. As a final test, I use a simple equality in means test. In this case, I also reject the hypothesis that summer and winter returns are different, with almost the same, highly significant, t-value (4.20).

3.7 Conclusion

This study investigates the Halloween effect for 108 countries over all the periods for which data is available.

The Halloween effect is prevailing around the world to the extent that mean returns are higher for the period of November-April than for May-October in 81 out of 108 countries, and the difference is statistically significant in 35 countries compared to only 2 countries having significantly higher May-October returns. The evidence reveals that the size of the Halloween effect does vary cross-nation. It is stronger in developed and emerging markets than in frontier and rarely studied markets. Geographically, the Halloween effect is more prevalent in countries located in Europe, North America and Asia than in other areas. Subsample period analysis shows that the strongest Halloween effect among countries are observed in the past 50 years since 1960 and concentrated in developed Western European countries.

The Halloween effect is still present out-of-sample in the 37 countries used in Bouman and Jacobsen (2002). The out-of-sample risk adjusted payoff from the Halloween trading strategy is still higher than for the buy and hold strategy in 36 of the 37 countries. When considering trading strategies assuming different investment horizons, the UK evidence reveals that investors with a long horizon would have remarkable odds of beating the market; with, for example, an investment horizon of 5 years, the chances that the Halloween strategy outperforms the buy and hold strategy is

80%, with the probability of beating the market increasing to 90% if I expand the investment horizon to 10 years.

Overall, the evidence suggests that the Halloween effect is a strong market anomaly that has strengthened rather than weakened in the recent years. Plausible explanations of the Halloween effect should be able to allow for time variation in the effect and explain why the effect has strengthened in the last 50 years.

Chapter 4 Vacation behaviour and seasonal patterns of stock market returns

4.1 Introduction

"In the United States the desire to excel seems to drive people and businesses to always go full tilt, winter, spring, summer and fall. By contrast, in Europe we have always taken our vacations seriously. It is a tradition that Paris empties in late July as everyone goes to the country for August. The London Stock Exchange has a saying, 'Sell in May and go away'…" Will Europe still slow in summer, Peter Clarke, EE Times, 1998

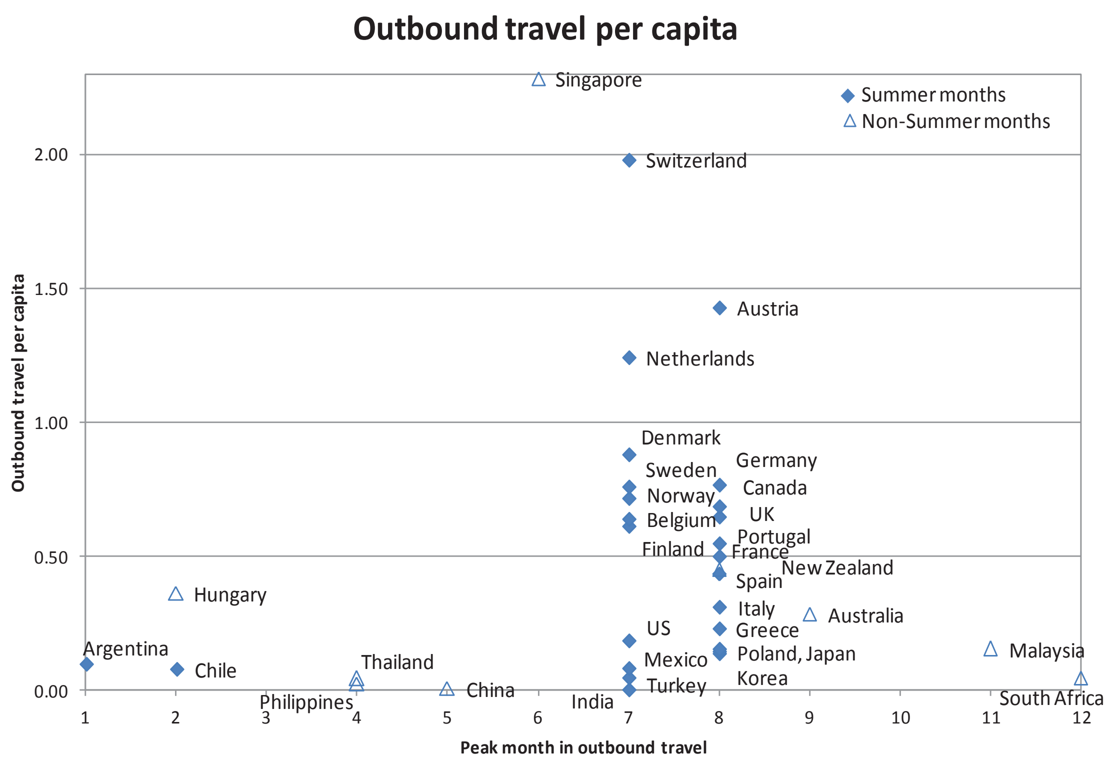
In Europe, general business activity tends to slow down during summer months as people take time off on vacations. A similar phenomenon seems to appear in the stock market as well. Investors refer to it as the summer doldrums, suggesting a quiet period of lower trading activities and lower returns. The Europeans have an old market saying "Sell in May and go away", which signals a period of bear markets starting from May. Empirical studies confirm that stock returns are indeed lower during summer months. Bouman and Jacobsen (2002) document the presence of a Sell in May effect (or the Halloween effect) wherein stock market returns tend to be lower during summer months (May through October) than winter months (November through April) in 36 of the 37 countries. Hong and Yu (2009) show that turnovers and returns are lower during summer months (July to September for Northern Hemisphere countries and January to March for Southern Hemisphere countries), especially for European and North American markets.

Whether this seasonal cycle in stock market returns can be attributed to vacation activities is, however, still subject to close scrutiny. This is due to the high correlation between the summer month dummy used to proxy the peak vacation period and alternative seasonal variables proposed in empirical studies to explain the same seasonal stock return pattern; for example, the hours of daylights in Kamstra, Kramer and Levi (2003), and temperatures in Cao and Wei (2005). The problem was emphasised in Jacobsen and Marquering (2008, 2009) as "*It could well be that any variable that shows a strong summer-winter seasonal effect can be used as explanatory variable. Lot of things are correlated with the seasons and it is hard to distinguish between them when trying to 'explain' seasonal patterns in stock returns.*" In fact, as an extreme illustration, Jacobsen and Marquering show the seasonal pattern in stock market returns could also be explained by a host of other variables with summer-winter seasonals, such as ice cream consumption and airline travel.

The aim of this study is to rigorously examine the validity of vacation hypothesis making it more distinguishable from other possible explanations on the seasonal return effects. To avoid the possibility of spurious correlations, any valid explanation on this seasonal pattern of stock returns should be able to explain not only the time series variation of returns within the countries, but also the cross sectional variation in the size of the seasonal return effects across countries. Using a unique dataset of 34 countries' monthly outbound travel record, I developed measures that capture both the timing and importance of vacation across countries. In this respect, I address an important assumption made in Hong and Yu (2009) that they fail to establish. In particular, using a summer dummy variable, Hong and Yu (2009) associate lower summer stock returns to lower summer trading volume, assuming that lower summer trading volume is caused by investors "*Gone fishin'* ". This is a strong assumption as it implies that summer months are correlated with the peak vacation season, while uncorrelated with other variables that may affect trading. This paper contributes to the literature by providing this missing link, as the data proxies exactly when and how many investors *went fishin'*. For example, Figure 4.1 highlights the rich information contained in outbound travel data that a simple summer dummy fails to capture. It plots the average peak month of outbound travel (timing of vacation) against the average annual outbound travel per capita (relative importance of vacation) for 34 countries. The triangle sign indicates that 9 of the 34 countries in the sample have their peak outbound travel season falling in

Figure 4.1 Average annual outbound travel per capita and peak outbound travel month of 34 countries

The figure plots average annual outbound travel per capita against the peak outbound travel month for 34 countries. The average annual outbound travel per capita is calculated from annual outbound travel and population data from the sample period 1988 to 2010. The peak outbound travel month is estimated from the monthly outbound travel data from 1988 to 1997. Δ indicates that the peak outbound travel month falls in to summer months, ♦ indicates that the peak outbound travel month falls into non-summer months. Summer months are defined as the period from July to September for countries located in the Northern Hemisphere and January to March for countries located in Southern Hemisphere, following Hong and Yu (2009).



non-summer months. In addition, it also shows that vacation importance does vary between countries. This variation allows reliable cross sectional analysis between vacation behaviour and seasonal return effects that has not been achieved in the previous literature.

The vacation hypothesis suggests that the lower summer returns (or the sell in May effect) are induced by investors' seasonal change in risk aversion due to vacation (Bouman & Jacobsen, 2002), or to a significant reduction in the total number of investors (Bouman & Jacobsen, 2002) and trading volumes (Hong & Yu, 2009) during vacation season. This implies that countries with summer persistently being the peak season for vacations and countries with strong vacation traditions will have stronger seasonal return effects. The strength of each country's summer (Halloween) seasonal in vacations is measured as the t-values estimated from a regression of monthly outbound travel on a summer (Halloween) dummy, and the relative importance of vacation as the outbound travel scaled by the population. In order to assess the cross sectional variation, the countries are cross sorted into portfolios based on geographical locations, quartile rankings of the relative importance of vacations, and the strength of summer (Halloween) seasonality in outbound travel.

The overall evidence is consistent with the vacation hypothesis. A lower summer return effect is stronger in the portfolios with higher vacation importance rankings and in the countries with stronger summer peak in outbound travel. However, the strength of this linkage does vary across regions. In particular, Europe reveals evidence most consistent with the vacation hypothesis, and the evidence is robust when controlling for cross market correlations and adjustment of risk differences between countries. Summer effects in other regions are either insignificant (i.e. Africa, Oceania and Latin America), or display patterns inconsistent with the vacation hypothesis, where I observe a lack of positive correlation between the strength of summer effects and vacation importance rankings (i.e. North America), or stronger summer effects in the portfolios with non-summer month peaks in vacations (e.g. Asia). Moreover, the summer effect in the portfolios of these non-European markets disappears after adjusting for the cross market correlation, suggesting the summer effects in these countries might be a by-product of market integration. For the Halloween effects, significantly lower May to October returns are prevalent across countries and strongly present in all regions except Oceania. In addition, this worldwide seasonal phenomenon is not caused by cross market correlation. The strength of the Halloween effects, however, seem to be unrelated to vacation behaviour; since the six-month period May to October covers the summer months in most of the countries in the sample, vacation activities may at best partially contribute to the Halloween effects in stock market returns.

To further investigate whether there is a direct linkage between vacation activities and stock market returns, I calculate the relative monthly outbound travel as outbound travel scaled by total population (outbound travel per capita), and regress the log of monthly outbound travel per capita on stock market returns for each individual country and cross sorted portfolio. Overall, outbound travel reveals a significant negative impact on stock market returns. Specifically, a 9% increase in relative outbound travel will lead stock market returns to drop by 0.1%. In addition, consistent with the vacation hypothesis, the explanatory power of outbound travel is stronger in the portfolios with higher vacation importance rankings. The results from portfolios grouped by geographical location show, however, that this significant negative impact and the positive correlation are solely attributed from the portfolios of European countries. To avoid the possibility of spurious correlation caused by summer-winter seasonal patterns in monthly outbound travel, as a final check, I regress annual summer and non-summer month (November-April and May-October) differences in returns on annual summer and non-summer month (November-April and May-October) differences in outbound travel for the whole sample and the regional portfolios. Consistent with the earlier evidence, summer seasonality in outbound travel has a significant negative impact on summer month returns over the whole sample and for European markets. The significant correlation is not, however, present for the Halloween effects.

Theories suggest that vacation behaviour may affect stock returns through two alternative ways: shifts in exogenous liquidity demand (Bouman & Jacobsen, 2002), and changes in trading activities (Hong & Yu, 2009). Another contribution of this paper is to investigate the validity of the theories by constructing these two volume related measures and examine whether the measures are also affected by outbound travel and exhibit the seasonal patterns consistent with the conjecture in the vacation hypotheses. Investigating volume related measures may also allow a better distinction between the vacation hypothesis and other explanations.

The monthly proxy for the exogenous liquidity demand is measured as average daily volume related return reversals in accordance with the exogenous liquidity demand model in Campbell, Grossman and Wang (1993). The reasoning behind the model is that investors may decide to liquidate their stock holdings, or transfer part of their risky portfolios to safer assets before, during, or after, taking summer vacations for cash needs, or to avoid paying attention to the stock market during holidays. If there is a large portion of investors selling stocks for this exogenous reason, investors who remain in the market will only trade with them if they are offered with higher risk premium, which will depress the current stock price. As, however, there is no reason to expect the intrinsic value of stocks to change, one should expect the price changes accompanied by large trading volumes caused by exogenous liquidity demand induced change in risk aversion to be reversed. The same intuition applies to the situation where a large portion of investors demand stocks for exogenous reasons.

The empirical findings reveal limited evidence of seasonal patterns in liquidity demands. Despite this, the absolute growth rate of outbound travel does significantly explain the variation in liquidity demands over the whole sample, and the evidence is consistent with the vacation explanation particularly for the European markets. That is, higher absolute outbound travel growth is associated with higher liquidity demands and the effect is stronger in the portfolios with higher rankings in vacation importance in Europe. In contrast, the effect of outbound travel on liquidity demands for other markets does not offer strong support on vacation explanations; the coefficient estimates are either insignificant (i.e. Africa and North America), or display opposite signs (i.e. Asia, Latin America), or reveal stronger explanatory power in the portfolios with lower vacation importance rankings (Oceania).

The seasonal pattern in trading activities is examined using monthly stock market turnovers. Based on a heterogeneous prior beliefs model, Hong and Yu (2009) argue that lower summer returns are induced by lower trading volume during summer months while investors are taking vacations. The idea is that investors with heterogeneous beliefs will trade against each other, with the presence of short sale constraints, higher trading volume should be associated with higher contemporaneous stock returns. Hence, lower summer returns is a consequence of vacation induced lower trading volumes during summer months.

The seasonality test and regression analysis reveal significant seasonality and the summer effect in stock market turnovers. Twenty-six of the thirty-four countries show lower summer turnover, of which thirteen countries are statistically significant. Geographically, Europe, North America and Oceania show significant summer turnover effects. The cross sorted portfolios for the whole sample grouped on the basis of vacation importance rankings and timing of vacations show vague evidence in support of the vacation explanation. In particular, despite significantly lower summer turnovers being exhibited only in the portfolios with significant summer peak in outbound travel, the strength of summer effects is not positively correlated with vacation importance rankings. The results from portfolios grouped by geographical locations show that this ambiguous pattern is due to the geographical difference among portfolios; portfolios of North American markets show evidence in line with the vacation hypothesis, in which the strength of summer effects on market turnovers increases monotonically with vacation importance rankings. The correlation between the summer effect in outbound travel and vacation importance rankings are in fact negative in the portfolios of European markets. Portfolios of other regions reveal either insignificant summer turnover effects, or patterns inconsistent with the vacation hypothesis.

The regression of monthly log turnover on log outbound travel per capita shows that outbound travel has a significant negative impact on turnovers over the whole sample, and in the portfolios of Asian, European and North American markets. For example, over the whole sample a 1% increase in relative outbound travels will lead stock market turnovers to drop by 0.27%, however, only the portfolios of North American markets show stronger explanatory power in higher vacation importance ranked portfolios. In addition, annual seasonal difference in outbound travel does not have significant explanatory power on annual seasonal difference in turnovers. Since significant summer seasonality is present in both turnover and outbound travel data in many countries the finding raises the possibility of spurious correlation. Nevertheless, it should be noted that the coefficient estimate in the regression of annual seasonal difference in turnovers on annual seasonal difference in outbound travel for the portfolio of North American markets has the correct sign, and the regression is run with only 20 observations. Given the positive cross sectional correlation between the strength of summer effects in turnovers and vacation importance rankings, as well as the positive correlation between the explanatory power of outbound travel on turnovers and vacation importance rankings in the portfolios of North American markets, the possibility that the summer effect in turnovers presented in the portfolios of North American markets is caused by seasonal vacation activities is still high, while the evidence is much weaker for other regions.

As a final remark, the findings of this paper offer strong support for vacation behaviour as an explanation for the lower summer return effect, especially among European countries. While significant seasonal patterns are not present in exogenous liquidity demands, outbound travel does have significant explanatory power on liquidity demands in line with the vacation hypothesis for the portfolios of European markets. This evidence is consistent with the vacation related change in exogenous liquidity demand and risk aversion hypothesis proposed in Bouman and Jacobsen (2002). In contrast, the summer effect in market turnover tends to be related to seasonal behaviour in vacations only in North America. However, lower summer returns in North America are unrelated to vacation activity. Moreover, the summer turnover effect in Europe is unrelated to vacation behaviour, but lower summer returns in Europe are strongly related to vacation activity. This contradicting evidence, thus, places doubt on Hong and Yu (2009)'s hypothesis that lower summer returns are caused by vacation induced lack of trading activities.

4.2 Literature review

4.2.1 A seasonal cycle of stock market returns

Stock market returns exhibit an annual seasonal pattern that tends to be lower during the six months from May through October than the six months from November through April. This phenomenon known as the Halloween effect, or the Sell in May effect, has quickly evolved into one of the most intriguing anomalies in the stock market since it was firstly documented by Bouman and Jacobsen in 2002. Contrary to the pattern of most anomalies, that tend to fade or disappear after their discovery (Schwert, 2002), the Halloween effect has become even stronger in recent out-of-sample periods (Andrade, Chhaochharia & Fuerst, 2012; Jacobsen & Zhang, 2012).

Many empirical studies confirm this seasonal pattern with plausible explanations. Although Bouman and Jacobsen (2002) pose the anomaly as a puzzle, their findings incline to support the summer vacation hypothesis after examining a number of alternative explanations. In an earlier version of their study, they proposed a model that links taking vacations to changes in risk aversion and the risk sharing capacity of the market. In particular, investors may choose to liquidate their stock holdings, or shift part of their risky portfolio to safer assets before, during, or after, taking summer vacations for cash needs (liquidity demand), or to avoid paying attention to the stock market during holidays (change in risk aversion). This exogenous increase in liquidity demand, or change in risk aversion, will lead the average risk aversion at market level to increase, since the investors who remain in the stock market will only bear the risk if they expect to receive higher premiums. This increase in the market risk aversion will drive the current stock price down when such a shift occurs. With a simple one period model, Bouman and Jacobsen show that stock price is positively related to the number of traders and negatively related to the average degree of market risk aversion. Their cross-sectional regression analysis finds variables that proxy the length and timing of summer vacations, as well as the impact of summer vacations on trading activity, significantly explain the size of the effect across countries. They also document a significant negative correlation between average calendar month travel and average calendar month stock returns.

In addition, an implication of Bouman and Jacobsen (2002)'s vacation model is a shift in the market liquidity story. With a large portion of investors selling stocks for exogenous reasons during the vacation season, one would expect reduced liquidity in the market, and a similar seasonal pattern in the liquidity measures. Jacobsen and Visaltanachoti (2009) show that in the US market there is no obvious seasonal pattern in liquidity measured by order flow related price changes in Pastor and Stambaugh (2003)'s model, implying that the Halloween effect may not be caused by vacation induced liquidity variations.

Another study by Hong and Yu (2009) argues that vacations lead to reduced trading activities and lower stock returns. They document significantly lower stock market turnovers and returns during summer months (July to September for Northern Hemisphere countries and January to March for Southern Hemisphere countries). Since turnover is not necessarily a measure of liquidity as suggested in Johnson (2008)[30], their findings do not conflict with Jacobsen and Visaltanachoti (2009). Hong and Yu (2009)'s argument is founded on the premise of heterogeneous beliefs, in which greater divergence of opinions among investors elicit higher turnover and higher returns. If the divergence of opinions among investors emphasised in Hong and Yu (2009) can be interpreted as a source of liquidity risk, or turnover proxies the liquidity risk in some way, this might imply lower liquidity risk during summer.

Despite the efforts of attributing the Halloween effect (or the lower summer returns) to seasonal demand for vacations, the empirical evidence is still weak due to the high correlation of the variables that proxy the vacation behaviour with other seasonal variables proposed to explain the anomaly. In fact, as shown by Jacobsen and Marquering (2008, 2009), many variables with a strong summer-winter seasonal effect can be used to explain this seasonal pattern in stock returns making it difficult to distinguish between them and the possibility of spurious correlation. A number of alternative explanations suggest the same seasonal cycle in stock market returns. Kamstra, Kramer and Levi (2003) argue that investors affected by seasonal affective disorder (SAD) become depressed and more risk averse starting from autumn as the length of daylight shortens and demand higher risk premia during winter months causing a similar seasonal stock market return pattern as the Halloween effect. Likewise, Cao and Wei (2005) find that stock returns are negatively related to temperature; the same stock market seasonal pattern is claimed to be caused by lower temperatures that make investors more aggressive in risk taking during winter. As the

[30] Johnson (2008) argues liquidity signals the average risk-bearing capacity of the market, while volume measures reflect compositional rearrangement of individuals to the average. The paper finds that volume is not related to liquidity, but is instead positively related to the second moment of liquidity (the liquidity risk).

explanatory variables; Halloween dummy (in Jacobsen and Visaltanachoti (2009)), summer dummy (in Hong and Yu (2009)), hours of daylight (in Kamstra, Kramer and Levi (2003)) and temperature (in Cao and Wei (2005)); all have a summer-winter seasonal pattern, it is very difficult to differentiate one potential cause from another.

4.2.2 Trading volume

Since all the studies associate the anomaly with investor trading behaviour, trading volumes may play an important role in distinguishing between explanations. As stated in Beaver (1968) "*an important distinction between price and volume tests is that the former reflects changes in the expectation of market as a whole, while the later reflects changes of individual investors.*" Despite the similar return patterns, different hypotheses may suggest very different trading patterns from investors. Before illustrating how trading activities might vary among different hypotheses, it is necessary to review the relevant literature on trading volumes and stock returns.

Trading can be classified as informational trading and non-informational trading (liquidity trading). Under the classical representative agent asset pricing model, trading volume is only created by an investor's unanticipated liquidity, or portfolio rebalancing needs. Arrival of new information about future cash flows will not incur trading, since everyone has a perfect information set and interprets information correctly when news arrives; with homogenous beliefs, price will be adjusted accordingly without high volumes of trade. In addition, risk aversion and expected risk premia are not expected to change. On the other hand, liquidity demand that is caused by exogenous motives will generate trading and lead to change in market risk aversion and expected risk premia. Campbell, Grossman and Wang (1993) present a model where non-informational traders sell stocks for exogenous reasons due to change in tastes, or risk aversion, causing expected returns in the market to change. Specifically, they introduce an economy with two types of investors; Type A with a constant risk aversion, and B (non-informational/liquidity trader) with time varying risk aversion. The decrease in stock demands from group B investors due to increasing risk aversion (or change in tastes) leads to the relocation of stocks from group B investors to group A investors. If there is a large proportion of group B investors, the average risk aversion in the market would increase as well, which leads to a drop in the current price (low current stock return) accommodated by a rise in trading volume and high expected return. Their extrapolation is that low returns accompanied by high trading volume with higher future returns, or relatively larger negative autocorrelations in returns, are more likely due to an exogenous liquidity demand induced increase in market risk aversion/expected risk premium, while a drop in stock price accompanied by low trading volume (or unaffected trading volumes) is more likely to be caused by shocks to the news about future dividends. The liquidity measure proposed in Pastor and Stambaugh (2003) captures the essence of Campbell, Grossman and Wang (1993)'s model, in which lower liquidity is associated with stronger volume-related return reversals.

News about future cash flows will make investors trade if heterogeneous prior beliefs among investors are introduced, as in the disagreement models summarised in Hong and Stein (2007). Combined with short sale constraints, the model's prediction is consistent with the empirical evidence that higher trading volume is associated with higher contemporaneous stock returns (Karpoff, 1987). It also suggests that the increase in the number of public news announcements about the stock will lead to higher trading volumes and higher prices.

4.2.3 Return and volume implications on Halloween effect explanations

Linking the volume and expected return implications of various models to the Halloween effect explanations, we will be able to differentiate one from another. The vacation explanation argues that investors taking vacations during summer months results in changes in risk aversion, or risk sharing capacity, in the economy (Bouman & Jacobsen, 2002). The idea is consistent with the exogenous liquidity demand outlined in Campbell, Grossman and Wang (1993). In particular, investors that do not take vacations will have constant risk aversion (type A), and investors that take summer vacations will have seasonal time varying risk aversion (type B). Prior to taking a vacation, type B investors may become more risk averse and demand less risky assets as they would rather be spending time relaxing than paying attention to the stock market, or they may simply liquidate the stocks to meet their increased cash needs due to their vacations. Type A investors would only be willing to buy risky assets if they are offered them in conjunction with higher expected returns. This liquidity demand and shift in expected returns is expected to occur prior to, during and after the investor takes vacations, which should correspond with the volume related return reversals (lower current returns accommodated with high volume and higher expected future returns).

If we also allow for heterogeneous beliefs, as investors pay less attention to the stock market and trade less during vacations, we would expect to see less trading activities accompanied with lower returns in the vacation season, as in Hong and Yu (2009).

The SAD effect examined in Kamstra, Kramer and Levi (2003) is relatively easy to distinguish from other effects by investigating the trading volume patterns, since the shift in risk aversion happens at a different time. According to this argument, investors affected by seasonal affective disorder (SAD) become depressed during the fall months and demand higher risk premia during winter months, causing this seasonal stock market return pattern. While both the vacation and SAD effects suggest the same return seasonals, they imply very different trading patterns from investors. According to the model in Campbell, Grossman and Wang (1993), investors affected by SAD would sell stocks starting in autumn when exposure to daylight decreases, inducing stronger volume related return reversals. During the period with relatively less daylight, with a smaller number of investors in the market, we would expect less trading with lower returns.

Two recent studies attempt to establish the link between vacations and trading activities to understand this seasonal return pattern. Using stock market trading data in Finland, Kaustia and Rantapuska (2012) show that the seasonal variation in the buy-sell ratio and trading volume are unrelated to length of daylight and sunniness, but related to summer vacation seasons. They find that individual investors sell stocks before and during summer holidays (May-July) and purchase stocks during fall months (August-October). In addition, trading volume drops for both individual investors and institutions during the holiday months of May-August. Similarly, Hong and Yu (2009) document that trading activities during summer months (July-September for Northern Hemisphere countries and January-March for Southern Hemisphere countries) are significantly reduced from the rest of the year, accompanied by lower stock returns. One important link these studies fail to establish is, however, a strong assumption that summer months are correlated with a higher number of people taking vacation, while uncorrelated with other variables that may affect trading. Although summer months are deemed to be the peak season of vacations from anecdotal evidence, it is not a decent proxy for high vacation activities, since a simple summer dummy may actually pick up other variations unrelated to vacation taking. For example, Cao and Wei (2005) find stock returns are negatively related to temperatures because investors become more aggressive in risk taking when temperatures are low, leading to higher winter month returns. This argument suggests that cold weather is associated with higher trading activities and higher returns. The trading volume and return pattern documented in Hong and Yu (2009) would also be consistent with this temperature hypothesis, in which summer is also a proxy for high temperature, resulting in the relatively lower trading volume and returns. Another example is Gerlach (2007), who claims that the Halloween effect is partially induced by more macroeconomic news arrivals during fall months, with the seasonal pattern disappearing if the returns are examined only using the 60% of trading days with no macroeconomic announcements. This implies that low trading volumes and returns during summer months could be due to the lower news arrival rate in summer instead of vacation taking activities. In addition, Ogden (2003) documents annual seasonal cycles of macroeconomic variables in the US market and finds that the predictive power of stock returns for quarters ending in December and March is greater than those ending in June and September, indicating that stock markets are more informative during winter months than summer months and investors forecast macroeconomic and risk conditions to pricing security only during winter months. In addition, the forecasting variables that are supposed to capture expected risk premium only have predictive power over the six months from October through March, indicating that stock prices may only be priced correctly from October through March. Adopting a simple summer dummy might attribute all these endogenous variations of economic activities that affect stock returns and trading activities in various ways to the exogenous vacation activities, raising the possibility of spurious correlation.

4.3 Research questions

This study attempts to overcome the problem outlined above using time series data of outbound travel for 34 countries as a more direct proxy for vacation taking activities. I intend to gain a deeper understanding of the possible association between vacation taking and seasonal patterns in stock returns. In addition, to make the vacation hypothesis more distinguishable from other explanations, I further attempt to assess the impact of vacations from two volume related measures that are claimed to link the vacation behaviour to stock market returns: Exogenous liquidity demand and turnovers derived from the models of exogenous liquidity demand induced changes in risk aversion (Bouman & Jacobsen, 2002; Campbell, Grossman & Wang, 1993); and change in trading volumes evoking change in returns supported by heterogeneous beliefs (Hong & Yu, 2009).

The paper addresses the following questions:

1. Do vacation activities have an impact on stock market returns; can vacation behaviour explain the seasonal pattern in stock market returns?
2. Are liquidity demand measures and trading volumes affected by vacation activities, and do they exhibit seasonal patterns consistent with the vacation hypothesis?

4.4 Data

The country level outbound travel data is sourced from the World Tourism Organization (WTO) for the period of 1988 to 2010. Data is available at monthly frequency from

1988 to 1997 and at annual frequency from 1998 to 2010[31]. The countries' market total index returns and trading volume data are collected from Datastream at daily and monthly frequency for the same sample period. I match each country's outbound travel data with its corresponding total return and volume data. This leaves a sample of 34 countries that have both sets of data available. The analysis is conducted predominantly for the whole sample period from 1998 to 2010. When monthly outbound travel data are involved in the analysis, I use a smaller sample from 1988 to 1997. Returns and volumes data at daily frequency are obtained to construct monthly liquidity demand measures. Panel A of Table 4.1 provides summary statistics for the 34 countries in the sample sorted by geographical locations. Column 1 shows the start and end dates of each country's sample period. The data for most of the countries begins from 1988 and ends with 2010, inclusive; some countries have smaller sample sizes due to the availability of return and volume data. The country with the latest start year is India, with data from 1995. I also report the latitude angle of each country obtained from the CIA Factbook, which is used to calculate the summer dummy in accordance with Hong and Yu (2009).

4.4.1 Proxies for the vacation activities

Table 4.1 provides two measures of outbound travel. Column 2 of Panel A shows the average annual outbound travel for each country. Germany has over 62 million outbound travellers per annum, which ranks among the highest in the 34 countries, while Chile with 1.24 million annual outbound travellers is the lowest among the countries examined. Column 3 measures the relative importance of outbound travel by

31 WTO stopped maintaining the data at monthly frequency after 1997.

scaling the annual outbound travel over the population. This allows cross-national comparison of the importance of outbound travel between countries. People in Singapore and Switzerland travel the most, with a ratio of 2.28 (1.98) indicating average Singaporean (Swiss) people travel overseas about twice a year. India has the lowest proportion of outbound travellers; only 3 out of 1000 Indians travel once per year. Over all, developed markets tend to have much higher ratios than emerging markets. I group the countries based on their geographical locations into six regions in Panel B. The sample consists of 18 European countries, 8 Asian countries, 3 countries from Latin America, 2 from North America, 2 from Oceania and 1 from Africa. European and North American countries have the largest number of outbound travellers on average. When measured relative to population, Europe with a ratio of 0.7 beats all the other regions. Africa and Latin America are the regions with the lowest number of outbound travellers in the sample.

If the seasonal behaviour in vacations is the root cause for the seasonal pattern in stock returns, I expect to find a cross sectional correlation between the strength of the seasonal stock returns and the importance and the timing of vacations in each country. Countries with strong vacation traditions, and with summer persistently being the peak vacation season, are expected to have stronger summer dips, or Halloween effects, in their stock market returns.

Table 4.1 Summary Statistics

Panel A provides latitude angle, sample start and end date, mean value of two measures of outbound travel; annual outbound travel, and outbound travel per capita calculated as annual outbound travel divided by total population; as well as basic descriptive statistics for the monthly returns, estimated monthly liquidity demands and turnovers of 34 countries in the sample listed by geographical locations. Return is the continuously compounded monthly return, turnover is calculated by dividing volume by value over total market value, and monthly liquidity demand is estimated from regression Equation (10) and rescaled by multiplying -1 to each estimates. Panels B-D report summary statistics for the portfolios sorted by countries' geographical locations, quartile rankings of vacation importance and strength of summer (Halloween) seasonal pattern in outbound travel.

Panel A: Country Level

Region	Country	Latitude	(1) Sample Period		(2) Outbound travel in mil.	(3) Outbound travel per capita	(4) Return (%)		(5) Liquidity		(6) Turnover (%)	
			Start	End			Mean	St Dev	Mean	St Dev	Mean	St Dev
Africa	South Africa	-29	01/1990	12/2010	1.976	0.044	1.28	6.06	0.19	0.96	3.52	2.13
Asia	China	35	08/1993	12/2010	10.242	0.008	1.13	10.91	0.28	0.87	13.73	9.15
	India	20	01/1995	12/2010	3.228	0.003	1.07	8.54	0.19	1.34	3.97	3.72
	Japan	36	12/1990	12/2010	19.548	0.155	-0.11	5.40	0.33	1.52	5.52	3.41
	Korea	40	01/1988	12/2010	6.563	0.138	0.76	9.02	0.18	1.22	10.14	5.58
	Malaysia	2.3	01/1988	12/2010	3.591	0.154	0.96	7.25	0.30	0.90	1.90	0.90
	Philippines	13	01/1990	12/2010	1.992	0.024	0.89	7.93	0.22	0.84	1.40	0.88
	Singapore	1.22	01/1988	12/2010	9.417	2.281	0.70	6.19	0.20	0.91	3.31	1.74
	Thailand	15	01/1988	12/2010	2.703	0.043	0.96	9.85	0.24	0.84	4.46	2.28
Europe	Austria	47.2	01/1988	12/2010	11.455	1.429	0.81	6.21	0.29	0.86	3.94	1.73
	Belgium	50.5	01/1988	12/2010	6.567	0.640	0.75	5.09	0.25	0.99	2.34	1.59
	Denmark	56	04/1988	12/2010	4.716	0.881	1.01	5.36	0.18	0.90	3.64	2.45
	Finland	64	04/1988	12/2010	3.175	0.613	0.86	8.46	0.07	0.78	5.87	5.09
	France	46	06/1988	12/2010	29.952	0.500	0.79	5.32	0.19	1.04	5.48	2.90
	Germany	51	06/1988	12/2010	62.773	0.767	0.70	5.50	0.28	1.04	8.05	8.13
	Greece	39	02/1990	12/2010	2.457	0.231	0.74	9.28	0.34	1.23	3.46	1.97
	Hungary	47	07/1991	12/2010	3.662	0.364	1.26	9.11	0.12	0.68	5.54	3.46
	Italy	42.5	01/1988	12/2010	17.961	0.311	0.49	6.23	0.24	1.15	7.38	5.39
	Netherlands	52.3	01/1988	12/2010	19.909	1.243	0.81	5.29	0.01	1.11	8.47	3.67
	Norway	62	01/1988	12/2010	3.245	0.717	1.14	6.78	0.06	0.91	6.93	3.61
	Poland	52	04/1994	12/2010	5.619	0.146	0.59	9.44	0.31	0.98	3.06	1.23
	Portugal	39.3	02/1990	12/2010	5.542	0.549	0.49	5.38	0.14	0.83	3.72	2.56
	Spain	40	02/1990	12/2010	17.424	0.434	0.77	5.80	0.15	1.05	7.14	3.48
	Sweden	62	01/1988	12/2010	6.761	0.760	1.08	6.74	0.19	1.02	7.07	4.28
	Switzerland	47	01/1989	12/2010	14.262	1.980	0.77	4.66	0.23	1.15	5.54	2.38
	Turkey	39	02/1988	12/2010	3.073	0.048	3.55	14.30	0.04	0.79	8.33	5.28
	United Kingdom	54	01/1988	12/2010	38.383	0.648	0.81	4.36	0.28	1.35	7.26	3.53
Latin America	Argentina	-34	09/1993	12/2010	3.655	0.099	1.11	9.20	0.17	0.80	1.11	0.60
	Chile	-30	08/1989	12/2010	1.241	0.080	1.73	5.63	0.14	0.77	0.96	0.45
	Mexico	23	06/1989	12/2010	8.513	0.083	1.96	7.22	0.10	1.04	3.26	2.15
North America	Canada	60	01/1988	12/2010	21.063	0.687	0.86	4.18	0.11	1.23	4.65	2.09
	United States	38	01/1988	12/2010	53.158	0.186	0.83	4.41	0.14	1.87	11.47	6.46
Oceania	Australia	-27	01/1988	12/2010	5.517	0.284	0.91	4.03	0.05	1.02	5.35	2.35
	New Zealand	-41	01/1990	12/2010	1.666	0.435	0.54	4.53	0.10	0.80	2.93	1.16

Panel B: Portfolios constructed based on geographical locations

Region		(1) Sample Period		(2) Outbound travel in mil.	(3) Outbound travel per capita	(4) Return (%)		(5) Liquidity		(6) Turnover (%)	
		Start	End			Mean	St Dev	Mean	St Dev	Mean	St Dev
Africa	1	01/1990	12/2010	2.07	0.05	1.28	6.06	0.19	0.96	3.52	2.13
Asia	8	01/1989	12/2010	7.68	0.38	0.69	8.24	0.24	1.08	5.40	5.61
Europe	18	01/1988	12/2010	14.68	0.70	0.99	7.19	0.19	1.01	5.84	4.33
Latin America	3	06/1989	12/2010	4.89	0.09	1.58	7.34	0.14	0.84	1.83	1.73
North America	2	01/1988	12/2010	37.11	0.44	0.85	4.29	0.13	1.58	8.06	5.89
Oceania	2	01/1988	12/2010	3.71	0.36	0.73	4.27	0.07	0.92	4.19	2.23

Panel C: Quartile ranked portfolios constructed based on importance of vacation

Importance	(1) Sample Period		(2) Outbound travel in mil.	(3) Outbound travel per capita	(4) Return (%)		(5) Liquidity		(6) Turnover (%)	
	Start	End			Mean	St Dev	Mean	St Dev	Mean	St Dev
4 (High)	01/1988	12/2010	17.65	1.32	0.83	4.76	0.16	0.49	6.03	2.29
3	01/1988	12/2010	15.30	0.52	0.85	4.48	0.18	0.46	5.02	2.32
2	01/1988	12/2010	12.31	0.20	0.86	4.83	0.21	0.44	5.01	2.34
1 (Low)	01/1988	12/2010	4.20	0.04	1.53	5.63	0.18	0.48	4.69	1.82

Panel D: Portfolios ranked based on the strength of summer seasonl and Halloween seasonal in outbound travels

Timing		No. of Contries	(1) Sample Period Start	End	(2) Outbound travel in mil.	(3) Outbound travel per capita	(4) Return (%) Mean	St Dev	(5) Liquidity Mean	St Dev	(6) Turnover (%) Mean	St Dev
Summer Timing	3 (High)	24	01/1988	12/2010	15.81	0.57	0.97	6.95	0.18	1.11	5.76	4.69
	2	5	01/1988	12/2010	4.96	0.10	1.08	8.49	0.20	0.95	5.36	6.07
	1 (Low)	5	01/1988	12/2010	4.63	0.64	0.77	6.75	0.17	0.90	3.65	2.16
Halloween Timing	3 (High)	23	01/1988	12/2010	16.16	0.61	0.93	6.61	0.18	1.11	5.78	4.40
	2	8	01/1988	12/2010	5.48	0.40	0.93	8.51	0.20	0.97	5.65	5.57
	1 (Low)	3	01/1988	12/2010	2.95	0.12	1.18	7.37	0.20	0.83	1.36	0.81

The importance of vacation and portfolios constructed based on quartile rankings of outbound travel per capita

I measure each country's relative importance of vacations as monthly outbound travel scaled by population. Figure 4.1 plots average outbound travel per capita against the peak outbound travel month for each country. Countries with relatively high levels outbound travel are primarily located in Europe, and countries positioned at the bottom of the graph tend to be emerging markets. It should be noted that outbound travel, however, is not a precise proxy for vacations; the measure can be very noisy, especially when comparing cross country variations and even after controlling for population. For example, outbound travel fails to consider inbound travel activities, which might understate the importance of vacations for larger countries, where travelling within the country is more common relative to smaller countries. An example of this bias in the sample is Singapore, which ranked highest in the outbound travel per capita measure. Being a small country, people ought to travel outside the country more often for vacation relative to other countries, especially larger countries like America and China. One way to mitigate this bias is to construct portfolios.

I group the countries into portfolios based on quartile rankings of each country's annual vacation importance measure. In each year from 1988 to 2010 I calculate each county’s annual outbound travel per capita, and allocate the countries to four portfolios based on individual countries’ quartile ranking of the measure[32]. Although I re-rank the countries every year, Appendix 4.1 shows that the ranking of the countries are quite persistent over time from 1988 to 2010. Panel C of Table 4.1 provides summary statistics of the portfolios ranked based on vacation importance. Portfolio 4 (1) consists of the countries with the highest (lowest) rank in vacation importance.

Timing of the vacation and portfolios constructed based on seasonal patterns of vacations

Despite the flaw that outbound travel data has in measuring cross sectional variations in the importance of vacations, the monthly outbound travel data can be a good proxy in gauging the timing of vacations for each country[33]. The assumption that summer is the most popular season for vacation hitherto relies only on anecdotes, while the vacation behaviour may vary among countries due to different geographical locations, cultures, norms and religions, as noted in Hong and Yu (2009). It will be more informative if we understand the precise seasonal pattern of people taking vacations among countries. Using monthly outbound travel data from 1988 to 1997, I am able to identify each county’s timing and the seasonal pattern of vacation activities.

[32] The countries are also ranked based on annual outbound travel per capita adjusted for stock market turnover measured as annual outbound travel per capita multiplying stock market total turnover scaled by population. The findings based on this measure do not change the conclusions. Since simple measures are often more intuitive to readers, I stay with outbound travel per capita as the proxy for vacation importance.

[33] As outbound travel data consists of both travel for leisure and travel for business activities, the timing measures of vacation will be biased if there is seasonality in business trips. Fortunately, studies seem to show that business trips tend to spread evenly over the year than holiday trips. For example in the article provided by Eurostat http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Seasonality_in_tourism_demand#Further_Eurostat_information and Koenig and Bischoff (2003). In addition, the Google Search Volume data downloaded from Google Trends also confirms that business trips tend to reveal limited seasonality over time. Appendix 4.2 provides more detailed evidence.

Figure 4.1 reveals the peak month of outbound travel for each country. The countries labelled with a triangle sign indicate that the peak month of vacation falls into non-summer months, as defined in Hong and Yu (2009). Nine of the thirty-four countries have the peak vacation season in non-summer months. European and North American countries and countries located in the Northern Hemisphere tend to have stronger summer vacations, while countries located in the Southern Hemisphere (e.g. New Zealand, Australia) and tropical regions (e.g. Singapore, Malaysia, Thailand and the Philippines) tend to take vacations in non-summer months.

Table 4.2 provides statistical evidence of the seasonal patterns in monthly outbound travel for the 34 countries listed by the countries' latitude angles from Southern Hemisphere to Northern Hemisphere. Column (1) shows the mean and standard deviation of percentage growth in outbound travel for each calendar month and column (2) reports the difference in mean and variance tests of 12 calendar months' outbound travel growth. The significant t-statistics indicate that all of the countries exhibit strong seasonality except for Malaysia and South Korea. In addition, most of these monthly changes in outbound travel are statistically significant, implying that the calendar month changes in outbound travels are quite reliable. I reveal whether there is a summer (Halloween) seasonal in outbound travel in the last two columns of Table 4.2. Columns (3) and (4) report the coefficient estimates and t-statistics of the regression equations:

$$Outbound_{i,t} = \alpha + \beta_{sum} Summer_{i,t} + YearDummies + \varepsilon_t \tag{4.1}$$

$$Outbound_{i,t} = \alpha + \beta_{Hal} Halloween_{i,t} + YearDummies + \varepsilon_t \tag{4.2}$$

where $Outbound_{i,t}$ is the number of outbound journeys in country i at month t. $Summer_{i,t}$ is the summer month dummy used in Hong and Yu (2009) that takes the value of 1 if month t falls in the period July-September for countries located in the Northern Hemisphere, January-March for countries located in the Southern Hemisphere and zero otherwise. $Halloween_{i,t}$ is the Halloween dummy, as in Bouman and Jacobsen (2002), that equals 1 if month t falls on the period from November through April and zero otherwise. Year dummies are included in both regressions to control for time trends and other noise unrelated to the seasonal effect. The coefficient β_{sum} represents the difference in mean outbound travel between summer months and non-summer months; I expect the coefficients to be significantly positive. Of the 34 countries, 20 countries exhibit significantly higher outbound travel during summer months. Consistent with the pattern revealed in Figure 4.1, all countries located in non-tropical Northern Hemisphere regions (except China and Hungary) show strong summer peak in outbound travel, while countries located in the Southern Hemisphere and tropical regions tend to show insignificant, or reversed, summer seasonality in outbound travel. β_{Hal} represents the 6-month difference in outbound travel between November to April and May to October. It is expected to be significantly negative for countries located in the Northern Hemisphere and positive for countries located in the South Hemisphere. Similar to the results from the summer dummy regressions, most of the countries located in non-tropical Northern Hemisphere regions reveal significantly higher outbound travel during the summer (May-October) period, with China, Hungary and South Korea being the only exceptions. Countries located in the Southern Hemisphere and tropical regions tend to have insignificant, or significantly higher, levels of winter (May-October) outbound travel.

This preliminary check indicates that the seasonal patterns in outbound travel among countries located in non-tropical Northern Hemisphere regions generally agrees with

Hong and Yu (2009)'s assertion. However, the results are mixed for countries located in the Southern Hemisphere and tropical areas.

For further analysis I also allocate countries into 3 portfolios in 2 alternative ways based on the strength of summer seasonals and Halloween seasonals in monthly outbound travel data from 1988 to 1997 (timing of vacation). Panel D of Table 4.1 provides summary statistics for the portfolios allocated using both timing measures. I assign the countries with a t-value for the summer dummy in Equation (1) greater or equal to 1.96 to summer timing 3, the countries with t-value smaller or equal to -1.96 to summer timing 1, and the countries with insignificant coefficient estimates to summer timing 2. Consequently, I have 24 countries in portfolio 3, 5 countries in portfolio 2 and 5 countries in portfolio 1. Similarly, I allocate countries with a t-value for the Halloween dummy in Equation (2) smaller or equal to -1.96 (higher outbound in travel May-October) to Halloween timing 3, the countries with t-value greater or equal to 1.96 to Halloween timing 1, and the countries with insignificant coefficient estimates to Halloween timing 2. This gives 23 countries in portfolio 3, 8 countries in portfolio 2, and 3 countries in portfolio 1.

Table 4.2 Percentage changes in outbound travel for each calendar month, the seasonality test, summer and Halloween effe

The table presents mean and standard deviation of the percentage changes in outbound travel every month for 34 countries listed on the basis of e values for tests of monthly difference of means and variances; the F-statistic is derived from the ANOVA (variance-weighted one-way ANOV (significant) difference in variance. Columns 3 and 4 provide coefficient estimates and t-statistics of the summer effect and the Halloween effect i statistics are calculated based on White (1980) standard errors.

*** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Country	Latitude	Statistics	(1) Month												
			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	dif. n
New Zealand	-41	Mean	-1.81	-16.91 ***	38.87 ***	8.58 **	13.83 **	5.67	12.19 ***	7.78 *	-3.58	-12.04 ***	-15.79 ***	1.16	4.0
		S.D.	64.10	7.28	10.72	10.94	18.90	17.58	7.51	13.02	8.29	4.00	4.35	26.37	
Argentina	-34	Mean	152.06 ***	-26.06 ***	-38.91 ***	-16.86	-19.33 **	-5.15	35.61 ***	-12.94 ***	4.17 ***	8.76 *	-8.50 **	47.13 ***	22.6
		S.D.	94.88	4.11	11.24	20.51	17.59	10.01	10.95	5.65	2.87	10.32	8.23	12.20	
Chile	-30	Mean	160.30	2.82	-25.06 ***	-12.98 *	2.17	17.94 ***	18.97 ***	-11.46 ***	1.57	-18.85 ***	-5.91 ***	32.90 ***	2.1
		S.D.	336.88	10.44	6.06	19.59	13.32	20.73	9.97	6.32	9.79	4.56	7.24	30.57	
South Africa	-29	Mean	17.25	-20.74 ***	40.68 ***	8.24	-11.88 ***	1.25	23.47 ***	-33.15 ***	46.42 ***	0.14	-23.61 ***	46.46 ***	14.3
		S.D.	64.47	9.92	23.24	25.89	10.87	12.99	23.06	13.87	34.93	13.33	8.99	22.76	
Australia	-27	Mean	-7.75 *	-24.03 ***	23.71 ***	3.75	4.25 ***	14.13 ***	6.66 ***	-8.35 ***	14.17 ***	-13.66 ***	-17.87 ***	26.13 ***	77.8
		S.D.	11.95	5.09	10.43	9.83	4.26	5.82	7.86	5.45	5.22	3.94	3.74	5.59	
Singapore	1.22	Mean	12.52	8.02	20.41 ***	-8.67 ***	3.81	49.53 ***	-37.70 ***	11.84	5.63	21.68	14.63 ***	23.71 ***	27.2
		S.D.	92.00	25.13	16.60	9.98	11.79	24.90	8.76	24.11	18.56	65.51	6.38	6.96	
Malaysia	2.3	Mean	60.90	43.55 ***	-8.08	12.36	0.41	-8.96	-8.95 *	26.18 ***	-10.10 **	26.80	29.18 ***	-13.09 *	1.3
		S.D.	205.43	41.90	20.70	26.24	10.88	17.18	15.44	22.86	14.05	54.76	11.52	21.86	
Philippines	13	Mean	-5.07	-2.35	22.21 ***	18.43 **	-1.71	-15.02 ***	-6.04 ***	9.27 ***	-3.71 **	9.67 ***	-4.04 ***	3.98	11.7
		S.D.	24.75	6.25	9.70	25.37	7.31	7.92	5.57	5.73	4.68	4.86	3.44	10.61	
Thailand	15	Mean	-1.58	-2.23	17.20 ***	40.24 ***	-15.56 ***	-20.46 ***	2.43	9.65	-1.84	61.59 ***	-29.15 ***	22.37 ***	9.2
		S.D.	32.11	9.21	10.97	16.77	11.46	10.87	16.65	26.22	10.03	68.23	6.56	15.85	
India	20	Mean	-21.27 ***	37.61	0.93	-15.55	1.84	46.65 ***	7.87 *	-29.86 ***	-6.41 ***	8.45	-6.14 ***	27.70 ***	9.2
		S.D.	1.90	45.86	62.86	19.03	9.85	18.83	7.88	5.68	3.12	10.27	4.47	17.26	
Mexico	23	Mean	-37.52 ***	-7.56 ***	35.87 ***	21.02 *	-5.22	10.83 **	64.26 ***	-11.27 ***	-30.81 ***	-0.84	-13.96 ***	41.64 ***	56.2
		S.D.	6.48	6.84	33.66	30.86	14.61	13.48	14.43	11.18	7.30	3.94	6.37	10.98	
China	35	Mean	31.10	-14.81 ***	18.76 ***	0.94	13.47 ***	-14.98 **	6.14	4.63	-14.03 ***	2.24	1.13	5.54 *	9.9
		S.D.	65.11	10.66	13.63	4.49	2.32	14.91	9.72	40.29	5.03	6.14	6.31	7.36	
Japan	36	Mean	-2.65	-1.82	14.75 ***	-16.14 ***	12.34 ***	9.08 ***	7.37 ***	10.50 ***	-6.03 ***	-11.09 ***	-6.03 ***	1.55	14.4
		S.D.	7.03	14.57	5.74	10.30	6.39	4.15	3.55	4.55	4.99	4.52	2.52	4.90	
United States	38	Mean	-9.56 ***	4.12 ***	26.64 ***	5.17 ***	29.72 ***	27.64 ***	22.10 ***	-7.00 ***	-25.31 ***	-16.51 ***	-26.99 ***	-2.22 ***	134.4
		S.D.	6.80	3.18	9.63	6.55	6.20	5.00	6.65	4.68	4.78	4.34	2.30	2.51	
Greece	39	Mean	-16.60 ***	-15.99 ***	23.58 ***	25.32 ***	-11.07 ***	12.21 ***	40.50 ***	36.19 ***	-33.51 ***	-22.16 ***	-16.90 ***	17.36 ***	31.6
		S.D.	15.63	8.08	19.75	12.47	12.02	13.40	15.05	7.46	7.35	5.71	8.81	16.82	
Turkey	39	Mean	-13.94 ***	-14.62 ***	13.72 ***	9.90 **	10.05 ***	69.28 ***	167.48 ***	1.38	-54.25 ***	-32.63 ***	-8.42	1.78	18.3
		S.D.	7.80	9.71	15.34	13.48	12.90	78.94	108.25	20.20	14.97	13.52	21.73	19.06	
Portugal	39.3	Mean	107.67	-0.95	17.93 ***	23.91 ***	-12.63 ***	15.14 ***	41.38 ***	58.99 ***	-36.38 ***	-24.36 ***	-25.20 ***	37.94 ***	21.6
		S.D.	412.47	25.99	20.15	27.23	10.25	11.80	29.90	19.21	13.88	6.86	10.71	35.00	

Table 4.2 Continued

Country	Latitude	Statistics	(1) Month												
			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	dif.
Korea	40	Mean	110.52 *	-30.83 ***	3.48	-5.01 *	1.22	-5.29 ***	28.14 ***	167.49	-30.93 ***	16.92 ***	1.14	-5.91	1.4
		S.D.	180.30	9.13	10.49	8.29	5.39	6.02	8.05	468.09	5.27	13.19	5.45	31.28	
Spain	40	Mean	-35.81 ***	-11.43 ***	47.65 ***	37.23 ***	-17.24 ***	-0.24	50.63 ***	61.54 ***	-47.64 ***	-19.26 **	-20.46 ***	22.89 ***	33.7
		S.D.	3.76	6.00	33.36	31.59	12.51	3.66	21.51	4.86	1.14	26.25	5.68	13.08	
Italy	42.5	Mean	-15.36 **	-16.92 ***	50.99 ***	35.87 ***	-20.24 ***	13.90 ***	49.67 ***	105.13 ***	-58.41 ***	-32.48 ***	-28.13 ***	41.39 ***	239.4
		S.D.	21.19	8.56	17.49	19.03	10.42	9.57	15.96	13.68	2.48	5.13	4.73	22.12	
France	46	Mean	-3.21	6.31 ***	16.22 ***	24.01 ***	7.09 ***	-5.84 ***	57.60 ***	27.71 ***	-45.32 ***	-18.91 ***	-22.02 ***	4.11	57.4
		S.D.	40.46	6.88	10.49	8.97	7.41	6.71	19.30	8.96	9.46	4.96	7.13	13.87	
Hungary	47	Mean	230.77	42.37 **	-16.20 **	13.11 **	-24.60 ***	14.21 ***	18.77 ***	19.39 ***	-41.12 ***	10.50 ***	-6.15 *	17.41 ***	15.9
		S.D.	404.41	44.70	17.69	15.98	5.84	6.68	13.58	13.19	24.20	10.30	8.88	12.04	
Switzerland	47	Mean	-14.33 ***	-4.49	16.45 ***	18.38 ***	10.93 ***	8.83 **	35.26 ***	-6.71 ***	-17.71 ***	-9.08 ***	-28.26 ***	11.94 ***	27.4
		S.D.	5.73	10.20	14.55	19.07	8.04	13.48	21.26	5.58	7.17	4.02	5.23	8.48	
Austria	47.2	Mean	-7.30	3.42	30.20 ***	16.54 ***	33.22 ***	7.29 *	24.02 ***	13.59 ***	-32.71 ***	-16.62 ***	-27.19 ***	-5.98 *	30.6
		S.D.	17.13	9.27	16.56	18.79	16.17	11.99	8.30	8.13	11.44	5.46	4.97	10.80	
Belgium	50.5	Mean	-10.34	11.37 ***	11.07 ***	28.41 ***	12.64 ***	25.11 ***	127.02 ***	-18.81 ***	-39.48 ***	-30.93 ***	-31.20 ***	6.63	50.8
		S.D.	26.91	8.05	13.44	24.09	13.16	20.58	42.35	7.83	12.63	5.70	4.19	12.81	
Germany	51	Mean	4.72	3.85	29.41 ***	1.90	33.17 ***	8.14	47.99 ***	7.83 ***	-29.56 ***	-25.93 ***	-47.58 ***	26.39 ***	142.4
		S.D.	18.20	7.17	19.67	28.19	28.49	19.13	18.51	8.39	7.73	4.42	3.21	5.99	
Poland	52	Mean	218.69	6.14	5.35	-0.34	15.75 ***	17.17 ***	74.56 ***	20.91 ***	-35.72 ***	-31.75 ***	-18.70 ***	-27.05 ***	42.9
		S.D.	263.07	7.98	11.20	6.67	8.68	11.10	6.21	6.17	11.19	6.94	13.46	10.93	
Netherlands	52.3	Mean	10.80 **	41.64 ***	-15.89 ***	-5.27	40.30 ***	20.76 ***	98.99 ***	-15.35 ***	-40.94 ***	-26.49 ***	-43.59 ***	27.74 ***	113.5
		S.D.	16.20	12.43	12.71	13.38	14.30	15.49	25.53	8.26	9.76	4.12	3.70	10.03	
United	54	Mean	-6.23	11.39 ***	21.40 ***	3.00	40.65 ***	8.36 ***	17.13 ***	3.64 ***	-7.25 ***	-22.15 ***	-36.05 ***	-5.36 ***	159.2
Kingdom		S.D.	18.86	4.68	7.10	9.48	10.95	5.85	6.22	1.94	6.66	5.32	2.94	4.60	
Denmark	56	Mean	9.37 ***	17.22 ***	17.08 ***	18.32 ***	14.01 ***	34.26 ***	77.85 ***	-30.05 ***	-21.98 ***	-21.52 ***	-41.80 ***	-11.29 ***	79.3
		S.D.	11.37	10.65	8.75	20.35	10.17	10.83	19.36	7.23	11.78	5.87	6.07	4.81	
Canada	60	Mean	10.88 ***	-8.39 ***	53.96 ***	-7.71 ***	-3.12 ***	-7.59 ***	70.41 ***	4.40 ***	-36.00 ***	-8.56 ***	-15.55 ***	-8.42 ***	166.0
		S.D.	7.28	3.07	5.59	5.34	3.27	3.61	13.75	5.44	4.28	3.17	4.20	3.80	
Norway	62	Mean	8.25 **	6.43	24.59 ***	9.41	14.48 ***	55.28 ***	69.43 ***	-32.80 ***	-22.83 ***	-29.79 ***	-28.37 ***	-15.96 ***	61.8
		S.D.	11.22	12.55	12.89	19.34	13.35	13.08	24.68	8.54	9.15	5.38	7.35	7.89	
Sweden	62	Mean	-9.16 *	21.57 ***	9.14 ***	14.82 ***	21.70 ***	31.56 ***	46.91 ***	-34.14 ***	-14.46 ***	-22.26 ***	-29.14 ***	3.12	80.9
		S.D.	14.30	8.61	11.54	13.40	17.88	13.34	10.49	5.66	8.64	3.65	5.66	9.23	
Finland	64	Mean	-4.58	-0.63	20.24 ***	17.31 ***	2.65	31.75 ***	19.37 ***	-18.67 ***	-4.81 **	-13.38 ***	-26.92 ***	3.25	9.9
		S.D.	18.06	8.60	7.58	12.28	9.85	33.92	17.53	7.52	7.68	15.44	13.36	29.34	

The summary statistics for the portfolios constructed on the basis of the timing of vacations reveal that the total number of outbound journeys seems to decrease with the strength of the summer seasonal (and Halloween seasonal) in outbound travel. The large values in outbound travel per capita observed in summer timing portfolio 1 (and Halloween timing portfolio 2) of Panel D are caused by extremely high values for Singapore. If I exclude Singapore from the observations, portfolio 3 possesses the highest vacation importance measure, followed by portfolio 1 and then portfolio 2 for both timing rankings, indicating a positive correlation between the importance of vacation and the strength of the seasonality in outbound travel regardless of the pattern. In other words, people in countries that view vacations as being important tend to take vacations at the same time.

While I provide findings for individual countries, my interpretation focuses on the results from the cross-sorted portfolios on the basis of vacation importance rankings and timing of vacations, as well as geographical locations.

4.5 Results

4.5.1 Preliminary statistics

Column 4 of Table 4.1 reports the mean and standard deviation of continuously compounded monthly returns for individual markets (Panel A) and for portfolios grouped based on geographical locations (Panel B), quartile rankings of vacation importance (Panel C) and timing of outbound travel (Panel D).

Individual countries

Panel A of Table 4.3 reports the estimates of seasonal effects for the 34 countries over the whole sample period from 1988 to 2010. I also describe each country's average rankings on vacation importance and strength of summer timing (Halloween timing) in outbound travel. Column (1) reports average summer and non-summer returns, as well as the coefficient estimates and t-statistics of the summer effect regression in Equation (4.3):

$$r_{i,t} = \alpha + \beta_{sum} Summer_{i,t} + YearDummies + \varepsilon_t \tag{4.3}$$

where $r_{i,t}$ is the continuously compounded monthly stock market return for country i at month t. $Summer_{i,t}$ is the summer dummy that equals 1 if month t falls in the period July-September for Northern Hemisphere countries and January-March for Southern Hemisphere countries, and zero otherwise. As in Hong and Yu (2009), I include year dummies in the regression to control for time trend and other noise unrelated to the seasonal effect. In line with Hong and Yu (2009), the summer return effect is very prevalent among countries, with 30 of the 34 countries having lower summer returns, of which 17 are statistically significant.

Column (2) of Panel A reports two 6-month Halloween period returns, and the slope estimates and t-statistics from the Halloween regression Equation (4.4) for individual countries:

$$r_{i,t} = \alpha + \beta_{Hal} Halloween_{i,t} + YearDummies + \varepsilon_t \tag{4.4}$$

Here I replace the summer dummy in Equation (4.3) with a Halloween dummy $Halloween_{i,t}$, which equals 1 if month t falls in the period from November through

April and zero otherwise. The country by country results show that the Halloween effect is even more pervasive than the summer return effect. Of the 34 sample countries, 33 show higher November-April returns than May-October returns, with 22 being statistically significant.

Cross-sectional regressions

A closer examination of Panel A of Table 4.3 reveals that countries with higher ranks in vacation importance tend to show significant summer (Halloween) effects. As a preliminary check for a correlation between the importance of vacation and stock return seasonals, I plot each country's sample average outbound travel per capita against the t-value of the summer return effect (Halloween effect) in Figure 4.2. Consistent with the vacation hypothesis, the plots reveal that outbound travel per capita is negatively correlated with the t-values of summer return effects and positively correlated with the t-values of Halloween effects, indicating that the summer effect and Halloween effect are stronger in the countries in which vacations are more important. Regressing the country's t-value for the summer return effect on outbound travel per capita gives a strongly significant coefficient estimate of -1.16 (t-value=-4.28), and the coefficient estimate of regressing the t-value of the Halloween effect on outbound travel per capita is 0.91 (t-value=2.34), which is also statistically significant at the 5% level. If I take the natural logarithm of the outbound travel per capita as the dependent variable to reduce the impact of outliers, the correlation becomes even stronger, with the t-statistic increasing to -5.05 for the summer effect regression and to 3.72 for the Halloween effect regression.

Table 4.3 Summer return effect and Halloween effect (1988-2010)

Panel A reports the summer effect and Halloween effect for 34 countries in the sample listed by countries' geographical locations. Column (1) shows average summer month (non-summer month) returns, coefficient estimates and t-statistics of the summer effect regression $return_{i,t} = \alpha + \beta_{sum} Summer_{i,t} + YearDummies + \varepsilon_t$, where $return_{i,t}$ is the continuously compounded return for country i at month t, $Summer_{i,t}$ is a dummy variable that equals one if the month falls into July-September in Northern Hemisphere countries and January-March in Southern Hemisphere countries and zero otherwise. Column (2) provides average monthly returns from May to October and from November to April, as well as coefficient estimates and t-statistics of the Halloween effect: $return_{i,t} = \alpha + \beta_{sum} Halloween_{i,t} + YearDummies + \varepsilon_t$, where $Halloween_{i,t}$ is the Halloween dummy that equals one when month t falls into November to April and zero otherwise. T-statistics are calculated based on White (1980) standard errors. Panel B report coefficient estimates and t-statistics for the summer effect and Halloween effect of the portfolios estimated using panel data regressions with country and year fixed effects clustered by month. The portfolios are constructed by cross sorting the countries based on geographical locations, quartile rankings of vacation importance and summer (Halloween) timing in outbound travel. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Panel A: Country Level

Region	Country	Impact	(1) Summer					(2) Halloween				
			Sum Timing	Return		Summer Effect		Hal Timing	Return		Halloween Effect	
				Sum	Non-Sum	β_{Sum}	t-value		May-Oct	Nov-Apr	β_{Hal}	t-value
Africa	South Africa	1.0	2	0.017	0.012	0.005	0.60	2	0.003	0.023	0.020	2.78 ***
Asia	China	1.0	2	0.005	0.009	-0.004	-0.22	2	0.010	0.005	-0.005	-0.34
	India	1.0	2	0.013	0.010	0.003	0.29	2	0.006	0.016	0.010	0.87
	Japan	2.0	3	-0.008	0.001	-0.008	-1.15	3	-0.008	0.006	0.014	2.16 **
	Korea	1.7	3	0.003	0.007	-0.005	-0.43	2	-0.001	0.013	0.014	1.37
	Malaysia	2.0	1	-0.006	0.014	-0.020	-1.92 *	1	0.000	0.017	0.017	2.01 **
	Philippines	1.0	2	-0.010	0.015	-0.025	-2.33 **	2	-0.001	0.019	0.019	2.15 **
	Singapore	3.8	1	-0.008	0.011	-0.019	-2.37 **	2	-0.001	0.014	0.015	2.1 **
	Thailand	1.0	1	-0.003	0.013	-0.016	-1.13	2	0.001	0.017	0.016	1.44
Europe	Austria	4.0	3	-0.005	0.013	-0.018	-2.05 **	3	-0.003	0.019	0.023	3.35 ***
	Belgium	3.1	3	-0.001	0.010	-0.012	-1.73 *	3	0.000	0.015	0.014	2.65 ***
	Denmark	3.7	3	-0.002	0.012	-0.014	-1.92 *	3	0.004	0.013	0.010	1.59
	Finland	3.1	3	-0.007	0.014	-0.021	-1.90 *	3	-0.002	0.019	0.021	2.21 **
	France	3.0	3	-0.007	0.012	-0.018	-2.42 **	3	-0.003	0.017	0.020	3.35 ***
	Germany	3.7	3	-0.013	0.013	-0.026	-3.16 ***	3	-0.003	0.016	0.018	2.93 ***
	Greece	2.0	3	-0.001	0.010	-0.008	-0.68	3	-0.006	0.021	0.026	2.42 **
	Hungary	2.6	2	0.015	0.014	0.001	0.11	2	0.005	0.023	0.018	1.59
	Italy	2.7	3	-0.008	0.009	-0.017	-2.16 **	3	-0.008	0.017	0.025	3.59 ***
	Netherlands	4.0	3	-0.006	0.013	-0.019	-2.53 **	3	-0.001	0.017	0.018	3.16 ***
	Norway	3.2	3	-0.006	0.017	-0.023	-2.64 ***	3	0.000	0.023	0.023	3.08 ***
	Poland	1.8	3	0.000	0.012	-0.012	-0.90	3	-0.004	0.023	0.026	2.24 **
	Portugal	2.8	3	-0.005	0.008	-0.013	-1.75 *	3	-0.003	0.013	0.015	2.52 **
	Spain	3.0	3	-0.003	0.013	-0.015	-1.84 *	3	0.001	0.017	0.016	2.34 **
	Sweden	3.6	3	-0.009	0.017	-0.026	-3.02 ***	3	-0.001	0.022	0.023	3.04 ***
	Switzerland	4.0	3	-0.007	0.013	-0.020	-2.82 ***	3	0.002	0.014	0.012	2.22 **
	Turkey	1.2	3	0.024	0.039	-0.015	-0.88	3	0.024	0.047	0.028	1.65 *
	United Kingdom	3.2	3	0.003	0.010	-0.007	-1.12	3	0.003	0.014	0.011	2.27 **
Latin America	Argentina	1.5	3	0.014	0.008	-0.004	-0.27	1	-0.002	0.021	0.018	1.56
	Chile	1.1	3	0.022	0.015	0.007	0.94	1	0.015	0.018	0.003	0.43
	Mexico	1.5	3	0.009	0.023	-0.011	-1.23	3	0.013	0.026	0.012	1.37
North America	Canada	3.4	3	-0.001	0.012	-0.012	-2.17 **	3	0.005	0.013	0.008	1.71 *
	United States	2.0	3	0.002	0.011	-0.009	-1.49	3	0.005	0.012	0.007	1.52
Oceania	Australia	2.1	1	0.006	0.010	-0.005	-0.92	3	0.007	0.011	0.004	1.00
	New Zealand	2.9	1	-0.001	0.007	-0.008	-1.46	3	0.005	0.006	0.001	0.26

Table 4.3 Continued

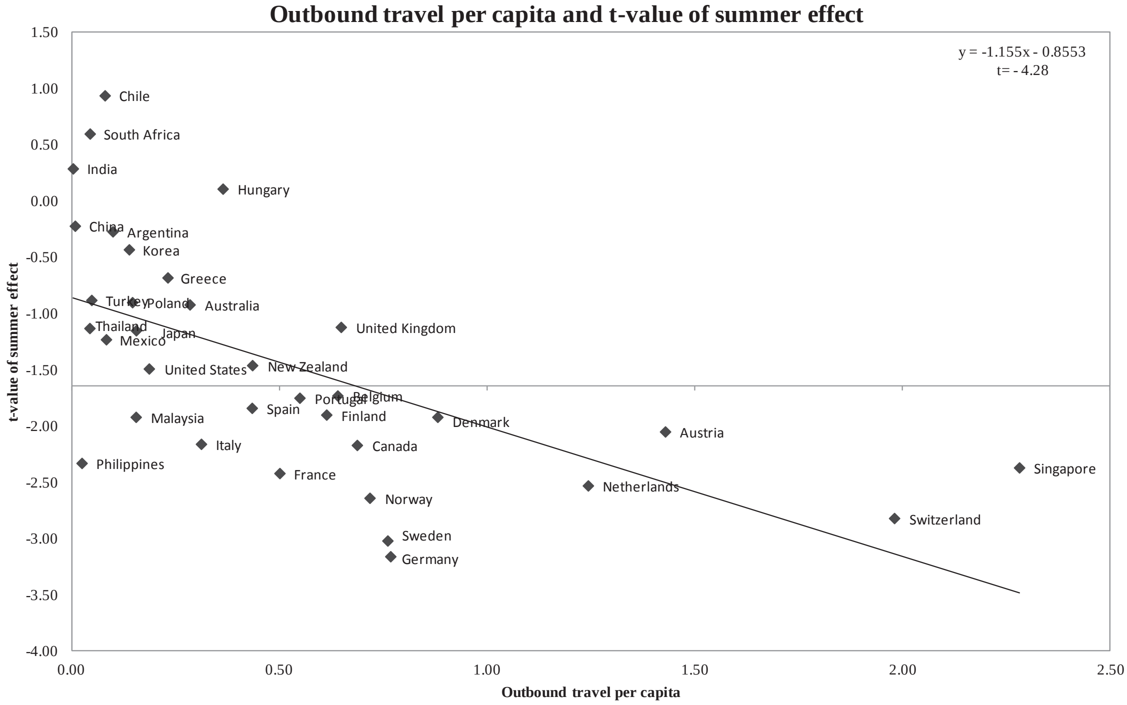
Panel B: Portfolios

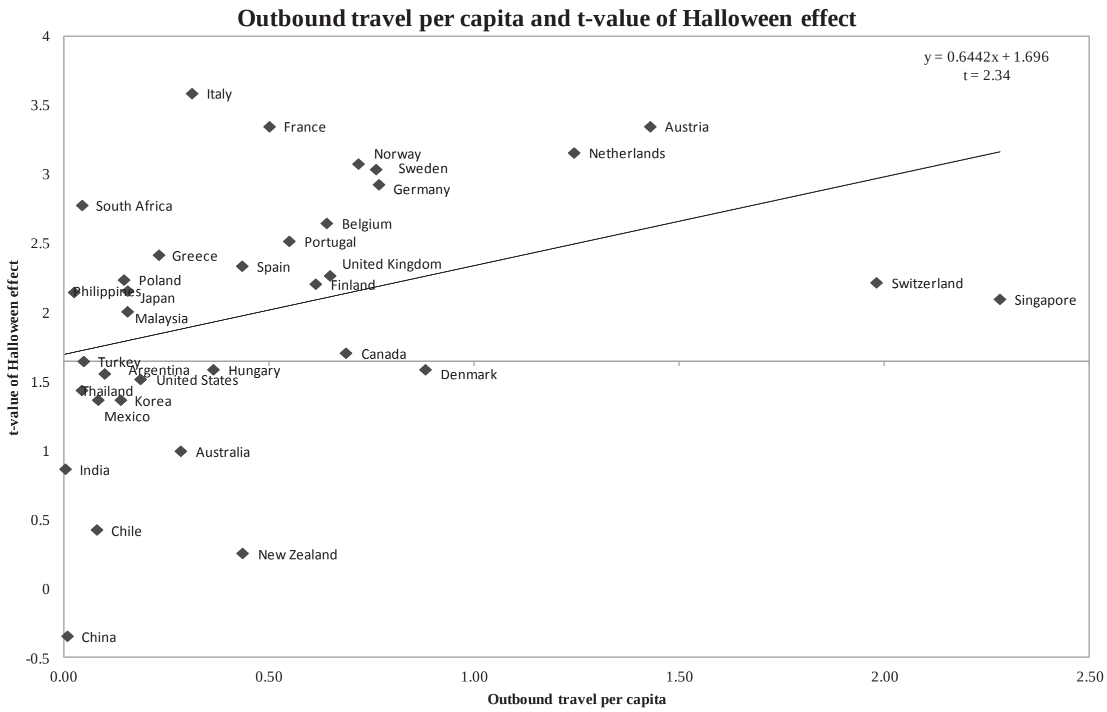
Region	Importance	Summer effect in stock market returns: Summer Timing 3 βSum	t-value	2 βSum	t-value	1 βSum	t-value	Overall β_{Sum}	t-value
Overall	4 (High)	-0.020	-2.87 ***	-0.008	-0.23	-0.013	-1.67 *	-0.019	-2.78 ***
	3	-0.016	-2.36 **	0.039	2.52 **	-0.015	-2.14 **	-0.014	-2.45 **
	2	-0.010	-1.71 *	-0.015	-0.71	-0.012	-2.15 **	-0.011	-1.92 *
	1 (Low)	-0.004	-0.49	-0.006	-0.86	-0.016	-1.22	-0.006	-1.03
	Overall	-0.014	-2.37 **	-0.004	-0.63	-0.014	-2.33 **	-0.013	-2.32 **
Africa	4 (High)								
	3								
	2								
	1 (Low)			0.005	0.60			0.005	0.60
	Overall			0.005	0.60			0.005	0.60
Asia	4 (High)					-0.013	-1.67 *	-0.013	-1.67 *
	3					-0.127	-2.22 **	-0.127	-2.22 **
	2	-0.005	-0.70			-0.021	-1.93 *	-0.011	-1.62
	1 (Low)	-0.013	-0.55	-0.010	-1.06	-0.016	-1.22	-0.012	-1.31
	Overall	-0.007	-0.83	-0.010	-1.06	-0.018	-1.89 *	-0.012	-1.64
Europe	4 (High)	-0.021	-2.88 ***	-0.008	-0.23			-0.020	-2.81 ***
	3	-0.016	-2.31 **	0.039	2.52 **			-0.014	-2.09 **
	2	-0.015	-1.73 *	-0.015	-0.71			-0.015	-1.60
	1 (Low)	-0.009	-0.59	-0.004	-0.24			-0.009	-0.60
	Overall	-0.017	-2.50 **	0.001	0.11			-0.016	-2.33 **
Latin America	4 (High)								
	3								
	2	-0.005	-0.51					-0.005	-0.51
	1 (Low)	0.001	0.15					0.001	0.15
	Overall	-0.001	-0.18					-0.001	-0.18
North America	4 (High)	-0.006	-0.89					-0.006	-0.89
	3	-0.018	-2.01 **					-0.018	-2.01 **
	2	-0.009	-1.41					-0.009	-1.41
	1 (Low)	-0.013	-0.68					-0.013	-0.68
	Overall	-0.011	-1.91 *					-0.011	-1.91 *
Oceania	4 (High)								
	3					-0.009	-1.51	-0.009	-1.51
	2					-0.003	-0.67	-0.003	-0.67
	1 (Low)								
	Overall					-0.006	-1.37	-0.006	-1.37

Region	Importance	Halloween: Hal Timing 3 β_{Hal}	t-value	2 β_{Hal}	t-
Overall	4 (High)	0.016	3.03 ***	0.016	1.
	3	0.016	3.15 ***	-0.011	-0.
	2	0.015	2.99 ***	0.021	2.
	1 (Low)	0.021	1.91 *	0.013	1.
	Overall	0.016	3.28 ***	0.014	2.
Africa	4 (High)				
	3				
	2				
	1 (Low)			0.020	2.
	Overall			0.020	2.
Asia	4 (High)			0.012	1.
	3			0.035	0.
	2	0.014	2.16 **	0.015	1.
	1 (Low)			0.012	1.
	Overall	0.014	2.16 **	0.012	1.
Europe	4 (High)	0.017	3.10 ***	0.037	1.
	3	0.018	3.41 ***	-0.021	-1.
	2	0.021	2.83 ***	0.031	1.
	1 (Low)	0.031	2.02 **	0.020	0.
	Overall	0.019	3.54 ***	0.018	1.
Latin America	4 (High)				
	3				
	2	0.024	2.31 **		
	1 (Low)	0.004	0.33		
	Overall	0.013	1.58		
North America	4 (High)	0.000	-0.07		
	3	0.015	2.06 **		
	2	0.008	1.54		
	1 (Low)	-0.001	-0.06		
	Overall	0.008	1.70 *		
Oceania	4 (High)				
	3	0.002	0.37		
	2	0.004	0.82		
	1 (Low)				
	Overall	0.003	0.69		

Figure 4.2 Outbound travel per capita and t-value of summer effect (Halloween effect) of 34 countries

This figure plots average annual outbound travel per capita against t-values of the summer (Halloween) return effects for 34 countries over the sample period 1988 to 2010. The t-values of the summer (Halloween) return effects are obtained by regressing monthly stock market returns on a summer month (Halloween) dummy. Year dummies are included in the regression to control for time trends.





4.5.2 Cross sorted portfolios

I investigate the relation between vacation behaviour and stock return seasonals in more detail in this section by cross sorting countries based on geographical location, quartile rankings of vacation importance and the strength of summer (Halloween) seasonals in outbound travel. The vacation hypothesis suggests portfolios with higher rankings in vacation importance and strong summer (Halloween) seasonals in vacation to have larger summer (Halloween) effects in stock returns. Panel B of Table 4.3 provides the results of the summer effects and Halloween effects for the cross sorted portfolios. The coefficients and t-statistics are obtained by regressing the countries' monthly returns on a summer dummy for the summer effect, or Halloween dummy for the Halloween effect; the estimations for the portfolios are based on panel data regression with country and year fixed effects clustered by month[34].

Summer return effect

Results for the summer effects are reported in the left table of Panel B. The first section shows the coefficient estimates from all countries cross sorted by vacation importance rankings and timing of vacations. Overall, summer month returns are, significantly, 1.3% lower than the rest of the year and the strength of the effects between portfolios

34 The use of two way fixed effect clustered by time is based on Petersen (2009). The panel data regression with country and year fixed effect controls for unobserved heterogeneity and time trend. This should remove the bias of standard errors if the country and time effects in the data are fixed, however, I find the residuals of the data still show a time effect even after including year dummies in the regression, suggesting that the time effect is not constant. The presence of a non-constant time effect can be intuitive. It suggests that a shock in a particular month to stock market returns may have a large effect on some countries, while having a much smaller effect on other countries. So, according to Petersen (2009), I estimate the standard errors clustered by time to remove the bias of any time effect in the residuals of the data.

seems to be consistent with the vacation hypothesis: the size and the significance of the summer effect increases monotonically with the ranking of the vacation importance and this positive correlation is only present in the portfolios with strong summer seasonals in outbound travel (summer timing 3).

Sections 2 to 7 of Panel B reports the estimates for the portfolios cross sorted based on geographical location, vacation importance and timing of vacations. The strength of the summer effect and the correlation between the size of the effects and vacation measures differ across regions. Only Europe and North America show an overall significant summer return effect. The European region reveals a clear pattern, in line with the vacation hypothesis: Significant lower summer returns only appear in the portfolios with correct summer timing in vacations (summer timing 3), and both the size and t-values of the effect increases with the importance of the vacation rankings. For example, the summer effect for the portfolio with the lowest vacation importance ranking is -0.9% and is insignificant. This compares to a highly significant coefficient estimate of -2.1% for the portfolio with the highest ranking. On the other hand, the evidence in North America does not completely agree with the vacation hypothesis: While there is an overall significant summer effect and a strong summer seasonal in outbound travel, no apparent correlation between the vacation importance ranking and the size of the effect is observed. For example, the summer effect is significantly present in the portfolio with vacation importance ranking 3, but not in the portfolio with vacation importance ranking 4. Lower summer returns are not significantly present in countries located in Africa, Oceania and Latin America. Consistent with the vacation hypothesis, the countries in these regions either have relatively low vacation importance rankings, or have peak vacation seasons falling in non-summer months. The most contradictory evidence against the vacation explanation appears in the portfolios of Asian countries. In particular, despite portfolios with higher vacation importance rankings not exhibiting significantly lower summer returns, the peak vacation season for those countries falls in non-summer months (timing portfolio 1) suggesting alternative explanations for the summer effects in Asia.

Halloween effect

The right table of Panel B reports coefficient estimates and t-statistics of the Halloween regressions for the cross sorted portfolios. The result from all countries shows that the November to April return is, on average, 9% (1.5% per month) higher than the May to October return, with a highly significant t-statistic of 3.07. In addition, the Halloween effects are prevalently present across portfolios and statistically significant in all regions except Oceania. European and Asian countries tend to have a stronger effect than other regions. The strength of the Halloween effect seems, however, unrelated to vacation importance and timing of vacations. For example, although the effect in Europe and North America is present in the portfolio with a strong May-October peak in vacations (timing portfolio 3), the size of the effect is not positively correlated with vacation importance rankings. Asian countries reveal significant Halloween effects in all 3 Halloween timing portfolios, and no correlation between vacation importance and the size of the effect. Africa shows a significant Halloween return effect even though there is no seasonal pattern in outbound travel. Despite portfolios with higher vacation importance rankings in Latin America showing a significant Halloween effect, the effect appears in the portfolios with both Halloween timing 1 and 3, and Oceania countries do not show a significant Halloween effect even though the portfolios are characterised with relatively high vacation importance rankings and correct timing in vacations.

Cross correlation between markets and risk adjustment

The cross sorted portfolios reveal that the magnitude of summer effect is positively correlated with the importance of vacations and the strength of the summer seasonal in outbound travel. However, the positive correlation is more evident in European countries while being less obvious in other regions. This raises another question: Could the effect in other countries be brought over by the cross market correlation with the European countries? How might the risk difference between countries affect the seasonal return pattern in the portfolios and the impact of vacation on seasonal stock returns? I answer these questions in this section.

To control for the cross market correlations, I re-estimate the portfolios' summer (Halloween) effects by incorporating the world market returns [35] as an additional explanatory variable in the panel regressions. Table 4.4 reports the coefficient estimates and t-statistics of the summer effects and Halloween effects for the cross-sorted portfolios. The results for the cross sorted portfolios over the whole sample do not change the conclusion. The summer effect is still stronger in the portfolios with higher vacation importance rankings and significant summer seasonal in outbound travel. Geographically, while the summer effects in other regions tend to fade away, the positive correlation between summer effects and vacation measures becomes even stronger for the European countries after controlling for the cross market correlations. This evidence offers strong support for vacation behaviour as an explanation for the summer effect in European countries, while the faded summer effect in other regions

[35] The world market index is obtained from the Datastream Global Equity Market index, which is a value weighted index consisting of 53 countries.

Table 4.4 Summer return effect and Halloween effect of cross-sorted portfolios adjusted for cross country correlation (1988

The table reports the summer effect and Halloween effect for portfolios controlled for world index returns. The portfolios are constructed by c locations, quartile rankings of vacation importance and summer (Halloween) timing in outbound travel. The coefficient β_{sum} (β_{Hal}) and t-valu $\beta_{sum} Summer_{i,t} + \beta_{world} rworld_t + \varepsilon_{i,t}$ ($r_{i,t} = \alpha + \beta_{Hal} Hal_{i,t} + +\beta_{world} rworld_t + \varepsilon_{i,t}$), where $r_{i,t}$ is the continuously compounded return f variable that equals one if the month falls into July-September in Northern Hemisphere countries and January-March in Southern Hemisphere c Halloween dummy that equals one when month t falls into November to April and zero otherwise. $rworld_t$ is the continuously compounded v based on panel data regressions with country and year fixed effects clustered by month. *** denotes significance at 1% level; ** denotes signific level.

		Summer effect in stock market returns							
Region	Importance	Summer Timing 3		2		1		Overall	
		β_{Sum}	t-value	β_{Sum}	t-value	β_{Sum}	t-value	β_{Sum}	t-value
Overall	4 (High)	-0.012	-3.09 ***	-0.007	-0.26	-0.006	-1.12	-0.011	-3.05 ***
	3	-0.009	-2.11 **	0.039	2.75 ***	-0.008	-1.72 *	-0.007	-2.06 **
	2	-0.004	-1.04	0.008	0.55	-0.007	-1.51	-0.004	-1.25
	1 (Low)	0.003	0.46	0.002	0.36	-0.011	-0.95	0.001	0.12
	Overall	-0.007	-2.18 **	0.004	0.82	-0.008	-1.79 *	-0.006	-2.06 **
Africa	4 (High)								
	3								
	2								
	1 (Low)			0.010	1.44			0.010	1.44
	Overall			0.010	1.44			0.010	1.44
Asia	4 (High)					-0.006	-1.12	-0.006	-1.12
	3					-0.075	-1.82 *	-0.075	-1.82 *
	2	0.001	0.11			-0.013	-1.54	-0.004	-1.03
	1 (Low)	0.003	0.12	-0.001	-0.12	-0.011	-0.95	-0.003	-0.5
	Overall	0.001	0.17	-0.001	-0.12	-0.011	-1.53	-0.004	-0.92
Europe	4 (High)	-0.013	-3.07 ***	-0.007	-0.26			-0.012	-2.94 ***
	3	-0.009	-2.00 **	0.039	2.75 ***			-0.007	-1.68 *
	2	-0.009	-1.35	0.008	0.55			-0.008	-1.07
	1 (Low)	0.000	-0.01	0.011	0.77			-0.001	-0.09
	Overall	-0.010	-2.42 **	0.011	1.11			-0.009	-2.15 **
Latin America	4 (High)								
	3								
	2	0.003	0.34					0.003	0.34
	1 (Low)	0.005	0.75					0.005	0.75
	Overall	0.004	0.77					0.004	0.77
North America	4 (High)	-0.004	-0.82					-0.004	-0.82
	3	-0.007	-1.57					-0.007	-1.57
	2	-0.002	-0.62					-0.002	-0.62
	1 (Low)	-0.008	-0.47					-0.008	-0.47
	Overall	-0.004	-1.44					-0.004	-1.44
Oceania	4 (High)								
	3					-0.005	-1.13	-0.005	-1.13
	2					-0.001	-0.2	-0.001	-0.2
	1 (Low)								
	Overall					-0.003	-0.89	-0.003	-0.89

		Halloween e			
Region	Importance	Hal Timing 3		2	
		β_{Hal}	t-value	β_{Hal}	t-
Overall	4 (High)	0.009	2.92 ***	0.008	1.
	3	0.009	2.92 ***	-0.004	-0.
	2	0.009	2.70 ***	0.006	0.
	1 (Low)	0.013	1.26	0.006	1.
	Overall	0.009	3.410 ***	0.006	1.2
Africa	4 (High)				
	3				
	2				
	1 (Low)			0.014	2.
	Overall			0.014	2.
Asia	4 (High)			0.003	0.
	3			0.067	2.
	2	0.006	1.23	0.007	0.
	1 (Low)			0.003	0.
	Overall	0.006	1.23	0.004	0.
Europe	4 (High)	0.010	3.05 ***	0.030	1.
	3	0.011	3.17 ***	-0.018	-1.
	2	0.015	2.38 **	0.006	0.
	1 (Low)	0.020	1.37	0.011	0.
	Overall	0.012	3.56 ***	0.007	0.
Latin America	4 (High)				
	3				
	2	0.011	1.66 *		
	1 (Low)	0.001	0.09		
	Overall	0.006	0.85		
North America	4 (High)	-0.002	-0.48		
	3	0.004	1.16		
	2	0.001	0.41		
	1 (Low)	-0.011	-0.74		
	Overall	0.001	0.38		
Oceania	4 (High)				
	3	-0.005	-1.12		
	2	0.001	0.14		
	1 (Low)				
	Overall	-0.002	-0.62		

implies lower summer returns can be a product of cross market correlation.

The findings regarding the Halloween effect do not provide much new information. The effect remains statistically significant in many portfolios suggesting that the worldwide prevalence of Halloween effects is not a by-product of market integration.

Table 4.5 reports summer effects and Halloween effects after adjusting for the risk differences between countries[36]. The risk of each country is estimated as the sample period standard deviation of the monthly returns. I then construct risk adjusted returns as each country's monthly returns scaled by the standard deviation. The coefficients and t-statistics are estimated by replacing the dependent variable of the summer (Halloween) effect regressions to risk adjusted returns. Summer effects estimated from risk adjusted returns provide consistent evidence with Table 4.3: Portfolios with reliable summer effects reported in Table 4.3 remain statistically significant after the risk adjustment, and the strength of the summer effects still increases monotonically with the importance of vacation rankings for the whole sample and for European markets.

While the conclusion regarding the summer effect is unchanged, an interesting finding is observed for the risk adjusted Halloween effects in the cross-sorted portfolios over the whole sample and for the European countries: For the portfolios with peak vacation season falling in the May to October period (Halloween timing 3), the size and the significant levels of the Halloween effect now tend to be positively correlated with the vacation importance rankings. One possible implication is that the Halloween effects

[36] I also tested the results for summer (Halloween) effects controlling for both cross market correlation and risk differences between countries. Since the evidence is similar to Table 4.4 the results are not reported here.

Table 4.5 Risk adjusted summer return effect and Halloween effect of cross-sorted portfolios (1988-2010)

The table reports risk adjusted summer effect and Halloween effect for portfolios constructed by cross sorting the countries based on geogr
importance and summer (Halloween) timing in outbound travel. The coefficient β_{sum} (β_{Hal}) and t-values are estimated from the regression $ret_{i,t}/$
$\beta_{Hal}Hal_{i,t} + \varepsilon_{i,t}$), where $ret_{i,t}/std_i$ is the continuously compounded return for country i at month t scaled by the standard deviation of the cou
Summeri,t is a dummy variable that equals one if month falls into July-September in Northern Hemisphere countries and January-March in Sou
Halloweeni,t is the Halloween dummy that equals one when month t falls into November to April and zero otherwise. The estimations are bas
fixed effects clustered by month. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

		Summer effect in stock market returns							
Region	Importance	Summer Timing 3		2		1		Overall	
		βSum	t-value	βSum	t-value	βSum	t-value	β_{Sum}	t-value
Overall	4 (High)	-0.0035	-2.91 ***	-0.0009	-0.23	-0.0021	-1.67 *	-0.0033	-2.84 ***
	3	-0.0028	-2.30 **	0.0042	2.52 **	-0.0029	-2.03 **	-0.0026	-2.52 **
	2	-0.0015	-1.84 *	-0.0016	-0.71	-0.0018	-2.03 **	-0.0016	-2.09 **
	1 (Low)	-0.0001	-0.17	-0.0006	-0.86	-0.0017	-1.26	-0.0006	-0.89
	Overall	-0.0023	-2.43 **	-0.0005	-0.64	-0.0021	-2.62 ***	-0.0020	-2.49 **
Africa	4 (High)								
	3								
	2								
	1 (Low)			0.0008	0.6			0.0008	0.6
	Overall			0.0008	0.6			0.0008	0.6
Asia	4 (High)					-0.0021	-1.67 *	-0.0021	-1.67 *
	3					-0.0204	-2.22 **	-0.0204	-2.22 **
	2	-0.0009	-0.86			-0.0029	-1.93 *	-0.0016	-1.71 *
	1 (Low)	-0.0015	-0.55	-0.0012	-1.18	-0.0017	-1.26	-0.0014	-1.4
	Overall	-0.0010	-0.95	-0.0012	-1.18	-0.0025	-2.01 **	-0.0017	-1.79 *
Europe	4 (High)	-0.0037	-2.92 ***	-0.0009	-0.23			-0.0036	-2.88 ***
	3	-0.0026	-2.22 **	0.0042	2.52 **			-0.0024	-2.08 **
	2	-0.0019	-1.90 *	-0.0016	-0.71			-0.0019	-1.76 *
	1 (Low)	-0.0004	-0.33	-0.0004	-0.24			-0.0004	-0.35
	Overall	-0.0028	-2.55 **	0.0002	0.11			-0.0026	-2.44 **
Latin America	4 (High)								
	3								
	2	-0.0008	-0.65					-0.0008	-0.65
	1 (Low)	0.0003	0.27					0.0003	0.27
	Overall	-0.0001	-0.12					-0.0001	-0.12
North America	4 (High)	-0.0014	-0.89					-0.0014	-0.89
	3	-0.0042	-2.01 **					-0.0042	-2.01 **
	2	-0.0020	-1.41					-0.0020	-1.41
	1 (Low)	-0.0030	-0.68					-0.0030	-0.68
	Overall	-0.0025	-1.92 *					-0.0025	-1.92 *
Oceania	4 (High)								
	3					-0.0022	-1.52	-0.0022	-1.52
	2					-0.0008	-0.65	-0.0008	-0.65
	1 (Low)								
	Overall					-0.0015	-1.35	-0.0015	-1.35

		Halloween ef			
Region	Importance	Hal Timing 3		2	
		β_{Hal}	t-value	β_{Hal}	t-v
Overall	4 (High)	0.0028	3.04 ***	0.0023	1.9
	3	0.0028	2.98 ***	-0.0009	-0.5
	2	0.0023	2.91 ***	0.0023	2.0
	1 (Low)	0.0018	1.79 *	0.0018	2.0
	Overall	0.0026	3.14 ***	0.0018	2.2
Africa	4 (High)				
	3				
	2				
	1 (Low)			0.0033	2.7
	Overall			0.0033	2.7
Asia	4 (High)			0.0020	1.7
	3			0.0056	0.7
	2	0.0026	2.16 **	0.0016	1.3
	1 (Low)			0.0014	1.6
	Overall	0.0026	2.16 **	0.0015	1.8
Europe	4 (High)	0.0030	3.14 ***	0.0041	1.0
	3	0.0031	3.30 ***	-0.0022	-1.4
	2	0.0027	3.06 ***	0.0034	1.8
	1 (Low)	0.0025	2.16 **	0.0021	0.8
	Overall	0.0030	3.50 ***	0.0020	1.5
Latin America	4 (High)				
	3				
	2	0.0033	2.31 **		
	1 (Low)	0.0006	0.33		
	Overall	0.0019	1.58		
North America	4 (High)	-0.0001	-0.07		
	3	0.0035	2.06 **		
	2	0.0018	1.54		
	1 (Low)	-0.0002	-0.06		
	Overall	0.0018	1.71 *		
Oceania	4 (High)				
	3	0.0005	0.36		
	2	0.0010	0.85		
	1 (Low)				
	Overall	0.0007	0.71		

may be partially affected by the seasonal pattern of vacation activities after risk differences between countries are controlled for. In other words, risk may play a role in explaining the Halloween effect as well.

Statistical significance

I examine whether the positive correlation between vacation importance and the size of the summer effects observed in the cross sorted portfolios from Table 4.3 to Table 4.5 is statistically significant in Table 4.6 using regression analysis. Panel A shows whether the strengths of summer (Halloween) effects are different between countries with and without significant summer (May-October period) peaks in outbound travel by running regression Equation (4.5):

$$r_{i,t} = a + \beta_1 Out_{S,i}.S_{i,t} + \theta_1(1 - Out_{S,i}).S_{i,t} + U_{i,t} \tag{4.5}$$

where $r_{i,t}$ is the continuously compounded monthly stock market return for country *i* at month *t*. $Out_{S,i}$ is a dummy variable for vacation timing that equals 1 if country *i* has statistically significant summer months (May-October period) peak in outbound travel for the summer effect regression (Halloween effect regression) and zero otherwise. $S_{i,t}$ is the summer dummy (Halloween dummy) for the summer effect regression (Halloween effect regression). β_1 represents the seasonal return effect for countries with strong summer (Halloween) peak in outbound travel and θ_1 shows the effect for the countries without a summer (Halloween) seasonal in outbound travel. The basic Model (1) is estimated using panel data regression with country and year fixed effects clustered by month. Model (2) controls for cross market correlation by including the world index return as an explanatory variable. Model (3) adjusts for risk difference between countries by replacing the dependent variable with risk adjusted returns[37]. All regressions reveal a similar result, which is consistent with the vacation hypothesis and the evidence observed in Table 4.3 to Table 4.5: The summer effect and the Halloween effect are stronger, and corresponding t-statistics are larger, for the countries with strong summer (Halloween period) seasonals in outbound travel than for those countries that do not have significant summer (Halloween) timing in outbound travel.

Panel B of Table 4.6 shows whether vacation importance has an incremental effect on the summer (Halloween) effect on stock market returns by running regression Equation (4.6):

$$r_{i,t} = a + \lambda_1 . S_{i,t} + \lambda_2 Log\left(\frac{out}{pop}\right)_{i,y} + \lambda_3 S_{i,t} . Log\left(\frac{out}{pop}\right)_{i,y} \quad (4.6)$$

where $Log(out/pop)_{i,y}$ is the natural logarithm of the annual outbound travel per capita for country i in year y. The coefficient of interest is λ_3 in front of the interaction term that represents the incremental effect that outbound travel has on seasonal return effects. Statistically significant estimates of λ_1 from all of the regressions shown in Panel B confirm the presence of a summer effect and a Halloween effect. Consistent with the vacation hypothesis, the coefficient estimates of the interaction term for the summer effect are all negative and statistically significant when controlled for cross market correlation (Model 2) and risk differences between markets (Model 3), indicating that countries with relatively higher outbound travel show a larger summer

[37] The regression result that adjusts both cross market correlation and risk differences is similar to the result from Model (2).

Table 4.6 Incremental effects of vacation behaviour on the summer (Halloween) effect in stock market returns (1988-2010)

Panel A reports the coefficient estimates and t-statistics for regression equation $r_{i,t} = a + \beta_1 Out_{S,i}.S_{i,t} + \theta_1(1 - Out_{S,i}).S_{i,t} + \varepsilon_{i,t}$, where $r_{i,t}$ is the
return for country i at month t, $Out_{S,i}$ is a dummy variable for vacation timing that equals 1 if country i has a statistically significant summer m
travel for the summer effect regressions (Halloween effect regressions) and 0 otherwise. $S_{i,t}$ is the summer dummy (Halloween dummy) for th
regressions). Panel B reports the coefficient estimates and t-statistics for regression equation: $r_{i,t} = a + \lambda_1.S_{i,t} + \lambda_2 Log(\text{out/pop})_{i,y} + \lambda_3 S_{i,t}.Log$
natural logarithm of the annual outbound travel per capita for country i in year y. Panel C reports the coefficient estimates and t-statistics
$\beta_2 Out_{S,i}.Log(\text{out/pop})_{i,y} + \beta_3 Out_{S,i}.S_{i,t}.Log(\text{out/pop})_{i,y} + \theta_1(1 - Out_{S,i}).S_{i,t} + \theta_2(1 - Out_{S,i}).Log(\text{out/pop})_{i,y} + \theta_3(1 - Out_{S,i}).S_{i,t}.Log(\text{out/pop})_{i,y} +$
basic model, Model (2) is estimated by incorporating world index returns as an additional explanatory variable and Model (3) replaces the depend
as monthly returns scaled by the sample period standard deviation. All regressions are estimated with panel data regression with country and y
countries' data for the sample period 1988-2010. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significanc

Panel A: $\boldsymbol{r_{i,t} = a + \beta_1 Out_{S,i}.S_{i,t} + \theta_1(1 - Out_{S,i}).S_{i,t} + \varepsilon_{i,t}}$

	Model	β_1	t-value	θ_1	t-value
Summer	(1)	-0.014	-2.37 **	-0.009	-1.60
effect	(2)	-0.007	-2.12 **	-0.003	-0.65
	(3)	-0.002	-2.42 **	-0.001	-1.89 *
Halloween	(1)	0.016	3.26 ***	0.014	2.14 **
effect	(2)	0.009	3.26 ***	0.007	1.54
	(3)	0.003	3.13 ***	0.002	2.21 **

Panel B: $\boldsymbol{r_{i,t} = a + \lambda_1.S_{i,t} + \lambda_2 Log(out/pop)_{i,y} + \lambda_3 S_{i,t}.Log}$

	Model	λ_1	t-value	λ
Summer	(1)	-0.016	-2.62 ***	-0
effect	(2)	-0.009	-2.74 ***	-0
	(3)	-0.003	-2.70 ***	0
Halloween	(1)	0.016	2.98 ***	-0
effect	(2)	0.008	2.99 ***	-0
	(3)	0.003	2.89 ***	-0

Panel C: $\boldsymbol{r_{i,t} = a + \beta_1 Out_{S,i}.S_{i,t} + \beta_2 Out_{S,i}.Log(out/pop)_{i,y} + \beta_3 Out_{S,i}.S_{i,t}.Log(pop/out)_{i,y} + \theta_1(1 - Out_{S,i}).S_{i,t} + \theta_2(1 - Out_{S,i}).Log(out/pop)_{i}}$

	Model	OUT_S								
		β_1	t-value	β_2	t-value	β_3	t-value	θ_1	t-value	θ_2
Summer	(1)	-0.018	-2.62 ***	-0.005	-1.82 *	-0.004	-1.69 *	-0.010	-1.93 *	0.0
effect	(2)	-0.011	-2.83 ***	-0.005	-1.85 *	-0.004	-1.94 *	-0.005	-1.23	0.0
	(3)	-0.003	-2.61 ***	-0.001	-2.17 **	-0.001	-2.34 **	-0.002	-2.29 **	0.0
Halloween	(1)	0.015	2.77 ***	-0.005	-1.52	-0.001	-0.61	0.016	2.07 **	-0.0
effect	(2)	0.007	2.42 **	-0.005	-1.46	-0.002	-0.92	0.007	1.47	-0.0
	(3)	0.003	2.81 ***	-0.001	-2.46 **	0.000	0.56	0.002	1.93 *	0.0

effect in stock market returns. In contrast, the coefficient estimates of the interaction term for the Halloween effect are all insignificant, which suggests that vacation activities may not be the main source of the Halloween effect.

Regression Equation (4.7) combines Equations (4.5) and (4.6), which reveals the incremental effects outbound travel has on the summer (Halloween) effect for the countries with and without significant summer (May-October period) peaks in outbound travel.

$$r_{i,t} = a + \beta_1 Out_{S,i}.S_{i,t} + \beta_2 Out_{S,i}.Log\left(\frac{out}{pop}\right)_{i,y} + \beta_3 Out_{S,i}.S_{i,t}.Log\left(\frac{out}{pop}\right)_{i,y} + \theta_1(1 - Out_{S,i}).S_{i,t} + \theta_2(1 - Out_{S,i}).Log\left(\frac{out}{pop}\right)_{i,y} + \theta_3(1 - Out_{S,i}).S_{i,t}.Log\left(\frac{out}{pop}\right)_{i,y} + U_{i,t} \tag{4.7}$$

The vacation hypothesis indicates that β_1 is significantly negative for the summer effect and positive for the Halloween effect. The incremental effects for countries with significant summer (May-October period) peaks in vacations are represented by the coefficient estimate β_3 of the interaction term $Out_{S,i}.Log(out/pop)_{i,y}$, which are expected to be significantly negative for the summer effect and positive for the Halloween effect. In addition, the estimates of θ_1 and θ_3 are expected to be insignificant, as it represents the seasonal effect on stock returns and the incremental effect of the countries that do not have the correct timing in vacations. The results reported in Panel C for the summer effect are consistent with the vacation explanation. All three models reveal significantly lower summer returns and negative incremental effects for the countries with strong summer month seasonals in vacations. In addition, the magnitudes of the summer return effect are smaller, and the incremental effects are insignificant, for countries without summer seasonality in vacations. The result for the Halloween regressions suggests that the Halloween effect may not be related to vacation activities, as the estimates of β_1 and θ_1 for the Halloween effects are about the same size and the coefficient estimates β_3 for the incremental effect are insignificant. All models are estimated using the full sample of 34 countries from 1988 to 2010. The incremental effect is not significantly present at the regional level; since countries located in the same region tend to have similar traditions in vacation taking, the insignificant results may be due to limited variation between countries.

4.5.3 Stock market returns and vacation activities

The findings for the summer effect are compatible with the vacation hypothesis, however, the evidence is a bit murky for the Halloween effect. If the seasonal patterns in vacation behaviour are related to the seasonality of stock returns, the vacation activities ought to also have a direct impact on stock market returns. In this section, I investigate directly whether vacations affects stock market returns using the shorter monthly data from 1988 to 1997.

The measure for the monthly vacation activities is $out_t/pop_{y,i}$, which is calculated as the natural logarithm of outbound travel of country i at month t divided by the total population of country i of the affiliated year y. The nature logarithm of the variable is used to reduce the impact of outliners. The basic regression model is based on Equation (4.8):

$$r_{i,t} = \alpha + \beta_{out/pop} out_t/pop_{y,i} + \varepsilon_{i,t} \tag{4.8}$$

where $r_{i,t}$ is the continuously compounded returns for country i at month t . As return and out_t/pop_t are all in the log term, the coefficient estimate $\beta_{out/pop}$ shows the elasticity of return with respect to the outbound travel per capita. All regressions for individual countries are controlled for time trend by including year dummies in the regression. Column 1 of Table 4.7 reports the coefficient estimates and t-statistics from the basic model. In addition, to control for the cross market correlations, the results reported in column 2 are estimated by incorporating world index returns as an additional explanatory variable. Since only the effect of outbound travel is of the interest, the coefficient estimates for the world index returns are not reported in the table[38]. The estimates obtained from both regressions reveal similar results. The point estimates are frequently negative, however, t-statistics are rarely significant. Since I only have a maximum of 10 years data for each country and outbound travel data can be a noisy measure for vacation activities, the country level results might be subject to small sample bias.

The portfolios estimated using panel data regression with country and year fixed clustered by month increase the sample size, while also control for unobserved heterogeneity. Panel B of Table 4.7 reports the coefficient estimates and t-statistics for the portfolios estimated from the basic regression Equation (8), while Panel C shows the results when controlling for cross market correlations by incorporating world index returns in the regressions. Over the whole sample, both regressions reveal that outbound travel has a significant negative impact on stock market returns; the coefficient estimate of -0.009 indicates that a 9% increase in relative outbound travel will cause stock market returns to drop by 0.1%. For example, the average growth rate in outbound travel in July over the full sample is 28%, implying a 0.25% decrease in average stock

[38] I also estimate Equation (8) with risk adjusted returns as the dependent variable. The risk adjusted returns are calculated as monthly returns divided by the sample period standard deviation. The results are not reported here, since the regression provides identical evidence to Equation (8)

Table 4.7 Impact of outbound travel measures on stock market returns (1988-1997)

Panel A reports the coefficient estimates of $out_t/pop_{y,i}$ and corresponding t-statistics for the regression equation $r_{i,t} = \alpha + \beta_{out/pop} out_t/pop_{y,i} + \varepsilon_{i,t}$ in column (1), and $r_{i,t} = \alpha + \beta_{out/pop} out_t/pop_{y,i} + \beta_{world} rworld_t + \varepsilon_{i,t}$ in column (2) for 34 individual countries over the sample period 1988 to 1997. $r_{i,t}$ is the continuously compounded monthly stock market return for country i at month t, $rworld_t$ is the continuously compounded world index return at time t and $out_t/pop_{y,i}$ is the nature logarithm of outbound travels of country i at month t scaled by total population of country i of the affiliated year y. The estimates are controlled for time trend by including year dummies in the regressions. Panel B (and Panel C) presents the coefficient estimates and t-statistics of $out_t/pop_{y,i}$ for the cross-sorted portfolios in the regression equation $r_{i,t} = \alpha + \beta_{out/pop} out_t/pop_{y,i} + \varepsilon_{i,t}$ (and $r_{i,t} = \alpha + \beta_{out/pop} out_t/pop_{y,i} + \beta_{world} rworld_t + \varepsilon_{i,t}$); the portfolios are grouped based on countries' geographical locations and quartile rankings of vacation importance. Panel D reports the coefficient estimates and t-statistics for the regression equation $Sr_{i,y}/std(r)_{i,y} = a + \beta_{Sout} Sout_{i,y}/std(out)_{i,y} + \epsilon_{i,y}$ where $Sr_{i,y}/std(r)_{i,y}$ is the seasonal difference in returns for country i at year y divided by the standard deviation of monthly returns for country i at year y. $Sr_{i,y}$ is the difference between summer months' and non-summer months' returns for the summer effect regression and between November-April returns and May-October returns for the Halloween effect regression.$Sout_{i,y}/std(out)_{i,y}$ is the seasonal difference in outbound travel for country i at year y divided by the standard deviation of year y, and $Sout_{i,y}$ is the difference between summer months' and non-summer months' outbound travel for the summer effect regression and the difference between November-April and May-October outbound travel for the Halloween effect regression. Estimates for individual countries are controlled for time trend by including year dummies in the regressions. The portfolios are based on panel data regression with country and year fixed effects clustered by month. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Panel A: Country Level

Region	Country	Importance	(1) $\beta_{out/pop}$	(1) t-value		(2) $\beta_{out/pop}$	(2) t-value	
Africa	South Africa	1.0	0.009	0.30		-0.006	-0.23	
Asia	China	1.0	-0.004	-0.06		-0.003	-0.05	
	India	1.0	0.097	1.70	*	0.093	1.63	
	Japan	2.0	-0.044	-0.75		0.014	0.33	
	Korea	1.7	0.004	0.25		0.008	0.53	
	Malaysia	2.0	0.013	0.74		0.014	1.01	
	Philippines	1.0	-0.014	-0.21		-0.058	-0.95	
	Singapore	3.8	-0.006	-0.45		-0.004	-0.41	
	Thailand	1.0	0.034	1.39		0.016	0.66	
Europe	Austria	4.0	-0.030	-1.90	*	-0.024	-1.63	
	Belgium	3.1	-0.017	-2.16	**	-0.015	-2.09	**
	Denmark	3.7	-0.013	-1.46		-0.014	-1.68	*
	Finland	3.1	0.009	0.40		0.008	0.36	
	France	3.0	-0.024	-1.60		-0.022	-1.76	*
	Germany	3.7	-0.027	-2.24	**	-0.026	-2.74	***
	Greece	2.0	-0.044	-1.12		-0.037	-1.09	
	Hungary	2.6	-0.017	-0.96		-0.030	-1.32	
	Italy	2.7	-0.013	-1.07		-0.009	-0.81	
	Netherlands	4.0	-0.007	-0.96		-0.006	-0.96	
	Norway	3.2	-0.023	-2.06	**	-0.020	-1.87	*
	Poland	1.8	-0.014	-0.40		-0.008	-0.22	
	Portugal	2.8	-0.020	-1.38		-0.017	-1.32	
	Spain	3.0	0.001	0.09		-0.005	-0.49	
	Sweden	3.6	-0.018	-1.17		-0.016	-1.23	
	Switzerland	4.0	-0.033	-2.07	**	-0.033	-2.59	**
	Turkey	1.2	-0.005	-0.27		-0.005	-0.26	
	United Kingdom	3.2	-0.012	-1.13		-0.006	-0.71	
Latin America	Argentina	1.5	-0.036	-0.95		-0.018	-0.52	
	Chile	1.1	0.015	0.55		0.017	0.6	
	Mexico	1.5	0.012	0.47		0.006	0.25	
North America	Canada	3.4	-0.011	-1.05		-0.006	-0.85	
	United States	2.0	-0.008	-0.84		-0.003	-0.44	
Oceania	Australia	2.1	0.019	0.78		0.024	1.11	
	New Zealand	2.9	0.029	1.59		0.027	1.79	*

Table 4.7 Continued

Panel B: Cross sorted portfolios

Region	Overall			Importance 4			3			2		1	
	$\beta_{out/pop}$	t-value		$\beta_{out/pop}$	t-value		$\beta_{out/pop}$	t-value		$\beta_{out/pop}$	t-value	$\beta_{out/pop}$	t-value
Overall	-0.009	-3.31	***	-0.017	-1.78	*	-0.013	-1.86	*	-0.014	-1.46	-0.006	-1.07
Africa	0.009	0.30		-	-		-	-		-	-	0.009	0.30
Asia	0.007	0.99		-0.003	-0.10		0.062	0.89		-0.018	-0.75	0.010	0.88
Europe	-0.011	-2.34	**	-0.019	-1.84	*	-0.014	-1.96	*	-0.015	-1.00	-0.015	-0.84
Latin America	-0.006	-0.76		-	-		-	-		-0.019	-0.56	0.000	0.04
North America	-0.009	-1.04		-0.011	-1.05		-	-		-0.008	-0.80	-0.006	-0.26
Oceania	0.025	1.48		-	-		0.028	1.50		0.022	0.85	-	-

Panel C: Cross sorted portfolios (controlled for cross market correlation)

Region	Overall			Importance 4			3			2		1	
	$\beta_{out/pop}$	t-value		$\beta_{out/pop}$	t-value		$\beta_{out/pop}$	t-value		$\beta_{out/pop}$	t-value	$\beta_{out/pop}$	t-value
Overall	-0.009	-3.56	***	-0.014	-2.03	**	-0.013	-2.16	**	-0.011	-1.17	-0.006	-1.17
Africa	-0.006	-0.23		-	-		-	-		-	-	-0.006	-0.23
Asia	0.006	1.00		0.007	0.36		-0.009	-0.14		-0.004	-0.16	0.008	0.81
Europe	-0.010	-2.45	**	-0.016	-2.15	**	-0.014	-2.24	**	-0.013	-0.89	-0.014	-0.74
Latin America	-0.005	-0.71		-	-		-	-		-0.002	-0.07	0.000	0.00
North America	-0.005	-0.79		-0.006	-0.85		-	-		-0.006	-0.83	0.009	0.42
Oceania	0.025	1.92	*	-	-		0.027	1.59		0.024	1.29	-	-

Panel D: $Sr_{i,y}/std(r)_{i,y} = a + \beta_{Sout}Sout_{i,y}/std(out)_{i,y} + \epsilon_{i,y}$

	Summer Effect			Halloween Effect		
	β_1	t-value		β_1	t-value	
Overall	-0.165	-2.60	***	-0.026	-0.25	
Africa	-	-		-	-	
Asia	-0.202	-0.90		0.031	0.17	
Europe	-0.165	-2.02	**	0.085	1.22	
Latin America	-0.149	-0.81		-0.252	-0.65	
North America	0.444	0.48		-1.276	-5.00	***
Oceania	0.169	1.22		0.029	0.12	

market returns in July due to the growth in outbound travel. I report the estimates for the portfolios grouped based on quartile rankings of vacation importance for all countries in the first row. In line with the vacation hypothesis, the size and significance of the coefficient estimates increase monotonically with the vacation importance rankings. Specifically, the negative coefficients are statistically significant in portfolios with vacation importance rankings of 4 and 3, while insignificant in portfolios with vacation importance rankings of 2 and 1. This significant coefficient seems, however, to be solely attributed to the European countries. The overall column of both panels reveal that Europe is the only region showing reliable negative coefficients, and the estimates are stronger in higher ranked portfolios (4 and 3) and insignificant in lower ranked portfolios (2 and 1).

It should be noted that these regressions are estimated from a shorter sample period. Appendix 4.3 shows that the summer return effect in this sub-period is much weaker than over the whole sample period. While a positive correlation between vacation importance and the strength of the summer return effect is still present in the estimates from the regressions controlled for work index returns and risk differences (Panels B and C), the effect disappears in the simple univariate regressions in Panel A. In contrast, the Halloween effects are still strong and show a positive correlation between the vacation importance rankings and the strength of the effects for the whole sample, as well as for countries located in Europe. While the significant coefficient estimates of $out_t / pop_{y,i}$ in the portfolios of European countries offer support for the vacation explanation, the lack of explanatory power of $out_t / pop_{y,i}$ on stock market returns in the regions outside Europe does not necessarily rule out seasonal behaviour of vacation activities as an explanation for the seasonal effect in stock returns, because the summer (Halloween) return effect is also very weak for non-European countries in this sub-period.

Since the monthly outbound travel data for many countries also exhibit a summer-winter seasonal pattern, as discussed earlier, the explanatory power of outbound travel could be from the seasonal pattern of other factors unrelated to vacations. As a final check, I conduct an additional regression analysis at annual frequency to remove the possibility of spurious correlation. Using the shorter subsample from 1988 to 1997, I construct two variables to measure the annual seasonal difference of returns and outbound travel, and examine whether the seasonal difference in outbound travels explains the seasonal difference in stock market returns. In particular, I estimate regression Equation (4.9) for portfolios with country and year fixed effects clustered by year:

$$\frac{Sr_{i,y}}{std(r)_{i,y}} = a + \beta_{Sout} \frac{Sout_{i,y}}{std(out)_{i,y}} + \epsilon_{i,y} \tag{4.9}$$

where $Sr_{i,y}/std(r)_{i,y}$ is the seasonal difference in returns for country *i* at year *y* divided by the standard deviation of monthly returns for country i at year y. $Sr_{i,y}$ is the difference between summer month and non-summer month returns for the summer effect regression and between November-April and May-October period returns for the Halloween effect regression. The explanatory variable $Sout_{i,y}/std(out)_{i,y}$ is the seasonal difference in outbound travel for country *i* at year *y* scaled by the standard deviation for the year. $Sout_{i,y}$ is the difference between summer month and non-summer month outbound travel for the summer effect regression, and is the difference between November-April and May-October period outbound travels for the Halloween effect regression. The coefficient estimates are expected to be negative for the summer effect and positive for the Halloween effect. Panel D of Table 4.7 reports the coefficient estimates and t-statistics for the summer effect and Halloween effect regression over the whole sample and by geographical regions. Consistent with earlier findings, seasonal outbound travel has a significant negative impact on the summer effect, while having no impact on the Halloween effect for both the whole sample and the European markets.

In a nutshell, the evidence supports the proposed link between vacation behaviour and the summer effect in stock returns, and the relation is especially strong among European countries. No obvious correlation is observed, however, between vacation activities and the size of the Halloween effect, suggesting that vacation behaviour is not the main contributor to the Halloween effect. Nevertheless, since outbound travel does affect stock market returns and the 6-month Halloween period (May-October) consists of summer months in most of the countries (especially for the European countries), the presence of the Halloween effect may, at best, be partially affected by the seasonal behaviour of vacation activities.

4.5.4 Exogenous liquidity demand and trading activities

Studies suggest two sources that may connect the stock market seasonal returns (Halloween effect and summer return dip) to vacation activities: exogenous liquidity demand (Bouman & Jacobsen, 2002), and trading activities (Hong & Yu, 2009). I construct a proxy for monthly liquidity demand and calculate monthly turnovers for each country, and assess whether taking vacations also affect liquidity demands and trading activities in a way indicated by the vacation hypothesis.

4.5.4.1 Liquidity Demand

Measure of exogenous liquidity demand

The vacation induced change in risk aversion hypothesis proposed in Bouman and Jacobsen (2002) is coherent with the model developed in Campbell, Grossman and Wang (1993). As such, I adopt their model to calculate a proxy for monthly exogenous liquidity demand. The idea is that if the Halloween effects, or lower summer returns, are caused by vacation related liquidity demand, one might also observe a similar seasonal pattern in stock market's exogenous liquidity demand measure, as implied in Campbell, Grossman and Wang (1993) .

To calculate monthly market liquidity demand, I run regression Equation (4.10) every month on the daily market return and turnover data for each country to get the coefficients $\gamma_{i,t}$of the interaction term.

$$r_{i,d+1,t} = \alpha + \beta_{i,t} r_{i,d,t} + \gamma_{i,t}\left(r_{i,d,t} \times v_{i,d,t}\right) + \epsilon_{i,d+1,t} \tag{4.10}$$

$r_{i,d,t}$ is stock market *i*'s return on day *d* in month *t*. The coefficient $\beta_{i,t}$ measures the autocorrelation of daily stock market returns for market *i* in month *t*. $v_{i,d,t}$ is the log turnover of stock market *i* on day *d* in month *t*. The coefficient estimate $\gamma_{i,t}$ of the interaction term reflects the incremental effect of trading volume on daily autocorrelations of stock market *i* in month *t*. The estimated $\gamma_{i,t}$ is the proxy for the monthly liquidity demand measure of market *i*. It represents the average effect that a given volume on day *d* has on the degree of stock return reversals on day *d+1*. The sign of $\gamma_{i,t}$ is expected to be negative, which is empirically confirmed by Campbell, Grossman and Wang (1993). The theoretical argument behind this is when there is a large number of investors selling stocks for exogenous liquidity reasons, the investor (or market makers) who trade with them will demand a higher risk premium that depresses the current stock price. As there is no reason to expect the intrinsic value of stocks to change, however, one should expect the price changes accompanied by large trading volumes to be reversed. The same intuition applies when a large portion of investors demand stocks for exogenous reasons.

Column 1 of Table 4.8 reports the coefficient estimate γ_i of each country for the whole sample period. As expected, most of the countries reveal significant negative point estimates. In Campbell, Grossman and Wang (1993)'s original model, they also include day of the week dummies as in regression Equation (4.11):

$$r_{i,d+1} = \alpha + \sum_{i=1}^{5} \beta_{i,t}(D_i \times r_{i,d}) + \gamma_{i,t}(r_{i,d} \times v_{i,d}) + \epsilon_{i,d+1} \quad (4.11)$$

The liquidity demand measures obtained from Equation (4.11) are reported in Column 2 of Table 4.8. Since the two models provide very similar results, I stay with Equation (10) to obtain the monthly estimates of liquidity demand measures.

Table 4.8 Market Liquidity Measures (1988-2010)

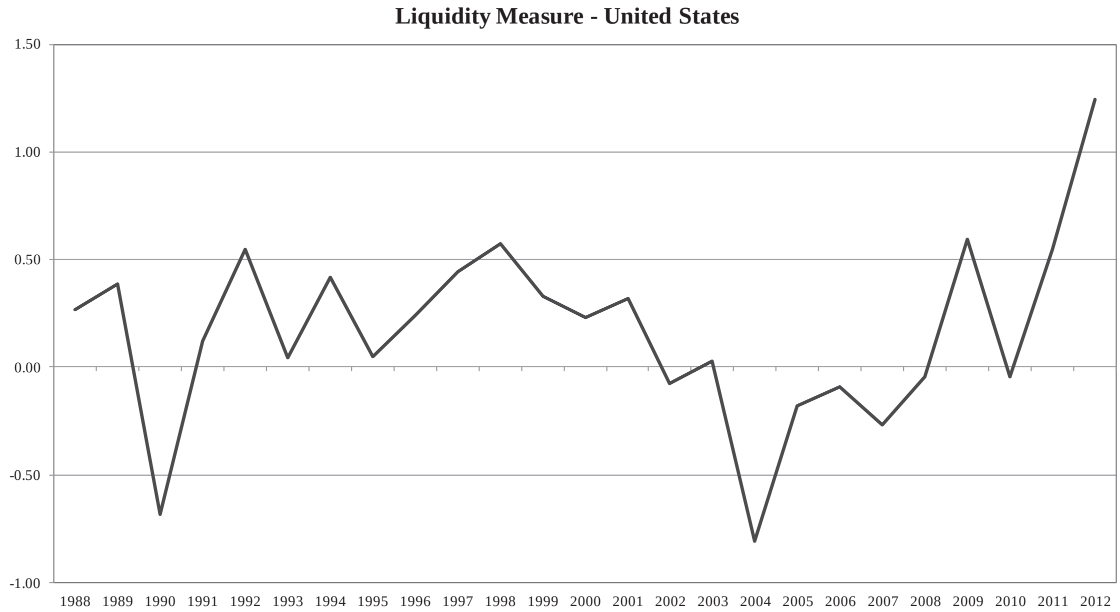
This table reports coefficient estimates and t-statistics for the liquidity measure γ_i from two regression equations: (1) $r_{i,d+1} = \alpha + \beta_i r_{i,d} + \gamma_i(r_{i,d} \times v_{i,d}) + \epsilon_{i,d+1}$, and (2) $r_{i,d+1} = \alpha + \sum_{i=1}^{5} \beta_i(D_i \times r_{i,d}) + \gamma_i(r_{i,d} \times v_{i,d}) + \epsilon_{i,d+1}$ where $r_{i,d}$ is stock market i's return on day d. $v_{i,d}$ is the log turnover of stock market i on day t. $r_{i,d} \times v_{i,d}$ is the interaction of the stock market return and log turnover. D_i is the day of the week dummies from Monday to Friday. T-statistics are calculated based on White (1980) standard errors. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Region	Country	Obs	Start	End	(1) γ_i	(1) t Value		(2) γ_i	(2) t Value	
Africa	South Africa	5252	01/1990	12/2010	-0.08	-4.39	***	-0.09	-4.68	***
Asia	China	4341	01/1994	12/2010	-0.15	-6.47	***	-0.16	-6.55	***
	India	3940	01/1995	12/2010	-0.01	-0.91		-0.03	-1.82	*
	Japan	4981	01/1991	12/2010	-0.09	-5.01	***	-0.10	-5.31	***
	Korea	5411	01/1989	12/2010	-0.03	-1.38		-0.03	-1.68	*
	Malaysia	5426	01/1989	12/2010	-0.23	-13.10	***	-0.23	-12.86	***
	Philippines	5194	01/1990	12/2010	-0.01	-0.52		-0.01	-0.60	
	Singapore	5522	01/1989	12/2010	-0.13	-5.87	***	-0.12	-5.73	***
	Thailand	5396	01/1989	12/2010	-0.15	-7.64	***	-0.16	-7.94	***
Europe	Austria	5651	01/1988	12/2010	-0.15	-6.34	***	-0.15	-6.20	***
	Belgium	5781	01/1988	12/2010	-0.06	-3.80	***	-0.07	-4.07	***
	Denmark	5478	01/1989	12/2010	-0.04	-4.01	***	-0.04	-4.05	***
	Finland	5515	01/1989	12/2010	-0.07	-6.80	***	-0.07	-6.93	***
	France	5561	01/1989	12/2010	-0.06	-4.03	***	-0.06	-4.13	***
	Germany	5565	01/1989	12/2010	0.00	-0.64		0.00	-0.45	
	Greece	5202	02/1990	12/2010	-0.05	-2.34	**	-0.05	-2.65	***
	Hungary	4737	01/1992	12/2010	-0.06	-3.92	***	-0.07	-4.23	***
	Italy	5811	01/1988	12/2010	-0.07	-6.37	***	-0.08	-6.75	***
	Netherlands	5846	01/1988	12/2010	-0.01	-0.32		-0.01	-0.72	
	Norway	5769	01/1988	12/2010	-0.10	-5.47	***	-0.11	-6.16	***
	Poland	4009	01/1995	12/2010	-0.05	-1.68	*	-0.06	-1.84	*
	Portugal	5242	02/1990	12/2010	-0.03	-3.69	***	-0.03	-3.75	***
	Spain	5045	01/1991	12/2010	-0.10	-4.07	***	-0.10	-4.14	***
	Sweden	5774	01/1988	12/2010	-0.11	-6.43	***	-0.12	-6.79	***
	Switzerland	5521	01/1989	12/2010	-0.10	-4.74	***	-0.11	-5.23	***
	Turkey	5392	02/1988	12/2010	-0.11	-7.01	***	-0.11	-7.24	***
	United Kingdom	5819	01/1988	12/2010	-0.15	-6.06	***	-0.16	-6.46	***
Latin America	Argentina	4211	01/1994	12/2010	-0.06	-2.78	***	-0.08	-3.84	***
	Chile	5227	01/1990	12/2010	-0.14	-6.26	***	-0.14	-6.31	***
	Mexico	4912	06/1989	12/2010	-0.06	-3.14	***	-0.08	-4.02	***
North America	Canada	5802	01/1988	12/2010	-0.23	-9.20	***	-0.23	-9.47	***
	United States	5800	01/1988	12/2010	-0.11	-5.41	***	-0.11	-5.24	***
Oceania	Australia	5821	01/1988	12/2010	-0.14	-6.27	***	-0.15	-6.84	***
	New Zealand	5276	01/1990	12/2010	-0.08	-3.66	***	-0.08	-3.71	***

Pastor and Stambough (2003) introduce a liquidity risk factor based on the same intuition as Campbell, Grossman and Wang (1993)'s model. They apply a regression by modifying the interaction term ($r_{i,d,t} \times v_{i,d,t}$) that measures the volume related return reversal to an "order flow" measure constructed as dollar volume signed by current return on the stock in excess of the market, and take the coefficient estimates of the order flow every month as the liquidity measure of the individual stocks. They suggest that the greater the expected reversal of the dollar volume, the lower the stock's liquidity. Their aggregated market liquidity is constructed as the equally weighted average of the liquidity measures of individual stocks. The signed order flow approach might be a better measure for the relative liquidity of individual stocks, but since this study uses market level data, I stay with Campbell, Grossman and Wang (1993)'s approach.

The setting of the regression in estimating the liquidity demands suggests the smaller the estimated value, the higher the liquidity demand will be, which makes the interpretation of the results difficult. To address this problem, I rescale the measure of liquidity demand by multiplying all estimates by -1. In that way, higher values indicate higher liquidity demand. As an illustration, Figure 4.3 plots the annual liquidity demand measure for the US market from 1988 to 2011. The trend of the liquidity measure seems to be consistent with the anecdotal evidence. It tends to be particularly large during major financial crises; for example, the Asian financial crisis in 1997, the recent financial crisis and the European sovereign-debt crisis from 2008 to 2012.

Figure 4.3 Annual liquidity demand measure of the US market from 1988 to 2011



Column 5 of Table 1 shows the means and standard deviations of the monthly liquidity demand measures for individual countries and portfolios. Greece has the highest liquidity demand, while the Netherlands shows the lowest value in the sample. The countries with higher liquidity demand indicate that larger trading volumes have a greater impact on stock prices. Geographically, Asia reveals the highest liquidity demand, while Oceania shows the lowest. Higher volume related return reversal is expected to be observed in the months when there is a large increase, or decrease, in outbound travel. In other words, the estimates of liquidity demands should be higher in months with larger absolute changes in outbound travel. In addition, a lagged (lead) relation can be present between outbound travel and liquidity demands when there is a large increase (decrease) in outbound travel.

Seasonal pattern in liquidity demands

Table 4.9 examines the seasonality in monthly estimated liquidity demand measures for 34 counties. Column 1 shows the mean and standard deviation of change in liquidity demands for each of the 12 calendar months. Insignificant mean values are commonly observed, indicating that changes in liquidity demand are not significantly different from zero and that there is a lack of seasonality in liquidity demand measures. This is confirmed by the insignificant F-values of the seasonality test shown in Column 2. Of the 34 countries, only India, Austria and Germany reveal reliable seasonalities in liquidity demands. To be more specific, I assess whether there is a summer seasonal, or a Halloween seasonal, in liquidity demands by running regressions of monthly estimated liquidity demands on a summer dummy (Halloween dummy) for the summer effect (Halloween effect), year dummies are again included in the regressions of individual countries to control for the time trend. Column 3 and 4 of Table 4.9 report the results. Not surprisingly, countries tend to have insignificant point estimates on the summer and Halloween dummies.

In addition, I check for the presence of the summer seasonal and Halloween seasonal in liquidity demands in cross sorted portfolios using panel data regression with country and year fixed effects clustered by month. Table 4.10 presents the coefficient estimates and t-statistics for the summer effects in the left table and for the Halloween effects in the right table. Consistent with the results of the individual countries, the seasonal patterns of liquidity demand revealed in the cross sorted portfolios are generally unremarkable. Most of the portfolios show insignificant coefficient estimates in both the summer effect and Halloween effect regressions. In addition, even for a few portfolios that do reveal significant summer effects (Halloween effects), the effects seem to be unrelated to vacation behaviour.

Table 4.9 Changes in liquidity demand for each calendar month, the seasonality test, summer and Halloween effect in liquic

The table presents the mean and standard deviation of the changes in liquidity demand every month for 34 countries listed on the basis of count values for tests of monthly difference in means and variances, the F-statistic is derived from the ANOVA (variance-weighted one-way ANOV (significant) difference in variance. Column 3 and 4 provide coefficient estimates and t-statistics of the summer effect and the Halloween effect ir $\gamma_{i,t} = \alpha + \beta_{sum} Summer_{i,t} + YearDummies + \varepsilon_t$ and $\gamma_{i,t} = \alpha + \beta_{Hal} Halloween_{i,t} + YearDummies + \varepsilon_t$. T-statistics for the regressions a errors. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Region	Country	Stat.	(1) Month										
			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
Africa	South Africa	Mean	0.37 **	-0.24	0.22	-0.40	0.40	-0.16	0.14	0.07	-0.35	0.55	-0.36
		S.D.	0.77	1.23	1.66	1.66	1.56	1.10	1.24	1.39	1.20	1.69	1.44
Asia	China	Mean	0.64 **	-0.45 **	0.17	-0.09	0.27	0.03	-0.45	0.26	-0.04	0.16	0.31
		S.D.	1.18	0.85	1.09	0.90	1.23	1.52	1.12	1.18	1.11	1.02	1.49
	India	Mean	-0.64	0.02	0.09	-0.96 **	1.05 *	-0.02	-0.14	-0.04	0.04	-0.32	-0.26
		S.D.	2.16	2.36	1.94	1.59	2.32	2.46	1.41	1.80	1.64	2.11	2.26
	Japan	Mean	0.47	-0.25	-0.09	0.45	-0.34	-0.14	0.40	-0.11	0.09	0.34	-0.66
		S.D.	1.40	2.37	2.31	2.35	2.45	1.90	1.89	2.11	1.73	2.42	2.14
	Korea	Mean	-0.40	-0.20	0.70 *	-0.03	-0.58 *	0.20	0.44	-0.45	0.36	-0.24	-0.03
		S.D.	1.61	1.86	1.74	1.61	1.45	1.70	1.61	2.04	2.16	2.04	1.41
	Malaysia	Mean	-0.15	0.01	-0.04	0.32	-0.54	0.02	0.03	0.14	0.07	-0.01	-0.08
		S.D.	0.90	1.25	1.24	1.06	1.62	1.67	1.11	1.25	1.24	1.18	1.03
	Philippines	Mean	-0.04	0.33	-0.45	0.37 *	-0.25	-0.32	0.30	-0.15	0.13	-0.11	0.03
		S.D.	0.89	1.58	1.45	0.92	1.05	1.22	0.96	1.05	0.97	0.99	1.52
	Singapore	Mean	0.09	-0.37	-0.10	0.90 ***	-0.62 **	0.18	0.05	-0.24	0.09	-0.20	0.04
		S.D.	0.79	1.47	1.40	1.47	1.15	1.44	1.06	1.31	1.50	1.23	1.20
	Thailand	Mean	-0.03	0.17	-0.03	-0.26	0.36	-0.43 *	0.21	0.37 *	-0.50 *	0.62 ***	-0.67 ***
		S.D.	1.46	1.34	1.12	0.76	0.99	1.06	0.99	0.91	1.26	0.99	1.05
Europe	Austria	Mean	0.02	-0.13	0.51 *	-0.40 *	-0.19	0.02	0.36	-0.59 **	0.02	0.33	-0.09
		S.D.	1.33	0.99	1.25	1.10	0.99	0.99	1.22	1.29	1.09	1.30	1.16
	Belgium	Mean	-0.05	-0.05	-0.07	-0.25	0.29	-0.33	0.19	-0.03	0.29	-0.20	-0.05
		S.D.	1.58	1.71	1.55	1.11	1.24	1.38	1.49	1.45	1.40	1.24	1.09
	Denmark	Mean	-0.26	-0.26	-0.07	0.05	0.33	-0.28	0.59 **	-0.73 **	0.11	0.10	0.05
		S.D.	1.14	0.89	1.13	0.83	1.45	1.34	1.29	1.33	0.84	1.29	1.61
	Finland	Mean	0.35 *	-0.43 **	0.45	-0.40	0.00	0.11	-0.01	0.11	-0.29	0.55 *	-0.36
		S.D.	0.80	0.94	1.26	1.29	0.76	0.95	0.86	0.68	1.52	1.37	1.14
	France	Mean	0.10	-0.02	0.25	-0.26	-0.18	0.03	-0.04	0.27	0.07	0.12	-0.12
		S.D.	0.92	1.41	1.70	1.99	2.09	1.44	1.53	1.28	1.54	1.31	1.29
	Germany	Mean	-0.03	-0.88 **	0.84 ***	0.40	-0.68	0.13	0.01	0.19	-0.12	0.26	-0.33
		S.D.	1.27	1.70	1.20	1.86	1.95	1.51	1.41	1.42	1.40	0.84	1.28
	Greece	Mean	0.16	-0.35 *	-0.23	0.12	-0.07	0.32	-0.36	-0.05	0.33	0.63	-0.81
		S.D.	0.87	0.88	1.13	1.17	1.22	1.04	1.07	1.01	1.07	3.19	3.36

Table 4.9 Continued

Region	Country	Stat.	(1) Month										
			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
	Hungary	Mean	0.19	-0.21	-0.01	0.04	0.42 **	-0.38 *	-0.08	-0.30	0.51 **	-0.21	0.07
		S.D.	1.23	1.14	0.86	0.73	0.84	0.94	0.80	0.76	0.88	0.82	1.06
	Italy	Mean	-0.33	0.36	-0.05	-0.18	-0.37	0.34	-0.18	0.15	0.16	0.15	-0.27
		S.D.	1.17	1.59	1.77	2.46	1.71	1.47	1.82	1.38	1.25	1.63	1.45
	Netherlands	Mean	0.00	0.03	0.05	-0.12	0.14	-0.15	-0.14	0.29	-0.22	0.23	0.26
		S.D.	1.14	1.34	1.49	2.19	2.21	1.78	1.60	1.68	1.40	1.42	1.53
	Norway	Mean	-0.11	0.04	0.17	-0.13	-0.07	-0.06	0.29	-0.32	0.44 *	-0.17	-0.01
		S.D.	1.16	1.16	1.57	1.17	0.98	0.92	1.17	1.20	1.09	1.92	2.12
	Poland	Mean	-0.28	0.05	0.24	-0.04	0.10	-0.12	-0.16	-0.24	0.74	-0.09	-0.32
		S.D.	0.88	1.09	1.34	0.90	1.17	1.15	1.26	1.87	1.90	2.00	1.59
	Portugal	Mean	0.04	-0.03	-0.17	0.01	-0.37 *	0.64 **	-0.30	0.02	0.04	0.25	-0.42 **
		S.D.	0.97	1.36	1.37	1.38	0.90	1.05	1.08	1.01	1.22	1.00	0.80
	Spain	Mean	-0.04	0.21	0.07	-0.39	0.15	0.80 *	-0.60	-0.16	0.03	0.45	-0.30
		S.D.	1.21	1.51	1.29	1.36	1.49	1.82	1.83	1.45	1.32	1.53	1.63
	Sweden	Mean	0.01	-0.05	0.30	-0.29	0.07	0.31	-0.25	-0.24	0.34	0.32	-0.32
		S.D.	1.16	1.48	1.43	1.36	1.32	1.60	1.55	1.39	1.45	1.42	1.72
	Switzerland	Mean	0.18	-0.23	0.07	-0.03	-0.29	0.10	0.07	-0.22	0.10	0.51	-0.14
		S.D.	1.32	1.83	1.24	1.89	1.73	1.30	1.33	1.41	1.33	1.84	1.63
	Turkey	Mean	0.63 ***	-0.40 *	0.32	-0.38	0.05	-0.34	0.27	0.14	-0.26	0.11	0.09
		S.D.	0.96	0.90	1.10	1.19	1.10	1.17	0.93	1.29	1.11	1.29	1.10
	United Kingdom	Mean	0.15	0.25	0.06	-0.18	-0.44	1.20 ***	-1.00 **	0.11	-0.13	0.14	-0.08
		S.D.	1.23	1.32	1.94	1.95	1.52	2.04	1.88	1.72	1.36	2.50	2.87
Latin America	Argentina	Mean	0.14	-0.40	0.34 *	-0.14	-0.20	-0.29	0.26	0.30	-0.23	0.14	-0.09
		S.D.	1.12	1.34	0.72	0.91	0.95	1.02	1.18	0.94	1.07	1.20	1.17
	Chile	Mean	0.33	0.14	-0.15	-0.30	0.15	-0.15	0.09	0.24	-0.08	0.10	-0.21
		S.D.	0.96	1.00	1.18	1.05	0.89	1.23	1.20	1.14	1.25	1.32	1.02
	Mexico	Mean	-0.18	0.26	-0.01	-0.06	-0.26	0.03	0.38	-0.38	0.23	0.07	-0.47
		S.D.	0.88	0.91	0.99	1.36	1.40	1.25	1.11	2.05	1.55	1.03	1.25
North America	Canada	Mean	0.03	-0.25	0.32	0.06	-0.09	0.16	-0.32	0.23	-0.52	0.44	0.30
		S.D.	1.60	1.55	1.23	1.41	1.88	1.69	1.47	1.67	2.15	2.21	2.08
	United States	Mean	0.16	-0.42	1.05	-0.80	0.23	-0.17	-0.23	-0.33	0.72	0.08	-0.34
		S.D.	1.89	2.57	3.24	2.95	3.26	3.09	1.65	2.64	3.30	2.51	2.25
Oceania	Australia	Mean	0.17	-0.48	-0.10	0.35	-0.15	0.05	0.14	-0.27	0.41	0.10	-0.49 **
		S.D.	1.21	1.56	1.40	2.00	1.71	1.44	1.56	1.53	1.25	1.17	1.05
	New Zealand	Mean	0.19	-0.50 **	0.23	0.37 *	-0.57 *	0.26	-0.03	-0.18	0.38	-0.05	-0.34
		S.D.	1.15	1.05	0.96	0.87	1.35	0.96	1.09	1.15	1.14	1.06	1.16

Table 4.10 Portfolio summer effect and Halloween effect in liquidity demands (1988-2010)

The table reports coefficient estimates and t-statistics for the summer effect and Halloween effect in liquidity demands for the portfolios con geographical locations, quartile rankings of vacation importance and summer (Halloween) timing in outbound travel. The coefficient β_{sum} (β_{Hal} $\gamma_{i,t} = \alpha + \beta_{sum}Summer_{i,t} + \varepsilon_{i,t}$ ($\gamma_{i,t} = \alpha + \beta_{Hal}Hal_{i,t} + \varepsilon_{i,t}$), where $\gamma_{i,t}$ is the monthly estimates of exogenous liquidity demand for country i at mo one if month falls into July-September in Northern Hemisphere countries and January-March in Southern Hemisphere countries and zero other equals one when month t falls into November to April and zero otherwise. The estimations are based on panel data regressions with country denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

		Summer effect in liquidity demands											
Region	Importance	Summer Timing 3			2			1		Overall			
		β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value	β_{Sum}	t-value		
Overall	4 (High)	-0.101	-1.45		-0.186	-0.89		0.042	0.31	-0.087	-1.35		
	3	-0.062	-0.92		0.124	0.93		-0.006	-0.05	-0.051	-0.85		
	2	-0.074	-1.04		-0.220	-1.45		-0.087	-0.96	-0.084	-1.48		
	1 (Low)	0.132	2.23	**	-0.024	-0.34		0.016	0.18	0.045	1.06		
	Overall	-0.050	-1.14		-0.042	-0.72		-0.024	-0.43	-0.045	-1.28		
Africa	4 (High)												
	3												
	2												
	1 (Low)				0.054	0.40				0.054	0.40		
	Overall				0.054	0.40				0.054	0.40		
Asia	4 (High)							0.042	0.31	0.042	0.31		
	3							0.032	0.06	0.032	0.06		
	2	0.118	0.71					-0.041	-0.35	0.059	0.53		
	1 (Low)	0.367	1.77	*	-0.047	-0.62		0.016	0.18	0.005	0.08		
	Overall	0.160	1.12		-0.047	-0.62		0.006	0.10	0.028	0.51		
Europe	4 (High)	-0.103	-1.41		-0.186	-0.89				-0.106	-1.46		
	3	-0.042	-0.62		0.124	0.93				-0.037	-0.56		
	2	-0.152	-2.06	**	-0.220	-1.45				-0.161	-2.33	**	
	1 (Low)	-0.027	-0.24		-0.390	-2.01	**			-0.043	-0.39		
	Overall	-0.081	-1.53		-0.131	-1.41				-0.084	-1.63		
Latin America	4 (High)												
	3												
	2	0.131	0.82							0.131	0.82		
	1 (Low)	0.147	2.21	**						0.147	2.21	**	
	Overall	0.142	1.93	*						0.142	1.93	*	
North America	4 (High)	-0.074	-0.37							-0.074	-0.37		
	3	-0.292	-1.15							-0.292	-1.15		
	2	-0.348	-1.38							-0.348	-1.38		
	1 (Low)	1.220	1.58							1.220	1.58		
	Overall	-0.239	-1.49							-0.239	-1.49		
Oceania	4 (High)												
	3							-0.008	-0.07	-0.008	-0.07		
	2							-0.132	-1.01	-0.132	-1.01		
	1 (Low)												
	Overall							-0.070	-0.75	-0.070	-0.75		

		Halloween effect in lic			
Region	Importance	Hal Timing 3		2	
		β_{Hal}	t-value	β_{Hal}	t-value
Overall	4 (High)	0.040	0.60	0.031	0.30
	3	0.020	0.35	-0.160	-1.26
	2	-0.022	-0.34	0.074	0.54
	1 (Low)	0.085	1.05	-0.054	-1.07
	Overall	0.019	0.43	-0.026	-0.60
Africa	4 (High)				
	3				
	2				
	1 (Low)			-0.153	-1.32
	Overall			-0.153	-1.32
Asia	4 (High)			0.026	0.23
	3			-0.115	-0.23
	2	-0.161	-0.84	0.079	0.4
	1 (Low)			-0.028	-0.48
	Overall	-0.161	-0.84	-0.006	-0.12
Europe	4 (High)	0.048	0.68	0.056	0.26
	3	0.014	0.22	-0.169	-1.5
	2	0.021	0.29	0.066	0.48
	1 (Low)	0.077	0.76	-0.207	-0.85
	Overall	0.031	0.62	-0.012	-0.14
Latin America	4 (High)				
	3				
	2	-0.093	-0.44		
	1 (Low)	0.100	0.91		
	Overall	0.020	0.19		
North America	4 (High)	-0.063	-0.36		
	3	0.158	0.78		
	2	0.076	0.35		
	1 (Low)	0.097	0.1		
	Overall	0.069	0.51		
Oceania	4 (High)				
	3	-0.019	-0.19		
	2	-0.079	-0.72		
	1 (Low)				
	Overall	-0.049	-0.62		

Liquidity demands and vacation activities

Taking vacations may affect exogenous liquidity demands even it does not cause a significant seasonal pattern in liquidity demands. This section investigates whether vacation activities affect liquidity demands formally using the following regression:

$$\gamma_{i,t} = \alpha + \beta_{i,1}\,|outg|_{i,t-1} + \beta_{i,2}\,|outg|_{i,t} + \beta_{i,3}\,|outg|_{i,t+1} + \epsilon_{i,t} \tag{4.11}$$

where $\gamma_{i,t}$ is the liquidity demand measure for country *i* at month *t* and $|outg|_{i,t}$ is the absolute growth rate of outbound travel at month *t*. I use the absolute value since both large increases and large decreases in outbound travel are expected to have a positive impact on exogenous liquidity demands. In addition, as I infer the liquidity demand could be affected before, during and after people taking vacations, I also include lagged one period and lead one period absolute outbound travel growth rates in the regression. Year dummies are added to control for the time trend in the regressions of individual countries, and the portfolio results are estimated using panel data regression with country and year fixed effects clustered by month. The coefficient estimates of absolute growth in outbound travel are expected to be significantly positive. Since monthly outbound travel data is used to measure the growth rate, the analysis is for the shorter sample period from 1988 to 1997.

Table 4.11 shows the coefficient estimates and t-statistics of each explanatory variable in Equation (4.11) as well as F-statistics for the joint significance test. The results for individual countries are presented in Panel A. Both the t-statistics of absolute outbound travel growth and the F-test of joint significance tend to be insignificant for most of the countries. The European markets seem to have more significant positive

Table 4.11 Impact of outbound travel on liquidity demands (1988-1997)

The table reports coefficient estimates and t-statistics of the regression equation $\gamma_{i,t} = \alpha + \beta_{i,1}\,|outg|_{i,t-1} + \beta_{i,2}\,|outg|_{i,t} + \beta_{i,3}\,|outg|_{i,t+1} + \epsilon_{i,t}$,where $\gamma_{i,t}$ is the liquidity demand measure of country i at month t, $|outg|_{i,t}$ is the absolute growth rate of outbound travels at month t. $|outg|_{i,t-1}$ is the lagged one period absolute growth of outbound travel for country i, and $|outg|_{i,t+1}$ is the lead one period absolute growth of outbound travel for country i. Panel A shows the results for individual countries listed by geographical locations. Year dummies are included in the regressions of individual countries to control for time trend. T-statistics for country level regressions are calculated based on White (1980) standard errors. Panel B reports the results for the portfolios grouped based on the country's geographical locations and Panel C shows the results for the portfolios grouped based on the quartile rankings of vacation impaction for the European countries. The estimates for the portfolios are based on panel data regression with country and year fixed effects clustered by month. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Panel A: Country Level

Region	Country	$\beta_{i,1}$	t-value	$\beta_{i,2}$	t-value	$\beta_{i,3}$	t-value	F-test
Africa	South Africa	-0.83	-1.57	0.55	1.44	-0.05	-0.10	1.40
Asia	China	0.29	1.23	0.18	0.39	-0.61	-1.44	0.63
	India	-1.14	-1.04	-0.18	-0.13	-1.32	-1.61	0.74
	Japan	-2.17	-1.30	-1.26	-0.58	-1.14	-0.57	0.88
	Korea	-0.08	-0.42	0.27	1.55	-0.07	-0.32	0.29
	Malaysia	0.03	0.06	0.73	1.62	-0.02	-0.04	0.53
	Philippines	1.79	1.83 *	-0.55	-0.64	1.31	1.38	2.18 *
	Singapore	0.04	0.10	-0.19	-0.65	0.01	0.02	0.08
	Thailand	-1.00	-1.56	0.52	0.78	0.37	0.72	1.49
Europe	Austria	0.26	0.64	-0.73	-2.32 **	-0.55	-1.47	1.40
	Belgium	-0.10	-0.28	-0.04	-0.13	0.16	0.48	0.06
	Denmark	0.66	2.51 **	0.01	0.05	0.05	0.19	1.73
	Finland	-0.30	-0.74	-0.23	-0.57	0.21	0.47	0.37
	France	0.38	1.25	0.22	0.66	-0.31	-1.09	0.82
	Germany	0.10	0.27	0.26	0.67	0.56	1.44	0.80
	Greece	-0.20	-0.31	0.12	0.19	-0.44	-0.58	0.16
	Hungary	-0.01	-1.53	0.02	2.63 **	-0.02	-2.47 **	0.12
	Italy	0.30	1.59	-0.15	-0.78	0.21	1.22	0.59
	Netherlands	0.15	0.46	0.48	1.66 *	0.11	0.39	0.71
	Norway	0.17	0.45	-0.23	-0.54	0.19	0.47	0.15
	Poland	0.67	0.52	-1.00	-1.21	-0.50	-0.44	0.38
	Portugal	0.01	1.14	0.04	1.89 *	-0.02	-2.11 **	1.21
	Spain	0.23	1.67 *	0.19	1.75 *	0.06	0.61	0.96
	Sweden	-0.53	-1.33	-0.20	-0.48	-0.19	-0.33	0.51
	Switzerland	0.58	0.82	1.88	2.75 ***	0.67	1.03	1.64
	Turkey	-0.28	-1.63	-0.28	-2.13 **	-0.06	-0.33	1.86
	United Kingdom	0.37	0.60	0.28	0.39	0.79	1.83 *	0.54
Latin America	Argentina	-0.30	-0.66	0.69	1.55	-0.62	-1.16	0.79
	Chile	-0.72	-2.09 **	0.60	1.94 *	-0.59	-1.87 *	2.34 *
	Mexico	-0.02	-0.07	-0.41	-1.21	-0.10	-0.32	0.51
North America	Canada	0.41	0.77	-0.23	-0.41	-0.15	-0.29	0.28
	United States	-0.43	-0.37	2.51	1.88 *	-0.91	-0.75	1.51
Oceania	Australia	0.57	0.68	-1.19	-1.64	2.65	2.95 ***	2.62 *
	New Zealand	-0.62	-2.17 **	0.19	0.52	0.27	1.04	0.89

Panel B: Portfolios grouped by geographical locations

Region	$\beta_{i,1}$	t-value	$\beta_{i,2}$	t-value	$\beta_{i,3}$	t-value	F-test
Overall	0.01	0.82	0.05	2.62 ***	-0.01	-1.00	13.53 ***
Africa	-0.83	-1.57	0.55	1.44	-0.05	-0.1	2.12
Asia	-0.16	-0.98	0.13	0.88	-0.10	-0.59	3.20 **
Europe	0.02	1.99 **	0.04	1.99 **	-0.01	-0.88	7.52 ***
Latin America	-0.21	-1.02	0.34	1.13	-0.24	-1.19	2.85 **
North America	0.28	0.52	0.66	1.09	-0.37	-0.73	1.73
Oceania	-0.27	-0.83	-0.02	-0.06	0.86	2.58 ***	2.14 *

Panel C: Portfolios grouped by quartile rankings of vacation importance for European and Oceania Markets

Region	Ranking	$\beta_{i,1}$	t-value	$\beta_{i,2}$	t-value	$\beta_{i,3}$	t-value	F-test
Europe	4 (High)	0.20	1.42	0.18	1.06	-0.01	-0.93	2.71 **
	3	0.03	0.80	0.04	1.31	-0.01	-0.64	3.90 ***
	2	-0.03	-1.15	-0.11	-3.52 ***	0.02	0.12	1.21
	1 (Low)	0.01	0.92	0.05	6.63 ***	-0.01	-0.05	1.61
Oceania	3	-0.67	-2.29 **	0.23	0.6	0.26	0.97	1.01
	2 (Low)	0.59	0.74	-1.16	-1.69 *	2.45	2.93 ***	3.02 **

coefficient estimates than the other markets, however, the F-statistics are also insignificant among the countries.

Portfolio results grouped based on geographical locations are reported in Panel B. Over the whole sample, the combined effect of three periods absolute outbound travel growth is 0.05 and the F-test for joint significance is strongly significant. Geographically, Asia, Europe, Latin America and Oceania reveal significant F-statistics, however, the combined effect for Asia and Latin America is negative, which contradicts the vacation hypothesis. Panel C further assesses the effects for the portfolios grouped based on vacation importance. I only report the results for the portfolios of European markets and Oceania markets, as these are the only two regions that reveal significant positive combined effects. Europe shows evidence consistent with the vacation hypothesis, where portfolios with higher vacation importance rankings (3 and 4) show a stronger combined positive effect, while the F-statistics for lower ranked portfolios (2 and 1) are insignificant. In contrast, a significant F-statistic is only observed in the lower ranked portfolio in Oceania.

Overall, with the absence of significant seasonalities in monthly liquidity demands, the positive impact absolute outbound travel growth has on liquidity demand in the European markets becomes actually more convincing, as the risk of running in to spurious correlation is substantially reduced.

4.5.4.2 Trading activities

Measure of trading activities

I measure trading activities using turnover. The standard turnover measure is the trading volume scaled by total shares outstanding. As Datastream does not provide the number of shares outstanding at market level, I proxy market turnover by dividing trading volume in value $\sum_1^n(Volume_t \times P_t)$ over the total market value of the index $\sum_1^n(P_t \times N_t)$ to filter out the price effect. Column 6 of Table 4.1 reports the mean and standard deviation of the monthly turnover for each individual country (Panel A) and for portfolios grouped based on geographical locations (Panel B), vacation importance (Panel C) and timing of outbound travel (Panel D). There are large differences in average turnover among countries in the sample; China has the highest average turnover (13.73% per month), while Chile has the lowest (0.96% per month).

Since I use volume data at index level, the data are expected to have less extreme observations and data errors than volume data from individual stocks. Nevertheless, I still use log turnover for the regression analysis to maintain consistency with the previous literature and to be able to interpret the results more comparably as percentage changes.

Seasonal pattern in turnovers

Vacation induced lack of trading activities supported by the heterogeneous beliefs model of Hong and Yu (2009) suggests that lower trading volume is accompanied by lower returns during the vacation season. I first reveal whether the implied seasonal pattern is present in the turnover data. Column 2 of Table 4.12 shows the seasonality test of log turnover data for 34 individual countries. Most of the countries reveal pronounced seasonality in log turnovers for the sample period 1988 to 2010. Only Malaysia, Finland and Turkey show insignificant F-statistics in the difference in mean test. Column 1 reports the mean and standard deviation of changes in log turnover for each calendar month. December (January) is the month in which most countries have a significant decrease (increase) in log turnovers, 22 (23) of the 34 countries show significant drops (growth) in log turnovers. In addition, many countries located in Europe tend to have reduced turnovers from June through August and bounce back in September.

I formally examine the presence of the summer effect and the Halloween effect in the turnover data using the regression of monthly log turnover on a summer dummy (Halloween dummy) for the summer effect (Halloween effect). Regressions for individual countries are controlled for time trend by including year dummies and the results are reported in Columns (3) and (4). Consistent with Hong and Yu (2009), the lower summer turnover effect is very strong in North American markets and present in many countries located in Europe. Overall, 26 out of 34 countries have negative point estimates, of which 13 countries are statistically significant. The evidence in the Halloween turnover effect is mixed, with an almost equal amount of positive and negative point estimates observed among the countries. This is also in line with the finding of no significant difference in trading volumes between two 6-month periods in Bouman and Jacobsen (2002).

Table 4.12 Changes in log turnover for each calendar month, the seasonality test, summer and Halloween effect in turnover

Column 1 presents the mean and standard deviation of the changes in log turnover every month for 34 countries listed based on countries' geog
tests of monthly differences in means and variances; the f statistic is derived from the ANOVA (variance-weighted one-way ANOVA of Welcl
difference in variance. Columns 3 and 4 provide coefficient estimates and significance levels of the summer effect and the Halloween effect
log $turnover_{i,t} = \alpha + \beta_{sum} Summer_{i,t} + YearDummies + \varepsilon_t$ and log $turnover_{i,t} = \alpha + \beta_{Hal} Halloween_{i,t} + YearDummies + \varepsilon_t$. T-statistic
(1980) standard errors. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Region	Country	Stat.	(1) Month											
			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Africa	South Africa	Mean	0.17 ***	0.01	0.11 ***	-0.22 ***	0.14 ***	0.06 *	0.09	-0.12	0.03	-0.02	0.01	-0.22
		S.D.	0.21	0.17	0.14	0.17	0.18	0.15	0.54	0.34	0.33	0.24	0.20	0.24
Asia	China	Mean	0.05	-0.20	0.25 *	0.03	0.05	-0.12	-0.02	0.11	-0.10	-0.03	0.16	-0.24
		S.D.	0.52	0.49	0.51	0.29	0.19	0.30	0.26	0.34	0.40	0.45	0.57	0.49
	India	Mean	0.14 *	-0.10 *	0.00	-0.18 **	0.18 **	0.12	0.03	-0.18 ***	0.06	0.09	-0.10 **	0.01
		S.D.	0.28	0.21	0.26	0.30	0.28	0.31	0.20	0.23	0.21	0.27	0.17	0.21
	Japan	Mean	0.03	0.05	0.16 **	-0.10 *	-0.06	0.04	-0.05	0.03	0.05	0.06	-0.05	-0.09
		S.D.	0.18	0.22	0.26	0.23	0.17	0.15	0.15	0.18	0.18	0.37	0.24	0.30
	Korea	Mean	0.10	-0.19 ***	0.11 *	0.02	0.02	-0.09	0.03	-0.04	-0.05	0.19 **	0.06	-0.13
		S.D.	0.27	0.28	0.25	0.36	0.29	0.39	0.49	0.27	0.33	0.39	0.41	0.33
	Malaysia	Mean	0.16 **	0.02	0.00	-0.02	0.05	-0.12 ***	0.08	-0.02	0.04	-0.03	-0.05	-0.05
		S.D.	0.34	0.42	0.35	0.38	0.28	0.20	0.28	0.31	0.29	0.35	0.37	0.29
	Philippines	Mean	0.24 ***	-0.19 **	-0.03	-0.03	0.34 **	-0.12	-0.14	0.14	-0.06	0.30 *	-0.30 **	-0.06
		S.D.	0.33	0.42	0.33	0.31	0.61	0.35	0.63	0.61	0.66	0.67	0.58	0.49
	Singapore	Mean	0.35 ***	-0.15 **	0.07	-0.05	0.13 **	-0.15 ***	-0.01	0.02	-0.04	0.10 *	-0.04	-0.20
		S.D.	0.20	0.30	0.20	0.25	0.24	0.22	0.20	0.25	0.32	0.25	0.31	0.25
	Thailand	Mean	0.42 ***	-0.23 ***	-0.14 *	-0.15 *	0.22 **	0.05	-0.07	0.01	0.11	-0.01	0.12 *	-0.27
		S.D.	0.47	0.35	0.33	0.37	0.37	0.29	0.31	0.32	0.37	0.38	0.31	0.35
Europe	Austria	Mean	0.25 ***	0.02	-0.02	-0.04	-0.03	0.09	-0.02	0.06	0.00	0.04	-0.15 **	-0.10
		S.D.	0.27	0.22	0.16	0.29	0.36	0.38	0.33	0.49	0.26	0.23	0.29	0.26
	Belgium	Mean	0.19 ***	0.05	0.10 **	-0.22 ***	0.08 **	0.05	-0.20 ***	0.06	0.16 ***	-0.01	-0.06	-0.13
		S.D.	0.17	0.25	0.21	0.27	0.18	0.18	0.22	0.25	0.27	0.29	0.22	0.24
	Denmark	Mean	0.36 ***	-0.21 ***	0.02	-0.14	0.13 **	-0.13 **	-0.04	0.15 *	-0.07	0.28	-0.01	-0.17
		S.D.	0.29	0.26	0.30	0.38	0.25	0.26	0.38	0.41	0.26	1.21	0.30	0.33
	Finland	Mean	0.17	-0.04	0.10 *	-0.05	-0.03	-0.13 *	0.02	0.04	0.04	0.15 **	-0.15 **	0.07
		S.D.	0.60	0.47	0.24	0.41	0.43	0.31	0.37	0.29	0.51	0.32	0.32	0.69
	France	Mean	0.18 ***	-0.03	0.06 *	-0.10 **	0.06	0.09 **	-0.03	-0.12 **	0.21 ***	-0.01	-0.09 **	-0.08
		S.D.	0.19	0.13	0.15	0.16	0.20	0.20	0.53	0.25	0.23	0.16	0.21	0.17
	Germany	Mean	0.22 ***	-0.08 *	0.17 ***	-0.23 ***	-0.12	0.00	-0.01	-0.08 *	0.04	0.05	-0.04	-0.13
		S.D.	0.32	0.20	0.19	0.28	0.45	0.42	0.20	0.19	0.29	0.26	0.22	0.23
	Greece	Mean	-0.05	0.04	0.03	-0.16 ***	0.22 ***	-0.06	-0.07	-0.13 *	0.20 **	0.00	-0.04	0.05
		S.D.	0.38	0.33	0.36	0.25	0.33	0.25	0.31	0.31	0.35	0.35	0.32	0.40

Table 4.12 Continued

Region	Country	Stat.	(1) Month											
			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	Hungary	Mean	0.13	-0.05	0.13	-0.13 *	0.26 **	-0.28 **	0.03	-0.04	0.07	0.12	-0.21 ***	0.15
		S.D.	0.46	0.39	0.58	0.31	0.47	0.57	0.40	0.78	0.38	0.31	0.30	0.59
	Italy	Mean	0.32 ***	0.01	0.09 **	-0.11 **	0.15 **	-0.03	-0.05	-0.20 ***	0.25 ***	0.01	-0.07	-0.19
		S.D.	0.22	0.28	0.16	0.25	0.27	0.27	0.30	0.29	0.37	0.25	0.28	0.23
	Netherlands	Mean	0.34 ***	-0.05	0.07 **	-0.10 ***	0.00	-0.02	0.07	-0.04	0.01	0.09 ***	-0.16 **	-0.20
		S.D.	0.13	0.14	0.16	0.15	0.18	0.17	0.21	0.24	0.27	0.15	0.27	0.13
	Norway	Mean	0.18 ***	-0.07 *	0.05	-0.06	-0.01	-0.05	-0.19 ***	0.31 ***	-0.06	0.14 **	-0.08	-0.05
		S.D.	0.26	0.20	0.28	0.29	0.32	0.25	0.31	0.32	0.30	0.29	0.24	0.25
	Poland	Mean	0.26 ***	-0.04	-0.04	-0.11	0.03	-0.09	0.12 *	-0.16 ***	0.13 **	0.05	-0.02	-0.11
		S.D.	0.29	0.29	0.16	0.38	0.20	0.22	0.22	0.20	0.19	0.28	0.39	0.20
	Portugal	Mean	0.11	0.06	0.03	-0.21 **	0.34 **	-0.12	-0.05	-0.27 ***	0.25 ***	-0.02	-0.01	0.18
		S.D.	0.47	0.52	0.46	0.42	0.60	0.41	0.24	0.23	0.26	0.47	0.35	0.47
	Spain	Mean	0.27 ***	-0.07	0.06 *	-0.14 ***	0.06	0.04	-0.03	-0.26 ***	0.27 ***	0.07 *	-0.08	-0.10
		S.D.	0.13	0.22	0.15	0.16	0.20	0.23	0.13	0.21	0.19	0.17	0.21	0.18
	Sweden	Mean	0.23 ***	0.02	-0.01	-0.05	-0.02	-0.11 ***	-0.10 ***	0.19 ***	0.10 *	0.11 ***	-0.15 ***	-0.14
		S.D.	0.19	0.18	0.18	0.19	0.24	0.13	0.14	0.22	0.24	0.17	0.21	0.18
	Switzerland	Mean	0.31 ***	-0.02	0.08 *	-0.13 ***	0.06	0.09	0.07	-0.06	0.01	0.07	-0.08	-0.20
		S.D.	0.17	0.22	0.19	0.21	0.39	0.32	0.21	0.18	0.26	0.19	0.26	0.16
	Turkey	Mean	0.14 **	-0.01	-0.04	-0.05	0.05	-0.10	0.03	-0.07	0.11	0.16 *	0.06	-0.14
		S.D.	0.27	0.40	0.38	0.36	0.39	0.33	0.35	0.34	0.34	0.41	0.41	0.32
	United	Mean	0.32 ***	-0.04	0.09 ***	-0.18 ***	0.03	0.04 *	0.00	-0.09 ***	0.11 **	0.03	-0.06	-0.24
	Kingdom	S.D.	0.14	0.15	0.12	0.13	0.14	0.09	0.15	0.15	0.20	0.12	0.17	0.13
Latin	Argentina	Mean	0.08	-0.04	0.07	-0.17 **	0.13 **	-0.14 *	0.07	-0.04	-0.04	0.24 ***	-0.13	-0.13
America		S.D.	0.31	0.33	0.26	0.29	0.20	0.28	0.33	0.34	0.44	0.31	0.42	0.29
	Chile	Mean	-0.01	-0.27 ***	0.29 ***	-0.06	0.09	-0.17 **	0.04	0.04	-0.21 ***	0.27 ***	0.02	0.01
		S.D.	0.21	0.29	0.34	0.30	0.36	0.32	0.21	0.31	0.27	0.34	0.40	0.24
	Mexico	Mean	0.31 ***	-0.08	-0.06	-0.02	0.08	-0.05	-0.03	-0.02	-0.06	0.12	-0.19 ***	-0.03
		S.D.	0.47	0.22	0.40	0.16	0.35	0.32	0.13	0.25	0.37	0.36	0.23	0.30
North	Canada	Mean	0.25 ***	-0.07 *	0.07 **	-0.10 ***	0.01	0.02	-0.12 ***	0.01	0.09 **	0.05	-0.04	-0.13
America		S.D.	0.19	0.17	0.13	0.11	0.17	0.16	0.13	0.19	0.20	0.16	0.15	0.12
	United States	Mean	0.20 ***	-0.11 ***	0.11 ***	-0.06 **	-0.02	0.01	-0.02	-0.02	-0.02	0.16 ***	-0.15 ***	-0.03
		S.D.	0.10	0.10	0.10	0.10	0.16	0.11	0.15	0.17	0.19	0.09	0.14	0.10
Oceania	Australia	Mean	0.04	0.12 ***	0.08 **	-0.14 ***	0.18 ***	0.02	-0.06	-0.04	0.02	0.01	0.00	-0.18
		S.D.	0.16	0.14	0.15	0.17	0.13	0.19	0.18	0.17	0.22	0.16	0.10	0.15
	New Zealand	Mean	-0.09	0.21 ***	0.12 *	-0.11	0.16 *	-0.18 ***	0.09	-0.02	-0.03	-0.05	0.09 *	-0.14
		S.D.	0.27	0.20	0.29	0.34	0.36	0.24	0.34	0.27	0.37	0.24	0.22	0.33

Table 4.13 shows whether the observed seasonal patterns in turnover are related to vacations through cross sorted portfolios based on geographical locations, vacation importance rankings and timing of vacations. The estimates are based on panel data regression with country and year fixed effects clustered by month. Overall, summer month turnovers are significantly lower than the rest of the year by 3.8% per month, and the effect is significantly present in Europe, North America and Oceania. The results from the cross sorted portfolio based on the all countries reported in the first section reveal that significantly lower summer turnovers are only present in the portfolios with strong summer seasonals in outbound travel (summer timing 3). However, the strength of the effect seems to be unrelated to the rankings of vacation importance. The results of cross sorted portfolios grouped by geographical locations reported in Sections 2 to 7 show that positive correlation between vacation importance rankings and summer turnover effects is more evident in North America than in other regions. In particular, the strength of summer turnover effects in North America increases monotonically with the rankings of vacation importance, while positive correlations are not present in other regions, in fact, Europe even reveals a negative correlation.

The portfolio results for the Halloween seasonal in turnovers are analogous to the findings at the country level; the coefficient estimates tend to be insignificant, and no obvious pattern is observed between vacation behaviour measures and the turnover seasonals.

Table 4.13 Portfolio summer effect and Halloween effect in log turnovers (1988-2010)

The table reports coefficient estimates and t-statistics for the summer effect and Halloween effect in log turnovers for the portfolios const geographical locations, quartile rankings of vacation importance and summer (Halloween) timing in outbound travel. The coefficient β_{sum} (β_{Hal} $Logturnover_{i,t} = \alpha + \beta_{sum}Summer_{i,t} + \varepsilon_{i,t}$ ($Logturnover_{i,t} = \alpha + \beta_{Hal}Hal_{i,t} + \varepsilon_{i,t}$), where $Logturnover_{i,t}$ is the natural logarithm of market turnove variable that equals one if month falls into July-September in Northern Hemisphere countries and January-March in Southern Hemisphere c Halloween dummy that equals one when month t falls into November to April and zero otherwise. The estimations are based on panel data clustered by month. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Region	Importance	Summer effect in log turnovers							
		Summer Timing 3		2		1		Overall	
		βSum	t-value	βSum	t-value	βSum	t-value	β_{Sum}	t-value
Overall	4 (High)	-0.014	-0.66	0.072	0.56	-0.045	-1.53	-0.016	-0.77
	3	-0.067	-3.28 ***	0.138	1.07	-0.051	-1.45	-0.059	-2.78 ***
	2	-0.044	-2.00 **	-0.112	-2.20 **	-0.022	-0.78	-0.043	-2.12 **
	1 (Low)	-0.063	-2.15 **	-0.011	-0.24	-0.012	-0.28	-0.033	-1.27
	Overall	-0.045	-2.61 ***	-0.009	-0.23	-0.030	-1.38	-0.038	-2.32 **
Africa	4 (High)								
	3								
	2								
	1 (Low)			-0.002	-0.07			-0.002	-0.07
	Overall			-0.002	-0.07			-0.002	-0.07
Asia	4 (High)					-0.045	-1.53	-0.045	-1.53
	3					-0.069	-0.28	-0.069	-0.28
	2	-0.060	-2.14 **			0.027	0.68	-0.027	-1.07
	1 (Low)	-0.039	-0.37	0.007	0.20	-0.012	-0.28	-0.002	-0.07
	Overall	-0.056	-1.89 *	0.007	0.20	-0.011	-0.37	-0.017	-0.71
Europe	4 (High)	-0.008	-0.36	0.072	0.56			-0.006	-0.25
	3	-0.067	-3.21 ***	0.138	1.07			-0.060	-2.84 ***
	2	-0.063	-1.95 *	-0.112	-2.20 **			-0.070	-2.29 **
	1 (Low)	-0.131	-3.38 ***	-1.167	-1.43			-0.175	-3.24 ***
	Overall	-0.050	-2.57 **	-0.063	-0.88			-0.050	-2.53 **
Latin America	4 (High)								
	3								
	2	0.033	0.86					0.033	0.86
	1 (Low)	-0.026	-0.78					-0.026	-0.78
	Overall	-0.005	-0.16					-0.005	-0.16
North America	4 (High)	-0.097	-3.78 ***					-0.097	-3.78 ***
	3	-0.063	-2.35 **					-0.063	-2.35 **
	2	-0.041	-2.41 **					-0.041	-2.41 **
	1 (Low)	-0.076	-1.61					-0.076	-1.61
	Overall	-0.060	-3.79 ***					-0.060	-3.79 ***
Oceania	4 (High)								
	3					-0.051	-1.44	-0.051	-1.44
	2					-0.069	-3.14 ***	-0.069	-3.14 ***
	1 (Low)								
	Overall					-0.060	-2.55 **	-0.060	-2.55 **

Region	Importance	Hallow			
		Hal Timing 3		2	
		β_{Hal}	t-value	β_{Hal}	t
Overall	4 (High)	-0.017	-0.84	-0.005	-0
	3	0.012	0.73	-0.194	-1
	2	-0.018	-1.00	0.012	0
	1 (Low)	0.065	2.15 **	-0.057	-2
	Overall	0.000	-0.01	-0.044	-2
Africa	4 (High)				
	3				
	2				
	1 (Low)			-0.100	-3
	Overall			-0.100	-3
Asia	4 (High)			-0.007	-0
	3			0.008	0
	2	-0.002	-0.08	0.015	0
	1 (Low)			-0.053	-1
	Overall	-0.002	-0.08	-0.036	-1
Europe	4 (High)	-0.021	-1.02	0.005	0
	3	0.024	1.29	-0.235	-2
	2	0.000	0.00	0.007	0
	1 (Low)	0.119	3.34 ***	0.506	0
	Overall	0.011	0.65	-0.031	-0
Latin America	4 (High)				
	3				
	2	-0.017	-0.53		
	1 (Low)	-0.039	-0.75		
	Overall	-0.029	-0.91		
North America	4 (High)	0.048	1.96 *		
	3	0.021	1.00		
	2	-0.003	-0.22		
	1 (Low)	0.019	0.28		
	Overall	0.015	1.11		
Oceania	4 (High)				
	3	-0.074	-2.71 ***		
	2	-0.096	-4.78 ***		
	1 (Low)				
	Overall	-0.085	-4.54 ***		

Market turnover and vacation behaviour

This section directly investigates whether there is a linkage between stock market turnovers and vacation activities by applying regression analysis as in Equation (4.12) using monthly turnover and outbound travel data from 1988 to 1997:

$$\log turnover_{i,t} = \alpha + \beta_{out/pop} out_t/pop_{y,i} + \varepsilon_{i,t} \tag{4.12}$$

where $\log turnover_{i,t}$ is the natural logarithm of market turnover of country *i* at month *t* and $out_t\ /pop_{y,i}$ is the natural logarithm of outbound travel of country *i* at month *t* divided by the total population of country *i* in the affiliated year *y*. Regressions for individual countries are controlled for time trends by including year dummies in the regression. For portfolios, I use panel data regression with country and year fixed effects clustered by month. The relative outbound travel measure $out_t/pop_{y,i}$ is expected to be negatively correlated with the stock market turnovers. Panel A of Table 4.14 reports the results for individual countries, with 23 out of the 34 countries revealing negative point estimates, in which 9 countries are statistically significant, while 4 countries exhibit significant positive coefficient estimates. Panel B reports the coefficient estimates and t-statistics for portfolios cross sorted by geographical locations and vacation importance rankings. Over the whole sample, relative outbound travel shows a significant negative impact on stock market turnover. In particular, a 1% increase in relative outbound travel will lead stock market turnover to drop by 0.27%, however, the strength of the negative impact varies across regions. Negative slope estimates are significantly presented in Asia, Europe and North America, with a 1% increase in relative outbound travel leading stock market turnover to drop by 0.126% in Asia, 0.214% in Europe and 0.102% in North America.

Table 4.14 Impact of outbound travel measures on log turnovers (1988-1997)

Panel A reports the coefficient estimates and t-statistics of the regressions: $\log turnover_{i,t} = \alpha + \beta_{out/pop} out_t/pop_{y,i} + YearDummies + \varepsilon_{i,t}$, where log $turnover_{i,t}$ is the nature logarithm of market turnovers for country i at month t, $out_t/pop_{y,i}$ is the nature logarithm of outbound travel of country *i* at month *t* divided by total population of country *i* for the affiliated year *y*. T-statistics are calculated based on White (1980) standard errors. Panel B reports regression results of portfolios cross sorted on the basis of countries' geographical locations and quartile rankings of vacation importance. Panel C reports the coefficient estimates and t-statistics for the regression equation $Sto_{i,y}/std(to)_{i,y} = a + \beta_{Sout} Sout_{i,y}/std(out)_{i,y} + \epsilon_{i,y}$ where $Sto_{i,y}/std(to)_{i,y}$ is the seasonal difference in log turnovers for country *i* at year y divided by the standard deviation of monthly logturnovers for country i at year y. $Sto_{i,y}$ is the difference between summer months and non-summer months logturnovers for the summer effect regression and between November-April and May-October period logturnovers for the Halloween effect regression. $Sout_{i,y}/std(out)_{i,y}$ is the seasonal difference in outbound travel for country i at year y divided by the standard deviation of outbound travel in year y. $Sout_{i,y}$ is the difference between summer months and non-summer months outbound travel for the summer effect regression and the difference between November-April and May-October outbound travel for the Halloween effect regression. The estimates for the portfolios in Panel B and Panel C are obtained from panel data regression with country fixed and year fixed effects clustered by time. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Panel A: Country Level

Region	Country	Vacation Importance	Log turnover $\beta_{out/pop}$	t-value	
Africa	South Africa	1.0	-0.137	-0.75	
Asia	China	1.0	-0.054	-0.13	
	India	1.0	0.899	2.15	**
	Japan	2.9	-0.197	-0.72	
	Korea	1.9	-0.111	-1.49	
	Malaysia	2.6	0.088	1.01	
	Philippines	1.1	0.227	0.57	
	Singapore	4.0	-0.195	-2.21	**
	Thailand	1.5	0.137	1.11	
Europe	Austria	2.4	0.002	0.02	
	Belgium	1.9	-0.115	-2.77	***
	Denmark	2.5	-0.276	-2.18	**
	Finland	3.0	-0.262	-1.65	
	France	2.4	0.162	1.20	
	Germany	2.0	0.004	0.09	
	Greece	1.6	-0.255	-2.06	**
	Hungary	1.6	-0.505	-2.89	***
	Italy	3.1	-0.016	-0.20	
	Netherlands	4.0	0.037	1.08	
	Norway	3.6	-0.251	-4.63	***
	Poland	1.2	-0.098	-1.03	
	Portugal	2.0	-0.190	-1.13	
	Spain	2.9	-0.129	-2.53	**
	Sweden	3.7	-0.187	-4.54	***
	Switzerland	3.4	0.347	2.88	***
	Turkey	2.4	-0.005	-0.09	
	United Kingdom	4.0	-0.004	-0.11	
Latin America	Argentina	1.2	0.290	3.52	***
	Chile	2.3	-0.082	-0.71	
	Mexico	1.5	-0.035	-0.36	
North America	Canada	3.4	-0.132	-2.70	***
	United States	3.0	-0.026	-0.82	
Oceania	Australia	3.8	0.186	1.90	*
	New Zealand	3.5	0.000	0.00	

Table 4.14 Continued

Panel B: Portfolios cross sorted based on geographical locations and quartile rankings of vacation importance

Region	Log Turnover							
	Importance 4		3		2		1	
	$\beta_{out/pop}$	t-value	$\beta_{out/pop}$	t-value	$\beta_{out/pop}$	t-value	$\beta_{out/pop}$	t-value
Overall	-0.036	-0.81	-0.268	-7.37 ***	-0.092	-1.73 *	-0.069	-3.09 ***
Africa							-0.137	-0.75
Asia	-0.357	-2.43 **	-1.009	-2.12 **	-0.205	-1.53	-0.031	-0.59
Europe	-0.013	-0.27	-0.266	-7.12 ***	-0.053	-0.83	-0.139	-1.92 *
Latin America					0.262	3.76 ***	-0.010	-0.22
North America	-0.132	-2.70 ***			-0.030	-0.87	0.003	0.03
Oceania			-0.044	-0.44	0.222	2.23 **		

Panel C: $Sto_{i,y}/std(to)_{i,y} = a + \beta_{Sout}Sout_{i,y}/std(out)_{i,y} + \epsilon_{i,y}$

	Summer Effect		Halloween Effect	
	β_1	t-value	β_1	t-value
Overall	0.046	0.61	-0.073	-0.57
Africa	-	-	-	-
Asia	-0.399	-1.31	-0.459	-2.33 **
Europe	0.150	1.12	0.153	1.02
Latin America	-0.083	-0.98	0.369	0.65
North America	-0.877	-0.98	0.583	0.72
Oceania	0.055	0.28	0.685	1.69 *

The results from the quartile ranked portfolios based on vacation importance provide mixed evidence. The first row of Panel B reveals that negative coefficient estimates are significantly present in all vacation importance ranked portfolios except Portfolio 4. Geographically, the explanatory power of the outbound travel measure in North America is stronger in the portfolio with higher vacation importance ranking (Portfolio 4). In addition, the summer effect and Halloween effect in turnovers in this portfolio for this sub-period shown in Appendix 4.4 are also significant, indicating that outbound travel has a negative impact on stock market returns and may also contribute to the seasonal turnover effects in North America. Since significant summer, or Halloween, effects in stock market returns are, however, not observed in North America the evidence suggests that the seasonal pattern in turnover induced by vacation activities is not large enough to have an impact on stock returns and the seasonal pattern in stock returns in North America. This contradicts Hong and Yu (2009)'s argument that lower turnover caused by people taking vacations leads to lower returns. While portfolios of Asian countries show significant explanatory power in outbound travel measures in higher vacation importance ranked portfolios, the summer effect and the Halloween effect in turnover for this sub-period (Appendix 4.4) is not statistically significant. This implies that outbound travel may have a negative impact on turnover, but does not evoke seasonality in stock market turnover in Asian countries. In Europe, the summer effect and Halloween effect on turnover in this sub-period are not statistically significant except for the portfolio with vacation importance ranking 1, and the outbound travel measure also only shows marginal explanatory power in this same portfolio. Table 4.7 reveals, however, that outbound travel in the same portfolio does not have a significant effect on stock market returns and the portfolio does not reveal seasonal patterns in stock returns either. In contrast, portfolios with higher vacation importance ranking (3 and 4) reveal significant seasonal effects in stock returns, but insignificant seasonal effects in turnovers. The evidence again conflicts with Hong and Yu (2009)'s proposition. The results from Africa, Latin America and Oceania are unremarkable. The coefficient estimates are either insignificant, or significant with unexpected positive signs. As a final check, I also run a regression similar to Equation (9), replacing the dependent variable $Sr_{i,y}/std(r)_{i,y}$ with the annual seasonal difference in log turnovers $Sto_{i,y}/std(to)_{i,y}$ where $Sto_{i,y}$ is the difference between summer month and non-summer month log turnovers for the summer effect regression and the difference between November-April and May-October period turnovers for the Halloween effect regression and $std(to)_{i,y}$ is the standard deviation of annual log turnovers for country *i* in year *y*. Panel C of Table 4.14 presents the results. I am only interested in the estimates for the North American portfolio since it is the only region revealing evidence consistent with the vacation caused seasonal turnover effect explanation. The coefficient estimates for both regressions are insignificant, but with the expected negative signs. Since the regressions for the North America portfolio are run with only 20 observations, despite the insignificant coefficient estimates, the evidence is still inclined to support vacation activities as an explanation for the seasonal pattern of market turnover in North America.

4.6 Conclusion

This paper examines the linkage between vacation behaviour and seasonal patterns of stock market returns using 34 countries' outbound travel data as a more direct proxy for vacation activities. The empirical results over the whole sample offer strong support for the seasonal behaviour of vacation activities as an explanation for the summer effects, and the evidence is especially strong for the European markets. In particular, cross sorted portfolios based on vacation importance rankings and summer timing in vacations show that the strength of the lower summer returns is stronger in the portfolios with higher vacation importance rankings and peak vacation seasons falling in summer months. In addition, outbound travel has a significant negative impact on stock market returns, and the strength of the explanatory power of outbound travel is also positively correlated with vacation importance rankings. The evidence is robust to the adjustment of cross market correlations, risk differences between countries and possible spurious correlations, however, similar evidence is not observed in other regions.

For the Halloween effect, I show that the prevalence of the Halloween effect worldwide is not caused by cross market correlation, however, the strength of the effect is not correlated with the measure of vacation behaviour. Since the 6-month period of May-October for the Halloween effect comprises summer months in many countries, vacation activities may, at best, only partially explain the Halloween effect.

In addition, I also examine the impact of outbound travel on liquidity demand and turnovers. The measure of liquidity demand does not reveal a significant seasonal pattern, however, the absolute outbound travel growth does have a positive impact on liquidity demand. The evidence of the European portfolios also reveals a positive correlation between the strength of the impact and the vacation importance rankings of the portfolios. Combined with the finding of a significant impact of vacation activities on stock market returns and summer effects in the European portfolios, the evidence offers strong support to the vacation induced changes in exogenous liquidity demand and the risk aversion hypothesis proposed in Bouman and Jacobsen (2002). While absolute outbound travel growth in other regions either has limited explanatory power for liquidity demands, or reveals unexpected signs in the coefficient estimates, or shows patterns in the coefficient estimates inconsistent with the vacation hypothesis, vacation activities also lack explanatory power on the stock market returns of the portfolios of these regions.

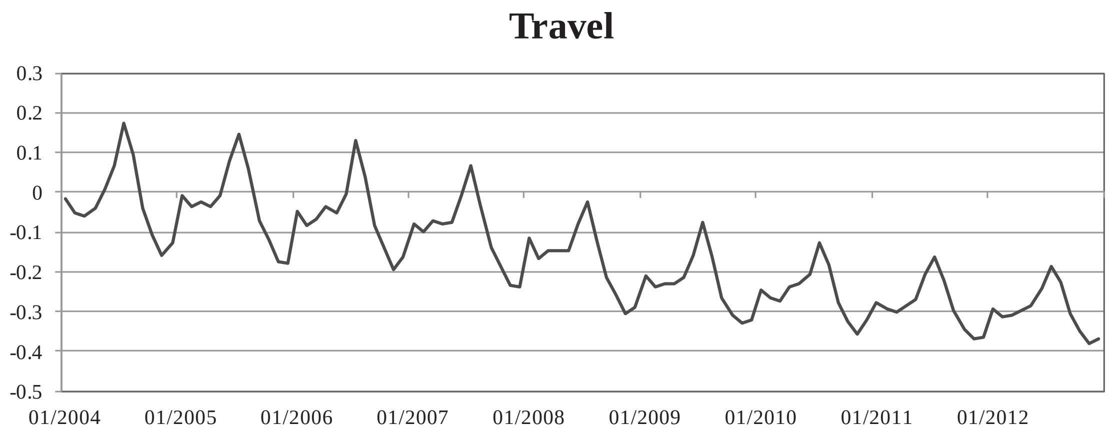
Significant lower summer turnovers are present in many countries and also in the portfolio of European, North American and Oceania markets. Despite this, only the portfolios of North American markets reveal patterns consistent with the vacation hypothesis, in that the strength of summer turnover effects increases monotonically with the portfolio's ranking of vacation importance, and the explanatory power of outbound travel on stock market turnover is stronger in the portfolios with high vacation importance rankings. As analysis of the stock market returns data shows, however, that the summer return effect in North America is not related to vacation activity measures, the evidence suggests that vacations do have an impact on turnover, but that the effect is not strong enough to affect stock market prices. In addition, while the summer turnover effects in the European portfolios are not related to vacation activity, lower summer returns in Europe are strongly related to vacations. Evidence in both the North American portfolios and the European portfolios casts doubt on Hong and Yu (2009)'s inference that lower summer returns in the stock market are a product of a vacation induced lack of trading activity.

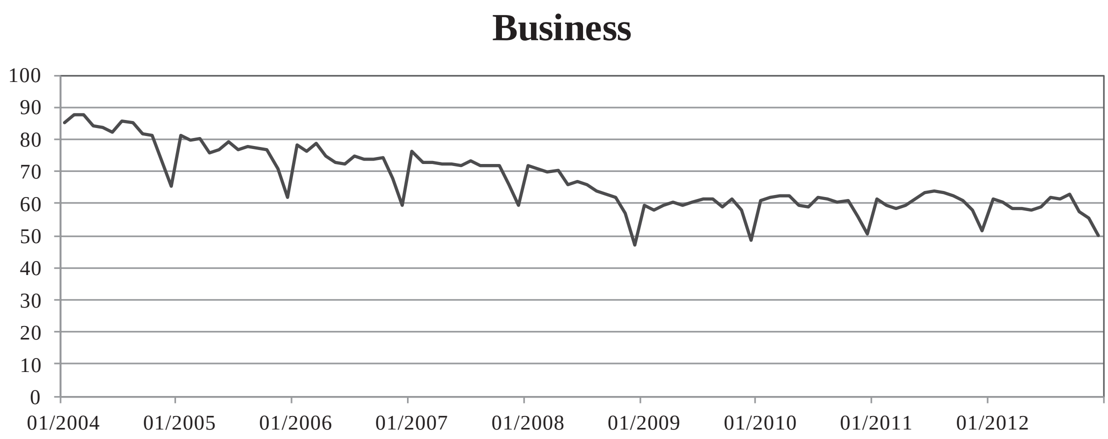
Appendix 4.1. Quartile rankings of vacation importance for 34 countries every year from 1988 to 2010

The table provides each country's annual quartile ranking of importance of vacation measure calculated as annual outbound travel divided by tota
of the annual vacation importance measure from 1988 to 2010. Overall column is the country's quartile ranking on vacation importance measured

Country	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	200
Austria	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Netherlands	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Switzerland	.	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Singapore	.	1	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Germany	.	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3
Denmark	.	3	3	3	3	3	4	3	3	4	4	4	4	4	4	4	4	4	4
Sweden	3	4	4	3	3	3	3	3	3	3	4	4	4	4	3	3	4	4	4
Canada	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	3
United Kingdom	3	3	3	3	3	3	3	3	3	3	3	4	4	3	3	3	4	3	4
Norway	2	2	3	2	3	2	3	3	3	3	3	3	3	3	4	4	3	4	4
Finland	.	3	3	3	2	2	3	2	3	3	3	3	3	4	4	4	3	3	3
Belgium	3	3	3	3	3	3	3	3	3	3	4	3	3	3	3	3	3	3	3
France	.	3	3	3	3	3	3	4	3	3	3	3	3	3	3	3	3	3	3
Spain	.	.	.	3	3	3	3	3	4	3	3	3	3	3	3	3	3	3	3
New Zealand	.	.	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
Portugal	.	.	4	4	4	4	1	3	2	2	3	3	3	3	3	2	2	2	3
Italy	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3
Hungary	.	.	.	.	1	3	4	4	4	4	2	2	2	2	2	3	3	3	2
Australia	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Greece	.	.	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Japan	.	.	.	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
United States	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Malaysia	.	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Poland	.	.	.	.	.	.	.	1	1	1	2	2	2	2	2	2	2	2	2
Korea	.	1	1	1	1	1	2	2	2	2	1	1	2	2	2	2	2	2	2
Argentina	.	.	.	.	.	.	2	2	2	2	2	2	2	2	1	1	1	1	1
Mexico	.	1	1	1	1	1	1	1	1	1	2	2	1	1	2	2	2	2	2
Turkey	1	2	2	1	2	1	1	2	1	1	1	1	1	1	1	1	1	1	1
Chile	.	.	1	1	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1
China	.	.	.	.	.	.	1	1	1	1	1	1	1	1	1	1	1	1	1
India	.	.	.	.	.	.	.	1	1	1	1	1	1	1	1	1	1	1	1
Philippines	.	.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
South Africa	.	.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Thailand	.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Appendix 4.2. Google Trend search volume from 2004 to 2012





Appendix 4.2 plots Google search volume from 2004 to 2012. The upper chart shows the total search volume within the travel category. The value measures the percentage growth of the worldwide search volume in the travel category at time *t* relative to the search volume at starting date of the database 01/Jan/2004. The words most often searched within the travel category is “hotel (s)” “flights” “beach” “travel” and “train”. The lower chart shows the total search volume for the word “business” within the travel category. The number represents the search volume of the term relative to the total number of searches done on Google over time, and the data is normalized to present on a scale from 0 to 100. The most searched terms with the word “business” within the

travel category are “business class” “business hotel” “business travel” “business air” and “business flights”. The data is obtained from Google Trends.

These two charts give us a taste on whether the number of business trips exhibit seasonality. As it can be seen, consistent with conventional wisdom and the results from outbound travel data, interests in searching under the travel category reveal pronounced seasonality, and it persistently peaks around the Northern Hemisphere summer time and bottoms in December. In contrast, the search volume for the term “business” under the travel category displays less seasonality, the number of searches tend to spread evenly except for a significant drop in December which may due to the Christmas season. This evidence implies that the bias due to measurement error results from the inclusion of business travellers in the outbound travel data is mitigated, and using the outbound travel data to proxy the timing of vacation is appropriate.

Appendix 4.3. Summer effect and Halloween effect in stock market returns for cross sorted portfolios (1988-1997)

The table reports the summer effect and Halloween effect in stock market returns for portfolios grouped by geographical locations and vacati period from 1988 to 1997. The coefficient β_{sum} (β_{Hal}) s and t-values in Panel A are estimated from the regression equation $r_{i,t} = \alpha + \beta_{sum}$ where $r_{i,t}$ is the continuously compounded return for country i at month t, $Summer_{i,t}$ is a dummy variable that equals one if the month falls into Ju and January-March in Southern Hemisphere countries and zero otherwise, and $Halloween_{i,t}$ is the Halloween dummy that equals one when otherwise. Panel B reports coefficient estimates and t-statistics for the summer effect and Halloween effect after controlling for cross market co additional explanatory variable. Panel C reports the summer effect and Halloween effect that controls both cross market correlation and risk dif are adjusted by replacing the dependent variable with risk adjusted returns calculated as monthly returns divided by the sample period standard c panel data regressions with country and year fixed effects clustered by month. *** denotes significance at 1% level; ** denotes significance at 5%

Panel A: Basic model

Summer effect in stock market returns

Region	Overall			Importance 4			3			2			1		
	β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value	
Overall	-0.011	-1.46		-0.016	-1.63		-0.013	-1.49		-0.011	-1.58		-0.005	-0.51	
Africa	0.007	0.53		-	-		-	-		-	-		0.007	0.53	
Asia	-0.010	-0.87		-0.009	-0.81		-0.127	-2.22	**	0.000	-0.01		-0.012	-0.92	
Europe	-0.015	-1.61		-0.019	-1.67	*	-0.011	-1.18		-0.023	-1.83	*	-0.003	-0.13	
Latin America	-0.001	-0.12		-	-		-	-		-0.018	-0.78		0.005	0.38	
North America	-0.005	-0.74		-0.006	-0.94		-	-		-0.003	-0.38		-0.010	-0.50	
Oceania	-0.008	-1.01		-	-		-0.015	-1.34		-0.004	-0.49		-	-	

Halloween effect i

Region	Overall			Importance 4			
	β_{Hal}	t-value		β_{Hal}	t-value		β
Overall	0.013	1.94	*	0.014	2.02	**	0.01
Africa	0.022	2.25	**	-	-		-
Asia	0.010	1.01		0.016	1.57		0.03
Europe	0.018	2.59	***	0.017	2.09	**	0.01
Latin America	0.003	0.24		-	-		-
North America	0.001	0.26		0.000	0.03		-
Oceania	-0.003	-0.44		-	-		-0.01

Panel B: Controlled for cross-market correlations

Summer effect in stock market returns

Region	Overall			Importance 4			3			2			1		
	β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value	
Overall	-0.009	-1.74	*	-0.014	-2.10	**	-0.011	-1.66	*	-0.009	-1.63		-0.003	-0.45	
Africa	0.009	0.72		-	-		-	-		-	-		0.009	0.72	
Asia	-0.009	-1.13		-0.011	-1.26		-0.075	-1.82	*	0.002	0.23		-0.012	-1.12	
Europe	-0.013	-1.90	*	-0.016	-2.08	**	-0.009	-1.33		-0.021	-1.86	*	-0.003	-0.13	
Latin America	0.002	0.23		-	-		-	-		-0.008	-0.43		0.007	0.61	
North America	-0.003	-0.67		-0.005	-0.89		-	-		-0.002	-0.38		-0.005	-0.27	
Oceania	-0.006	-0.90		-	-		-0.015	-1.80	*	-0.001	-0.07		-	-	

Halloween effect i

Region	Overall			Importance 4			
	β_{Hal}	t-value		β_{Hal}	t-value		β
Overall	0.011	2.31	**	0.013	2.42	**	0.01
Africa	0.022	2.35	**	-	-		-
Asia	0.008	1.10		0.012	1.47		0.06
Europe	0.017	2.86	***	0.016	2.51	**	0.01
Latin America	0.002	0.21		-	-		-
North America	-0.001	-0.15		-0.002	-0.36		-
Oceania	-0.005	-0.87		-	-		-0.01

Panel C: Controlled for cross-market correlations and risk difference between countries

Summer effect in stock market returns

Region	Overall			Importance 4			3			2			1		
	β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value		β_{Sum}	t-value	
Overall	-0.002	-1.95	*	-0.003	-2.26	**	-0.002	-1.86	*	-0.001	-1.59		0.000	-0.29	
Africa	0.002	0.72		-	-		-	-		-	-		0.002	0.72	
Asia	-0.001	-1.33		-0.002	-1.26		-0.014	-1.82	*	0.000	0.36		-0.002	-1.29	
Europe	-0.002	-2.05	**	-0.003	-2.29	**	-0.002	-1.53		-0.003	-2.09	**	0.000	0.18	
Latin America	0.000	0.36		-	-		-	-		-0.001	-0.33		0.001	0.67	
North America	-0.001	-0.68		-0.001	-0.89		-	-		-0.001	-0.38		-0.001	-0.27	
Oceania	-0.001	-0.81		-	-		-0.003	-1.80	*	0.000	-0.05		-	-	

Halloween effect i

Region	Overall			Importance 4			
	β_{Hal}	t-value		β_{Hal}	t-value		β
Overall	0.002	2.40	**	0.002	2.42	**	0.00
Africa	0.004	2.35	**	-	-		-
Asia	0.001	1.32		0.002	1.47		0.01
Europe	0.003	2.95	***	0.003	2.66	***	0.00
Latin America	0.000	0.15		-	-		-
North America	0.000	-0.15		-0.001	-0.36		-
Oceania	-0.001	-0.74		-	-		-0.00

Appendix 4.4. Summer effect and Halloween effect in stock market turnovers for cross sorted portfolios (1988-1997)

The table reports coefficient estimates and t-statistics for the summer effect and Halloween effect in log turnovers for the portfolios const geographical locations and quartile rankings of vacation importance for the subsample period from 1988 to 2007. The coefficient β_{sum} (β_{Hal} $Logturnover_{i,t} = \alpha + \beta_{sum} Summer_{i,t} + \varepsilon_{i,t}$ ($Logturnover_{i,t} = \alpha + \beta_{Hal} Hal_{i,t} + \varepsilon_{i,t}$), where $Logturnover_{i,t}$ is the nature logarithm of mark a dummy variable that equals one if the month falls into July-September in Northern Hemisphere countries and January-March in Southern Halloween$_{i,t}$ is the Halloween dummy that equals one when month t falls into November to April and zero otherwise. The estimations are based fixed effects clustered by month. *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Region	Log Turnover								
	Importance 4			3		2			1
	β_{sum}	t-value		β_{sum}	t-value	β_{sum}	t-value		β_{sum}
Overall	0.010	0.33		-0.047	-1.19	-0.032	-0.99		-0.020
Africa									0.037
Asia	-0.045	-0.83		-0.069	-0.28	-0.045	-0.85		0.021
Europe	0.039	1.05		-0.050	-1.45	-0.058	-1.08		-0.187
Latin America						0.307	4.83	***	0.022
North America	-0.095	-3.71	***			-0.051	-2.06	**	-0.067
Oceania				-0.008	-0.10	-0.081	-2.40	**	

Region	Log Turnover								
	Importance 4			3		2			1
	β_{Hal}	t-value		β_{Hal}	t-value	β_{Hal}	t-value		β_{Hal}
Overall	-0.032	-1.01		0.027	0.90	-0.003	-0.11		-0.038
Africa									-0.127
Asia	0.040	0.74		0.008	0.04	0.025	0.46		-0.091
Europe	-0.057	-1.52		0.026	0.78	-0.024	-0.50		0.141
Latin America						0.161	2.35	**	-0.014
North America	0.045	1.84	*			0.008	0.37		0.002
Oceania				0.040	0.72	-0.097	-2.79	***	

References

Acheson, G. G., Hickson, C. R., Turner, J. D., and Ye, Q. (2009). Rule Britannia! British stock market return, 1825-1870. *Journal of Economic History*, 69, 1107-1137.

Anderson, L. R., Gerlach, J. R., and DiTraglia, F. J. (2007). Yes, Wall Street, There is a January Effect! Evidence from laboratory auctions. *Journal of Behavioral Finance*, 8(1), 1-8.

Andrade, S. C., Chhaochharia, V., and Fuerst, M. (2012). "Sell in May and Go Away" Just Won't Go Away. *Working Paper*, University of Miami, *Available at SSRN: http://ssrn.com/abstract=2115197*.

Ariel, R. A. (1987). A monthly effect in stock returns. *Journal of Financial Economics*, 18, 161-174.

Barry, C. B., and Brown, S. J. (1984). Differential information and the small firm effect. *Journal of Financial Economics*, 13, 283-294.

Beaver, W. H. (1968). The information content of annual earnings announcements. *Journal of Accounting Research, 6*, 67-92.

Berges, A., McConnell, J. J., and Schlarbaum, G. G. (1984). The turn-of-the-year in Canada. *Journal of Finance*, 39, 185-192.

Bouman, S., and Jacobsen, B. (2002). The Halloween indicator, "Sell in May and go away": Another puzzle. *American Economic Review*, 92, 1618-1635.

Brown, P., Keim, D., Kleidon, A., and Marsh, T. A. (1982). Stock return seasonalities and the tax-loss selling hypothesis: Analysis of the arguments and Australian evidence, *Journal of Financial Economics*, 12, 105-127.

Brown, R. L., and Easton, S. A. (1989). Weak-form efficiency in the nineteenth century: A study of daily prices in London market for 3 per cent Consols, 1821-1860. *Economica*, 56, 61-70.

Brown Jr., W. O., Burdekin, R. C. K., and Weidenmier, M. D. (2006). Volatility in an era of reduced uncertainty: Lessons from Pax Britannica. *Journal of Financial Economics*, 79, 693-707.

Campbell, J. Y. (2000). Asset pricing at the millennium. *Journal of Finance, 55*, 1515-1567.

Campbell, J. Y., Grossman, S. J., and Wang, J. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics, 108*, 4, 905-939.

Cao, M., and Wei, J. (2005). Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance, 29*, 1559-1573.

Chae, J. (2005). Trading volume, information asymmetry, and timing information. *Journal of Finance*, LX, 1, 413-441.

Choudhry, T. (2001). Month of the year effect and January effect in pre-WW1 stock returns: Evidence from a non-linear Garch model. *International Journal of Finance and Economics,* 6, 1-11.

Ciccone, S. J. (2011). Investor optimism, false hopes and the January effect. *Journal of Behavioral Finance*, 12(3), 158-168.

Clare, A. D., Psaradakis, Z., and Thomas, S. H. (1995). An analysis of seasonality in the UK equity market. *Economic Journal*, 105, 398-409.

Cooper, M. J., McConnell, J. J., and Ovtchinnikov, A. V. (2006). The other January effect. *Journal of Financial Economics*, 82, 315-341.

Corhay, A., Hawawini, G., and Michel, P. (1987). Seasonality in the risk-return relationship: Some international evidence. *Journal of Finance*, 42, 49-68.

Dimson, E., and Marsh, P. (2001). U.K. Financial Market Returns, 1955-2000. *Journal of Business*, 74(1), 1-31.

Darrat, A. F., Li, B., Liu, B., and Su, J. J. (2011). A fresh look at seasonal anomalies: An international perspective. *International Journal of Business and Economics*, 10, 93-116.

Ferson, W. E. (2007). *Market efficiency and forecasting*: UK: Elsevier. ISBN# 978-0-7506-8321-0.

Fountas, S., and Segredakis, K. N. (2002). Emerging stock markets return seasonalities: The January effect and the tax-loss selling hypothesis. *Applied Financial Economics*, 12, 291-299.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, 8, 55-69.

Gayer, A. D., Rostow, W. W., and Schwartz, A. J. (1975). *The Growth and Fluctuation of the British Economy 1790-1850: An Historical, Statistical, and Theoretical Study of Britain's Economic Development*. The Harvester Press Limited.

Gerlach, J. R. (2007). Macroeconomic news and stock market calendar and wealther anomalies. *Journal of Financial Research*, XXX, 283-300.

Gibbons, M. R., and Hess, P. (1981). Day of the week effects and asset returns. *Journal of Business*, 54, 579-596.

Glasner, D. (1997). Business Cycles and Depressions – An Encyclopedia. New York & London: Garland Publishing Inc.

Goetzmann, W. N. (1993a). Accounting for taste: Art and the financial market over three centuries. *American Economic Review*, 83(5), 1370-1376.

Goetzmann, W. N. (1993b). Patterns in three centuries of stock market prices. *Journal of Business*, 66, 249-270.

Goetzmann, W. N., and Ibbotson, R. G. (2005). History and the equity risk premium, in Mehra, R. (Ed.), *Handbook of the Equity Risk Premium*, pp. 515-529

Goetzmann, W. N., Ibbotson, R. G., and Peng, L. (2001). A new historical database for the NYSE 1815 to 1925: Performance and predictability. *Journal of Financial Markets*, 4, 1-32.

Goetzmann, W. N., and Jorion, P. (1995). A longer look at dividend yields. *Journal of Business*, 68, 483-508.

Goetzmann, W. N., Li, L., and Rouwenhorst, K. G. (2005). Long-term global market correlations. *Journal of Business*, 78(1), 1-38.

Grimbacher, S. B., Swinkels, L. A. P., and Vliet, P. V. (2010). An Anatomy of Calendar Effects. *Working Paper*, Erasmus Univeristy Rotterdam, Robeco Investment Soluation & Research, Robeco Asset management.

Grossman, R. S. (2002). New indices of British equity prices, 1870-1913. *Journal of Economic History*, 62, 121-146.

Grossman, R. S., and Shore, S. H. (2006). The cross section of stock returns before World War I. *Journal of Financial and Quantitative Analysis*, 41(2), 271-294.

Gugten, T. van der (2010). Stock market calendar anomalies and macroeconomic news announcements, *Working paper*, Erasmus University Rotterdam.

Gugten, T. v. d. (2010). Stock market calendar anomalies and macroeconomic news announcements. *Working Paper*, Erasmus University Rotterdam.

Gultekin, M. N., and Gultekin, N. B. (1983). Stock market seasonality international evidence. *Journal of Financial Economics*, 12, 469-481.

Haggard, K. S., and Witte, H. D. (2010). The Halloween effect: Trick or treat? *International Review of Financial Analysis, 19*(5), 379-387.

Harrison, P. (1998). Similarities in the Distribution of Stock Market Price Changes between the Eighteenth and Twentieth Centuries. *Journal of Business*, 71(1), 55-79.

Haugen, R., and Lakonishok, J. (1987). *The Incredible January Effect: The Stock Market's Unsolved Mystery*. Homewood, Ill: Dow-Jones-Irwin.

Heston, S. L., and Sadka, R. (2007). Seasonality in the cross-section of stock returns. *Journal of Financial Economics*, 87, 418-445.

Ho, Y-K. (1990). Stock return seasonalities in Asia Pacific markets. Journal of *International Financial Management and Accounting*, 2, 48-77.

Hong, H., and Stein, J. C. (2007). Disagreement and the stock market. *Journal of Economic Perspectives, 21*, 2, 109-128.

Hong, H., and Yu, J. (2009). Gone fishin': Seasonality in trading activity and asset prices. *Journal of Financial Markets*, 12, 672-702.

Huber, P. J. (1973). Robust regression: Asymptotics, Conjectures, and Monte Carlo. *Annals of Statistics*, 1(5), 799-821.

Jacobsen, B., and Dannenburg, D. (2003). Volatility clustering in monthly stock returns. *Journal of Empirical Finance*, 10, 479-503.

Jacobsen, B., Mamun, A., and Visaltanachoti, N. (2005). Seasonal, size and value anomalies, *working paper*, Massey University, University of Saskatchewan.

Jacobsen, B., and Marquering, W. (2008). Is it the weather? *Journal of Banking and Finance*, 32, 526-540.

Jacobsen, B., & Marquering, W. (2009). Is it the weather? Response. *Journal of Banking & Finance, 33*, 583-587.

Jacobsen, B., and Visaltanachoti, N. (2009). The Halloween Effect in US Sectors. *Financial Review*, 44(3), 437-459.

Jacobsen, B., and Zhang, C. Y. (2012). The Halloween Indicator: Everywhere and all the time. *Working Paper,* Massey University, *Available at SSRN:* *http://ssrn.com/abstract=2154873*

Johnson, T. C. (2008). Volume, liquidity, and liquidity risk. *Journal of Financial Economics*, *87*, 388-417.

Jones, C. P., Pearce, D. K., and Wilson, J. W. (1987). Can tax-loss selling explain the January effect? A note. *Journal of Finance*, 42, 453-461.

Jones, S. L., Lee, W., and Apenbrink, R. (1991). New evidence on the January effect before personal income tax. *Journal of Finance*, 46, 1909-1924.

Jorion, P., and Goetzmann, W. N. (1999). Global stock markets in the twentieth century. *Journal of Finance*, 54(3), 953-980.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2003). Winter blues: A sad stock market cycle. *American Economic Review*, 93, 324-343.

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis*, *22*, 1, 109-126.

Kato, K., and Schallheim, J. S. (1985). Seasonal and size anomalies in the Japanese stock market. *Journal of Financial and Quantitative Analysis*, 20(2), 243-260.

Kaustia, M., and Rantapuska, E. (2012). Does mood affect trading behavior? *Working Paper*,Aalto University School of Economics, *Available at SSRN:* *http://ssrn.com/abstract=1875645*

Keef, S. P., and Khaled, M. S. (2011). A review of the seasonal affective disorder hypothesis. *Journal of Socio-Economics*, *40*, 959-967.

Kelly, P. J., and Meschke, F. (2010). Sentiment and stock returns: The SAD anomaly revisited. *Journal of Banking & Finance*, *34*, 1308-1326.

Keim, D. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics*, 12, 13-32.

Kelly, P.J., and Meschke, F. (2010). Sentiment and stock returns: The SAD anomaly revisited. *Journal of Banking and Finance*, 34, 1308-1326.

Kim, D. (2006). On the information uncertainty risk and the January effect. *Journal of Business*, 79(4), 2127-2161.

Koenig, N., & Bischoff, E. E. (2003). Seasonality of tourism in Wales: a comparative analysis. *Tourism Economics, 9*(3), 229-254.

Lakonishok, J., and Levi, M. D. (1982). Weekend effects on stock returns. *Journal of Finance*, 37, 883-889.

Lakonishok, J., Shleifer, A., Thaler, R., and Vishny, R. (1991). Window dressing by pension fund managers. *American Economic Review*, 81(2), 227-231.

Lakonishok, J., and Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies*, 1, 403-425.

Lean, H. H. (2011). The Halloween puzzle in selected Asian stock markets. *Int. Journal of Economics and Management* 5(1), 216-225.

Lucey, B. M, and Zhao, S. (2007). Halloween or January? Yet another puzzle. *International Review of Financial Analysis, 17*, 1055-1069.

Lundblad, C. (2007). The risk return tradeoff in the long run: 1836-2003. *Journal of Financial Economics*, 85, 125-150.

Maberly, E. D., & Pierce, R. M. (2003). The Halloween Effect and Japanese Equity Prices: Myth or Exploitable Anomaly. *Asia-Pacific Financial Markets*, *10*, 319-334.

Maberly, E. D., & Pierce, R. P. (2004). Stock market efficiency withstands another challenge: Solving the "sell in May/ buy after Halloween" puzzle. *Econ Journal Watch*, *1*, 29-46.

Merton, R. C. (1980). On estimating the expected return on the market. *Journal of Financial Economics*, 8, 323-361.

Mirowski, P. (1981). The rise (and retreat) of a market: English joint stock shares in the eighteenth century. *Journal of Economic History*, 41, 559-577.

Moller, N., & Zilca, S. (2008). The evolution of the January effect. *Journal of Banking & Finance, 32*, 447-457.

Neal, L. (1987). The integration and efficiency of the London and Amsterdam stock markets in the eighteenth century. *Journal of Economic History*, 47(1), 97-115.

Newey, W. K., and West, K. D. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55, 7003-7708.

Ng, L., and Wang, Q. (2004). Institutional trading and the turn-of-the-year effect. *Journal of Financial Economics*, 74, 343-366.

Ogden, J. P. (1990). Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and January effects. *Journal of Finance*, 45(4), 1259-1272.

Ogden, J. P. (2003). The calendar structure of risk and expected returns on stocks and bonds. *Journal of Financial Economics*, 70, 29-67.

Ogden, J. P., and Fitzpatrick, J. (2010). Do five asset pricing anomalies share a common mispricing factors? Multifaceted empirical analyses of failure risk proxies, external financing, and stock returns, *working paper*, SUNY at Buffalo.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, *22*, 1, 435-480.

Poterba, J. M., and Weisbenner, S. J. (2001). Capital gains tax rules, tax-loss trading, and turn-of-the-year returns. *Journal of Finance*, 56(1), 353-368.

Powell, J. G., Shi, J., Smith, T., and Whaley, R. E. (2009). Political regimes, business cycles, seasonalities, and returns. *Journal of Banking & Finance*, *33*, 1112-1128.

Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in January - empirical tests for tax-loss selling effects. *Journal of Financial Economics*, 12, 89-104.

Reinganum, M. R., and Shapiro, A. C. (1987). Taxes and stock return seasonality: Evidence from the London stock exchange. *Journal of Business*, 60, 281-295.

Roll, R. (1983). Vas ist das? The turn-of-the-year effect and the return premia of small firms. *Journal of Portfolio Management*, Winter, 18-28.

Rozeff, M. S., and Kinney, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics*, 3, 379-402.

Schultz, P. (1985). Personal income taxes and the January effect: Small firm stock returns before the War Revenue Act of 1917: A note. *Journal of Finance*, 40, 333-343.

Schwert, W. G. (2002). Anomalies and market efficiency. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of Economics and Finance*. Amsterdam, Netherlands: North-Holland.

Shea, S. G. (2000). The course of the exchange: Measuring and interpreting returns process in 18th and early 19th century Britain, *Working Paper*, Department of Economics University of St Andrews.

Shiller, R. J. (1989). Comovements in stock prices and comovements in dividends. *Journal of Finance*, 44, 719-729.

Starks, L. T., Yong, L., and Zheng, L. (2006). Tax-loss selling and the January effect: Evidence from municipal bond closed-end funds. *Journal of Finance*, LXI(6), 3049-3067.

Sullivan, R., Timmermann, A., & White, H. (2001). Dangers of data mining: The case of calendar effects in stock returns. *Journal of Econometrics, 105*, 249-286.

Tinic, S. M.,Adeshi, B. G., and West, R. R. (1987). Seasonality in Canadian stock prices: A test of the "tax-loss-selling" hypothesis. *Journal of Financial and Quantitative Analysis*, 22, 51-63.

Trefgarne, G. (2005). Should You Sell in May and Buy Another Day? http://www.telegraph.co.uk/finance/2914779/Should-you-sell-in-May-and-buy-another-day.html, access date 10/09/2010.

Wachtel, S. B. (1942). Certain Observations on Seasonal Movements in Stock Prices. *Journal of Business, 15*(2), 184-193.

Wilson, J. W., and Jones, C. P. (2002). An anaysis of the S&P500 index and Cowles' extensions: Price indexes and stock returns. *Journal of Business*, 75, 505-533.

Van den Bergh, W. M., and Wessels, R. E. (1985). Stock market seasonality and taxes: An examination of the tax-loss selling hypothesis. *Journal of Business Finance & Accounting*, 12, 515-530.

Zarour, B. A. (2007). The Halloween effect anomaly: Evidence from some Arab countries equity markets. *Studies in Business and Economics*, 13(1), 68-76.

Zhang, C., and Jacobsen, B. (2012). Are monthly seasonals real? A three century perspective. Forthcoming in *Review of Finance*.

APPENDIX 5. STATEMENT OF CONTRIBUTION TO DOCTORAL THESIS

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
TO DOCTORAL THESIS CONTAINING PUBLICATIONS

(To appear at the end of each thesis chapter/section/appendix submitted as an article/paper or collected as an appendix at the end of the thesis)

We, the candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of Candidate: Yi Zhang (Cherry)

Name/Title of Principal Supervisor: Professor Ben Jacobsen

Name of Published Research Output and full reference:

Name: Are monthly seasonals real? A three century perspective
Reference: Zhang, C., and Jacobsen, B. (2012). Are monthly seasonals real? A three century perspective. Forthcoming in Review of Finance

In which Chapter is the Published Work: Chapter 2

Please indicate either:

- The percentage of the Published Work that was contributed by the candidate:

  and / or

- Describe the contribution that the candidate has made to the Published Work:

  Academic work does not work in percentages or specific contributions, just like you cannot say exactly how much an individual player contributed to a team. Cherry is the first author on this paper and her total contribution is more than enough to be included in her thesis.

Yi Zhang
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Candidate's Signature

21/02/2013

Date

com.apple.idms.appleid.prd.4a356133755a7553523743646c6475414b66426e6b673d3d
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Principal Supervisor's signature

21/02/2013

Date