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The Halloween indicator, "Sell in May and Go Away": Everywhere and all the time ☆

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ABSTRACT

To answer the sceptics, we use all historical data (62962 observations) on all stock market indices worldwide to verify the robustness of the so-called Halloween Indicator or Sell in May effect. The effect seems remarkably robust with returns on average 4% higher during November-April period than during May-October. A new test for the effect offers some additional insights. Worldwide excess returns during summer seem negative (around −1%) and often significantly so suggesting a flat or negative risk return relation. Only for Mauritius do we find a significantly positive risk return relation during May-October. Our dataset also allows for a new (upper bound) estimate for the equity premium of around 4%.

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 stirred a fierce debate both in the academic literature and the popular press. Bouman and Jacobsen (2002) find that returns during winter (November through April) are significantly higher than during summer (May-October) in 36 out of the 37 countries in their study. As it seemed to challenge market efficiency they called it: 'another puzzle'.

One purpose of this paper is to add to the debate whether such anomaly truly exists by rigorously re-examining the Halloween or Sell in May puzzle using all historical data available from all countries world-wide. This may resolve that part of this debate is stirred by academics, investors and journalists only considering data from specific countries or time periods which may result in data mining, sample selection bias, statistical problems, outliers and affect economic significance. While the anomaly has been validated out of sample by studies like Andrade, Chhaochharia, and Fuerst (2013) and Jacobsen and Visaltanachoti (2009), doubt on the existence of the anomaly has been reported by among others Maberly and Pierce (2003, 2004), Lucey and Zhao (2007), Zhang and Jacobsen (2013) and Powell, Shi, Smith and Whaley (2009). Part of these mixed findings may be a result of sample selection. Considering all historical stock market data available may not only overcome these problems but help getting more attention for this anomaly that defies economic gravity. Or, as the referee of this

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paper put it: "While the empirics are super strong, there is a lack of seriousness from the academic community of treating this topic with respect. Perhaps this overview will help."

Another reason why we use all data in all countries is that Zhang and Jacobsen (2013) show even with an extremely large sample for just one country (the same UK dataset we use here) it is hard to determine whether monthly anomalies exist. The problem is the same as put forward by Lakonishok and Smidt (1988): "*To detect monthly anomalies one needs samples of at least ninety years, or longer, to get any reliable estimates.*" Looking at all historical data across all countries seems the best remedy. It seems fair to say that at least this makes the 'Sell in May' effect the most extensively tested anomaly in the world. In this way our paper also addresses more general data and estimation concerns in finance like the over reliance of evidence from one country (for instance, Jacobs and Müller, 2019) or the serious concerns of p-hacking and data mining as voiced by among others Harvey, Liu and Zhu (2016) and de Prado (2015) leading the former to conclude that: *"Most claimed research findings in financial economics are likely false.*" To be rigorous, we consider all stock markets worldwide using the full history of stock market indices available for each market (no matter how big or small, developed or developing) to safeguard as much as possible against data mining and sample selection bias. To the best of our knowledge our paper is the first to use all worldwide historical stock market data available.[1]

We also add a simple new test for this market wisdom. We add this new test for two reasons. Firstly, while similar to the test we perform one could argue that the test in Bouman and Jacobsen (2002) is not a proper test of the Sell in May wisdom. Bouman and Jacobsen test whether winter returns are higher than summer returns. However, all the market wisdom suggests, is that one should not invest in stock markets during the summer months. Therefore a formally more correct test of the adage would be to test whether summer returns are significantly higher than short term interest rates during the summer months. If excess returns are not significantly different from zero, or even negative, it might make little sense for risk averse investors to invest in the stock market during summer. Indeed, then, as the adage indicates, one would be better off by 'going away'. This is the new test we perform.[2] The second reason for this new test is that it reveals another, mostly ignored, aspect of the Sell in May effect. Not only, would the market wisdom defy market efficiency because returns vary predictably with the seasons, it would also show the absence of a positive risk return trade-off during a substantial part of the year and predictably so. This test is also interesting as we still lack a proper explanation on what causes the effect (see for instance, Jacobsen & Marquering, 2008) and this tested results cast doubt on explanations that rely only on seasonal behavioural changes in risk aversion to explain the anomaly. Investors have to become systematically risk seeking to explain zero or negative equity premia in the long run.

Our data consist of all 114 stock markets in the world for which stock market price indices exist[3] and in total we have almost 63,000 monthly returns. The sample starts with the UK stock market in 1693 and ends with the addition of the stock market of Rwanda which starts in 2013. Our tests for the historical equity premia rely on total return data and short term interest rates which are jointly available for 65 stock markets, the sample starts with the UK stock market in 1694 and ends with Jordan which starts in 2006. For each individual market we use all historical data available for that market. An additional advantage of using all data available, is that this cross country evidence allows us to estimate the historical equity premium based on all historical total return data and short term interest data available worldwide. Of course, as our data will be hampered by survivorship bias, this is most likely an upper bound. Still, in the absence of a good estimate of the equity premium this upper bound provides useful information. On average we find an historical estimate for the equity premium based on the 37,167 observations for these 65 countries of 4% annually, with a confidence interval of (3.01%, 4.88%) obtained from an unrestricted random sampling bootstrap procedure. This means estimate is slightly lower than the 4.5% estimated in Dimson et al. (2011).

When we consider whether excess returns in summer are significantly higher than zero, results are less comforting. In none of the 65 countries for which we have total returns and short term interest rates available –with the exception of Mauritius - can we reject a Sell in May effect based on our new test. Only for Mauritius do we find evidence of significantly positive excess returns during summer (significant at the 10% level). Fig. 1 summarises our main result. It plots the average risk premia during the summer months for 65 countries.

Summer risk premiums are not only not significantly positive, they are in most cases not even marginally positive. In 45 countries the excess returns during summer have been negative, and in 7 significantly so. Overall based on 37,167 observations we find that average stock market returns (including dividends) during May to October have been 1.1% (or 0.18% per month) lower than the short term interest rate and these negative excess returns tend to be significantly different from zero. Only in the winter months do we find evidence of a positive risk return relation. Average excess returns from November to April are 5.1% or (0.85% per month) and these are significant with a t-value of 16.75. Of course, risk would be an obvious (partial) explanation for this difference between summer and winter but if anything, standard deviations are higher during summer.[4]

[1] Or, as an author on the Seeking Alpha website described our approach based on an earlier version of this paper: "it is the lethal weapon against skepticism." http://seekingalpha.com/article/1183461-seasonal-patterns-in-stock-markets-319-years-of-evidence.

[2] In the Bouman and Jacobsen test, summer returns may be lower than winter returns but if summer returns are higher than the short term interest rates it might still pay to stay in the stock market.

[3] We thank for the anonymous referee pointing us to the newly available historical monthly market indices data collected by Goetzmann, Cabolis and Radchenko for the St. Petersburg Stock Exchange from 1865 to 1914. Our test shows no significant Halloween effect in this old sample period.

[4] In Appendix 3 we test this possibility in more detail using GARCH(1,1) models where we can assess risk differences in conjunction with differences in mean returns between summer and winter. In 23 out of the 55 countries (and also for the world market index) for which we have enough data to test for risk differences, we find that risk is significantly higher in summer than winter. Winter shows significantly higher risk only in 8 countries. This suggests that not only stock market returns may be lower during summer. If anything, after correcting for Sell in May mean effects and volatility clustering effects, volatility may be higher too, further increasing the puzzle on the risk return trade off.

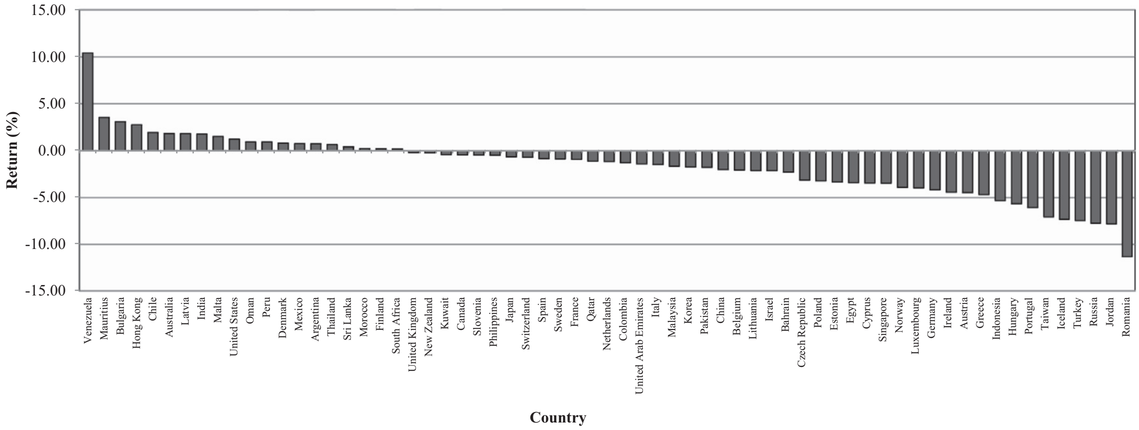


Fig. 1. Summer (May-October) risk premiums for 65 countries.

The evidence on negative risk premia we report here suggests that the Halloween effect differs from other seasonalities alike, for instance, the same month seasonal reported by Heston and Sadka (2008, 2010) or 'Day-of-the-week'-effect. Both seasonals are recently considered by Keloharju et al. (2016) and they find these seasonals may be risk related if risk factor loadings may not accrue evenly through the year and suggest an explanation might be driven by changing risk aversion rather than changing risk over time.

Our comprehensive dataset allows us to revisit the old test in Bouman and Jacobsen (2002). Our evidence shows the effect continues to persist. This is surprising as the adage has been 'publicly available information' for a very long time even before the Bouman and Jacobsen (2002) sample.[5] Nevertheless, it seems to defy economic gravity. It does not disappear or reverse itself, as theory dictates it should (Campbell, 2000; Schwert, 2002), or seems to happen to many other anomalies (Dimson and Marsh, 1999; McLean and Pontiff, 2016). In fact, a number of papers have appeared recently that find some results similar to ours with respect to the Bouman and Jacobsen (2002) out of sample evidence.[6] The fact that trading on this strategy is particularly simple makes its continued existence even more surprising.[7]

Overall, the 62,962 monthly observations over 323 years show a strong Halloween effect when measured the way as suggested in Bouman and Jacobsen (2002). Winter returns – November through April - are 4.2% (t-value 3.80) 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 89 out of 114 countries. The difference is statistically significant in 42 countries, compared to only 1 country having significantly higher May-October returns. Our 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. As we show, however, this may also be due to the small sample sizes yet available for many of these newly emerged markets. The effect is even more robust in our total return and risk premium estimates. Out of the 65 markets, 63 total market returns (and 63 risk premium series) show positive point estimates for a Halloween effect, and for 36 (and 35) markets these results are statistically significant.

Using time series subsample period analysis by pooling all market indices together, we show over 32 ten-year subperiods 21 have November-April returns higher than the May-October returns. The difference becomes statistically significant in the last 50 years starting from the 1960s, and the difference in these two 6-month period returns is very persistent and economically large ranging from 5% to 8.3% for the most recent five 10-year sub-periods. The world index from Global Financial Data reveals a similar trend. Subsample period analysis of 20 individual countries with data available for over 90 years also confirms this strengthening trend in the Halloween effect.

We investigate 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 2017. The out-of-sample gains from the Halloween strategy are still higher than the buy and hold strategy in 30 of the 37 countries. In addition, given that the United Kingdom is the home of this old market wisdom (and has shown a Halloween effect throughout its history) we examine the performance consistency of the trading strategy using long time series of over 300 years of UK data. The bootstrap 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.

[5] As we show here the market wisdom was already reported in 1935 and at that time already well known, at least in the United Kingdom.

[6] See for instance, Andrade et al., 2013; Swinkels and van Vliet, 2012; Jacobsen and Visaltanachoti, 2009.

[7] Our results on the Halloween strategy out-of-sample robustness complements to Jacobs and Müller (2019)'s persistent post-publication returns of international cross-sectional anomalies.

Moreover, we address a number of methodological issues concerning the sample size, impact of time varying volatility, outliers and problems with statistical inference raised in the debate which followed Bouman and Jacobsen (2002)'s publication using UK long time series data of over 300 years. In particular, extending the evidence in Zhang and Jacobsen (2013), we 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 most often significant if measured this way. Although even within this long sample there are subsamples where the effect is not always significant. Point estimates are always positive based on traditional regressions and estimates taking GARCH effects into account, but estimates with outlier robust regressions occasionally show negative point estimates halfway through the previous century.

This dataset also allows us 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, we address this concern by regressions using 6 monthly, rather than monthly, returns. The bias if any seems marginal at best. We find almost similar standard errors regardless of whether we use the 6-month intervals, or the monthly data, to estimate the effect.

We feel our paper adds to the literature in a number of ways. Firstly, by looking at all historical returns of 114 countries the Halloween effect seems a bigger puzzle than we may have realised before.

Secondly, we introduce a simple new tests that not only shows that the Halloween effect is interesting from a market efficiency point of view but highlights how the empirical evidence systematically seems to violate the positive long run relation we would expect to see between risk and return. In this sense we reveal a new puzzling aspect of this phenomenon: in no country – apart from Mauritius – do we find evidence of a significantly positive risk return relation during the summer months. While it is possible risk premiums can be negative, this predictable, consistent and persistent finding of an absence of risk premia seems to pose a challenge for conventional asset pricing theory.

Thirdly, an interesting by-product and one might call this another contribution is that we provide a new upper bound for the equity premium (4%) using probably the largest cross county dataset over the historically longest period available.

Fourthly, we show how none of the arguments against the existence of the Halloween effect put forward to date survives closer scrutiny. 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 results. In short, the results we provide 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.

Last but not least, our results help to contribute on answering 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 we can say is that any 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. If we assume human behaviour does not change over time this seems to rule out just behavioural explanations and suggest changes in society play a role. Additionally, and maybe more importantly from a theoretical perspective, this explanation should also be able to account for the negative excess returns during the May-October period in stock markets around the world. While we may never find a smoking gun, the circumstantial evidence we report confirms more recent empirical evidence (Kaustia and Rantapuska, 2016; Jacobsen, Molchanov and Zhang, 2014) that vacations are the most likely explanation. At least, the vacation explanation is consistent with all empirical evidence to date. The evidence also casts more doubt on Seasonal Affective Disorder as an explanation for this seasonality in stock returns.

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 et al. (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. They find the effects is strongest in production related sectors. Fiore and Saha (2015) find that stocks with low beta and low idiosyncratic volatility outperform stocks with high beta and high idiosyncratic volatility in the US during summer months.

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 1991–2008, 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 could have been aware of. This reduces the likelihood of data mining.[8] Bouman and Jacobsen investigate several possible explanations, but find none, although they cannot reject that the Halloween effect might be caused by summer vacations, which would also explain why the effect is predominantly European.

Our long-term history of UK data are 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. Bouman and Jacobsen, 2002 report a quote from 1964 in the Financial Times as the oldest reference they could find at the time. With more and more information becoming accessible online we 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.[9] 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. Many of the early newspaper articles link the adage to vacation behaviour.

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. Van der Gugten and Smant (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 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 recent studies by Jacobsen et al., 2019 and Kaustia and Rantapuska (2016). Jacobsen et al., 2019 look at vacation data in 34 countries and finds strong support for vacation behaviour as an explanation for the lower summer return effect, especially among European countries. Kaustia and Rantapuska (2016) consider actual trading decisions of Finnish 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 et al. (2003). Kamstra et al. (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 (2016) not support the SAD hypothesis, but the Kamstraet al. (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 our 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. Moreover, increased risk aversion caused by SAD might explain lower returns but still would not explain persistent negative excess returns or negative risk premia as we report here. And, last but not least, one has to worry whether a SAD effect actually exists. A recent study by Traffanstedt et al. (2016) finds no evidence. They conclude: "*Results do not support the validity of a seasonal modifier in major depression. The idea of seasonal depression may be strongly rooted in folk psychology, but it is not supported by objective data. Consideration should be given to discontinuing seasonal variation as a diagnostic modifier of major depression.*" This seems to rule out a SAD effect in stock returns. Similar arguments also apply for a mood effect caused by temperature changes, as suggested by Cao and Wei (2005), who find a high correlation between temperature and stock market returns.

The long time series data we use here allows us 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 pre-

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

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

sent 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 1954–2008.

Using 20-year sub-period analysis over the period of 1926–2002, 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 20 countries for over 90 years, we are able to reduce the impact of outliers, as well as increase the sample size in examining the out of sample robustness and the persistence of the Halloween effect in these countries. As we 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. Data and methodology

We collect monthly price index data from Global Financial Data (GFD), Datastream,[10] and individual stock exchanges for all the countries in the world that have stock market indices available. Our sample consists of 114 countries' stock market indices data,[11] consisting of all 23 developed markets, 23 emerging markets, 22 frontier markets classified by the MSCI market classification framework and an additional 46 countries that are not included in the MSCI market classification. We denote them as *rarely studied markets.*[12] Our sample has of course a considerable geographical coverage: we have 18 African countries, 21 countries in Asia, 39 countries from Europe, 13 countries located in the Middle East, 11 countries from North America and 9 from South America, as well as 3 countries in Oceania. We also obtain total return indices and risk free rate data for 65 countries[13] in order to address the possible impact of dividend payments and reveal the pattern of market risk premiums. This smaller sample covers all the stock markets for which we can find total market return indices. We use Treasury bills or the nearest comparable short term instrument as the proxy for risk free rates. Appendix 1 presents the sources and sample periods of the price index, total return index and the proxy of the risk free rate for each country grouped on the basis of their MSCI market classification and geographic region. For many of the countries, the time series almost cover the entire trading history of their stock market. In particular, we have over 320 years of monthly market index prices for the United Kingdom, more than 220 years for the United States and over 90 years data for another 18 countries. The world index is the GFD world price index and GFD world return index that goes back to 1919 and 1926 respectively.[14] For the price indices, there are 20 countries in total having data available for over 90 years. These long time series data allow us to examine the evolution of the Halloween effect by conducting sub-period analysis. We also have countries with very small sample size; for example, there are 9 countries with data for less than 10 years. All price indices are quoted at local currency, except Georgia where the only index data available is in USD.

It may be good to note that especially with historical data the exact timing and payments of dividends may be an issue that affect the size of the effects we measure here. In Finland, for instance, dividends were paid in either March, April or May. The long historical total return assumes dividends payments are paid in April. However, in many other long historical datasets this is simply no longer known. Historical total market return series may have also been constructed by adding back 1/12 of the annual dividend to each month separately if dividend payments timing is not known. However, if the dividend was in fact paid during the summer, the ex-dividend price would have dropped during the summer period. Adding back 1/12 of the dividend to each month of the year would artificially introduce a Halloween effect if more stocks would have paid

[10] When data are available from both GFD and Datastream, we choose the one with longer sample periods.

[11] Initially, we find a total of 150 countries with active stock exchanges, but many newly established markets only trade a limited number of stocks and do not maintain a market index. These countries include Guyana, Angola, Cameroon, Cape Verde, Lesotho, Libya, Mozambique, Seychelles, Somalia, Zimbabwe, Anguilla, Antigua and Barbuda, Cayman Islands, Curacao, Dominica, Dominican Republic, Grenada, Guatemala, Haiti, Honduras, Montserrat, Nicaragua, Saint Kitts and Nevis, Saint Lucia, Bolivia, Myanmar, Afghanistan, Bhutan, Maldives, Gibraltar, Moldova, Albania, Armenia, Azerbaijan, Belarus, Channel Islands, Faroe Islands. As a result, our sample size reduces to 114 countries.

[12] Our market classification is based on "MSCI Global Investable Market Indices Methodology" published in August 2011 and the market classification updated in 2017. 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.

[13] We excluded Brazil from the sample even we do have the date of total returns and short term interest rates, because of the extremely high observations due to the hyperinflation from 1980s to 1994.

[14] The index is capitalization 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 assumed unchanged until 1970. The local index values were converted into a dollar index by dividing the local index by the exchange rate.

dividends during the summer than during the winter months. Unfortunately, in many cases it is simply not possible to verify how indices have been constructed historically. However, the evidence that is available suggests that in many cases this is not likely to be the driving effect. For instance, Zhang and Jacobsen (2013) show that the UK series we use is unlikely to be affected by mismeasurement of dividend seasonality. For the other countries where we do have some evidence on dividend payments this does not seem likely to affect our results.[15]

Our main test is whether excess returns are significantly positive. Of course, it would entirely be possible that the original idea referred to the small positive equity premium not being worth the risk of investing in stocks, rather than implying that the equity risk premium would be zero during summer. However, as that would strengthen our results in favour of a Halloween effect we use a zero summer return as our boundary.

Apart from our new test on whether excess returns in summer are significantly positive we also investigate the statistical significance of the Halloween effect using the Halloween dummy regression model the traditional way:

$$r_t = \alpha + \beta Hal_t + \varepsilon_t \tag{1}$$

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 we 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.

4. Price returns, risk premiums and dividend yields

4.1. Overall results

We first calculate continuously compounded monthly returns for both price indices and total return indices. We also estimate the risk premiums for the countries by subtracting monthly risk free rate from the total return series. Table 1 presents summary statistics of the price returns, total returns and risk premiums.

The top section of the table shows the annualised mean returns and standard deviations for the world index and pooled countries. The statistics for the price returns are calculated from 62,962 sample observations over 114 countries from year 1693 to 2017, and the results for the total return and risk premium are computed based on 37,167 observations from 65 countries for the period 1694–2017. The average price returns and total returns are 8.7% and 10.7% over the entire sample, if we only consider the 65 countries that have total return data available, the mean capital gain is about 7.2% per annum, which lead to an estimation of the historical average dividend yield of 3.5%. This result coincides with a similar dividend yield of 3.8% inferred from the world total return and price return indices over the period 1926–2017.

Fig. 2 plots 30-year moving averages of total returns, price returns, risk premiums and dividend yield from pooled 65 countries over the period 1694–2017. In Fig. 3 we zoom in on the more recent period as for that period results are based on a larger number of countries. Fig. 2 makes clear that dividend yield weights a large portion of total returns in the first two centuries, in fact, dividend is almost the sole contributor to the total returns up to around 1850s. The weight of the price returns starts catching up since 1910s. We observe a continuous trend of declining dividend yields accompanied with increased price returns over the recent 50 years beginning from 1960s. For example, the dividend yield only weights for 30% of the total return in the latest 30-year observation.[16]

For individual countries, we observe 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 price returns for all developed markets in our sample is 6.4%, comparing to higher average returns for the emerging markets (14.9%), the frontier markets (10.4%) and the rarely studied markets (8.8%). Meanwhile, the volatility for the emerging markets is among the highest, with an annualised standard deviation of 30.6% comparing to 19.9% for the developed markets, and 26.2% and 26% for the frontier and rarely studied markets. Despite of a smaller sample size, total returns reveal a similar pattern, the mean returns (standard deviations) are 9.3% (19.9%), 14.7% (32.5%), 10.7% (24.2%) and 11.4% (31%) for developed, emerging, frontier and rarely studied markets, respectively. The highest increase in monthly index returns is 146.3% in Argentina in February 1990 and the largest plunge in index prices in a single month is 378.9% in Uruguay in January 2008 (Note that because we use log returns, drops of more than 100% are possible).

Table 1 also reveals some interesting observations about the risk premium. The pooled 65 countries' result over 323-years history suggests an average and significant risk premium of 4.0%, with a confidence interval of (3.010, 4.8768) based on unrestricted random sampling bootstrapping.[17] This is a bit lower than 4.5% estimated in Dimson, Marsh and Staunton (2011) using 19 countries data over the period 1900–2011, but it confirms their argument that a 6% risk premium commonly used in finance text books is too high. Moreover, as noted before our estimate is most likely an upper bound on the actual risk premium due to

[15] Results available on request from the authors.

[16] It seems this offsetting trend between dividend yield and price returns are driven by three major markets: UK, US and Australia, the level of dividend yields tend to be quite fixed over time for other countries. In Appendix 2 we plot the 30-year moving averages for 11 countries that have data available for over 60 years.

[17] We resample the entire observations 10,000 times with replacement to get the estimates of the confidence interval of the mean estimate.

Table 1

Summary statistics for market price returns, total returns and risk premiums, the table presents starting date, ending date and number of observations, as well as some basic descriptive statistics, for 114 market price indices, 65 market total return indices, and the world index. The statistics for pooled price returns are calculated based on 114 stock market price indices, while for pooled total returns and risk premiums are calculated based on 65 stock market total return indices. Risk premium is the difference between monthly total market returns and risk free rates. Mean and standard deviation expressed as percentage are annualised by multiplying by 12 and $\sqrt{12}$, t-value shows if the mean is significantly different from zero. Countries are grouped based on the MSCI market classification and geographical regions. *** denotes significance at 1% level; **denotes significance at 5% level; *denotes significance at 10% level.

			Price Return						Total Return						Risk Premium		
Status	Region	Country	Start	End	Obs	Mean	t–value	St Dev	Start	End	Obs	Mean	t–value	St Dev	Mean	t–value	St Dev
World			02/1919	04/2017	1179	4.5	3.31 ***	13.5	01/1926	04/2017	1096	8.3	5.47 ***	14.5	–	–	–
Pooled 114 countries			02/1693	04/2017	62,962	8.7	25.10 ***	25.2	–	–	–	–	–	–	–	–	–
Pooled 65 countries			–	–	–	–	–	–	09/1694	04/2017	37,167	10.7	24.05 ***	24.7	4.0	9.07 ***	24.5
Developed	Asia	Hong Kong	01/1965	04/2017	628	11.0	2.54 **	31.4	01/1970	04/2017	568	14.5	3.08 ***	32.3	9.2	1.95 *	32.4
		Japan	01/1915	04/2017	1204	7.4	3.56 ***	20.9	01/1921	04/2017	1156	10.6	5.11 ***	20.4	6.2	3.18 ***	18.8
		Singapore	01/1966	04/2017	616	6.4	1.80 *	25.4	08/1973	04/2017	525	6.3	1.65 *	25.2	2.5	0.65	25.2
	Europe	Austria	02/1922	04/2017	1069	8.2	2.95 ***	26.2	01/1970	04/2017	568	7.2	2.56 **	19.3	1.8	0.64	19.4
		Belgium	02/1897	04/2017	1347	3.7	2.24 **	17.7	01/1951	04/2017	796	9.2	4.97 ***	15.0	3.7	1.98 **	15.1
		Denmark	01/1921	04/2017	1155	5.8	3.97 ***	14.4	01/1970	04/2017	568	12.0	4.83 ***	17.1	6.5	2.61 ***	17.1
		Finland	01/1913	04/2017	1237	8.4	4.09 ***	21.0	11/1912	04/2017	1254	13.0	6.47 ***	20.5	6.6	3.27 ***	20.6
		France	01/1802	04/2017	2162	5.2	3.61 ***	19.4	02/1895	04/2017	1467	10.1	6.01 ***	18.5	5.3	3.05 ***	18.7
		Germany	01/1870	04/2017	1696	2.8	1.35	24.8	01/1870	04/2017	1768	5.8	1.99 **	35.5	0.9	0.30	35.5
		Ireland	02/1934	04/2017	999	6.8	3.57 ***	17.3	12/1972	04/2017	533	11.8	3.50 ***	22.4	4.9	1.46	22.4
		Italy	01/1906	04/2017	1323	6.0	2.66 ***	23.9	01/1925	04/2017	1108	10.1	3.89 ***	25.0	4.1	1.56	25.0
		Netherlands	02/1919	04/2017	1131	4.1	2.39 **	16.7	01/1951	04/2017	796	10.6	5.13 ***	16.8	6.7	3.21 ***	16.9
		Norway	01/1970	04/2017	568	9.2	2.56 **	24.7	01/1980	04/2017	448	11.3	2.83 ***	24.4	4.2	1.04	24.5
		Portugal	01/1934	04/2017	962	5.8	1.72 *	30.1	02/1988	04/2017	351	3.3	0.93	19.3	−1.6	−0.45	19.5
		Spain	01/1915	04/2017	1178	6.0	3.41 ***	17.3	04/1940	04/2017	925	11.1	5.39 ***	18.1	5.0	2.40 **	18.2
		Sweden	01/1906	04/2017	1334	5.7	3.45 ***	17.4	01/1919	04/2017	1180	9.8	5.74 ***	16.9	4.8	2.82 ***	17.0
		Switzerland	01/1916	04/2017	1216	3.9	2.59 ***	15.1	02/1966	04/2017	615	7.4	3.33 ***	15.9	4.6	2.07 **	15.9
		United Kingdom	02/1693	04/2017	3879	1.6	2.11 **	13.7	09/1694	04/2017	3872	6.5	9.33 ***	12.6	2.2	3.12 ***	12.6
	Mid East	Israel	02/1949	04/2017	819	20.8	7.59 ***	22.6	12/1992	04/2017	293	7.5	1.82 *	20.5	1.2	0.30	20.5
	North America	Canada	02/1915	04/2017	1227	5.0	3.28 ***	15.4	03/1934	04/2017	998	9.2	5.69 ***	14.7	4.9	3.01 ***	14.8
		United States	01/1792	04/2017	2704	3.1	3.11 ***	15.0	02/1800	04/2017	2607	8.2	8.02 ***	15.1	4.3	4.17 ***	15.1
	Oceania	Australia	02/1875	04/2017	1707	5.2	4.46 ***	13.9	07/1928	04/2017	1066	10.8	6.57 ***	15.5	5.7	3.48 ***	15.5
		New Zealand	01/1931	04/2017	1036	5.3	3.51 ***	14.2	07/1986	04/2017	370	6.7	2.14 **	17.3	−0.4	−0.13	17.5

			Price Return						Total Return						Risk Premium		
Status	Region	Country	Start	End	Obs	Mean	t-value	St Dev	Start	End	Obs	Mean	t-value	St Dev	Mean	t-value	St Dev
Emerging	Africa	Egypt	01/1993	04/2017	291	17.2	2.75 ***	30.7	09/1996	04/2017	248	14.6	2.17 **	30.5	4.6	0.69	30.5
		South Africa	02/1910	04/2017	1287	8.0	4.82 ***	17.3	02/1960	04/2017	687	14.9	5.41 ***	20.8	6.0	2.18 **	20.9
	Asia	China	01/1991	04/2017	316	13.6	1.79 *	39.0	01/1993	04/2017	292	1.4	0.20	34.1	−3.2	−0.46	34.2
		India	01/1923	04/2017	1107	6.5	2.96 ***	21.2	01/1988	04/2017	352	16.2	3.02 ***	29.1	3.8	0.71	26.1
		Indonesia	03/1983	04/2017	410	11.2	2.13 **	30.8	01/1988	04/2017	352	17.2	2.58 ***	36.0	4.6	0.68	36.3
		Korea	02/1962	04/2017	661	12.6	2.49 **	37.5	02/1962	04/2017	663	19.5	3.86 ***	37.6	8.3	1.63	37.6
		Malaysia	01/1974	04/2017	520	7.5	1.90 *	26.0	12/1972	04/2017	533	8.4	2.06 **	27.3	4.3	1.04	27.3
		Philippines	01/1953	04/2017	772	5.1	1.49	27.2	01/1982	04/2017	424	14.4	3.11 ***	27.6	3.7	0.79	27.6
		Taiwan	02/1967	04/2017	603	9.0	1.98 **	32.3	01/1988	04/2017	352	7.8	1.33	31.8	4.5	0.77	31.8
		Thailand	01/1976	04/2017	496	8.5	1.86 *	29.2	05/1975	04/2017	504	10.9	2.42 **	29.2	6.2	1.27	28.7
	Europe	Czech Republic	12/1993	04/2017	281	4.3	0.83	24.8	11/1993	04/2017	282	8.3	1.63	24.8	4.3	0.85	24.9
		Greece	01/1954	04/2017	759	7.0	1.99 **	28.1	01/1977	04/2017	484	9.0	1.70 *	33.5	−3.4	−0.64	34.0
		Hungary	07/1991	04/2017	310	10.1	1.68 *	30.4	02/1991	04/2017	315	13.1	2.32 **	29.0	0.8	0.13	29.0

			Price Return							Total Return							Risk Premium			
Status	Region	Country	Start	End	Obs	Mean	t-value		St Dev	Start	End	Obs	Mean	t-value		St Dev	Mean	t-value		St Dev
		Poland	03/1994	04/2017	278	2.1	0.33		30.7	05/1991	04/2017	312	16.0	2.24	**	36.4	2.7	0.38		36.3
		Russia	01/1994	04/2017	280	30.9	3.29	***	45.4	01/1995	04/2017	268	13.4	1.24		50.9	−7.0	−0.70		45.5
		Turkey	02/1986	04/2017	375	36.7	4.24	***	48.3	02/1986	04/2017	375	40.7	4.60	***	49.4	−4.6	−0.52		49.2
	Mid East	Qatar	01/2000	04/2017	208	11.6	1.82	*	26.6	12/2003	04/2017	161	11.7	1.42		30.2	9.0	1.09		30.2
		United Arab Emirates	01/1988	04/2017	339	8.2	2.21	**	19.6	12/2003	04/2017	161	12.8	1.59		29.5	10.3	1.27		29.6
	North America	Mexico	02/1930	04/2017	1047	15.3	5.82	***	24.6	01/1988	04/2017	352	22.6	4.87	***	25.1	6.2	1.36		24.5
	South America	Brazil	01/1990	04/2017	327	53.7	5.58	***	50.3	–	–	–	–	–		–	–	–		–
		Chile	01/1927	04/2017	1084	25.6	8.38	***	29.0	01/1983	04/2017	412	20.5	5.75	***	20.9	7.7	2.21	**	20.5
		Colombia	02/1927	04/2017	1083	8.4	4.29	***	18.6	01/1988	04/2017	352	13.5	1.42		51.5	−3.0	−0.31		51.9
		Peru	01/1933	04/2017	1012	27.8	6.92	***	36.8	01/1993	04/2017	292	17.2	2.84	***	29.8	8.4	1.38		30.0
Frontier	Africa	Kenya	02/1990	04/2017	327	5.0	1.16		22.4	–	–	–	–	–		–	–	–		–
		Mauritius	01/1990	04/2017	328	10.4	3.60	***	15.1	08/1989	04/2017	333	14.9	5.25	***	15.0	7.6	2.66	***	15.0
		Morocco	01/1988	04/2017	339	10.4	3.84	***	14.4	03/1994	04/2017	278	11.6	3.77	***	14.8	7.1	2.30	**	14.8
		Nigeria	01/1988	04/2017	340	17.7	4.44	***	21.2	–	–	–	–	–		–	–	–		–
		Tunisia	01/1996	04/2017	256	3.7	1.16		14.8	–	–	–	–	–		–	–	–		–
Frontier	Asia	Bangladesh	02/1990	04/2017	327	7.9	1.38		30.2	–	–	–	–	–		–	–	–		–
		Kazakhstan	01/2001	04/2017	196	16.4	1.93	*	34.5	–	–	–	–	–		–	–	–		–
		Pakistan	01/1961	04/2017	672	8.7	2.72	***	23.9	01/1988	04/2017	352	15.9	2.55	**	33.8	6.3	1.00		33.9
		Sri Lanka	01/1985	04/2017	388	11.7	2.63	***	25.4	05/1987	04/2017	360	14.3	3.00	***	26.1	2.1	0.45		26.2
		Viet Nam	01/2001	04/2017	196	7.8	0.90		35.1	–	–	–	–	–		–	–	–		–
	Europe	Croatia	02/1997	04/2017	243	2.9	0.46		28.2	–	–	–	–	–		–	–	–		–
		Estonia	01/1996	04/2017	256	15.4	2.14	**	33.3	08/1995	04/2017	261	16.3	2.28	**	33.4	13.7	1.91	*	33.4
		Lithuania	01/1996	04/2017	256	5.0	0.91		25.4	01/1996	04/2017	256	8.6	1.35		29.4	3.7	0.58		29.6
		Romania	01/1997	04/2017	244	14.3	1.50		42.8	12/1996	04/2017	245	18.2	1.93	*	42.6	−6.4	−0.68		42.7
		Serbia	01/2009	04/2017	100	4.1	0.39		30.2	–	–	–	–	–		–	–	–		–
		Slovenia	01/1996	04/2017	257	3.0	0.65		21.1	12/1998	04/2017	221	4.6	1.14		17.3	0.2	0.05		17.2
	Mid East	Bahrain	01/1991	04/2017	316	3.0	1.24		12.6	12/2003	04/2017	161	5.6	1.51		13.5	4.0	1.06		13.7
		Jordan	02/1978	04/2017	471	5.4	1.58		21.4	06/2006	04/2017	131	0.2	0.04		18.4	−6.2	−1.11		18.5
		Kuwait	01/1995	04/2017	268	8.7	2.22	**	18.4	12/2003	04/2017	161	4.6	0.87		19.3	2.6	0.50		19.3
		Lebanon	02/1996	04/2017	255	1.1	0.22		24.4	–	–	–	–	–		–	–	–		–
		Oman	01/1993	04/2017	290	6.6	1.70	*	19.0	09/2005	04/2017	140	5.9	1.16		17.5	4.7	0.91		17.5
	South America	Argentina	01/1967	04/2017	604	58.8	6.63	***	62.8	07/1993	04/2017	286	18.2	2.70	***	32.9	6.6	0.98		32.8
Rarely Studied	Africa	Algeria	02/2008	04/2017	111	2.7	0.94		8.6	–	–	–	–	–		–	–	–		–
		Botswana	01/1990	04/2017	328	15.1	5.89	***	13.4	–	–	–	–	–		–	–	–		–
		Cote D'Ivoire	01/1996	04/2017	256	7.5	2.11	**	16.4	–	–	–	–	–		–	–	–		–
		Ghana	01/1996	04/2017	255	10.7	2.78	***	17.7	–	–	–	–	–		–	–	–		–
		Malawi	03/2001	04/2017	181	20.9	2.58	***	31.5	–	–	–	–	–		–	–	–		–
		Namibia	01/1994	04/2017	280	9.4	1.99	**	22.7	–	–	–	–	–		–	–	–		–
		Rwanda	04/2013	04/2017	49	−0.2	−0.07		6.3	–	–	–	–	–		–	–	–		–
		Swaziland	01/2000	04/2017	148	4.4	1.28		12.0	–	–	–	–	–		–	–	–		–
		Tanzania	01/2007	04/2017	124	7.7	2.08	**	11.9	–	–	–	–	–		–	–	–		–
		Uganda	10/2004	04/2017	151	11.6	1.61		25.6	–	–	–	–	–		–	–	–		–
		Zambia	12/1996	04/2017	244	15.2	2.47	**	27.8	–	–	–	–	–		–	–	–		–
	Asia	Cambodia	01/2013	04/2017	52	−15.2	−1.35		23.5	–	–	–	–	–		–	–	–		–
		Kyrgyzstan	07/1995	04/2017	214	−10.3	−0.47		92.7	–	–	–	–	–		–	–	–		–
		Laos	02/2011	04/2017	75	−7.7	−1.11		17.4	–	–	–	–	–		–	–	–		–
		Mongolia	01/1996	04/2017	256	23.7	2.64	***	41.5	–	–	–	–	–		–	–	–		–
		Nepal	02/1994	04/2017	260	5.2	0.52		46.9	–	–	–	–	–		–	–	–		–

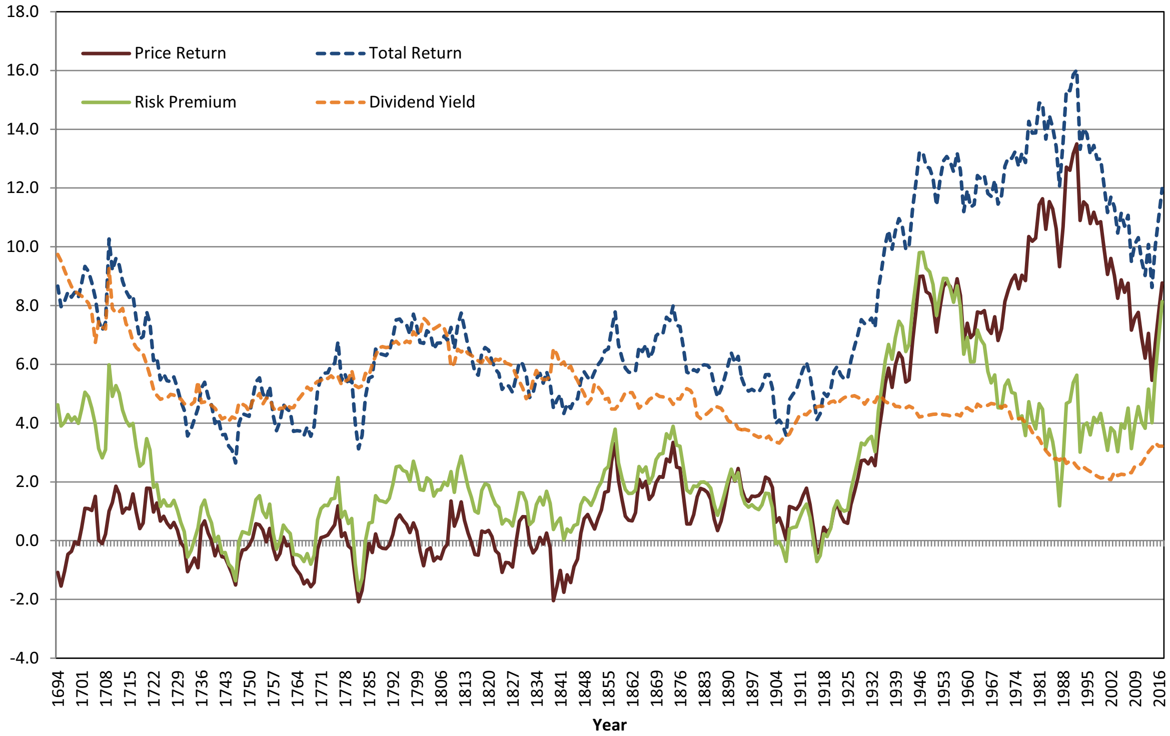


Fig. 2. 30-year moving average of pooled 65 countries' price returns, total returns, risk premiums and dividend yield for the period 1694 to 2016.

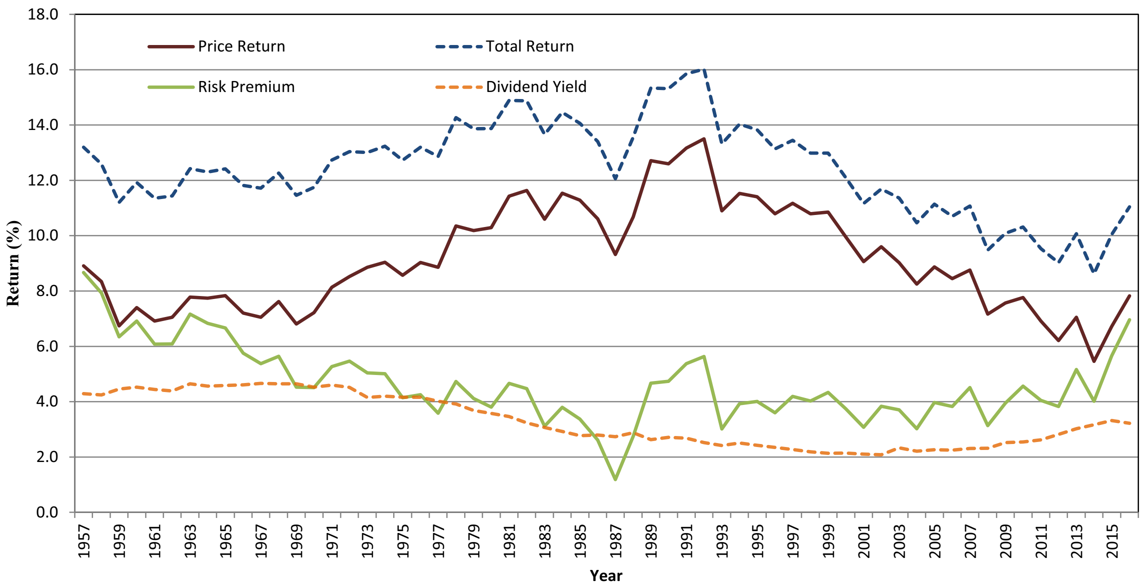


Fig. 3. 30-year moving average of pooled 65 countries' price returns, total returns, risk premiums and dividend yield for the period 1957 to 2016.

survivorship bias. Many markets (like Russia) have collapsed at some stage during their history and many of those (most likely low and negative return data) are no longer available. The green line of Fig. 2 depicts a 30-year moving average of the risk premiums of the pooled countries. The risk premiums rarely excess 4% in the first 230 years. It grows up to 10% in the late 1940s, then gradually declines to 1.2% in 1987 and bounce around 4% in the latest 30 years until its recent new peaks of 6% and 8% in 2016 and 2017. This confirms the widely held believe that the high risk premium in the recent past may be due to the exceptional growth in the economies around the world.

4.2. Total returns and risk premiums in summer and winter

The total return data and short term interest rates allow us to investigate the behaviour of risk premiums in summer and winter. As we discussed before "Sell in May and go away" suggests leaving the stock market altogether. Even summer returns are significantly lower than winter returns, investors might still be better off to remain in the market if these returns are greater than the risk free rate. Hence, one could argue that a better test of the Sell in May effect is whether excess returns are positive during summer. If summer returns are not significantly different from (or even significantly lower than) interest rates the market wisdom seems to holds. The results of this test will, of course, correlate positively with the Bouman and Jacobsen (2002) test. While the Bouman and Jacobsen (2002) reveals an interesting pattern, the advantages of our new test are two-fold. Firstly, this test is more in line with the actual market wisdom, and, additionally, this new test illustrates much more clearly what makes the anomaly interesting beyond a market efficiency point of view. It not only violates the notion that returns should be difficult to predict, but also that there is no risk return trade off during long predictable time periods. In Fig. 4 we plot the risk premia in summer (as in Fig. 1) and add the winter risk premia for comparison.

Table 2 compares the total return, risk free rate and risk premium between two 6-month periods for 65 markets. The coefficient estimates of the regression on 6-month total return difference confirm the prevalence of the Halloween effect. However, the risk free rate shows limited 6-month seaonality, the coefficients are all close to zero and insignificant.

We observe the presence of negative summer risk premium in 45 out of 65 countries. In 7 countries these risk premia are significantly below zero. Average excess summer returns are lower than winter returns for most of the countries except for 2 markets. Summer returns tend to be insignificant even before deducting the risk free rates. This is in striking contrast with winter (excess) returns which are often significantly greater than zero, especially in developed and emerging markets. When we pool the data we find that over the entire 37,167 monthly observations, the average risk premium during 6-month summer period is −1.1% (t-value 3.58) compared with 5.1% (t-value 16.75) during the winter months period. We use a bootstrapping methodology to test the reliability of this pooled summer negative risk premiums. Our bootstrapping strategy enables us to get the confidence interval of the negative risk premiums while allowing for cross-sectional correlation between markets. First, we obtain the coefficient estimates of the Halloween regression dummy for each of the 65 country in our sample, and subtract the Halloween period return for each countries monthly observations. This gives us a sample of no-Halloween effect risk premium. Second, we resample our data using unrestricted random sampling technique to get 10,000 replicates, and estimate the average return for each sample to obtain the confidence interval. The average of our no-Halloween effect risk premium in the original sample is −0.1937 (1.16% 6-monthly), and the 95% confidence interval is (−0.2681, −0.1206).

This low or even negative excess return during summer which is predictable, persistent and consistent seems not easy to reconcile with a positive risk return relationship. The coefficient estimates of the Halloween dummy are statistically significant in 36 (and 35) of the 65 countries' total return indices (and risk premium indices), which is even more pronounced than the results for our price return indices as we will show below.[18] Substantial risk differences might explain a huge difference in returns between summer and winter. However, simple standard deviations do not indicate a difference. If anything, risk is higher during summer. We address this in more detail in Appendix 3.

5. The Halloween indicator revisited

As noted before the existence of a Halloween effect has been debated. It may be good to consider some of the arguments put forward in the debate. We do this based on the old test which allows comparison with previous results in the literature. We also use price indices as this allows us to test an even bigger sample of countries (and as we have shown above dividends hardly seem to affect results). Moreover, we include some additional tests that may help shed further light on what may or what may not cause this effect.

5.1. Out of sample performance

To be relevant we must first 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 – as the authors show - the market wisdom was already known before their sample period.). Many anomalies indeed seem to follow the theoretical prediction. McLean and Pontiff (2016) investigates the performance of 95 published stock return predictors out of sample and post publication, they show that predictor's return declines 31% on average after taking statistical biases into account.

To investigate whether the Halloween effect has weakened, we start with an out of sample test of the Halloween effect in the 37 countries examined in Bouman and Jacobsen (2002). Table 3 compares in-sample performance for the period 1970 to August 1998[19] with out-of-sample performance for the period of September 1998 to April 2017. The in-sample test using a dif-

[18] This also reinforces the finding of Zhang and Jacobsen (2013) that there is no strong seasonal effect in dividend payments.

[19] 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 start later than 1970.

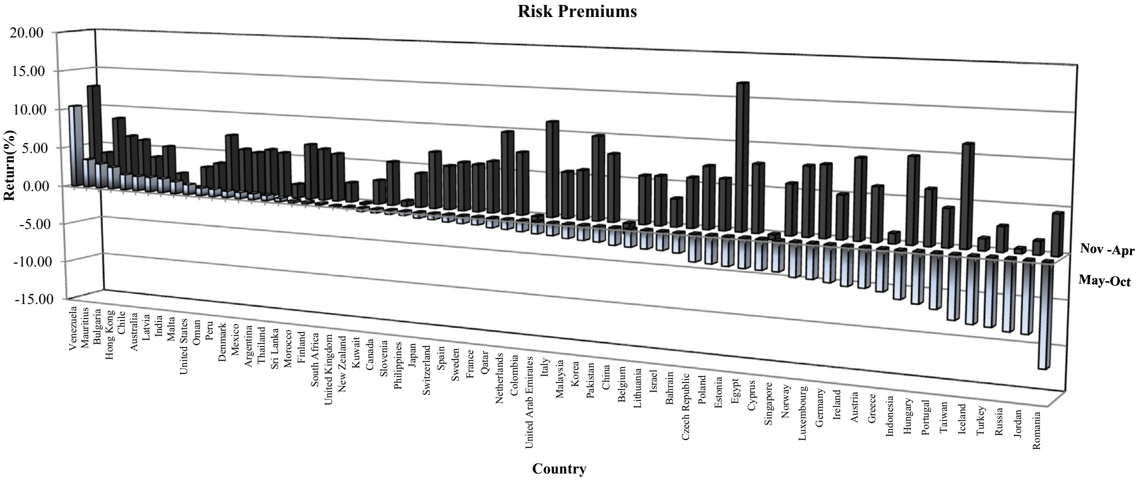


Fig. 4. Summer (May-October) and Winter (November-April) risk premiums for 65 countries.

ferent 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 21 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 20 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. 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. It is over 15 years since Bouman and Jacobsen (2002) published their study, the Halloween effect still remain significant making it an even more puzzling anomaly.

5.2. Overall results

Using all historical data for all countries available seems the most logical way to deal with sample selection bias and data mining issues. All 62,962 monthly observations for all 114 countries over 323 years combined (reported in the first row of Table 4) give a general impression of how strong the Halloween effect is. The average 6-month winter return (November through April) is 6.4%, compared to the summer return (May through October) of 2.3%. This difference between winter and summer returns is 4.1%, with a significant t-value of 3.76 estimated with a panel data approach based on two-way cluster-robust standard errors. The world index returns in the second row reveals a similar result. The average 6-month winter return is 4.8% (t-value 3.89) higher than the 6-month summer return.

5.3. 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 114 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 87 out of 114 countries and that the difference is statistically significant in 42 countries, compared to only 1 country having significantly higher May-October returns.

5.3.1. Market development status, geographical location and the Halloween effect

Fig. 5(A–D) plots the November-April and the May-October price returns for all 114 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. Fig. 5-A compares the two 6-month period returns for the 23 developed markets; with Finland being the only exception, 22 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 (Fig. 5-B) shows a similar pattern; 21 of the 23 countries have November-April returns that exceed the May-October returns, and 8 countries have negative mean returns for May-October. As we move to the frontier and rarely studied markets, this pattern becomes less distinctive. Fig. 5-C and -D reveal that 17 out of 22 (77%) countries in the frontier markets and 29 out of 46 (63%) countries in the rarely studied markets have November-April returns greater than their May-October returns.

Table 4 shows the Halloween effect across countries. The table reports average values and standard deviations for the two 6-month period returns, 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, statistically significant Halloween effects is prevalent not only among the European countries, but also among the countries located in Asia and North America. The Halloween effect is statistically significant in 16 out of 23 (70%) 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 we observe similar or even lower standard deviations in the November-April returns. The number of countries with a statistically significant Halloween effect reduces as we move to less developed markets. Among 23 emerging countries, 10 countries have November-April returns significantly higher than their May-October returns. For the frontier markets, although over 77% (17/22) of the countries show higher average returns during November-April than during May-October, only 6 countries have significant t-statistics. For the rarely studied markets, the countries with a significant Halloween effect drops to 10 out of 46. Over the total 114 countries, we only observe 1 country (Bangladesh from the frontier markets group) to have 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.

5.4. The evolution of the Halloween effect over time

5.4.1. Pooled sub-sample period regression analysis

We provide an overview of how the Halloween effect has evolved over time using time series analysis by pooling all countries in our sample together. This gives us a long time series data from 1693 to 2017. We divide the entire sample into thirty-two 10-year sub-periods[20] and compare the two 6-month period returns in Table 5. These sub-period estimates allow us to detect whether there is any trend over time in general. 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 century and reaches 112 in the most recent subsample period. Columns 4–7 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 6.4%, compared to only 2.3% for the period of May-October. Fig. 6 graphically plots the 6-month return differences of 32 10-year sub-periods, 21 of the 32 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% for November-April and 18.6% 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 of Table 5 show the Halloween coefficients of Equation (1) and the corresponding t-statistics. 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% significantly higher than the May-October returns in all of the sub-periods except for the sub-period 2001–2010.[21] We 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, 25 of the 32 sub-periods have greater returns for the period of November-April than for May-October for over 50% of the years.

Fig. 7 also reveals the trend of the Halloween effect in the Global Financial Data's world index returns from 1919 to 2017. It 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, and we also indicate the upper and lower 95% confidence intervels for the estimates with lighter dotted lines. The plots reveal that the Halloween effect is consistently present during 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.

5.4.2. 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, we would expect to observe the Halloween effect emerging around the same period. Alternatively, if the Halloween effect is simply a fluke or a market mistake, we would expect arbitragers to take the riskless profit away, with a weakening Halloween effect following its discovery. Longer time series data are essential for the subsample period analysis. In this section, we divide countries with over 90 years' data into several 10-year subsample periods to test whether or not there is any persistence of the Halloween effect in the market. Despite small sample size may reduce the power of the test, we choose 10-year subsamples for the

[20] To be precise, the first sub-period is 8 years from 1693 to 1710 and the last sub-period is 6 years from 2011 to 2017.

[21] The t-statistics for the sub-periods with only one country are estimated using Newey-West standard errors, for the sub-periods with more than one countries, the t-statistics are corrected based on two-way cluster-robust standard errors.

Table 2

Six-month difference in market total returns, risk free rates and risk premiums, This table provides two 6-month periods' mean returns and standard deviations of market total return indices, risk free rates and risk premiums of 65 countries. 6-mth diff and t-value are the coefficient estimates and t-statistics for the Halloween effect regression $r_t = \alpha + \beta Hal_t + \varepsilon_t$. t-values of the regression coefficients for individual countries are adjusted using Newey-West standard errors. The t-value of pooled 65 countries is estimated based on two-way cluster-robust standard errors. The t-value of the risk premiums are the zero mean test of the two period. 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.

	Total Return						Risk Free Rate						Risk Premium							
	Nov-Apr		May-Oct		6-mth diff	t-value	Nov-Apr		May-Oct		6-mth diff	t-value	Nov-Apr			May-Oct			6-mth diff	t-value
Country	Mean	St Dev	Mean	St Dev			Mean	St Dev	Mean	St Dev			Mean	St Dev	t-value	Mean	St Dev	t-value		
World	6.6	9.4	1.7	11.0	4.9	3.71 ***														
Pooled 65 countries	8.5	17.1	2.1	17.7	6.4	4.16 ***	3.3	2.0	3.3	1.8	0.0	0.81	5.1	17.0	16.75 ***	−1.1	17.6	−3.58 ***	6.3	4.11 ***
Developed markets																				
Asia																				
Hong Kong	9.1	22.6	5.4	23.2	3.7	0.78	2.6	0.8	2.6	0.8	0.0	0.35	6.4	22.6	1.96 **	2.8	23.3	0.81	3.7	0.77
Japan	9.4	15.5	1.2	13.0	8.2	3.54 ***	2.0	0.6	2.0	0.6	0.0	−0.04	6.9	14.1	4.70 ***	−0.7	12.4	−0.51	7.5	3.97 ***
Singapore	7.8	16.1	−1.5	19.2	9.3	2.29 **	1.9	0.6	1.9	0.6	−0.1	−0.65	5.9	16.1	2.42 **	−3.5	19.2	−1.18	9.3	2.29 **
Europe																				
Austria	8.9	12.2	−1.7	14.7	10.6	3.78 ***	2.7	0.6	2.7	0.6	0.0	−0.81	6.2	12.3	3.48 ***	−4.5	14.7	−2.08 **	10.6	3.78 ***
Belgium	8.4	10.0	0.7	11.0	7.7	4.32 ***	2.8	0.7	2.8	0.7	0.0	−0.10	5.7	10.0	4.64 ***	−2.1	11.1	−1.51	7.7	4.31 ***
Denmark	8.4	11.4	3.6	12.6	4.8	2.22 **	2.7	0.7	2.8	0.7	0.0	−0.65	5.7	11.5	3.39 ***	0.8	12.6	0.44	4.8	2.24 **
Finland	9.6	14.6	3.4	14.4	6.1	3.00 ***	3.2	0.7	3.2	0.7	0.0	0.61	6.3	14.6	4.45 ***	0.2	14.4	0.15	6.1	2.98 ***
France	8.5	13.2	1.6	12.8	6.9	3.87 ***	2.2	0.7	2.2	0.7	0.0	−0.07	6.2	13.3	5.04 ***	−0.9	13.0	−0.78	7.1	3.85 ***
Germany	7.5	21.1	−1.7	28.4	9.2	3.11 ***	2.5	0.4	2.5	0.5	0.0	−0.67	5.0	21.1	2.90 ***	−4.2	28.5	−1.78 *	9.2	3.12 ***
Ireland	12.7	14.6	−1.1	16.5	13.8	3.88 ***	3.5	1.2	3.3	1.0	0.2	1.20	9.2	14.5	4.24 ***	−4.4	16.6	−1.77 *	13.6	3.83 ***
Italy	8.4	17.3	1.7	17.9	6.7	2.49 **	3.1	1.0	3.1	1.0	0.0	0.10	5.5	17.3	3.07 ***	−1.5	18.0	−0.78	7.0	2.68 ***
Netherlands	9.5	10.7	1.1	12.7	8.3	4.21 ***	2.0	0.6	2.0	0.6	0.0	−0.73	7.5	10.8	5.68 ***	−0.9	12.8	−0.56	8.4	4.21 ***
Norway	11.5	15.4	−0.3	18.7	11.9	2.43 **	3.6	1.0	3.6	0.9	0.0	−0.33	8.0	15.4	3.18 ***	−3.9	18.8	−1.26	11.9	2.44 **
Portugal	6.8	12.8	−3.5	14.3	10.3	2.72 ***	2.4	1.0	2.5	1.0	−0.1	−0.61	4.3	12.9	1.82 *	−6.0	14.3	−2.28 **	10.4	2.72 ***
Spain	8.8	12.6	2.3	12.9	6.5	3.45 ***	3.0	0.9	3.1	1.0	−0.1	−1.57	5.8	12.6	4.05 ***	−0.8	13.0	−0.57	6.7	3.50 ***
Sweden	8.2	12.1	1.6	11.7	6.6	3.92 ***	2.5	0.7	2.5	0.7	0.0	−0.84	5.7	12.1	4.69 ***	−0.9	11.8	−0.75	6.6	3.92 ***
Switzerland	6.6	10.0	0.8	12.2	5.8	2.84 ***	1.4	0.6	1.5	0.6	−0.1	−0.83	5.3	10.1	3.76 ***	−0.7	12.2	−0.41	6.0	2.90 ***
United Kingdom	4.6	8.8	2.0	9.0	2.6	3.86 ***	2.2	0.5	2.2	0.5	0.0	1.13	2.4	8.7	4.91 ***	−0.2	9.0	−0.41	2.6	3.80 ***
Mid-East																				
Israel	6.4	15.1	1.1	13.8	5.3	1.22	3.1	1.1	3.2	1.0	−0.1	−0.47	3.3	15.1	1.08	−2.1	13.8	−0.75	5.4	1.23
North America																				
Canada	7.5	9.5	1.7	11.2	5.7	3.73 ***	2.1	0.8	2.2	0.8	0.0	−0.37	5.3	9.5	5.10 ***	−0.4	11.2	−0.36	5.8	3.72 ***
United States	5.0	10.0	3.2	11.3	1.8	1.77 *	2.0	0.5	2.0	0.5	0.0	0.03	3.0	10.0	4.49 ***	1.2	11.4	1.61	1.8	1.77 *
Oceania																				
Australia	6.4	9.6	4.4	12.1	2.1	1.30	2.5	0.8	2.5	0.8	0.0	0.14	3.9	9.6	3.84 ***	1.8	12.2	1.41	2.1	1.29
New Zealand	3.3	10.8	3.3	13.5	0.0	0.01	3.5	0.9	3.5	0.8	0.0	−0.10	−0.2	11.2	−0.09	−0.2	13.6	−0.09	0.0	0.01

Country	Total Return						Risk Free Rate						Risk Premium							
	Nov-Apr		May-Oct		6-mth diff	t-value	Nov-Apr		May-Oct		6-mth diff	t-value	Nov-Apr			May-Oct			6-mth diff	t-value
	Mean	St Dev	Mean	St Dev			Mean	St Dev	Mean	St Dev			Mean	St Dev	t-value	Mean	St Dev	t-value		
Emerging markets																				
Africa																				
Egypt	12.8	23.6	1.6	19.1	11.2	1.79 *	5.0	0.5	5.0	0.4	0.0	−0.16	7.8	23.6	1.53	−3.4	19.1	−0.80	11.3	1.80 *
South Africa	10.3	13.9	4.6	15.5	5.7	1.69 *	4.4	0.9	4.4	1.0	0.0	−0.26	5.9	13.9	3.18 ***	0.2	15.6	0.09	5.7	1.69 *
Asia																				
China	1.1	23.84	0.3	24.49	0.8	0.12	2.3	0.57	2.3	0.57	0.01	0.19	−1.2	23.9	−0.25	−2.0	24.5	−0.40	0.8	0.11
India	8.2	20.94	8.0	20.24	0.3	0.05	4.1	0.47	4.0	0.45	0.05	0.56	2.0	18.7	0.53	1.8	18.2	0.48	0.2	0.05
Indonesia	16.0	23.38	1.0	27.16	15.0	2.26 **	6.3	1.54	6.3	1.84	−0.03	−0.09	9.7	23.2	2.28 **	−5.3	27.7	−1.03	15.0	2.25 **
Korea	15.6	27.50	3.9	25.44	11.7	2.00 **	5.6	1.48	5.6	1.41	0.00	0.03	9.9	27.5	2.69 ***	−1.7	25.4	−0.51	11.7	2.00 **
Malaysia	7.9	18.63	0.4	19.82	7.4	1.75 *	2.1	0.29	2.1	0.31	−0.03	−0.94	5.8	18.6	2.10 **	−1.7	19.9	−0.55	7.5	1.76 *
Philippines	9.7	17.09	4.7	21.70	5.1	1.16	5.3	1.63	5.1	1.57	0.11	0.54	4.1	17.0	1.45	−0.5	21.8	−0.13	4.6	1.07
Taiwan	13.0	21.58	−5.4	22.78	18.4	2.96 ***	1.6	0.51	1.7	0.51	−0.02	−0.46	11.3	21.5	2.87 ***	−7.1	22.9	−1.66 *	18.4	2.96 ***
Thailand	8.1	18.03	2.8	22.95	5.2	1.10	2.8	0.84	2.8	0.81	−0.01	−0.05	5.5	17.4	1.86 *	0.7	22.7	0.17	4.9	1.03
Europe																				
Czech Republic	9.2	19.03	−1.1	15.62	10.4	2.23 **	2.0	0.78	2.0	0.82	−0.04	−0.32	7.3	19.0	1.87 *	−3.1	15.7	−0.95	10.4	2.23 **
Greece	7.8	22.89	1.1	24.50	6.7	1.25	6.6	5.50	5.8	2.42	0.83	0.82	1.2	23.4	0.32	−4.7	24.6	−1.20	5.8	1.08
Hungary	12.4	20.11	0.6	20.66	11.8	2.43 **	6.1	1.89	6.3	1.87	−0.15	−0.56	6.3	20.1	1.61	−5.6	20.8	−1.38	11.9	2.45 **
Poland	12.3	22.65	3.7	28.40	8.6	1.55	6.4	2.47	6.9	2.79	−0.54	−0.98	5.9	22.5	1.34	−3.2	28.4	−0.58	9.1	1.63
Russia	15.4	31.02	−2.3	40.24	17.7	1.53	11.1	9.88	9.7	7.08	1.37	0.52	0.5	31.8	0.08	−7.7	32.6	−1.07	8.3	0.78
Turkey	25.7	36.41	14.9	33.28	10.7	1.28	22.8	7.22	22.6	7.18	0.18	0.18	2.8	35.8	0.43	−7.4	33.7	−1.23	10.2	1.23
Mid-East																				
Qatar	11.0	24.25	0.3	17.63	10.8	1.34	1.3	0.42	1.4	0.44	−0.15	−1.05	9.8	24.3	1.50	−1.1	17.6	−0.23	10.9	1.37
United Arab Emirates	12.5	19.91	0.0	21.71	12.5	1.80 *	1.2	0.47	1.4	0.50	−0.19	−1.26	11.3	20.0	2.10 **	−1.4	21.7	−0.23	12.7	1.84 *
North America																				
Mexico	14.5	17.57	8.1	17.95	6.4	1.66 *	8.7	4.24	7.3	2.43	1.37	1.44	5.3	16.8	1.73 *	0.8	17.7	0.23	4.6	1.14
South America																				
Chile	12.8	14.94	7.6	14.56	5.2	1.53	6.6	2.94	6.2	2.54	0.41	1.09	6.2	14.5	2.53 **	1.4	14.4	0.58	4.8	1.40
Colombia	6.6	48.48	6.9	16.97	−0.3	−0.03	8.1	2.30	8.2	2.41	−0.12	−0.36	−1.7	48.8	−0.19	−1.3	17.3	−0.40	−0.4	−0.04
Peru	11.6	20.44	5.4	21.71	6.2	0.93	4.3	1.71	4.5	1.89	−0.20	−0.53	7.3	20.6	1.77 *	0.9	21.8	0.21	6.4	0.96

Country	Total Return						Risk Free Rate						Risk Premium							
	Nov-Apr		May-Oct		6-mth diff	t-value	Nov-Apr		May-Oct		6-mth diff	t-value	Nov-Apr			May-Oct			6-mth diff	t-value
	Mean	St Dev	Mean	St Dev			Mean	St Dev	Mean	St Dev			Mean	St Dev	t-value	Mean	St Dev	t-value		
Frontier markets																				
Africa																				
Mauritius	7.7	10.69	7.2	10.52	0.5	0.20	3.7	0.78	3.7	0.74	0.06	0.48	4.0	10.7	1.99 **	3.5	10.5	1.77 *	0.5	0.18
Morocco	9.0	11.82	2.5	8.69	6.5	2.31 **	2.2	0.53	2.3	0.53	−0.02	−0.25	6.8	11.8	2.77 ***	0.2	8.7	0.13	6.5	2.32 **
Asia																				
Pakistan	12.7	24.44	3.0	23.19	9.7	1.98 **	4.8	0.71	4.8	0.70	−0.05	−0.49	8.0	24.6	1.76 *	−1.8	23.3	−0.41	9.7	1.99 **
Sri Lanka	7.8	17.45	6.5	19.46	1.3	0.26	6.1	0.75	6.1	0.74	0.02	0.18	1.7	17.4	0.54	0.4	19.6	0.12	1.3	0.25
Europe																				
Estonia	18.1	23.11	−2.0	23.48	20.1	3.06 ***	1.3	0.31	1.3	0.33	−0.07	−1.19	16.8	23.1	3.41 ***	−3.3	23.5	−0.66	20.1	3.07 ***
Lithuania	8.3	21.85	0.2	19.58	8.0	1.21	2.5	1.17	2.3	0.94	0.15	0.58	5.8	21.9	1.22	−2.1	19.8	−0.49	7.9	1.19
Romania	17.2	32.19	0.6	27.52	16.6	1.83 *	12.7	5.25	11.9	4.70	0.75	0.88	4.6	32.0	0.65	−11.3	27.9	−1.82 *	15.9	1.78 *
Slovenia	3.1	12.13	1.5	12.33	1.6	0.40	1.9	0.76	1.9	0.77	−0.08	−0.63	0.7	12.1	0.23	−0.5	12.2	−0.16	1.1	0.27
Mid East																				
Bahrain	6.8	9.69	−1.5	9.21	8.3	2.54 **	1.0	0.29	1.0	0.33	−0.02	−0.31	5.8	9.7	2.23 **	−2.3	9.4	−0.85	8.1	2.35 **

(continued on next page)

Jordan	4.8	11.61	−4.6	14.18	9.4	1.66	*	3.2	0.54	3.2	0.51	0.04	0.32	1.5	11.6	0.43		−7.8	14.2	−1.81	*	9.3	1.66	*
Kuwait	3.9	14.34	0.5	12.86	3.4	0.63		1.0	0.37	1.0	0.34	0.04	0.41	2.9	14.4	0.76		−0.4	12.9	−0.12		3.3	0.62	
Oman	4.3	11.28	1.6	13.52	2.7	0.44		0.6	0.31	0.7	0.33	−0.03	−0.37	3.6	11.3	1.12		0.9	13.5	0.23		2.7	0.44	
South America																								
Argentina	11.7	25.36	6.4	20.90	5.3	0.89		5.9	3.37	5.7	2.61	0.19	0.26	5.8	25.3	1.13		0.7	20.8	0.17		5.1	0.90	
Rarely studied markets																								
Europe																								
Bulgaria	9.9	22.05	4.5	22.74	5.5	0.70		1.3	0.41	1.4	0.40	−0.08	−0.96	8.6	22.1	1.61		3.1	22.8	0.55		5.5	0.71	
Cyprus	1.1	23.41	−1.7	29.40	2.8	0.32		1.7	0.48	1.7	0.47	−0.05	−0.76	−0.6	23.4	−0.13		−3.4	29.4	−0.57		2.9	0.32	
Iceland	5.4	18.30	−3.3	35.68	8.7	1.17		4.1	0.84	4.0	0.70	0.09	0.46	1.3	18.7	0.28		−7.3	35.9	−0.78		8.6	1.15	
Latvia	7.1	20.15	3.7	24.22	3.4	0.46		1.8	0.57	1.9	0.67	−0.11	−0.59	5.4	20.2	1.22		1.8	24.2	0.35		3.5	0.48	
Luxembourg	10.5	11.71	−1.7	14.91	12.2	3.37	***	2.2	0.70	2.2	0.67	−0.02	−0.22	8.3	11.7	4.04	***	−4.0	14.9	−1.50		12.2	3.37	***
Malta	1.5	11.71	2.7	8.95	−1.3	−0.52		1.1	0.36	1.2	0.37	−0.07	−1.07	0.3	11.8	0.12		1.5	9.0	0.70		−1.2	−0.48	
South America																								
Venezuela	21.0	30.49	18.8	30.18	2.2	0.24		8.3	1.36	8.4	1.66	−0.13	−0.29	12.7	30.5	1.90	*	10.4	30.5	1.53		2.3	0.25	

Table 3
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 our sample depending on data availability) to August 1998. The out-of-sample period is from September 1998 to April 2017. The coefficient β represents the 6-month return difference between November-April and May-October. T-values are adjusted using Newey-West standard errors. %+ is the percentage of years of greater November-April return. *** 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	2.6	0.20		66%	4.8	0.60		60%
Australia	6.5	1.72	*	59%	3.8	1.54		55%
Austria	7.2	2.13	**	59%	13.0	3.43	***	60%
Belgium	12.5	5.04	***	93%	6.5	1.69	*	70%
Brazil	34.8	1.69	*	78%	8.4	1.57		50%
Canada	6.3	2.28	**	69%	6.5	2.34	**	70%
Chile	−7.9	−0.74		45%	2.4	0.91		55%
Denmark	3.6	1.23		66%	7.6	2.01	**	75%
Finland	9.2	2.79	***	76%	8.4	1.60		55%
France	13.7	3.58	***	79%	9.3	2.71	***	70%
Germany	8.5	3.03	***	66%	10.5	2.73	***	70%
Greece	10.9	1.86	*	66%	4.6	0.76		55%
Hong Kong	5.8	0.84		69%	1.1	0.19		40%
Indonesia	14.3	1.67	*	56%	14.4	2.42	**	70%
Ireland	11.4	2.49	**	69%	12.6	3.19	***	80%
Italy	15.1	3.52	***	76%	12.3	3.03	***	65%
Japan	9.2	2.70	***	76%	10.8	2.50	**	65%
Jordan	4.5	1.08		52%	3.7	1.25		55%
Korea	1.3	0.31		52%	8.5	1.55		60%
Malaysia	12.6	1.84	*	68%	3.6	0.94		45%
Mexico	3.6	0.58		55%	5.4	1.43		60%
Netherlands	10.9	3.77	***	86%	9.3	2.28	**	60%
New Zealand	1.6	0.41		48%	3.5	1.78	*	65%
Norway	5.6	1.16		59%	8.2	1.80	*	60%
Philippines	12.9	1.98	**	62%	5.3	1.11		55%
Portugal	3.7	0.36		65%	10.3	2.56	**	75%
Russia	−24.7	−0.65		40%	15.0	1.84	*	65%
Singapore	8.6	1.39		62%	4.7	1.12		60%
South Africa	7.7	1.39		62%	2.1	0.50		55%
Spain	10.8	2.95	***	66%	4.7	1.26		55%
Sweden	12.3	3.31	***	76%	12.2	3.32	***	75%
Switzerland	8.1	2.97	***	79%	5.0	1.69	*	60%
Taiwan	20.0	3.53	***	72%	11.0	1.75	*	65%
Thailand	−0.7	−0.10		48%	6.5	1.04		50%
Turkey	9.4	0.60		62%	12.1	1.41		55%
United Kingdom	12.4	3.08	***	66%	5.5	2.01	**	60%
United States	4.9	2.09	**	66%	6.2	2.39	**	60%

purpose to reveal the trend of the Halloween effect. Table 6 presents the sub-period results for 20 countries that meet the sample size criterion, grouped according to market classification and regions. It consists of 16 countries from the developed markets and 4 countries from the emerging markets. The table reports coefficient estimates and t-statistics of the Halloween effect regression for the whole sample period and 10 sub-sample periods. The sub-period analysis not only enables us 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 1960 s and has become stronger over time, especially among the European countries. The coefficient estimates become positive in 19 of the 20 countries, in which 5 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 European countries. Of 20 countries, the Halloween effect is statistically significant in 12 countries, this group comprises of all the European countries except Denmark. In addition, the sizes of the Halloween effect are much stronger in European countries than in other areas. Although the most recent 17 years reveal a weaker Halloween effect, the higher November-April returns are still present in all developed markets.

6. Economic significance

6.1. 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

Table 4

Cross country analysis – market price returns, 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 114 countries' market price index and the world price index. βrepresents the 6-month mean returns difference between November-April and May-October. T-values for individual countries are adjusted using Newey-West standard errors. T-value of pooled 114 countries is estimated based on two-way cluster-robust 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	Nov-Apr		May-Oct		Halloween Effect			
					Mean	St Dev	Mean	St Dev	β	t-value		%+
Pooled 114 countries		02/1693	04/2017		6.4	17.0	2.3	18.6	4.2	3.80	***	58%
World		02/1919	04/2017		4.6	8.9	−0.1	10.1	4.8	3.89	***	68%
Developed	Asia	01/1965	04/2017	Hong Kong	7.0	20.7	4.0	23.6	3.0	0.69		57%
		01/1915	04/2017	Japan	8.1	15.9	−0.7	13.4	8.9	3.68	***	67%
		01/1966	04/2017	Singapore	6.7	17.2	−0.4	18.6	7.2	1.90	*	63%
	Europe	02/1922	04/2017	Austria	4.5	15.3	3.7	21.2	0.9	0.23		52%
		02/1897	04/2017	Belgium	4.0	11.8	−0.3	13.1	4.3	2.79	***	65%
		01/1921	04/2017	Denmark	4.8	9.9	1.0	10.4	3.8	2.79	***	65%
		01/1913	04/2017	Finland	4.2	14.5	4.3	15.2	−0.1	−0.03		50%
		01/1802	04/2017	France	4.6	14.7	0.6	12.6	3.9	2.54	**	59%
		01/1870	04/2017	Germany	4.3	14.3	−1.5	20.2	5.8	2.52	**	58%
		02/1934	04/2017	Ireland	7.3	11.5	−0.6	12.8	7.9	4.10	***	73%
		01/1906	04/2017	Italy	6.5	16.9	−0.5	16.8	6.9	2.89	***	59%
		02/1919	04/2017	Netherlands	5.7	10.7	−1.6	12.7	7.3	4.36	***	67%
		01/1970	04/2017	Norway	7.9	16.5	1.3	18.3	6.6	1.96	*	60%
		01/1934	04/2017	Portugal	5.1	26.0	0.7	15.1	4.4	1.28		63%
		01/1915	04/2017	Spain	6.4	12.3	−0.4	12.1	6.8	4.08	***	65%
		01/1906	04/2017	Sweden	5.8	12.6	−0.1	11.9	5.9	3.56	***	63%
		01/1916	04/2017	Switzerland	4.5	9.3	−0.7	11.9	5.2	3.64	***	66%
		02/1693	04/2017	United Kingdom	2.5	9.2	−0.9	10.2	3.4	4.46	***	59%
	Mid East	02/1949	04/2017	Israel	12.1	16.3	8.7	15.7	3.4	1.47		61%
	North America	02/1915	04/2017	Canada	5.1	9.5	−0.1	12.0	5.1	3.66	***	63%
		01/1792	04/2017	United States	2.4	10.0	0.7	11.2	1.7	1.73	*	56%
	Oceania	02/1875	04/2017	Australia	3.4	9.1	1.8	10.5	1.6	1.50		53%
		01/1931	04/2017	New Zealand	3.0	9.7	2.4	10.4	0.6	0.39		52%
Emerging	Africa	01/1993	04/2017	Egypt	14.3	22.9	2.8	20.2	11.5	2.33	**	60%
		02/1910	04/2017	South Africa	5.2	11.6	2.8	12.8	2.3	1.15		55%
	Asia	01/1991	04/2017	China	10.1	24.7	3.4	30.2	6.8	0.78		59%
		01/1923	04/2017	India	4.0	15.1	2.6	14.9	1.4	0.61		45%
		03/1983	04/2017	Indonesia	12.8	21.9	−1.6	21.3	14.3	2.77	***	63%
		02/1962	04/2017	Korea	11.0	27.7	1.5	25.1	9.5	1.63		57%
		01/1974	04/2017	Malaysia	8.1	17.1	−0.7	19.4	8.8	2.16	**	59%
		01/1953	04/2017	Philippines	7.4	18.4	−2.3	19.9	9.7	2.61	***	60%
		02/1967	04/2017	Taiwan	12.2	21.4	−3.3	23.8	15.5	3.83	***	71%
		01/1976	04/2017	Thailand	5.5	18.6	2.9	22.6	2.6	0.55		50%
Emerging	Europe	12/1993	04/2017	Czech Republic	5.7	18.9	−1.6	15.9	7.3	1.78	*	52%
		01/1954	04/2017	Greece	7.3	19.4	−0.3	20.2	7.5	2.13	**	58%
		07/1991	04/2017	Hungary	10.5	22.8	−0.5	19.9	11.0	2.41	**	59%
		03/1994	04/2017	Poland	6.9	21.3	−4.8	21.9	11.7	2.23	**	63%
		01/1994	04/2017	Russia	18.9	26.3	11.9	37.2	7.0	0.63		58%
		02/1986	04/2017	Turkey	23.7	35.8	12.9	32.4	10.8	1.26		56%
	Mid East	01/2000	04/2017	Qatar	5.8	20.1	5.8	17.4	0.1	0.01		44%
		01/1988	04/2017	United Arab Emirates	4.3	13.8	3.9	14.0	0.4	0.11		52%
	North America	02/1930	04/2017	Mexico	8.9	17.3	6.4	17.5	2.5	1.12		57%
	South America	01/1990	04/2017	Brazil	34.8	35.8	18.8	35.1	16.0	2.06	**	57%
		01/1927	04/2017	Chile	11.0	16.7	14.6	23.7	−3.6	−0.95		52%
		02/1927	04/2017	Colombia	5.3	13.4	3.0	12.8	2.3	1.14		57%
		01/1933	04/2017	Peru	12.2	22.1	15.6	29.5	−3.4	−0.82		47%
Frontier	Africa	02/1990	04/2017	Kenya	5.0	18.6	−0.1	12.4	5.1	1.42		54%
		01/1990	04/2017	Mauritius	5.3	10.8	5.2	10.6	0.1	0.04		50%
		01/1988	04/2017	Morocco	9.8	10.8	0.6	9.2	9.2	3.29	***	66%
		01/1988	04/2017	Nigeria	8.7	14.3	9.0	15.7	−0.3	−0.07		52%
		01/1996	04/2017	Tunisia	4.1	11.0	−0.4	9.9	4.5	1.73	*	77%
	Asia	02/1990	04/2017	Bangladesh	−4.8	21.4	12.9	20.7	−17.7	−2.11	**	25%
		01/2001	04/2017	Kazakhstan	16.4	23.7	−0.3	24.7	16.8	1.58		59%
		01/1961	04/2017	Pakistan	7.8	16.7	0.9	17.1	7.0	2.64	***	67%

Status	Region	Start Date	End Date	Country	Nov-Apr		May-Oct		Halloween Effect			
					Mean	St Dev	Mean	St Dev	β	t-value		%+
		01/1985	04/2017	Sri Lanka	4.7	17.8	7.1	18.1	−2.4	−0.47		52%
		01/2001	04/2017	Viet Nam	10.3	25.3	−2.8	24.1	13.0	1.26		53%
	Europe	02/1997	04/2017	Croatia	6.4	18.1	−3.7	21.6	10.1	1.90	*	57%
		01/1996	04/2017	Estonia	18.2	23.2	−3.1	23.1	21.3	3.22	***	77%
		01/1996	04/2017	Lithuania	5.7	16.3	−0.8	19.5	6.5	1.17		59%
		01/1997	04/2017	Romania	14.7	32.2	−0.6	27.9	15.3	1.68	*	48%
		01/2009	04/2017	Serbia	2.3	21.9	1.8	21.0	0.5	0.04		56%
		01/1996	04/2017	Slovenia	1.8	16.1	1.2	13.7	0.6	0.17		55%
	Mid East	01/1991	04/2017	Bahrain	0.6	8.6	2.5	9.3	−2.0	−0.76		44%
		02/1978	04/2017	Jordan	4.7	14.7	0.6	15.5	4.1	1.59		55%
		01/1995	04/2017	Kuwait	4.4	13.2	4.3	12.9	0.1	0.03		48%
		02/1996	04/2017	Lebanon	−2.1	16.8	3.3	17.7	−5.4	−0.92		64%
		01/1993	04/2017	Oman	4.3	12.9	2.2	14.0	2.1	0.57		44%
	South America	01/1967	04/2017	Argentina	31.5	41.5	27.3	47.3	4.2	0.53		65%
Rarely Studied	Africa	02/2008	04/2017	Algeria	0.4	4.7	2.4	7.4	−2.0	−0.66		50%
		01/1990	04/2017	Botswana	5.8	8.5	9.4	10.4	−3.6	−1.19		46%
		01/1996	04/2017	Cote D'Ivoire	6.5	11.0	0.9	12.1	5.5	1.88	*	77%
		01/1996	04/2017	Ghana	8.9	13.6	1.7	11.1	7.2	1.83	*	68%
		03/2001	04/2017	Malawi	9.2	21.1	11.7	23.4	−2.4	−0.28		31%
		01/1994	04/2017	Namibia	9.3	14.1	−0.1	17.7	9.3	2.07	**	67%
Rarely Studied	Africa	04/2013	04/2017	Rwanda	2.2	3.6	−2.5	5.1	4.8	1.91	*	80%
		01/2000	04/2017	Swaziland	2.9	11.2	1.4	4.1	1.6	0.49		38%
		01/2007	04/2017	Tanzania	1.9	6.6	6.0	10.0	−4.0	−1.28		18%
		10/2004	04/2017	Uganda	12.5	17.5	−1.4	18.3	13.9	2.10	**	64%
		12/1996	04/2017	Zambia	2.9	21.5	12.5	17.4	−9.5	−1.35		50%
	Asia	01/2013	04/2017	Cambodia	−3.1	11.8	−12.9	20.9	9.8	1.04		40%
		07/1995	04/2017	Kyrgyzstan	11.9	33.5	−23.6	87.5	35.5	1.69	*	61%
		02/2011	04/2017	Laos	1.5	13.6	−9.6	10.5	11.1	1.86	*	71%
		01/1996	04/2017	Mongolia	9.1	27.8	14.7	30.9	−5.6	−0.72		32%
		02/1994	09/2017	Nepal	−7.2	40.3	12.7	23.1	−19.8	−1.55		33%
	Europe	01/2004	04/2017	Bosnia And Herzegowina	−0.8	19.7	0.9	20.5	−1.7	−0.23		43%
		10/2000	04/2017	Bulgaria	8.6	21.8	3.8	23.2	4.8	0.50		44%
		01/1984	04/2017	Cyprus	−1.5	21.0	−0.9	25.4	−0.6	−0.11		50%
		01/2009	12/2010	Georgia	31.9	60.6	47.3	31.2	−15.4	−0.51		50%
		01/1993	04/2017	Iceland	6.1	16.1	−1.0	28.3	7.2	1.47		56%
		02/1996	04/2017	Latvia	7.1	20.2	3.0	23.8	4.1	0.56		55%
		01/1954	04/2017	Luxembourg	7.4	9.6	0.5	11.2	6.9	3.50	***	69%
		01/2002	04/2017	Macedonia	2.9	22.8	4.5	21.9	−1.6	−0.19		50%
		01/1996	04/2017	Malta	5.5	13.2	1.8	10.1	3.8	1.10		64%
		01/2004	04/2017	Montenegro	7.2	24.1	10.2	27.4	−3.0	−0.29		43%
		01/1994	04/2017	Slovak Republic	5.6	25.2	−1.2	13.7	6.7	1.15		58%
		02/1998	04/2017	Ukraine	19.3	27.1	−12.3	29.1	31.6	3.39	***	70%
	Mid East	01/1991	04/2017	Iran	11.0	11.7	12.3	14.6	−1.4	−0.39		52%
		01/2005	04/2017	Iraq	4.0	31.9	−5.3	33.0	9.3	0.47		31%
		07/1997	04/2017	Palestine	7.5	21.5	−13.2	63.9	20.7	1.35		67%
		01/1993	04/2017	Saudi Arabia	5.0	16.1	0.3	15.9	4.7	1.12		52%
		01/2010	04/2017	Syrian Arab Republic	11.6	18.9	3.5	14.5	8.1	0.67		25%
	North America	12/2002	12/2012	Bahamas	2.8	6.1	1.5	4.5	1.3	0.68		36%
		04/1989	04/2017	Barbados	1.6	7.4	1.5	10.0	0.1	0.03		50%
		01/1997	04/2017	Bermuda	2.5	14.6	1.3	13.2	1.3	0.24		62%
		02/1997	04/2017	Costa Rica	4.5	19.5	8.7	14.7	−4.2	−0.77		45%
		01/2004	12/2013	El Salvador	2.1	6.3	3.3	3.4	−1.1	−0.48		20%
		01/1970	04/2017	Jamaica	11.2	17.5	5.2	17.4	6.0	1.56		56%
		01/1993	04/2017	Panama	6.8	7.5	5.3	7.1	1.5	0.62		56%
		01/1996	04/2017	Trinidad And Tobago	6.5	9.2	3.7	8.4	2.9	1.06		55%
	Oceania	02/2009	04/2017	Fiji	2.9	5.9	−1.4	5.5	4.3	1.72	*	67%
	South America	02/1994	04/2017	Ecuador	0.3	16.9	2.2	16.2	−1.9	−0.45		58%
		01/1994	12/2007	Paraguay	3.8	7.8	7.9	7.6	−4.1	−1.22		23%
		02/2008	07/2016	Uruguay	6.8	8.4	1.7	13.3	5.1	0.71		44%
		01/1937	04/2017	Venezuela	9.1	21.6	8.8	20.3	0.3	0.09		47%

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. We investigate the out-of-sample performance of this trading strategy in this section.

Our approach is to see how investors might profit from the Halloween effect if they follow the Halloween trading strategies from November 1998 to April 2017. Table 7 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). We use 3-month Treasury Bill Yields in the local currency of each country 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 30 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, in which 16 markets are statistically significant based on studentized circular block bootstrapping approach suggested in Ledoit & Wolf (2008). 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.

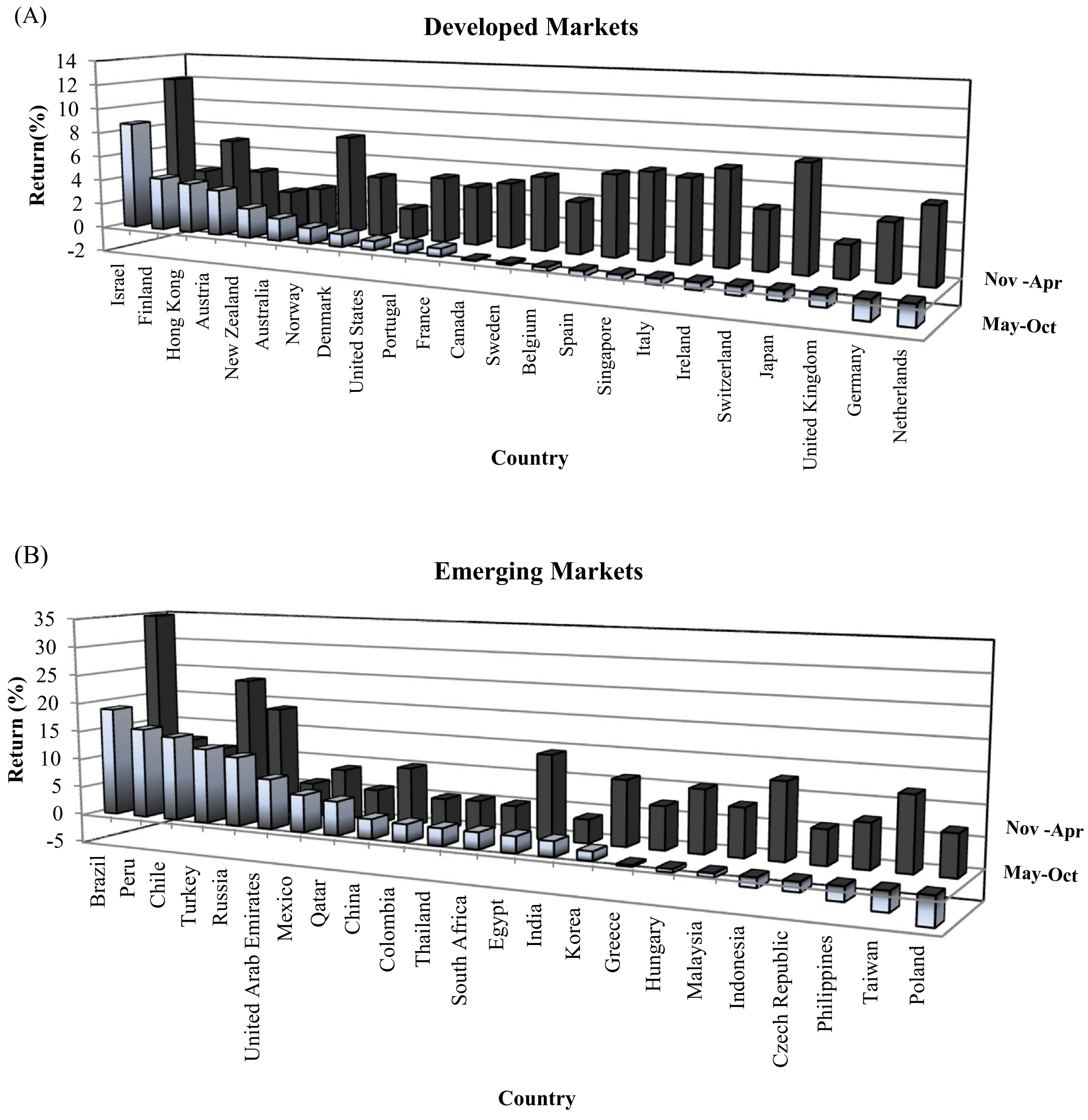
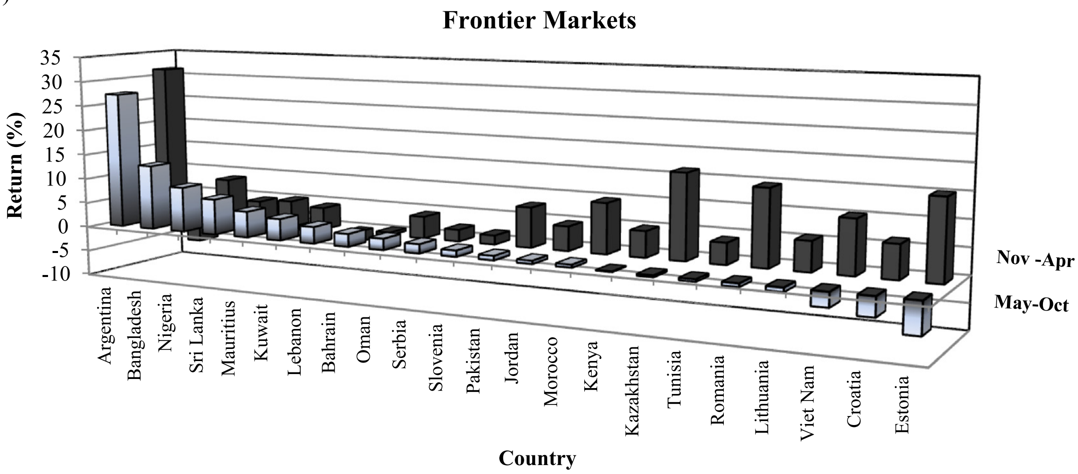


Fig. 5. Two 6-month sub-period (November-April and October-May) returns comparison for the developed markets, emerging markets, frontier markets and rarely studied markets.

(C)



(D)

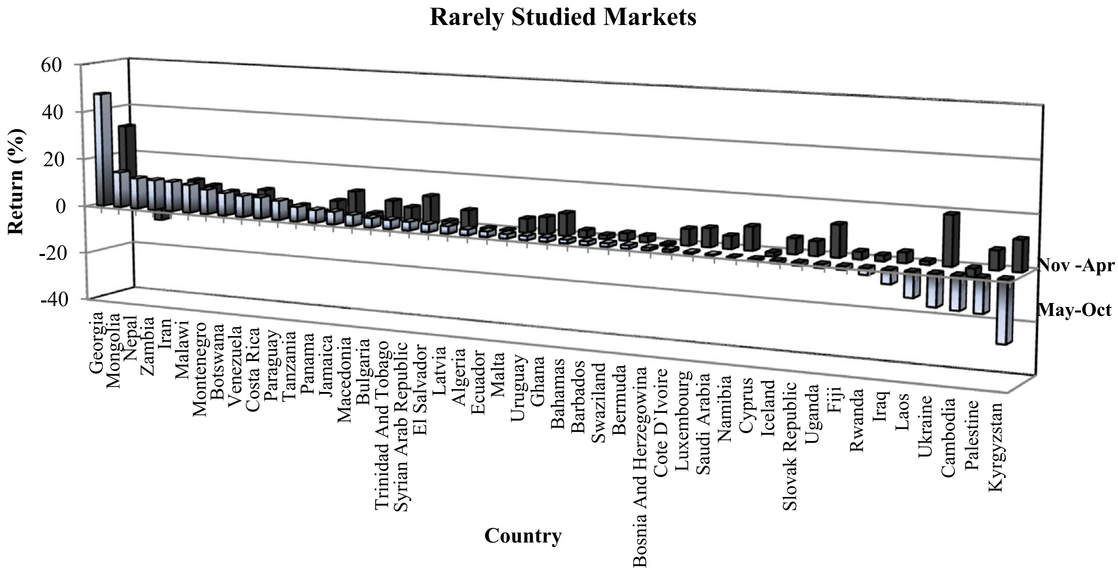


Fig. 5 (*continued*)

6.2. Long term performance of the Halloween strategy in the UK data

With the availability of long time series data for UK stock market returns, we are able to examine the performance of this Halloween strategy over 320 years. Investigating the long term performance of the strategy in the UK market is especially interesting, since the United Kingdom seems to be the origin of the market adage ''Sell in May and go away" as noted in section two the oldest reference on paper dates back to 1935 and the saying was at the time already considered an old market wisdom.

Table 8 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 eleven 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 we 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 8 also

Table 5
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 32 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 for sub-periods consist of only one country, and are estimated based on two-way cluster-robust standard errors for the rest. 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	Nov-Apr		May-Oct		Halloween Effect			% of Positive
			Mean	St Dev	Mean	St Dev	β	t-value		
1693–2017	114	62,962	6.4	17.0	2.3	18.6	4.2	3.80	***	58%
1693–1710	1	215	−0.1	14.1	−3.7	15.4	3.6	0.83		61%
1711–1720	1	120	8.7	12.4	−2.0	32.9	10.7	1.14		60%
1721–1730	1	120	−1.6	7.9	−0.6	8.6	−1.0	−0.4		50%
1731–1740	1	120	0.6	2.9	−2.6	5.0	3.2	2.04	**	80%
1741–1750	1	120	−0.6	4.7	2.1	3.7	−2.7	−1.75	*	20%
1751–1760	1	120	−0.7	3.1	−2.1	2.9	1.4	1.43		80%
1761–1770	1	120	2.6	5.4	−1.4	6.1	4.0	1.52		70%
1771–1780	1	120	−1.2	5.6	−0.7	3.8	−0.4	−0.14		60%
1781–1790	1	120	3.3	5.5	−1.1	5.2	4.4	1.93	*	70%
1791–1800	2	228	−0.7	7.2	1.6	5.2	−2.4	−2.11	**	47%
1801–1810	3	348	−0.2	6.8	0.4	6.4	−0.5	−0.38		34%
1811–1820	3	360	−1.1	9.4	0.4	10.4	−1.5	−0.36		60%
1821–1830	3	360	2.0	14.4	−0.9	6.0	3.0	1.02		60%
1831–1840	3	360	1.2	7.7	0.1	7.9	1.1	0.52		57%
1841–1850	3	360	−0.9	20.7	0.3	8.9	−1.2	−0.30		57%
1851–1860	3	360	1.6	10.6	−2.2	11.9	3.8	0.77		63%
1861–1870	4	300	3.6	7.1	2.3	8.6	1.2	0.72		52%
1871–1880	4	431	1.1	9.0	0.0	9.2	1.1	0.43		53%
1881–1890	4	480	−0.4	5.6	1.9	5.9	−2.3	−2.14	**	43%
1891–1900	6	563	2.2	7.0	0.1	7.3	2.1	0.89		62%
1901–1910	9	851	1.9	6.2	0.6	6.7	1.3	1.42		51%
1911–1920	15	1326	−1.0	11.9	−0.7	10.9	−0.3	−0.11		53%
1921–1930	21	2205	2.3	13.4	0.2	17.9	2.1	1.08		64%
1931–1940	26	2800	1.6	12.8	0.1	14.0	1.5	0.48		54%
1941–1950	27	3006	2.9	14.1	3.6	15.5	−0.7	−0.38		44%
1951–1960	30	3503	4.2	9.8	5.2	9.7	−1.0	−0.60		46%
1961–1970	38	4075	5.0	12.9	−0.8	12.4	5.8	3.02	***	65%
1971–1980	41	4700	9.1	20.3	3.8	18.9	5.3	1.70	*	60%
1981–1990	54	5412	14.4	22.0	9.4	27.0	5.0	2.28	***	65%
1991–2000	94	9137	11.1	23.0	2.8	26.9	8.3	2.21	**	62%
2001–2010	111	12,322	6.9	18.3	2.4	19.1	4.5	1.11		56%
2011–2017	112	8300	4.8	12.4	−1.0	12.8	5.8	2.66	***	55%

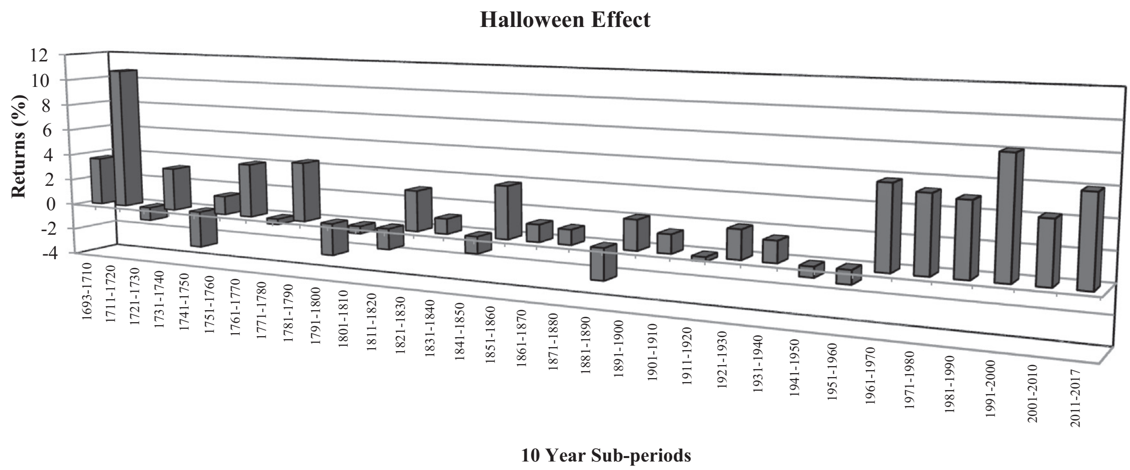


Fig. 6. Size of the Halloween effect (difference between 6-month returns November-April and May-October) for 32 ten-year sub-periods from 114 pooled countries over the period 1693–2017.

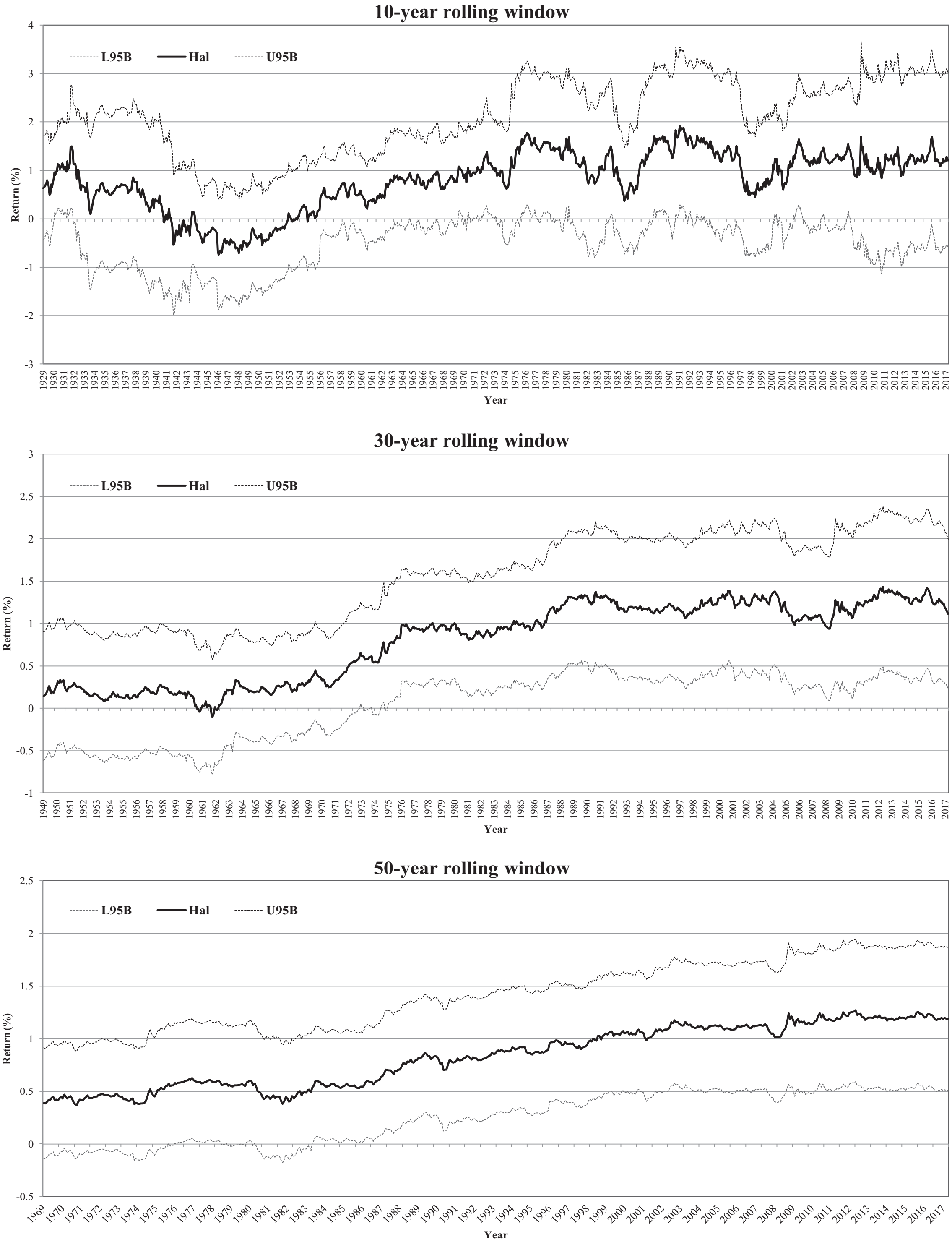


Fig. 7. Rolling window regressions of the Halloween effect in the GFD world index returns (1919–2017), the figure plots Halloween effects in the GFD world index returns from 1919 to 2017 using a 10-year rolling window, a 30-year rolling window and a 50-year rolling window. The dark solid line indicates the coefficient estimates of the effect, the light dotted lines indicates the upper and lower 95% confidence interval based on Newey-West standard errors.

Table 6

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 30 countries that have data available over 90 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.

Country	Start Date	End Date	Whole Sample			Prior to 1931			1931–1940			1941–1950			1951–1960		
			β_{Hal}	t-value		β_{Hal}	t-value		β_{Hal}	t-value		β_{Hal}	t-value		β_{Hal}	t-value	
World	02/1919	04/2017	4.8	3.89	***	4.5	1.62		0.5	0.12		−2.6	−0.99		2.3	1.04	
Developed markets																	
Asia																	
Japan	01/1915	04/2017	8.9	3.68	***	2.5	0.56		9.7	1.85	*	28.5	1.54		−4.3	−0.69	
Europe																	
Austria	02/1922	04/2017	0.9	0.23		−30.0	−1.16		9.8	1.03		−23.8	−1.05		−10.5	−3.10	***
Belgium	02/1897	04/2017	4.3	2.79	***	−1.4	−0.45		2.9	0.37		−2.2	−0.46		−3.2	−1.32	
Denmark	01/1921	04/2017	3.8	2.79	***	1.1	0.30		−1.6	−0.59		0.5	0.21		3.4	2.05	**
Finland	01/1913	04/2017	−0.1	−0.03		−8.5	−1.56		−6.2	−1.87	*	−18.2	−1.99	**	−2.4	−0.66	
France	01/1802	04/2017	3.9	2.54	**	−0.3	−0.15		13.9	2.39	**	−8.9	−0.79		1.3	0.33	
Germany	01/1870	04/2017	5.8	2.52	**	3.5	0.76		7.2	1.44		12.3	0.90		−5.2	−1.19	
Italy	01/1906	04/2017	6.9	2.89	***	4.6	1.25		−4.1	−0.82		6.8	0.40		−7.4	−1.77	*
Netherlands	02/1919	04/2017	7.3	4.36	***	3.0	0.66		−0.5	−0.08		5.9	1.11		3.2	0.82	
Spain	01/1915	04/2017	6.8	4.08	***	5.9	3.32	***	19.6	2.17	**	0.4	0.07		3.2	1.03	
Sweden	01/1906	04/2017	5.9	3.56	***	4.8	1.89	*	−4.7	−0.59		1.3	0.46		−4.3	−1.40	
Switzerland	01/1916	04/2017	5.2	3.64	***	3.8	1.23		4.2	0.68		−2.9	−1.26		3.4	0.81	
United Kingdom	02/1693	04/2017	3.4	4.46	***	2.3	3.06	***	1.2	0.20		−0.7	−0.19		−2.2	−0.51	
North America																	
Canada	02/1915	04/2017	5.1	3.66	***	2.0	0.74		3.8	0.53		−1.1	−0.25		6.6	1.74	*
United States	01/1792	04/2017	1.7	1.73	*	1.1	0.92		−10.2	−1.10		−3.3	−0.66		5.0	1.97	*
Oceania																	
Australia	02/1875	04/2017	1.6	1.50		0.1	0.13		−2.7	−0.70		−2.8	−0.83		−3.3	−1.29	
Emerging markets																	
Africa																	
South Africa	02/1910	04/2017	2.3	1.15		−3.5	−1.59		5.6	1.24		−1.9	−0.47		−6.1	−1.40	
Asia																	
India	01/1923	04/2017	1.4	0.61		1.4	0.42		−2.3	−0.58		−3.3	−0.73		−1.4	−0.52	
South America																	
Chile	01/1927	04/2017	−3.6	−0.95		6.8	1.22		4.4	0.55		−5.9	−1.56		−11.8	−1.27	
Colombia	02/1927	04/2017	2.3	1.14		−3.5	−0.97		−2.7	−0.59		−5.3	−1.13		1.7	0.84	

Country	1961–1970			1971–1980			1981–1990			1991–2000			2001–2010			2011–2017		
	β_{Hal}	t-value		β_{Hal}	t-value		β_{Hal}	t-value		β_{Hal}	t-value		β_{Hal}	t-value		β_{Hal}	t-value	
World	5.8	2.08	**	7.7	1.50		10.1	2.22	**	6.0	1.85	*	6.1	1.31		9.3	2.02	**
Developed markets																		
Asia																		
Japan	8.7	1.58		11.4	1.90	*	13.9	2.60	**	5.6	1.03		11.5	1.73	*	8.9	1.26	
Europe																		
Austria	6.2	1.19		2.3	0.99		8.6	1.24		11.9	2.09	**	15.3	2.65	***	12.2	2.04	**
Belgium	7.5	2.71	***	14.8	3.58	***	11.1	2.15	**	8.1	2.15	**	8.2	1.45		8.5	1.53	
Denmark	9.0	2.98	***	−5.0	−0.82		7.0	1.63		7.1	1.60		4.4	0.92		16.1	2.72	***
Finland	−1.3	−0.46		7.9	1.87	*	9.0	2.13	**	19.1	2.11	**	2.9	0.42		5.6	0.79	
France	11.8	2.22	**	7.3	0.88		19.2	3.62	***	16.3	3.97	***	6.9	1.41		11.3	1.85	*
Germany	5.2	1.28		11.0	2.20	**	5.4	1.12		11.9	2.77	***	8.8	1.61		11.4	1.65	
Italy	5.5	1.14		0.6	0.06		21.6	2.49	**	24.4	4.57	***	9.2	1.95	*	14.1	1.74	*
Netherlands	7.5	1.49		14.9	2.59	**	9.8	3.09	***	12.0	2.55	**	9.6	1.59		7.3	1.21	
Spain	1.7	0.62		10.4	2.10	**	7.9	1.14		15.2	2.57	**	3.2	0.58		5.4	0.74	
Sweden	2.9	0.85		14.4	3.72	***	8.9	1.39		18.0	2.34	**	10.1	2.04	**	11.2	2.05	**
Switzerland	7.7	1.26		10.2	1.78	*	5.9	1.90	*	10.5	2.62	***	3.6	0.78		6.9	1.66	
United Kingdom	8.3	1.70	*	17.9	1.83	*	13.7	3.73	***	6.9	1.81	*	5.0	1.24		6.5	1.61	
North America																		
Canada	9.6	3.33	***	8.1	1.84	*	5.7	1.15		5.8	1.45		6.9	1.68	*	6.0	1.53	
United States	5.5	1.65		7.1	1.56		4.3	1.28		3.7	1.05		6.4	1.77	*	7.1	1.75	*
Oceania																		
Australia	4.0	0.88		7.8	0.99		6.7	1.27		6.6	1.45		0.5	0.14		8.9	2.57	**
Emerging markets																		
Africa																		
South Africa	9.4	1.07		1.6	0.17		2.3	0.26		16.5	2.49	**	3.7	0.54		1.9	0.51	
Asia																		
India	2.0	0.71		6.8	1.91	*	−4.8	−0.66		17.8	1.28		0.0	0.00		−4.3	−1.02	
South America																		
Chile	2.9	0.37		−40.2	−1.57		13.0	2.04	**	1.2	0.16		−1.9	−0.52		6.0	2.11	**
Colombia	3.1	1.45		7.3	1.75	*	−3.4	−0.39		14.1	1.46		5.9	0.94		2.0	0.37	

Table 7

Out-of-sample Performance of Buy & Hold strategy versus Halloween strategy, The table presents the annualized average returns, standard deviations in percentages, and Sharpe ratios of the buy and hold strategy and the Halloween strategy, as well as the Sharpe ratio difference between the returns of the Halloween strategy and the Buy & Hold Strategy. t-value is estimated based on studentized circular block bootstrap approach in Ledoit & Wolf (2008). The last column shows the percentage of years that the Halloween strategy outperforms the Buy & Hold strategy for the sample period from October 1998 to April 2017.

Country	Buy & Hold Strategy			Halloween Strategy			Diff in Sharp Ratios			% of Winning
	Return	St Dev	Sharpe	Return	St Dev	Sharpe	SR_{Hal}-$SR_{B\&H}$	t-value		
Argentina	16.75	32.82	0.51	17.52	25.27	0.69	0.18	1.01		45%
Australia	5.03	13.57	0.37	6.69	8.93	0.75	0.38	1.89	*	55%
Austria	4.40	19.67	0.22	9.94	11.86	0.84	0.62	2.20	**	55%
Belgium	3.11	17.89	0.17	5.76	11.40	0.51	0.33	1.28		30%
Brazil	11.92	23.13	0.52	17.32	16.28	1.06	0.55	2.48	**	60%
Canada	6.09	15.06	0.40	7.49	9.75	0.77	0.36	1.65		40%
Chile	8.52	14.26	0.60	7.22	10.16	0.71	0.11	0.62		45%
Denmark	8.25	18.38	0.45	8.97	12.09	0.74	0.29	1.21		35%
Finland	4.23	28.57	0.15	7.43	21.32	0.35	0.20	1.18		40%
France	3.63	18.74	0.19	7.40	11.70	0.63	0.44	2.01	*	45%
Germany	3.17	19.80	0.16	7.77	12.73	0.61	0.45	1.98	*	45%
Greece	−11.16	31.80	−0.35	0.11	21.08	0.01	0.36	1.51		55%
Hong Kong	7.40	22.54	0.33	5.37	13.93	0.39	0.06	0.24		35%
Indonesia	11.77	25.78	0.46	18.38	17.00	1.08	0.62	2.23	**	50%
Ireland	3.08	20.55	0.15	8.82	12.64	0.70	0.55	2.26	**	40%
Italy	−0.34	20.19	−0.02	6.94	13.91	0.50	0.52	2.65	***	55%
Japan	2.03	18.55	0.11	6.51	12.69	0.51	0.40	1.75	*	60%
Jordan	5.05	17.76	0.28	7.12	12.74	0.56	0.27	1.53		65%
Korea	11.31	25.86	0.44	11.71	18.57	0.63	0.19	1.08		50%
Malaysia	10.11	18.71	0.54	8.47	12.29	0.69	0.15	0.70		35%
Mexico	13.80	17.91	0.77	13.62	12.71	1.07	0.30	1.39		40%
Netherlands	1.65	20.09	0.08	6.50	11.86	0.55	0.47	1.85	*	50%
New Zealand	4.91	11.75	0.42	6.55	7.38	0.89	0.47	2.21	**	55%
Norway	6.01	21.31	0.28	9.01	13.71	0.66	0.37	1.55		45%
Philippines	9.67	20.50	0.47	9.87	12.78	0.77	0.30	1.31		40%
Portugal	−2.66	19.61	−0.14	4.69	11.68	0.40	0.54	2.63	***	50%
Russia	23.95	35.62	0.67	23.98	24.79	0.97	0.30	1.36		45%
Singapore	6.88	20.30	0.34	6.50	12.68	0.51	0.17	0.77		40%
South Africa	12.75	17.70	0.72	11.65	12.15	0.96	0.24	1.10		40%
Spain	2.56	19.93	0.13	4.60	12.40	0.37	0.24	1.22		40%
Sweden	5.98	21.12	0.28	10.14	14.86	0.68	0.40	2.00	**	45%
Switzerland	2.71	15.15	0.18	4.23	9.83	0.43	0.25	1.21		50%
Taiwan	2.44	23.07	0.11	7.55	14.80	0.51	0.40	1.75	*	50%
Thailand	10.28	27.24	0.38	9.73	18.20	0.53	0.16	0.69		50%
Turkey	19.11	38.87	0.49	29.30	31.91	0.92	0.43	2.07	**	55%
United Kingdom	2.67	15.00	0.18	5.54	8.94	0.62	0.44	1.91	*	45%
United States	5.03	16.88	0.30	6.57	11.53	0.57	0.27	1.58		45%

reveals the persistence of the outperformance of the Halloween strategy within each of the subsample periods by indicating the t-values of the Sharpe ratio differences as well as 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% (204/323) of the years and the Sharpe ratio difference is statistically significant. All of the 100-year and 50-year subsample periods have a winning rate higher than 50%, with one (1901–1950) of six 50-year subsamples shows insignificant t-value in Sharpe ratio difference. Only two of the 30-year subsamples have a winning rate below 50% (1941–1970, 43% and 2001–2017, 47%) and three (1693–1730, 1911–1940, and 1941–1970) of the eleven 30-year subsamples present statistically insignificant Sharpe ratio differences.

Most investors will, however, have shorter investment horizons than the subsample periods used above. Using this large sample of observations allows us a realistic indication of the strategy over different short-term investment horizons. Table 9 contains our results. It compares the descriptive statistics of both strategies over incremental investment horizons, ranging from one year to twenty years. We obtained the confidence interval of the mean returns and the proportion that Halloween strategy beats the buy and hold strategy through bootstrap procedure.

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 Fig. 8 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 8

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 Sharpe ratio difference between the returns of the Halloween strategy and the Buy & Hold Strategy. t-value is estimated based on studentized circular block bootstrap approach in Ledoit & Wolf (2008). The last column shows the percentage of times that the Halloween strategy outperforms the Buy & Hold strategy for the whole sample period from 1693 to 2017 of the UK market index returns, three subsamples of around 100 years, six 50-year subsamples, and ten 30-year subsamples.

Sample Periods	Buy & Hold Strategy			Halloween Strategy			Diff in Sharpe Ratios			% of Winning
	Return	St Dev	Sharpe ratio	Return	St Dev	Sharpe ratio	SR_{Hal}-$SR_{B\&H}$	t-value		
1693–2017	1.61	14.46	0.11	4.65	10.52	0.44	0.33	5.12	***	63%
100-year interval										
1693–1800	−0.48	11.65	−0.04	2.97	8.85	0.34	0.38	2.61	***	65%
1801–1900	0.68	11.90	0.06	3.90	8.19	0.48	0.42	3.54	***	70%
1901–2017	4.37	18.06	0.24	6.87	13.12	0.52	0.28	4.24	***	54%
50-year interval										
1693–1750	−0.55	13.34	−0.04	3.26	10.74	0.30	0.35	1.76	*	55%
1751–1800	−0.41	9.46	−0.04	2.63	6.05	0.43	0.48	4.57	***	76%
1801–1850	−0.21	14.81	−0.01	4.66	10.46	0.45	0.46	2.89	***	76%
1851–1900	1.58	8.07	0.20	3.14	5.01	0.63	0.43	3.60	***	64%
1901–1950	0.35	11.13	0.03	1.57	6.05	0.26	0.23	1.48		55%
1951–2017	7.31	21.39	0.34	10.75	15.40	0.70	0.36	3.79	***	54%
30-year interval										
1693–1730	−0.71	15.75	−0.04	3.93	13.05	0.30	0.35	1.44		58%
1731–1760	−1.12	6.60	−0.17	1.75	3.50	0.50	0.67	3.64	***	67%
1761–1790	0.54	9.77	0.05	3.90	6.50	0.60	0.55	4.04	***	73%
1791–1820	−0.22	11.48	−0.02	3.09	5.75	0.54	0.56	3.39	***	70%
1821–1850	−0.39	16.82	−0.02	4.73	12.92	0.37	0.39	2.37	**	77%
1851–1880	1.45	9.03	0.16	3.48	5.57	0.63	0.46	3.15	***	63%
1881–1910	0.84	6.73	0.13	2.33	3.59	0.65	0.53	2.63	**	67%
1911–1940	−0.99	12.02	−0.08	1.07	7.11	0.15	0.23	1.31		55%
1941–1970	6.23	15.62	0.40	5.64	10.10	0.56	0.16	0.86		43%
1971–2000	10.86	25.37	0.43	16.46	19.48	0.84	0.42	3.14	***	63%
2001–2017	1.94	17.15	0.11	5.02	4.06	1.24	1.12	1.95	*	47%

This is also confirmed if we consider the maximum and minimum returns of the strategies shown in Table 9. 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 two column of Table 9 presents the percentage of times that the Halloween strategy outperforms the buy and hold strategy. The results calculated from the full sample and bootstrap procedure indicate that, for example, when investing in the Halloween strategy for any two-year horizon over the 323 years, an investor would have a 70% chance of beating the market. Once we 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 81%. As the horizon expands to ten years this probability increases to a striking 92%.

As a last indication of the persistency of the Halloween strategy in the UK market over time, in Fig. 9 we compare 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.

7. Methodological issues

7.1. Sample size and the Halloween effect

From Table 4, we observe that 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 among developed markets is Norway, which has 47 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."*

Table 9

Strategy performance over different trading horizons of the UK market, The table shows average returns, 95% bootstrap confidence interval of the mean return, standard deviations, skewness, 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 UK market index from 1693 to 2017. The %>B&H is the percentage of times that the Halloween strategy beats the Buy & Hold strategy, the corresponding confidence interval is obtained from 10,000 bootstrap simulation.

Holding Horizon	Buy & Hold Strategy							Halloween Strategy							% > B&H	Sim (2.5%,97.5%)
	Return	Sim (2.5%,97.5%)	St Dev	Med	Skewness	Maximum	Minimum	Return	Sim (2.5%,97.5%)	St Dev	Med	Skewness	Maximum	Minimum		
1-Year	1.72	1.72 (0.15, 3.27)	14.27	2.04	−48.79	65.25	−78.31	4.67	4.68 (3.54, 5.87)	10.69	4.13	168.25	78.42	−46.85	62.3%	62.4% (56.8%, 67.6%)
2-Year	3.47	3.47 (1.39, 5.57)	19.51	3.20	−31.31	67.62	−87.24	9.40	9.40 (7.83, 11.08)	14.83	7.39	139.80	94.56	−37.63	69.7%	69.7% (64.6%, 74.6%)
3-Year	5.31	5.31 (2.82, 7.90)	23.17	4.87	16.98	99.90	−74.15	14.19	14.18 (12.19, 16.29)	18.49	11.47	151.95	121.66	−34.00	72.7%	72.6% (67.7%, 77.3%)
4-Year	7.25	7.25 (4.45, 10.09)	25.80	4.81	48.06	101.50	−64.73	18.98	18.97 (16.56, 21.46)	22.30	15.01	132.44	122.85	−46.29	79.1%	79.1% (74.8%, 83.5%)
5-Year	9.10	9.08 (5.91, 12.21)	28.32	3.52	65.61	113.02	−66.46	23.75	23.73 (20.95, 26.63)	26.14	18.14	146.63	151.93	−35.18	81.3%	81.3% (76.9%, 85.6%)
6-Year	10.91	10.90 (7.54, 14.27)	30.97	5.61	80.43	139.12	−89.79	28.53	28.52 (25.33, 31.84)	29.86	22.66	150.57	164.64	−46.08	81.8%	81.8% (77.4%, 85.9%)
7-Year	12.67	12.65 (9.00, 16.29)	32.97	6.58	99.57	135.39	−90.84	33.34	33.32 (29.65, 37.07)	33.43	26.75	156.34	178.89	−46.09	85.2%	85.2% (81.1%, 89.0%)
8-Year	14.44	14.42 (10.63, 18.28)	35.34	7.37	122.53	160.44	−71.47	38.09	38.07 (34.06, 42.28)	37.27	31.03	163.50	196.05	−33.12	87.1%	87.1% (83.3%, 90.5%)
9-Year	16.25	16.24 (12.16, 20.43)	37.88	9.01	131.56	174.08	−79.64	42.89	42.88 (38.46, 47.57)	41.19	34.87	167.83	215.17	−40.39	90.8%	90.8% (87.7%, 94.0%)
10-Year	17.98	17.94 (13.51, 22.48)	40.91	11.00	139.32	196.88	−79.17	47.71	47.68 (42.86, 52.74)	45.11	37.58	173.89	239.13	−37.11	92.1%	92.1% (88.9%, 94.9%)
15-Year	27.20	27.14 (21.24, 33.24)	54.58	11.99	157.20	265.30	−94.95	71.82	71.76 (64.87, 78.98)	63.71	56.33	191.72	340.51	−18.41	92.9%	92.9% (90.0%, 95.5%)
20-Year	36.50	36.45 (29.13, 44.26)	67.73	15.39	168.67	307.23	−65.79	95.77	95.70 (86.94, 105.07)	81.60	67.82	191.64	395.84	−1.22	94.1%	94.1% (91.3%, 96.4%)

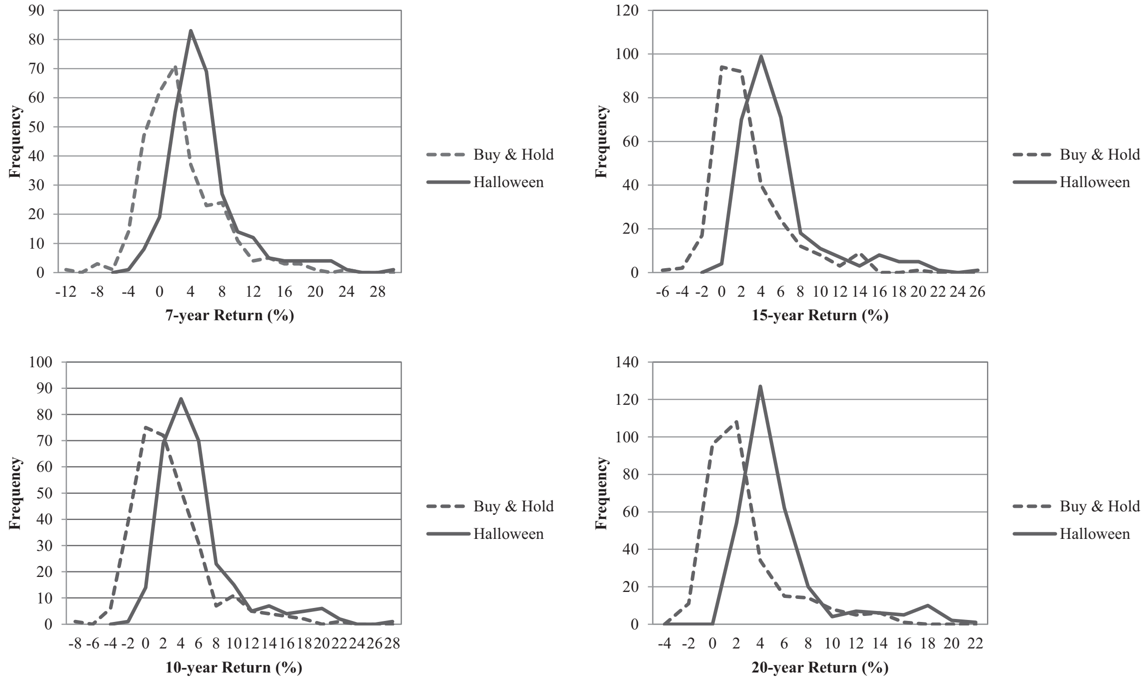


Fig. 8. Return frequency distribution of Buy & Hold strategy and Halloween strategy. The figure shows the return frequencies of the Buy & Hold strategy and the Halloween strategy for the holding periods of seven years, ten years, fifteen years and twenty years. The returns are annualised and expressed in percentages.

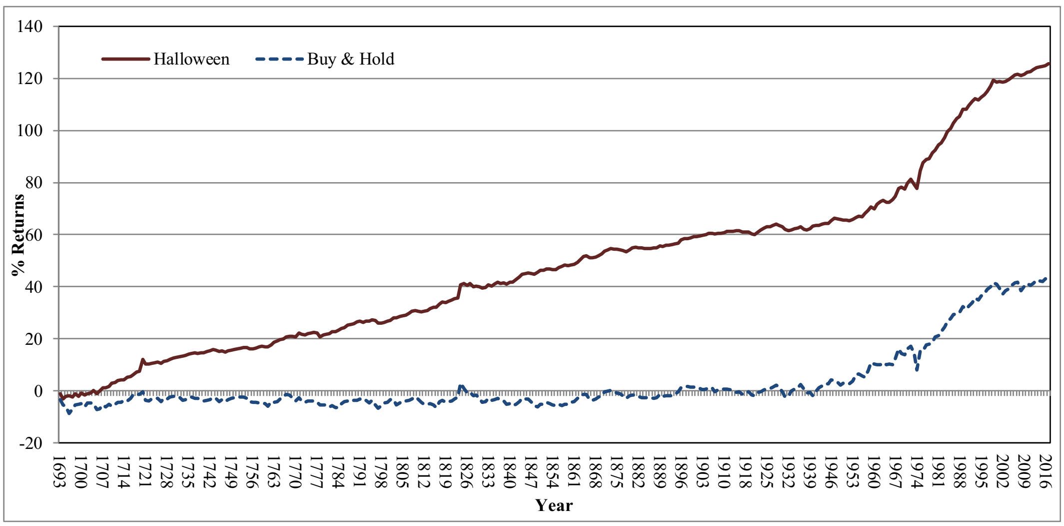


Fig. 9. End of period wealth for the buy and hold strategy and the Halloween strategy for the period 1693 to 2017.

We examine whether there is a possible linkage between the Halloween effect and the sample size among countries. Fig. 10 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.

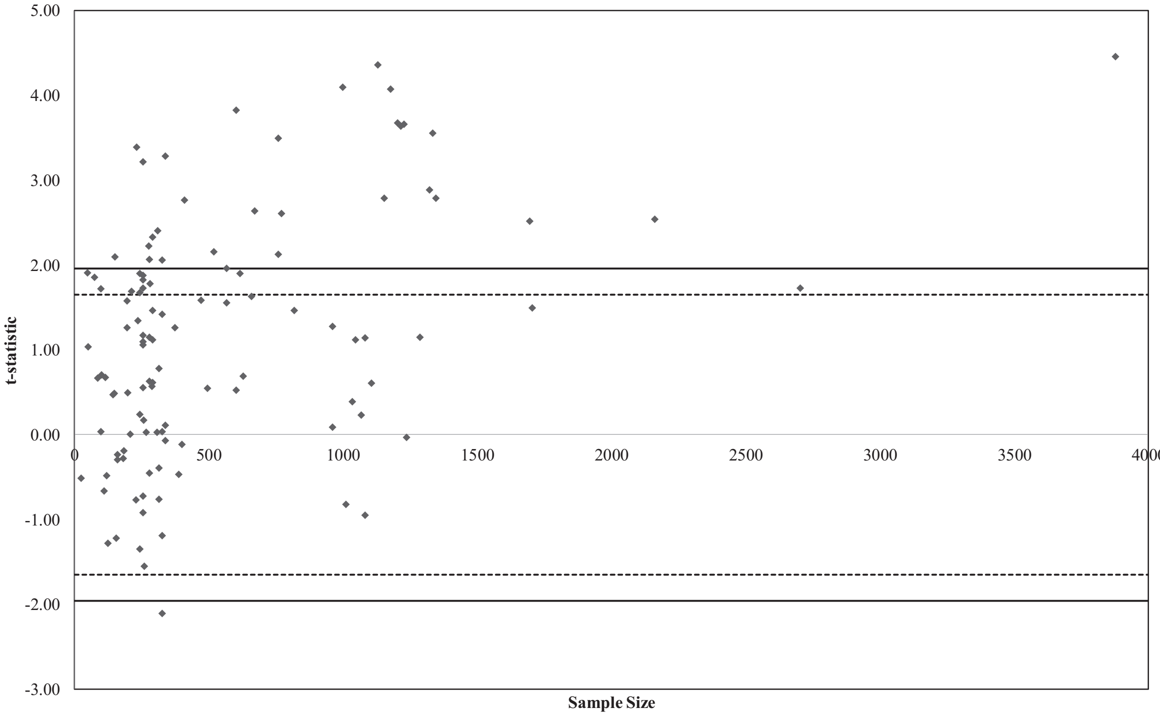


Fig. 10. Halloween effect & sample size.

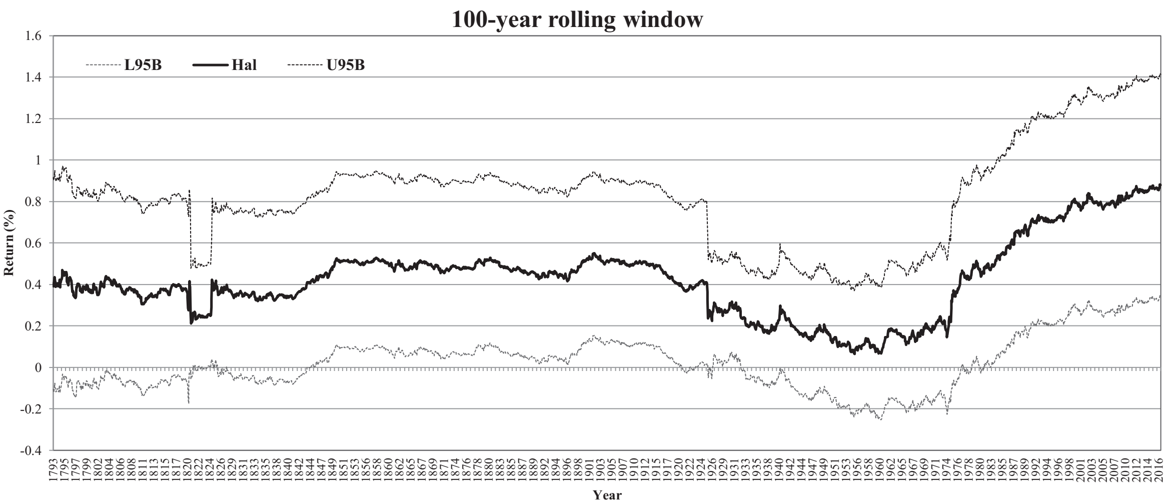


Fig. 11. UK Halloween effect 100-year rolling window OLS regressions, the figure plots 100-year rolling window estimates of the Halloween effect for the UK monthly stock market index returns over the period 1693 to 2017. The dark solid line indicates the coefficient estimates of the effect, the light dotted lines show the upper and lower 95% bounds calculated based on Newey-West standard errors.

If we follow the advice of Lakonishok and Smidt (1988) to the letter and only consider countries for which we have stock market data for more than ninety years, we find strong evidence of a Halloween effect. It is significantly present in 13 out of these 20 countries and the world market index.

The long time series of over 300 years UK monthly stock market index returns allows us to address this issue in another way using rolling windows larger than 90 years. Fig. 11 extends the evidence in Zhang and Jacobsen (2013) 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

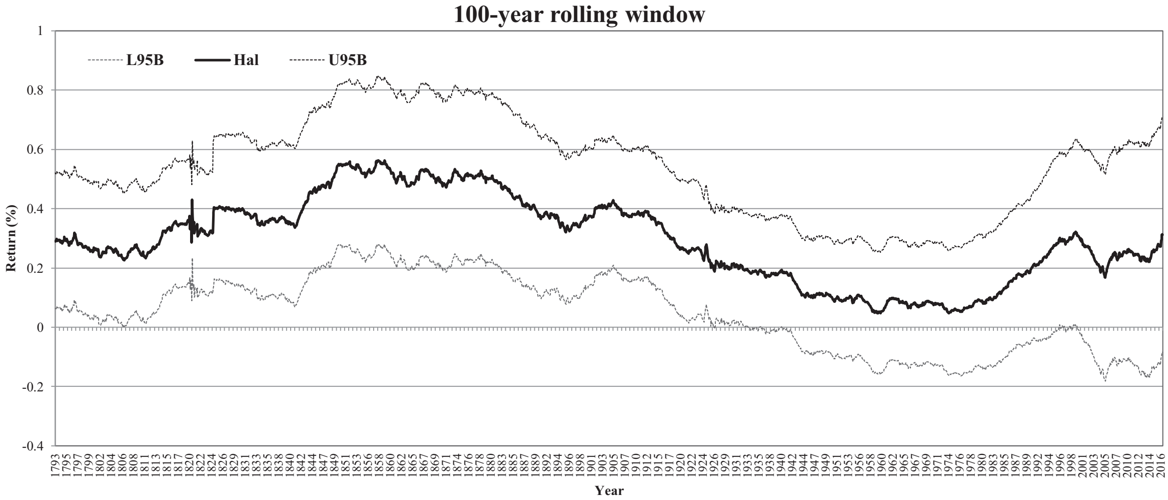


Fig. 12. UK Halloween effect 100-year rolling window regressions estimated with GARCH (1,1), The figure plots 100-year rolling window estimates of the Halloween effect based on time varying volatility GARCH (1,1) model for the UK monthly stock market index returns over the period 1693 to 2017. The dark solid line indicates the coefficient estimates of the effect and the light dotted lines show the upper and lower 95% bounds.

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 Fig. 7 and the sub-sample period analysis in Table 5 and 6, the Halloween effect keeps increasing in strength starting from the second half of the twentieth century.

7.2. Time varying volatility and outliers

To verify the impact of volatility clustering and outliers in the monthly index return we also show the rolling window estimates controlling for conditional heteroscedasticity using a GARCH model (Fig. 12) and outliers using OLS robust regressions (Fig. 13). We 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:

Fig. 13. 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 2017. The dark solid line indicates the coefficient estimates of the effect and the light dotted lines show the upper and lower 95% bounds.

Table 10
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 Periods	Semi-annual data			Monthly data		
	β	t-value		β	t-value	
1693–2017	3.36	4.51	***	0.56	4.46	***
100-year Interval						
1693–1800	2.08	1.92	*	0.34	1.68	*
1801–1900	3.13	3.72	***	0.52	2.78	***
1901–2017	4.72	2.92	***	0.80	3.25	***
50-year Interval						
1693–1750	2.88	1.63		0.48	1.41	
1751–1800	1.15	1.11		0.18	0.96	
1801–1850	4.95	3.86	***	0.84	2.43	**
1851–1900	1.31	2.26	**	0.20	1.57	
1901–1950	0.31	0.23		0.05	0.19	
1951–2017	8.00	3.89	***	1.34	3.71	***

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

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

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

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

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.

7.3. 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. We find that statistical significance is not affected if we examine the statistical significance of the Halloween effect 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 10 presents the coefficient estimates and *t*-statistics.

The results drawn from semi-annual data do not change our earlier conclusion based on monthly returns. If anything, these results show an even stronger Halloween effect. The periods with significant Halloween effects in our earlier tests remain statistically significant, with t-values based on semi-annual data. As a final test, we use a simple equality in means test. In this case, we also reject the hypothesis that summer and winter returns are different, with almost the same, highly significant, t-value (4.51).

8. Conclusion

This study investigates the Halloween effect for 114 countries market price returns and 65 market total returns and risk premium over all the periods for which data are available.

Based on 37,167 monthly returns, we find an overall historical market risk premium of 4%, however, this premium is solely contributed from the returns generated from November-April. Overall, summer returns (May-October) are significantly lower than the risk free rate by 1.1%, 45 out of 65 market show negative average risk premium during summer time. This finding does not only challenge the notion of market efficiency but also seem to defy the positive risk return trade-off.

The Halloween effect is prevailing around the world to the extent that mean price returns are higher for the period of November-April than for May-October in 87 out of 114 countries, and the difference is statistically significant in 42 countries compared to only 1 country having significantly higher May-October returns. The results are even stronger if we consider total returns and risk premiums: 63 out of 65 countries show positive point estimates on the Halloween effect in both the total return and risk premium series, in which the effect is statistically significant in 36 countries for total return series and in 35 countries for risk premium series. Our 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 all 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 we expand the investment horizon to 10 years.

Overall, our 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.

In sum what we can say for certain is that the Halloween effect is alive and kicking. The claims that the effect is not present in earlier studies using limited data are likely caused by the specific samples used. The Halloween effect is not induced through methodological persistent dummy issue as suggested by Powell et al. (2009) and Ferson (2007), and it is not a result of risk considerations if we correct for time varying volatility. The Halloween effect is robust no matter how it is measured either in the old way or with our new test.

While we have no smoking gun, the evidence we report here further favours buying and selling as a result of vacations as an explanation. The effect is becoming stronger over time especially in developed countries which would be in line with the growing importance of vacations in developing societies. Our results further cast reasonable doubt on changing risk aversion caused by Seasonal Affective Disorder as an explanation. Firstly, if such a disorder would exist (as already questioned in the psychological literature by for instance Traffanstedt, Mehta and LoBello, 2016), the effect should have been persistent over time as there is no reason why people might be more SAD prone than in the past (and if anything they should be less SAD prone over time as more people tend to work indoors). Moreover, this explanation becomes more problematic as we observe negative risk premia during summer which would be hard to reconcile with a simple change in positive equity premia induced by risk aversion.[22] An explanation based on shift in risk aversion should be able to account for negative or zero risk premia during summer.

CRediT authorship contribution statement

Cherry Y. Zhang: Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation. **Ben Jacobsen:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Supervision.

Appendix 1. Data sources

Status	Region	Country	Market Price Index Name	Sample Period		Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period	
				Start	End			Start	End
	World		GFD World Price Index	02/1919	04/2017	GFD World Return Index	–	01/1926	04/2017
Developed	Asia	Hong Kong	Hong Kong Hang Seng Composite Index	01/1965	04/2017	Hang Seng Composite Return Index	Hong Kong 3-month HIBOR	01/1970	04/2017
		Japan	Nikkei 225 Stock Average (w/GFD extension)	01/1915	04/2017	Japan Topix Total Return Index	Japan Overnight LIBOR, Japan 3-month Treasury Bill Yield from Jan 1960	01/1921	04/2017
		Singapore	Singapore FTSE All-Share Index	01/1966	04/2017	Singapore SE Return Index	Singapore 3-month SIBOR	08/1973	04/2017

[22] And in unreported results we find no link between latitudes of countries and the size of the effect, further arguing against a SAD effect.

Appendix 1. (*continued*)

Status	Region	Country	Market Price Index Name	Sample Period		Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period	
				Start	End			Start	End
	Europe	Austria	Austria Wiener Boersekammer Share Index (WBKI)	02/1922	04/2017	Vienna SE ATX Total Return Index	Austria 3-month Treasury Bill Rate from Jan 1970, Europe 3-mth EURIBOR from Dec 1990	01/1970	04/2017
		Belgium	Brussels All-Share Price Index (w/GFD extension)	02/1897	04/2017	Brussels All-Share Return Index (GFD extension)	Belgium 3-month Treasury Bill Yield	01/1951	04/2017
		Denmark	OMX Copenhagen All-Share Price Index	01/1921	04/2017	OMX Copenhagen All-Share Gross Index	Denmark National Bank Discount Rate, Denmark 3-month Treasury Bill Yield from Jan 1976	01/1970	04/2017
		Finland	OMX Helsinki All-Share Price Index	01/1913	04/2017	OMX Helsinki All-Share Gross Index	Finland Central Bank Discount Rate, Bank of Finland Repo Rate from Dec 1977	11/1912	04/2017
		France	France CAC All-Tradable Index (w/GFD extension)	01/1802	04/2017	France CAC All-Tradable Total Return Index	Bank of France Discount Rate, France 3-month Treasury Bill Yield from Jan 1931	02/1895	04/2017
		Germany	Germany CDAX Composite Index (w/GFD extension)	01/1870	04/2017	Germany CDAX Total Return Index (w/GFD extension)	Germany Bundesbank Discount Rate, Germany 3-month Treasury Bill Yield from Jan 1953	01/1870	04/2017
		Ireland	Ireland ISEQ Overall Price Index (w/GFD extension)	02/1934	04/2017	Datastream Global Equity Indices	Ireland 3-month Treasury Bill Yield	12/1972	04/2017
		Italy	Banca Commerciale Italiana Index (w/GFD extension)	01/1906	04/2017	Italy BCI Global Return Index (w/GFD extension)	Bank of Italy Discount Rate, Italy 3-month Treasury Bill Yield from Jan 1940	01/1925	04/2017

Status	Region	Country	Market Price Index Name	Sample Period		Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period	
				Start	End			Start	End
Developed	Europe	Netherlands	Netherlands All-Share Price Index (w/GFD extension)	02/1919	04/2017	Netherlands All-Share Return Index (w/GFD extension)	Netherlands 3-month Treasury Bill Yield	01/1951	04/2017
		Norway	Oslo SE All-Share Index	01/1970	04/2017	Datastream Global Equity Indices	Norway 3-month OIBOR	01/1980	04/2017

(*continued on next page*)

Appendix 1. (*continued*)

Status	Region	Country	Market Price Index Name	Sample Period		Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period	
				Start	End			Start	End
		Portugal	Oporto PSI-20 Index	01/1934	04/2017	Lisbon BVL General Return Index	Portugal 3-month Treasury Bill Yield	02/1988	04/2017
		Spain	Madrid SE General Index (w/GFD extension)	01/1915	04/2017	Barcelona SE-30 Return Index (w/GFD extension)	Bank of Spain Discount Rate, Spain 3-month MIBOR from Jun 1973, Spain 3-month T-Bill Yield from Jul 1982	04/1940	04/2017
		Sweden	Sweden OMX Aff?rsv?rldens General Index	01/1906	04/2017	OMX Stockholm Benchmark Gross Index (GFD extension	Sweden Riksbank Reference Rate, Sweden 3-month Treasury Bill Yield from Jan 1955	01/1919	04/2017
		Switzerland	Switzerland Price Index (w/GFD extension)	01/1916	04/2017	Swiss Performance Index	Switzerland Overnight LIBOR, Switzerland 3-month Secondary Market T-Bill Yield from Jan 1980	02/1966	04/2017
		United Kingdom	UK FTSE All-Share Index (w/GFD extension)	02/1693	04/2017	UK FTSE All-Share Return Index (w/GFD extension)	UK 3-month Treasury Bill Yield, Bank of England Base Lending Rate from Jan 1900	09/1694	04/2017
	Mid East	Israel	Tel Aviv All-Share Index	02/1949	04/2017	Datastream Global Equity Indices	Israel 3-month Treasury Bill Yield	12/1992	04/2017
	North America	Canada	Canada S&P/ TSX 300 Composite (w/GFD extension)	02/1915	04/2017	Canada S&P/ TSX-300 Total Return Index	Canada 3-month Treasury Bill Yield	03/1934	04/2017
		United States	S&P 500 Composite Price Index (w/GFD extension)	01/1792	04/2017	S&P 500 Total Return Index (w/GFD extension)	GFD Central Bank Discount Rate Index at annual frequency (interest rates are treated as same every month within a year), USA Government 90-day T-Bills Secondary Market from Jan 1920	02/1800	04/2017
	Oceania	Australia	Australia ASX All-Ordinaries (w/GFD extension)	02/1875	04/2017	Australia ASX Accumulation Index-All Ordinaries	Australia 3-month Treasury Bill Yield from Jul 1928	07/1928	04/2017
		New Zealand	New Zealand SE All-Share Capital Index	01/1931	04/2017	New Zealand SE Gross All-Share Index	New Zealand 3-month Treasury Bill Yield	07/1986	04/2017

Status	Region	Country	Market Price Index Name	Sample Period		Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period	
				Start	End			Start	End
Emerging	Africa	Egypt	Cairo SE EFG General Index	01/1993	04/2017	Datastream Global Equity Indices	Egypt 3-month Treasury Bill Yields	09/1996	04/2017
		South Africa	FTSE/JSE All-Share Index (w/GFD extension)	02/1910	04/2017	Johannesburg SE Return Index	South Africa 3-month Treasury Bill Yield	02/1960	04/2017
	Asia	China	Shanghai SE Composite	01/1991	04/2017	China Stock Return Index	China Central Bank Discount Rate, China 3 Month Repo on Treasury Bills from Mar 1990	01/1993	04/2017
		India	Bombay SE Sensitive Index (w/GFD extension)	01/1923	04/2017	India Stocks Total Return Index	India 3-month Treasury Bill Yield	01/1988	04/2017
		Indonesia	Jakarta SE Composite Index	03/1983	04/2017	Indonesia Stock Return Index	Indonesia Overnight Interbank Rate, Indonesia 3-month JIBOR from Dec 1993	01/1988	04/2017
		Korea	Korea SE Stock Price Index (KOSPI)	02/1962	04/2017	Korea Stocks Total Return Index	Bank of Korea Discount Rate, Korea Overnight Interbank Rate Aug 1976	02/1962	04/2017
		Malaysia	Malaysia KLSE Composite	01/1974	04/2017	Kuala Lumpur SE Return Index	Malaysia 3-month T-bill Discount Rate	12/1972	04/2017
		Philippines	Manila SE Composite Index	01/1953	04/2017	Philippines Return Stock Index	Philippines 3-month Treasury Bill Yield	01/1982	04/2017
		Taiwan	Taiwan SE Capitalization Weighted Index	02/1967	04/2017	Taiwan FTSE/ TSE-50 Return Index	Taiwan 3-month T-bill Yield	01/1988	04/2017
		Thailand	Thailand SET General Index	01/1976	04/2017	Bangkok SE Return Index	Bank of Thailand 1-day Repurchase Rate, Thailand 3-month Treasury Bill Yield Jan 1977	05/1975	04/2017
	Europe	Czech Republic	Prague SE PX Index	12/1993	04/2017	Datastream Global Equity Indices	Czech Republic 3-month Treasury Bill Yield	11/1993	04/2017
		Greece	Athens SE General Index (w/GFD extension)	01/1954	04/2017	ASE Total Return General Index	Bank of Greece Discount Rate, Greece 3-month Treasury Bill Yield from Jan 1980	01/1977	04/2017
		Hungary	Vienna OETEB Hungary Traded Index (Forint)	07/1991	04/2017	Budapest Stock Exchange Index (BUX)	Hungary 3-month Treasury Bill Yield	02/1991	04/2017
		Poland	Warsaw SE 20-Share Composite	03/1994	04/2017	Warsaw SE General Index (WIG)	Poland 3-month WIBOR	05/1991	04/2017

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Appendix 1. (*continued*)

Status	Region	Country	Market Price Index Name	Sample Period Start	Sample Period End	Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period Start	Sample Period End
		Russia	Russia AK&M Composite (50 shares)	01/1994	04/2017	Russian Depository Total Return Index	Russia 3-month Treasury Bill Yield	01/1995	04/2017
		Turkey	Istanbul SE IMKB-100 Price Index	02/1986	04/2017	Turkey ISE-100 Total Return Index	Turkey 3–6 month Treasury Bill Yield	02/1986	04/2017

Status	Region	Country	Market Price Index Name	Sample Period Start	Sample Period End	Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period Start	Sample Period End
Emerging	Mid East	Qatar	Qatar SE Index	01/2000	04/2017	Datastream Global Equity Indices	Qatar 3-month Interbank Rate	12/2003	04/2017
		United Arab Emirates	Abu Dhabi Securities Market All-Share Index	01/1988	04/2017	Datastream Global Equity Indices	United Arab Emirate 3-month Interbank Rate	12/2003	04/2017
	North America	Mexico	Mexico SE Indice de Precios y Cotizaciones (IPC)	02/1930	04/2017	Mexico SE Return Index	Mexico 3-month Cetes Yield	01/1988	04/2017
	South America	Brazil	MSCI Brazil	01/1990	04/2017	–	–	–	–
		Chile	Santiago SE Indice General de Precios de Acciones	01/1927	04/2017	Santiago SE Return Index	Chile Central Bank Mimimum Interest Rate, Chile Repo 7 Day from Aug 1994	01/1983	04/2017
		Colombia	Colombia IGBC General Index (w/GFD extension)	02/1927	04/2017	Colombia Stock Return Index	Colombia Bank of the Republic Discount Rate, Colombia TBS Interbank Rate from Jan 1989, Colombia 3-month Treasury Bill Yield from Jan 1998	01/1988	04/2017
		Peru	Lima SE General Index (w/GFD extension)	01/1933	04/2017	Peru Stock Return Index	Central Bank of Peru Discount Rate, Peru Interbank Offer Rate Sep 1995	01/1993	04/2017
Frontier	Africa	Kenya	Kenya Nairobi Stock Exchange	02/1990	04/2017	–	–		
		Mauritius	Securities Exchange of Mauritius Index (SEMDEX)	01/1990	04/2017	Mauritius Semdex Total Return Index Rupees	Mauritius Interbank Overnight Rate, Mauritius 3-month Treasury Bill Yield from Dec 1996	08/1989	04/2017

Appendix 1. (*continued*)

Status	Region	Country	Market Price Index Name	Sample Period Start	Sample Period End	Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period Start	Sample Period End
		Morocco	Casablanca Financial Group 25 Share Index	01/1988	04/2017	Datastream Global Equity Indices	Morocco Interbank Offer Rate, Morocco 3-month Treasury Bill Yield from Jan 2008	03/1994	04/2017
		Nigeria	Nigeria SE Index	01/1988	04/2017	–	–	–	–
		Tunisia	Standard and Poor's Tunisia Broad Market Index	01/1996	04/2017	–	–	–	–
	Asia	Bangladesh	Bangladesh Stock Exchange All Share Price	02/1990	04/2017	–	–	–	–
		Kazakhstan	Kazakhstan SE KASE Index	01/2001	04/2017	–	–	–	–
		Pakistan	Pakistan Karachi SE-100 Index	01/1961	04/2017	Pakistan Stock Return Index	Pakistan Overnight Repo Rate, Pakistan 3-month Treasury Bill Rate from Mar 1991	01/1988	04/2017
		Sri Lanka	Colombo SE All-Share Index	01/1985	04/2017	Datastream Global Equity Indices	Sri Lanka 3-month Treasury Bill Yield	05/1987	04/2017
		Viet Nam	Viet Nam Stock Exchange Index	01/2001	04/2017	–	–	–	–

Status	Region	Country	Market Price Index Name	Sample Period Start	Sample Period End	Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period Start	Sample Period End
Frontier	Europe	Croatia	Croatia Bourse Index (CROBEX)	02/1997	04/2017	–	–	–	–
		Estonia	OMX Tallinn (Omxt)	01/1996	04/2017	OMX Talinn SE Total Return Index	Europe 3-mth EURIBOR	08/1995	04/2017
		Lithuania	Standard and Poor's Lithuania Broad Market Index	01/1996	04/2017	OMX Vilnius VILSE Total Return Index	Lithuania 3-month Treasury Bill Yield	01/1996	04/2017
		Romania	Bucharest SE Index in Lei	01/1997	04/2017	Datastream Global Equity Indices	Romania National Bank Refinancing Rate	12/1996	04/2017
		Serbia	MSCI Serbia	01/2009	04/2017	–	–		
		Slovenia	HSBC Slovenia Euro	01/1996	04/2017	Datastream Global Equity Indices	Slovenia 3-month T-bill Yield	12/1998	04/2017

(*continued on next page*)

Appendix 1. (*continued*)

Status	Region	Country	Market Price Index Name	Sample Period Start	Sample Period End	Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period Start	Sample Period End
	Mid East	Bahrain	Bahrain BSE Composite Index	01/1991	04/2017	Datastream Global Equity Indices	Bahrain 3-month Treasury Bill Yield	12/2003	04/2017
		Jordan	Jordan AFM General Index	02/1978	04/2017	Datastream Global Equity Indices	Jordan 6–12-month Treasury Bill Yield	06/2006	04/2017
		Kuwait	Kuwait SE Index	01/1995	04/2017	Datastream Global Equity Indices	Kuwait 3-month Interbank Offer Rate	12/2003	04/2017
		Lebanon	Beirut Stock Exchange Index	02/1996	04/2017	–	–		
		Oman	Muscat Stock Market General Index	01/1993	04/2017	Datastream Global Equity Indices	Oman 3-month Interbank Rate	09/2005	04/2017
	South America	Argentina	Buenos Aires SE General Index (IVBNG)	01/1967	04/2017	Datastream Global Equity Indices	Argentina Interbank up to 15 day-term	07/1993	04/2017
Rarely Studied	Africa	Algeria	SGBV marekt index	02/2008	04/2017	–	–	–	–
		Botswana	Botswana SE Domestic Companies Index	01/1990	04/2017	–	–	–	–
		Cote D'Ivoire	Cote d'Ivoire Stock Market Index	01/1996	04/2017	–	–	–	–
		Ghana	Standard and Poor's Ghana Broad Market Index	01/1996	04/2017	–	–	–	–
		Malawi	Malawi SE Index	03/2001	04/2017	–	–	–	–
		Namibia	Namibia Stock Exchange Overall Index	01/1994	04/2017	–	–	–	–
		Rwanda	Rwanda Stock Exchange Share Index	04/2013	04/2017			–	–
		Swaziland	Swaziland Stock Market Index	01/2000	04/2017	–	–	–	–
		Tanzania	Dar-Es-Saleem SE Index	01/2007	04/2017	–	–	–	–
		Uganda	USE All Share Index	10/2004	04/2017	–	–	–	–
		Zambia	Zambia Lusaka All-Share Index (LASI)	12/1996	04/2017	–	–	–	–

Status	Region	Country	Market Price Index Name	Sample Period Start	Sample Period End	Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period Start	Sample Period End
Rarely Studied	Asia	Cambodia	CSX Index	01/2013	04/2017			–	–
		Kyrgyzstan	Kyrgyz Stock Exchange Index	07/1995	04/2017	–	–	–	–

Appendix 1. (*continued*)

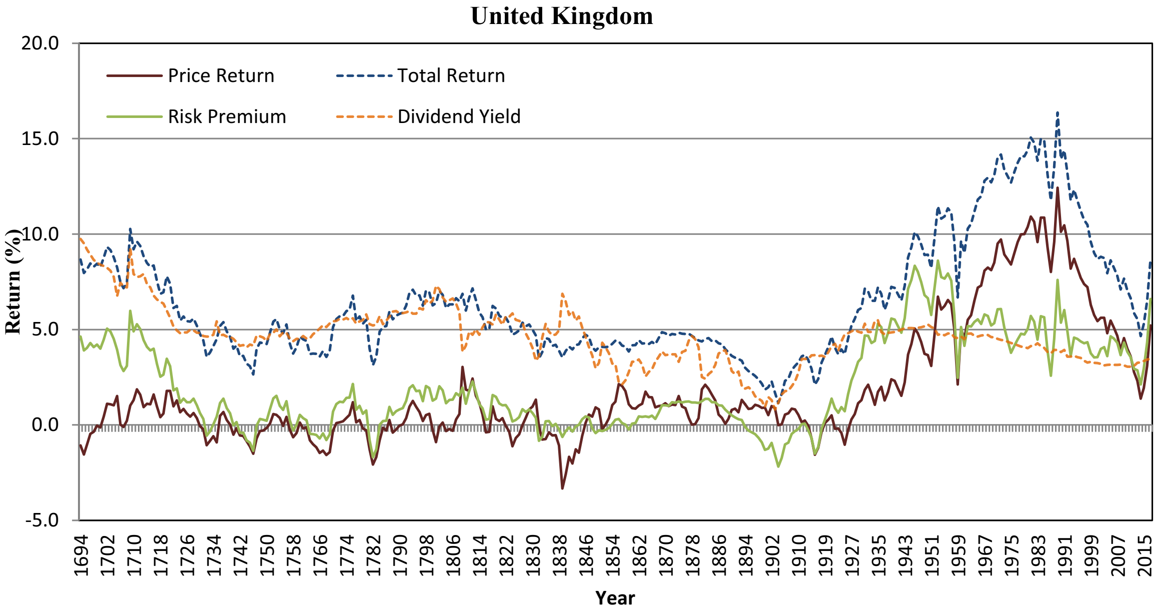
Status	Region	Country	Market Price Index Name	Sample Period		Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period	
				Start	End			Start	End
		Laos	Lao Securities Exchange Market Index	02/2011	04/2017			–	–
		Mongolia	Mongolia SE Top-20 Index	01/1996	04/2017	–	–	–	–
		Nepal	Nepal NEPSE Stock Index	02/1994	04/2017	–	–	–	–
	Europe	Bosnia And Herzegowina	Sarajevo SE Bosnian Investment Funds Index	01/2004	04/2017	–	–	–	–
		Bulgaria	Bulgaria SE SOFIX Index	10/2000	04/2017	Datastream Global Equity Indices	Bulgaria 1-Mth Sofibor	09/2000	04/2017
		Cyprus	Cyprus CSE All Share Composite	01/1984	04/2017	Datastream Global Equity Indices	Cyprus 3-month Treasury Bill Yield, Europe 3-mth EURIBOR from Nov 1982	12/1992	04/2017
		Georgia	Standard and Poor's/IFCG Extended Front 150 Georgia Dollar	01/2009	12/2010	–	–		
		Iceland	OMX Iceland All-Share Price Index	01/1993	04/2017	OMX Iceland All-Share Gross Index	Iceland 3-month Treasury Bill Yield	07/2002	04/2017
		Latvia	Nomura Latvia	02/1996	04/2017	OMX Riga SE Total Return Index	Latvia 3-month Treasury Bill Yield	05/1996	04/2017
		Luxembourg	Luxembourg SE LUXX Index (w/GFD extension)	01/1954	04/2017	Luxembourg SE Total Return Index	Europe 3-mth EURIBOR	01/1985	04/2017
		Macedonia	Macedonia MBI-10 Index	01/2002	04/2017				
		Malta	Malta SE Index	01/1996	04/2017	Datastream Global Equity Indices	Malta 3-month T-bill Yield	01/2000	04/2017
		Montenegro	Montenegro NEX-20 Index	01/2004	04/2017	–	–	–	–
		Slovak Republic	Bratislava SE SAX Index	01/1994	04/2017	–	–	–	–
		Ukraine	Ukraine PFTS OTC Index	02/1998	04/2017	–	–	–	–
	Mid East	Iran	Tehran SE Price Index (TEPIX)	01/1991	04/2017	–	–	–	–
		Iraq	Iraq SE ISX Index	01/2005	04/2017	–	–	–	–
		Palestine	Palestine Al-Quds Index	07/1997	04/2017	–	–	–	–

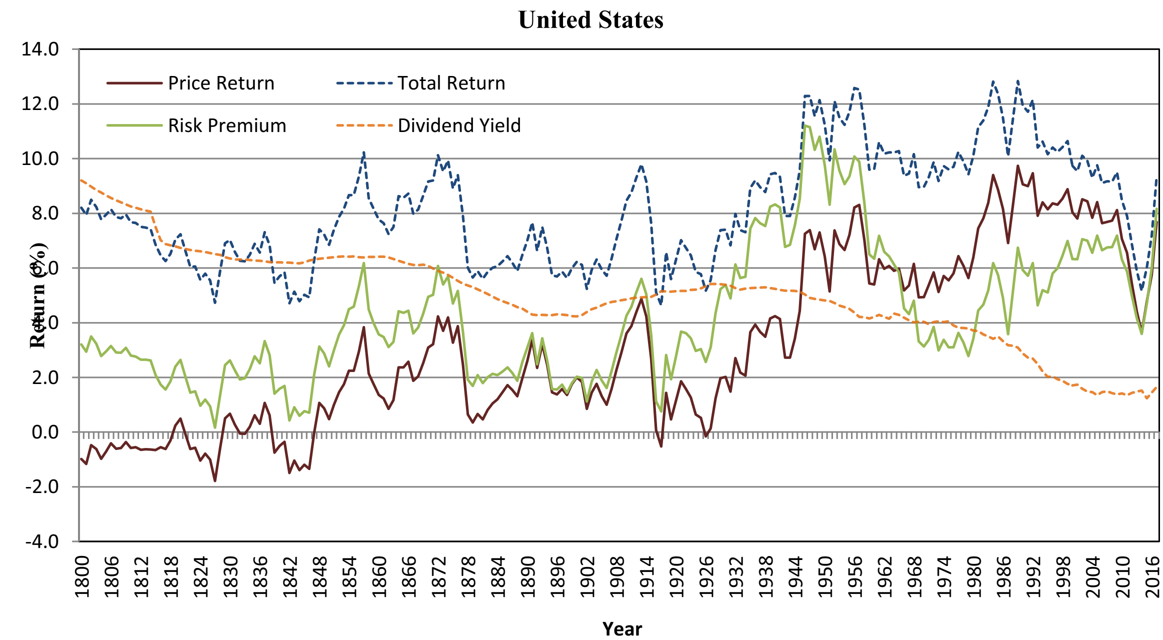
(*continued on next page*)

Appendix 1. (*continued*)

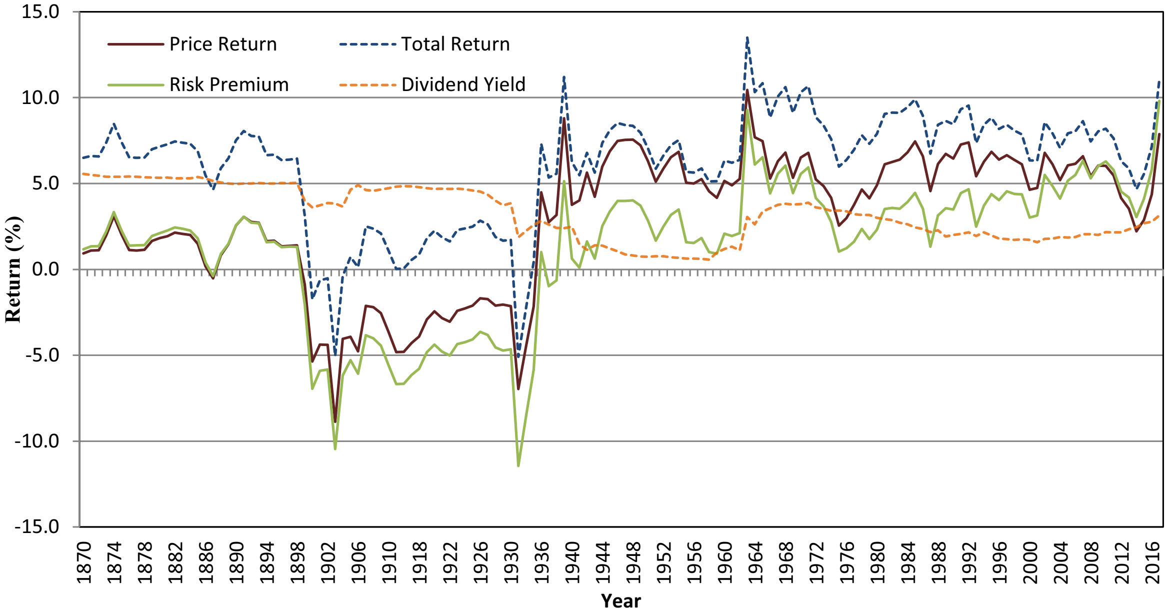
Status	Region	Country	Market Price Index Name	Sample Period Start	Sample Period End	Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period Start	Sample Period End
		Saudi Arabia	Saudi Arabia Tadawul SE Index	01/1993	04/2017	–	–	–	–
		Syrian Arab Republic	Damascus Securities Exchange Weighted Index	01/2010	04/2017	–	–	–	–
Status	Region	Country	Market Price Index Name	Sample Period Start	Sample Period End	Market Total Return Indices	Proxy for the Risk Free Rate	Sample Period Start	Sample Period End
Rarely Studied	North America	Bahamas	BISX All Share Index	12/2002	12/2012	–	–	–	–
		Barbados	Barbados SE Local Stock Index	04/1989	04/2017	–	–	–	–
		Bermuda	Bermuda Royal Gazette BSX Composite Index	01/1997	04/2017	–	–	–	–
		Costa Rica	BCT Corp. Costa Rica Stock Market Index	02/1997	04/2017	–	–	–	–
		El Salvador	El Salvador Stock Market Index	01/2004	12/2013	–	–	–	–
		Jamaica	Jamaica Stock Exchange All-Share Composite Index	01/1970	04/2017	–	–	–	–
		Panama	Panama Stock Exchange Index (BVPSI)	01/1993	04/2017	–	–	–	–
		Trinidad And Tobago	Standard and Poor's Trinidad and Tobago Broad Market Index	01/1996	04/2017	–	–	–	–
	Oceania	Fiji	SPSE Market Capitalization-Weighted Price Index	02/2009	04/2017				
	South America	Ecuador	Ecuador Bolsa de Valores de Guayaquil (Dollars)	02/1994	04/2017	–	–	–	–
		Paraguay	Asuncion SE PDV General Index	01/1994	12/2007	–	–	–	–
		Uruguay	Bolsa de Valores de Montevideo Index	01/2008	07/2016	–	–	–	–
		Venezuela	Caracas SE General Index (w/GFD extension)	01/1937	04/2017	Datastream Global Equity Indices	Venezuela 3-month Treasury Bill Yields	12/1996	04/2017

Appendix 2. 30-year moving average of price returns, total returns, risk premiums and dividend yield for individual countries that have over 60 years data available, the charts are arranged by descending order of sample size

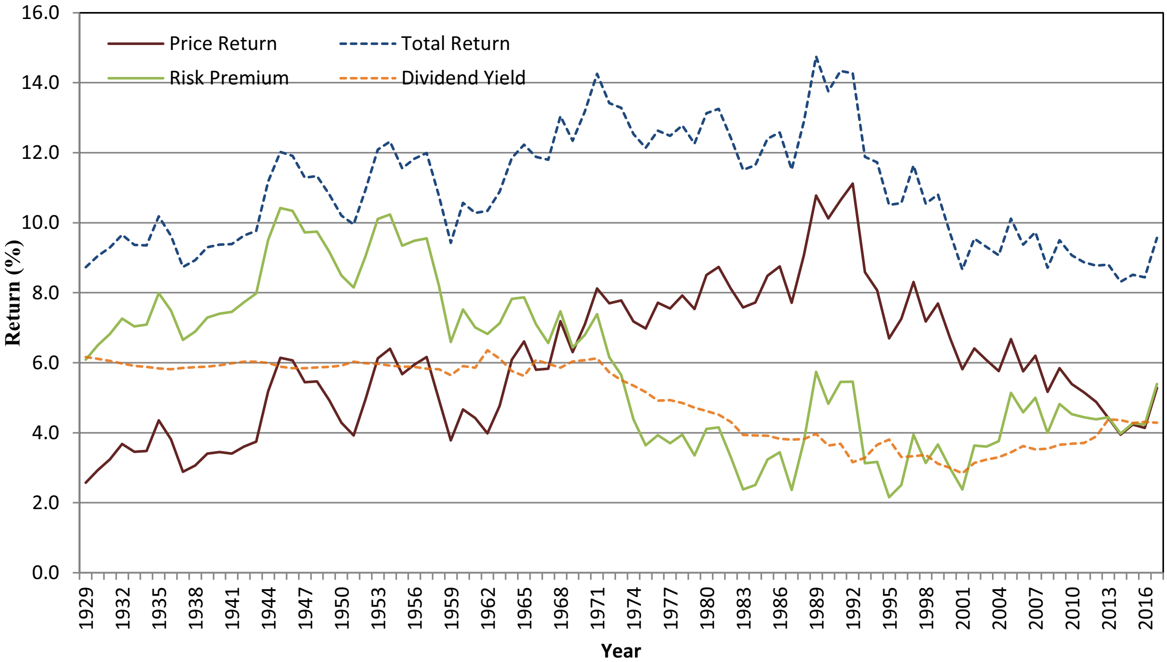


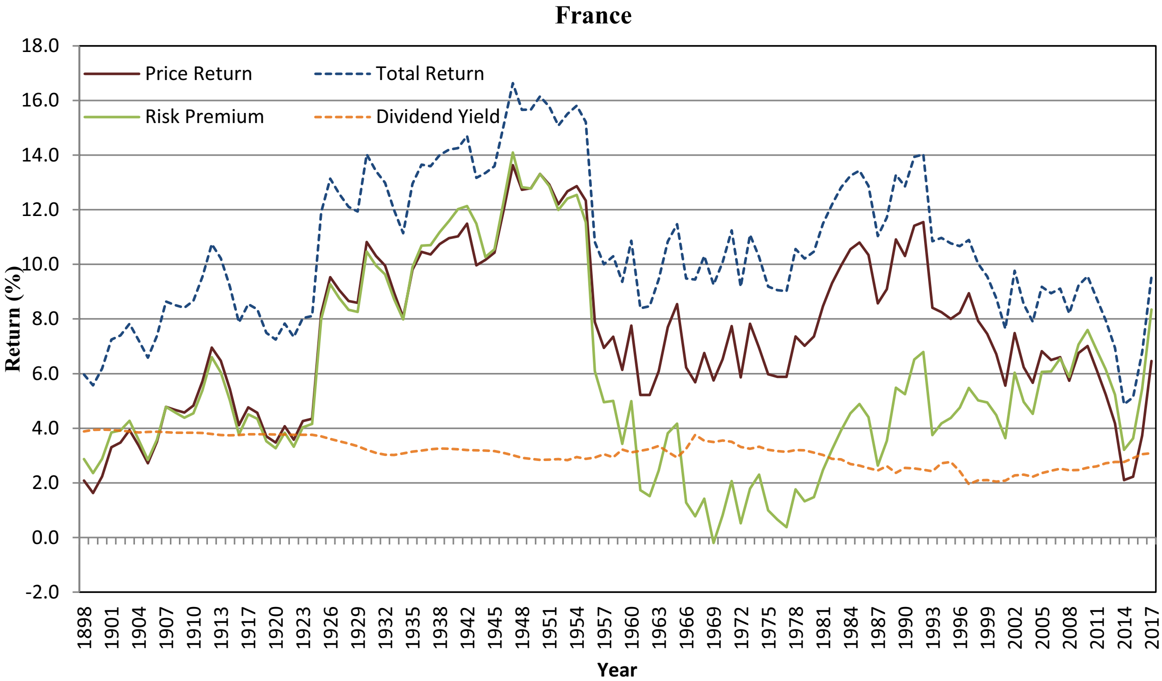


Germany



Australia




France
Price Return
Total Return
Risk Premium
Dividend Yield
Return (%)
Year
18.0
16.0
14.0
12.0
10.0
8.0
6.0
4.0
2.0
0.0
-2.0
1898
1901
1904
1907
1910
1913
1917
1920
1923
1926
1929
1932
1935
1938
1942
1945
1948
1951
1954
1957
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1981
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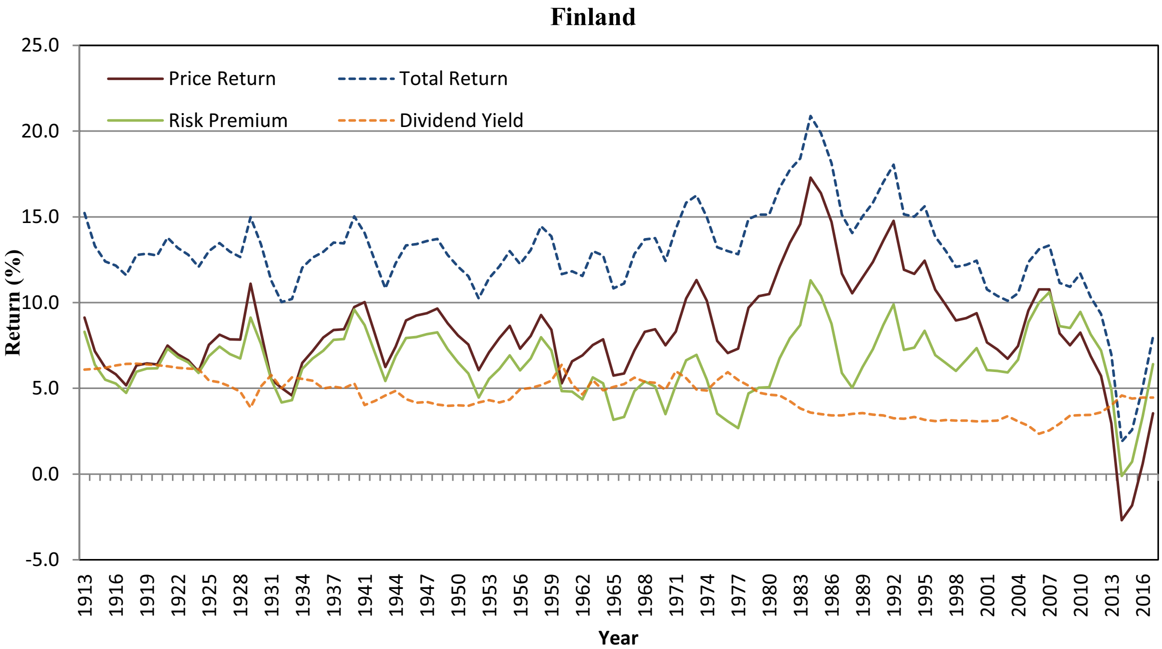
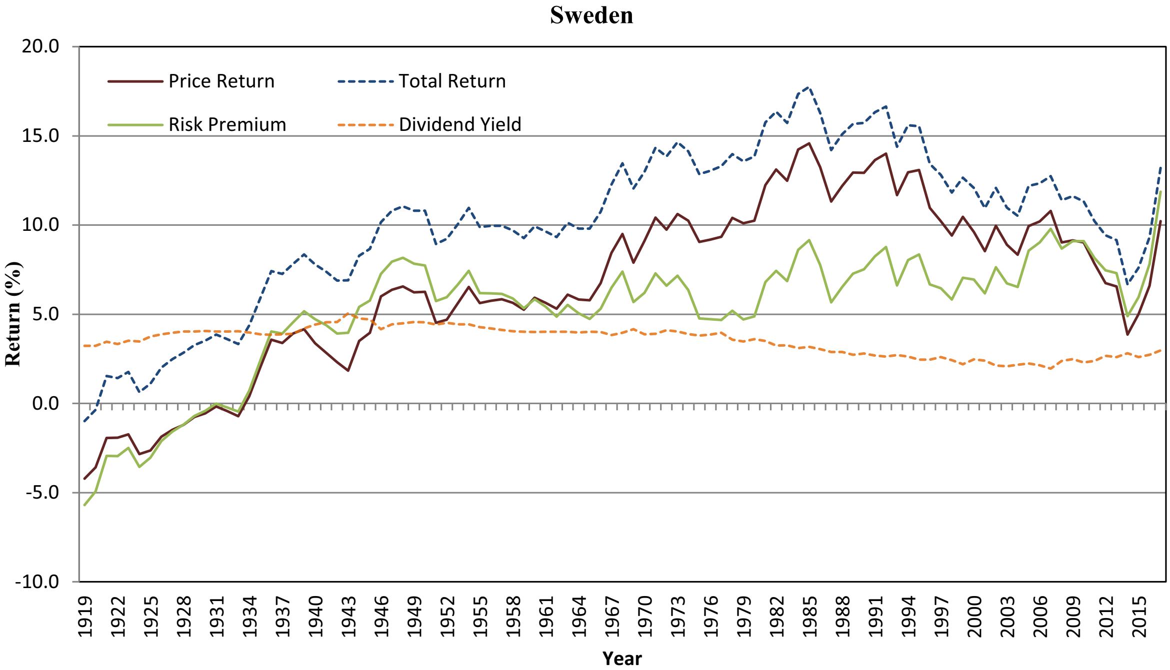
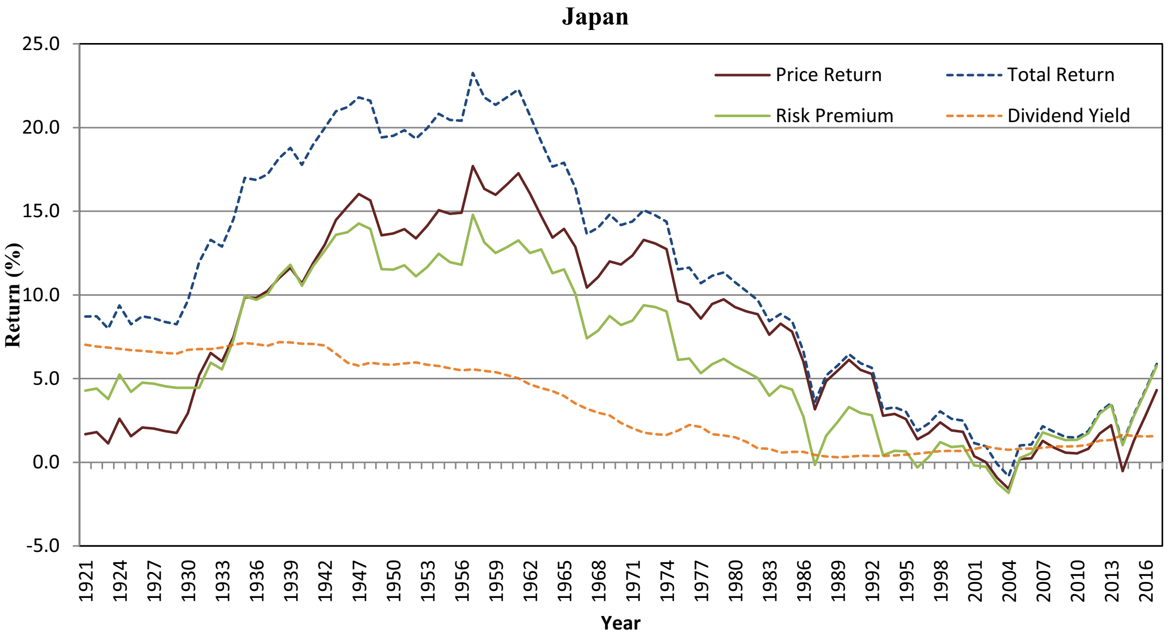
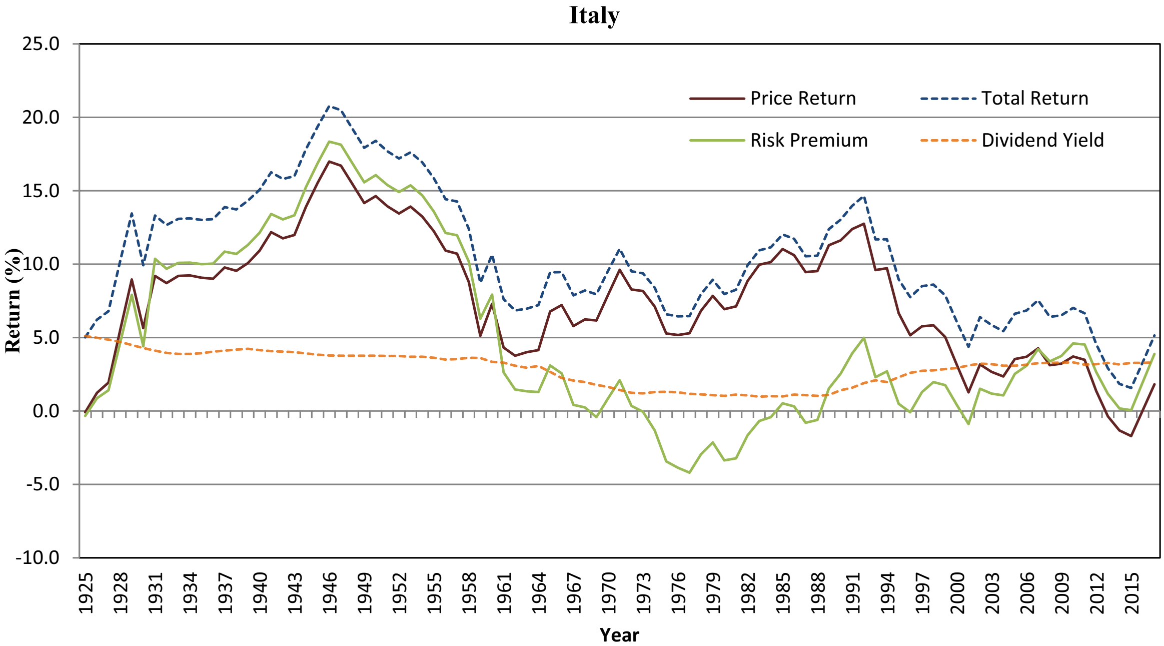
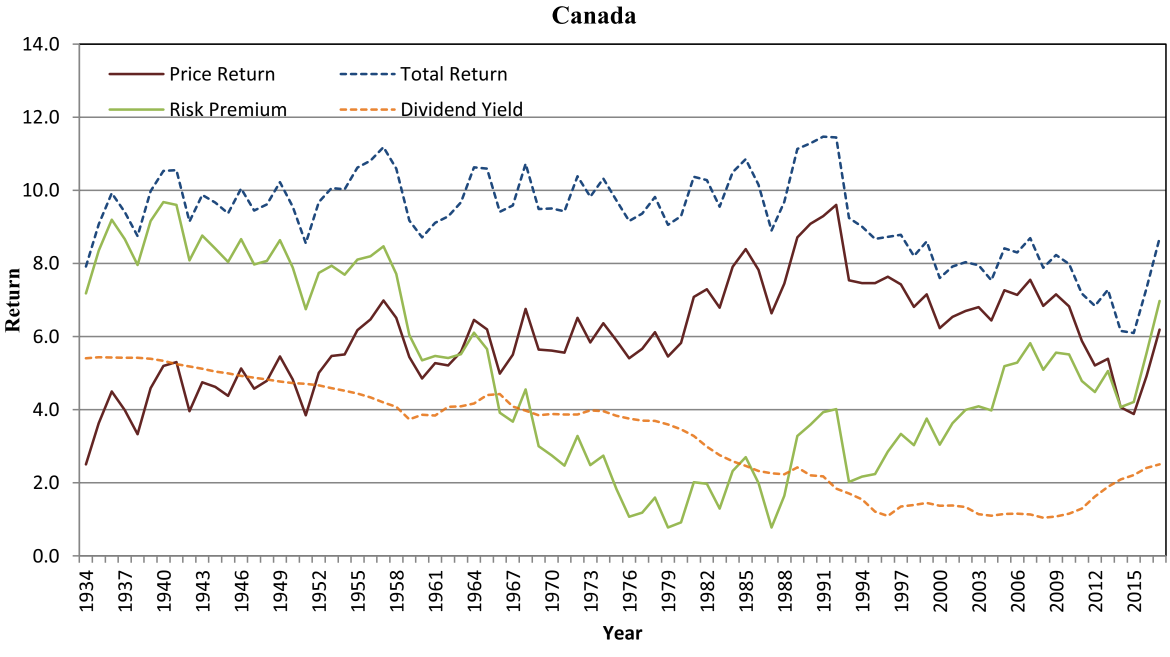
1993
1996
1999
2002
2005
2008
2011
2014
2017

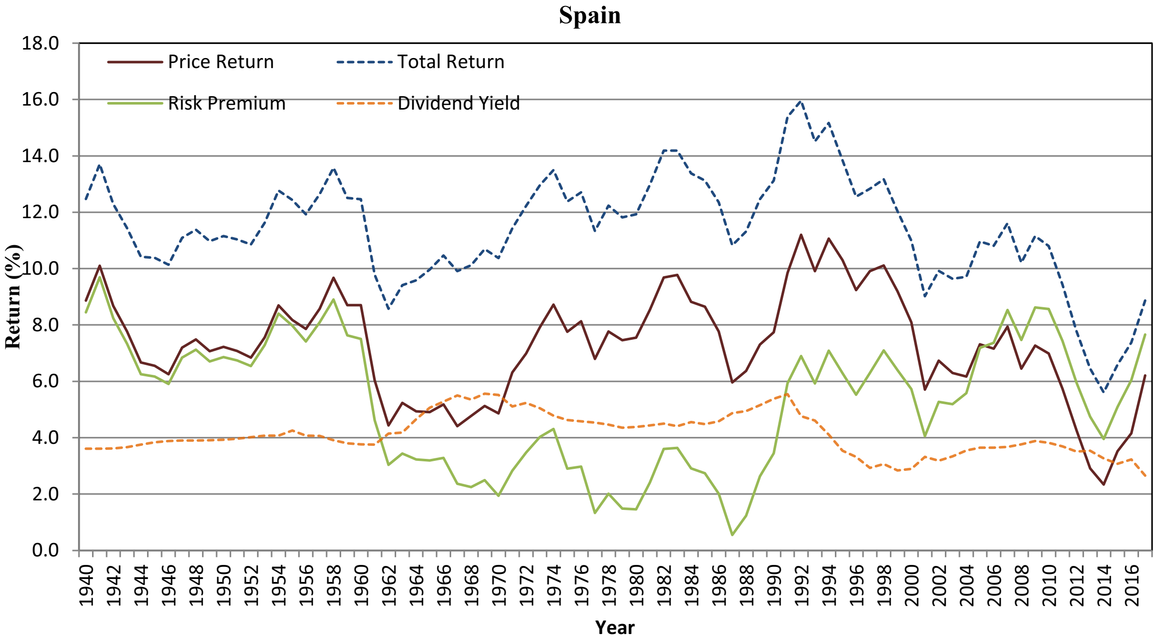

Finland
Price Return
Total Return
Risk Premium
Dividend Yield
Return (%)
Year
25.0
20.0
15.0
10.0
5.0
0.0
-5.0
1913
1916
1919
1922
1925
1928
1931
1934
1937
1941
1944
1947
1950
1953
1956
1959
1962
1965
1968
1971
1974
1977
1980
1983
1986
1989
1992
1995
1998
2001
2004
2007
2010
2013
2016


Sweden
Price Return
Total Return
Risk Premium
Dividend Yield
Return (%)
Year


Japan
Price Return
Total Return
Risk Premium
Dividend Yield
Return (%)
Year


Italy
Price Return
Total Return
Risk Premium
Dividend Yield
Return (%)
Year


Canada
Price Return
Total Return
Risk Premium
Dividend Yield
Return
Year


Spain
Price Return
Total Return
Risk Premium
Dividend Yield
Return (%)
Year
18.0
16.0
14.0
12.0
10.0
8.0
6.0
4.0
2.0
0.0
1940
1942
1944
1946
1948
1950
1952
1954
1956
1958
1960
1962
1964
1966
1968
1970
1972
1974
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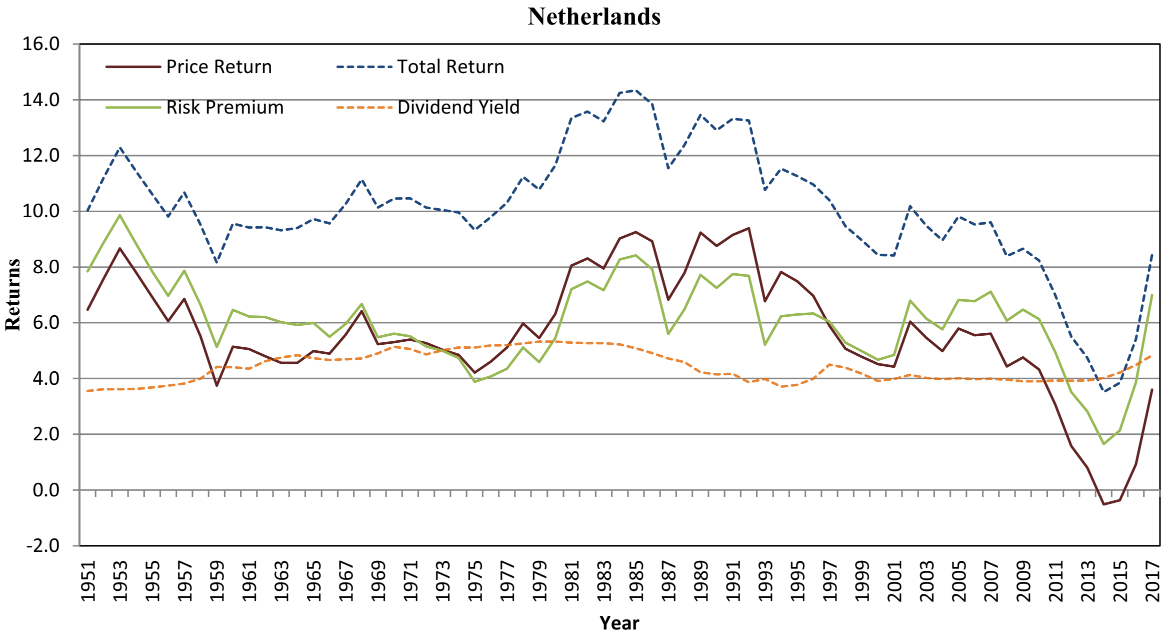
2008
2010
2012
2014
2016


Netherlands
Price Return
Total Return
Risk Premium
Dividend Yield
Returns
Year
16.0
14.0
12.0
10.0
8.0
6.0
4.0
2.0
0.0
-2.0
1951
1953
1955
1957
1959
1961
1963
1965
1967
1969
1971
1973
1975
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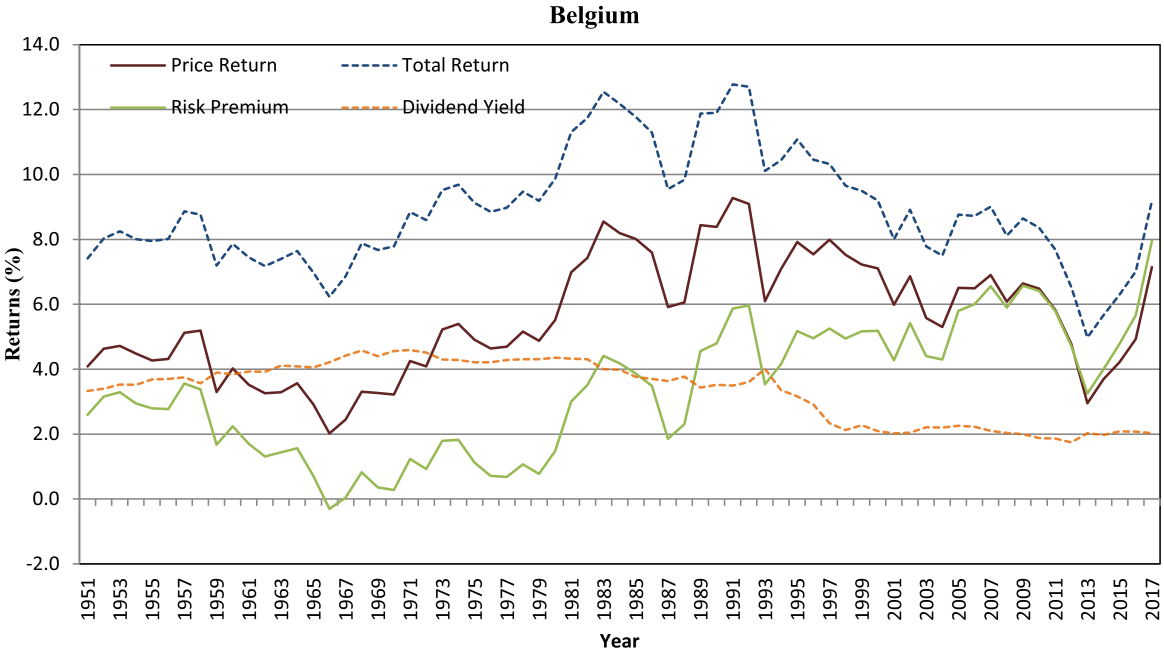
2009
2011
2013
2015
2017



Appendix 3. Halloween effect in both mean and variance

We use GARCH (1,1) with a Halloween dummy in the variance equation (Equation 2) to model a Halloween seasonal in the mean and variance of returns.

$$r_t = \alpha + \beta_H Hal_t + \varepsilon_t,$$

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

$$\sigma_t^2 = \mu_0 + \mu_1\varepsilon_{t-1}^2 + \mu_2\sigma_{t-1}^2 + \beta_V Hal_t \quad (2)$$

We include world index and 55 countries that have total return indices data available for over 20 years. Table 11 reports the Halloween effects in returns and in variance for the world and individual markets. In theory, if there is a significantly higher winter return, we would expect the variance to be higher in winter than in summer. However, 34 of the 55 countries actually have a smaller variance in winter than in summer, in which 23 are even significant. This evidence suggests risk difference can not explain the existence of the Halloween effect, if anything, the risk in summer months is strikingly higher than winter months.

Table 11
Halloween effect -GARCH (1,1), This table provides the results for the Halloween effect estimated with GARCH (1,1) in mean model: $r_t = \alpha + \beta_H Hal_t + \varepsilon_t$, $\varepsilon_t|\Phi_{t-1}\ N(0, \sigma_t^2), \sigma_t^2 = \mu_0 + \mu_1\varepsilon_{t-1}^2 + \mu_2\sigma_{t-1}^2 + \beta_V Hal_t$ for 55 countries that have data for over 20 years and the world index. Hal_t is the Halloween dummy that equals one if the month falls in the period of November through April. T-values are adjusted using Newey-West standard errors. *** 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.

Country	Start Date	End Date	Halloween Effect			Variance		
			βH	t-value		βv	t-value	
World	01/1926	04/2017	0.82	3.50	***	−2.03	−5.72	***
Developed markets								
Asia								
Hong Kong	01/1970	04/2017	1.03	1.94	*	−12.13	−5.29	***
Japan	01/1921	04/2017	1.20	3.68	***	0.73	0.84	
Singapore	08/1973	04/2017	1.63	3.79	***	−4.94	−3.72	***
Europe								
Austria	01/1970	04/2017	0.90	2.88	***	0.23	0.47	
Belgium	01/1951	04/2017	1.16	4.10	***	−2.37	−4.26	***

(continued on next page)

Table 11 (*continued*)

Country	Start Date	End Date	Halloween Effect			Variance		
			β_H	t-value		βv	t-value	
Denmark	01/1970	04/2017	0.74	1.81	*	−2.80	−2.31	**
Finland	11/1912	04/2017	1.15	4.98	***	1.76	3.69	***
France	02/1895	04/2017	0.82	3.70	***	−0.31	−1.36	
Germany	01/1870	04/2017	0.33	3.55	***	0.51	4.12	***
Ireland	12/1972	04/2017	1.64	3.53	***	−1.65	−0.86	
Italy	01/1925	04/2017	0.64	1.92	*	−0.67	−0.65	
Netherlands	01/1951	04/2017	1.30	3.87	***	−4.01	−5.10	***
Norway	01/1980	04/2017	1.62	2.30	**	−6.82	−2.78	***
Portugal	02/1988	04/2017	1.63	2.68	***	−2.49	−1.29	
Spain	04/1940	04/2017	0.60	2.08	**	0.30	0.34	
Sweden	01/1919	04/2017	0.59	2.70	***	−0.69	−1.45	
Switzerland	02/1966	04/2017	1.20	3.43	***	−3.59	−4.43	***
United Kingdom	09/1694	04/2017	0.14	2.12	**	0.02	0.30	
Mid East								
Israel	12/1992	04/2017	0.56	0.91		1.77	0.80	
North America								
Canada	03/1934	04/2017	0.90	3.67	***	−2.81	−5.92	***
United States	02/1800	04/2017	0.15	1.39		−0.46	−3.08	***
Oceania								
Australia	07/1928	04/2017	0.12	0.81		−1.23	−4.71	***
New Zealand	07/1986	04/2017	0.71	1.97	**	−2.52	−2.24	**
Emerging markets								
Africa								
Egypt	09/1996	04/2017	1.50	1.37		28.50	2.78	***
South Africa	02/1960	04/2017	0.63	1.62		−2.52	−1.91	*
Asia								
China	01/1993	04/2017	−0.07	−0.09		−16.11	−3.66	***
India	01/1988	04/2017	−0.44	−0.61		2.20	0.54	
Indonesia	01/1988	04/2017	2.03	2.05	**	−18.78	−4.86	***
Korea	02/1962	04/2017	0.48	1.01		1.58	1.17	
Malaysia	12/1972	04/2017	1.11	2.73	***	−3.36	−3.94	***
Philippines	01/1982	04/2017	0.86	1.48		−2.66	−0.99	
Taiwan	01/1988	04/2017	1.12	4.72	***	−3.51	−2.45	**
Thailand	05/1975	04/2017	0.53	1.06		−7.26	−5.44	***
Country	**Start Date**	**End Date**	**Halloween Effect**			**Variance**		
			β_H	**t-value**		**βv**	**t-value**	
Europe								
Czech Republic	11/1993	04/2017	1.21	1.72	*	−5.47	−2.04	**
Greece	01/1977	04/2017	1.15	1.93	*	2.95	1.43	
Hungary	02/1991	04/2017	2.81	3.28	***	−0.43	−0.12	
Poland	05/1991	04/2017	1.00	1.28		−4.44	−1.63	
Russia	01/1995	04/2017	0.53	0.50		8.67	2.70	***
Turkey	02/1986	04/2017	1.69	1.48		−8.34	−0.89	
North America								
Mexico	01/1988	04/2017	0.28	0.52		−2.30	−1.62	
South America								
Chile	01/1983	04/2017	0.69	1.34		−2.35	−1.34	
Colombia	01/1988	04/2017	0.47	0.59		0.85	0.19	
Peru	01/1993	04/2017	0.94	1.01		−11.25	−4.64	***
Frontier markets								
Africa								
Mauritius	08/1989	04/2017	0.23	0.54		−1.32	−1.72	*
Morocco	03/1994	04/2017	0.95	1.71	*	3.68	2.71	***
Asia								
Pakistan	01/1988	04/2017	1.24	2.07	**	4.53	1.48	
Sri Lanka	05/1987	04/2017	−0.26	−0.33		−13.78	−3.41	***
Europe								
Estonia	08/1995	04/2017	1.69	2.71	***	0.85	0.57	
Lithuania	01/1996	04/2017	1.33	2.56	**	0.30	0.23	
Romania	12/1996	04/2017	−0.16	−0.18		3.83	0.82	
South America								
Argentina	07/1993	04/2017	0.75	0.66		20.49	2.04	**
Europe								
Cyprus	12/1992	04/2017	−0.14	−0.16		16.81	5.20	***
Latvia	05/1996	04/2017	0.35	0.38		−11.44	−5.21	***
Luxembourg	01/1985	04/2017	1.22	2.41	**	−4.44	−4.00	***
South America								
Venezuela	12/1996	04/2017	1.77	1.74	*	20.61	4.10	***

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