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ECONOMICS &
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UNIVERSIDADE DE LISBOA

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MASTER'S FINAL WORK
DISSERTATION

THE IMPACT OF FINANCIAL DEVELOPMENT ON STOCK MARKET CALENDAR EFFECTS

PATRÍCIA DA SILVA MACEDO

JUNE - 2019

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SUPERVISION:
RAQUEL MEDEIROS GASPAR

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ABSTRACT

Having weakened for some samples, but persisted for others, calendar effects are still a relevant challenge to market efficiency. Their decline for some markets suggests that the inefficiencies responsible for the presence of calendar effects should disappear with improvements in financial development. This research aims to help fill a gap in the existing literature, by clearly drawing a relationship between the presence of calendar effects and financial development. The goal is to clarify whether calendar effects can be partly explained by a lack of financial development.

In this work, we investigate weekly and monthly calendar effects in 46 international stock markets, for a 25 years-period, and relate our findings to their degree of financial development. The evidence suggests that some calendar anomalies – the Friday and January effects – clearly decrease with financial development, while others – the Monday, April, and Halloween effects – are statistically significant, regardless of it. We build three alternative aggregate measures for the presence and severity of calendar effects in markets, and find that less financially developed countries have more calendar anomalies, not only in number, but in intensity as well.

Keywords: Calendar effects, financial development, Day of the Week effects, Month of the Year effects, Halloween effect.

RESUMO

Tendo enfraquecido para algumas amostras, mas persistido para outras, os efeitos de calendário são ainda uma contradição relevante à eficiência de mercado. O seu declínio para alguns mercados sugere que as ineficiências responsáveis pela presença de efeitos de calendário tendem a desaparecer com um melhor desenvolvimento financeiro. Este trabalho procura ajudar a preencher uma lacuna na literatura existente, ao traçar claramente uma relação entre a presença de efeitos de calendário e o desenvolvimento financeiro. O objetivo é clarificar se os efeitos de calendário podem ser parcialmente explicados por um baixo nível de desenvolvimento financeiro.

Neste trabalho, investigamos efeitos de calendário semanais e mensais em 46 mercados de ações internacionais, para um período de 25 anos, e relacionamos os resultados com o seu nível de desenvolvimento financeiro. Os resultados sugerem que algumas das anomalias – os efeitos de sexta-feira e de janeiro – claramente diminuem com o desenvolvimento financeiro, enquanto outras – os efeitos de segunda-feira, abril, e *Halloween* – são estatisticamente significativos, independentemente do desenvolvimento financeiro. Construímos três medidas agregadas para a presença e intensidade de efeitos de calendário nos mercados, e concluímos que os países menos desenvolvidos financeiramente têm não só mais anomalias de calendário em número, mas em intensidade também.

Palavras-chave: Efeitos de calendário, desenvolvimento financeiro, efeitos Dia da Semana, efeitos Mês do Ano, efeito de Halloween.

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A todos — o meu sincero obrigada! Este trabalho não existiria sem o vosso contributo e precioso apoio.

CONTENTS

ACRONYMS

CES Calendar Effects Score. 17, 25, 30, 40, 41

DOTW Day of the Week. 7, 14, 15

FD Financial Development. 1, 8, 9, 12, 13, 14, 16, 19, 20, 22, 25, 30, 37

FE Fixed Effects. 40

GLM Generalized Linear Model. 17

IMF International Monetary Fund. 1, 8, 30

MOTY Month of the Year. 14, 15, 20

OLS Ordinary Least Squares. 14, 17, 40

RE Random Effects. 40

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1 INTRODUCTION

Calendar effects have been a prominent topic of empirical research for several decades. Earlier studies show evidence for the presence of these anomalies in developed countries (Cross, 1973; French, 1980; Keim, 1983; Reinganum, 1983), while the more recent literature documents their weakening, and relates it to improved market efficiency (Gu, 2003; Kohers et al., 2004; Floros & Salvador, 2014; Urquhart & McGroarty, 2014). At the same time, there has been a resurgence of studies focusing on the presence of the aforementioned anomalies for emerging markets, or dividing the analysis into emerging and developed markets (Kumar, 2016; Seif et al., 2017; Zhang et al., 2017). While this methodology allows for a comparison between the groups, it is not conclusive enough, as it concerns a too broad and static division. There is not, to our knowledge, empirical work in existing literature that clearly draws a relationship between the presence of calendar effects and financial development. This research aims to help filling that gap.

It is important to clarify whether there is a relationship between calendar effects and financial development, as, over the years, there has not been a consensus on the explanations offered for most of these effects. Justifications such as the tax-loss selling hypothesis, patterns in information disclosure, or the size effect, have been both supported and rejected by different studies (see, for instance, Keim (1983), Jaffe & Westerfield (1985b), Clare et al. (1995), or Zhang & Jacobsen (2012)). If financial development (or lack thereof) is, at least partly, responsible for the existence of calendar effects, it could also help clear up why the effects can be explained for some samples and not others. The inefficiencies responsible for the presence of calendar effects should disappear with improvements in financial development.

This work differs from existing literature, as we employ the International Monetary Fund's Financial Development (FD) index as a measure for financial development. It also allows for a more dynamic analysis, comparing countries with varying degrees of financial development over time. The goal is to clarify whether calendar effects can be partly explained by a lack of financial development, or if there is no relationship between the two.

We investigate 46 international stock markets, for a 25 years-period, and relate our findings to their degree of financial development. Our focus is on weekly and monthly effects, and we build three alternative aggregate measures for the presence and severity of calendar effects in markets.

The remainder of this work is organized as follows: Section 2 contains a brief review of some of the most relevant literature regarding calendar effects and their varying behaviour, and the definition of financial development; in Section 3 we go over the data used in this work, its sources, present some summary statistics, and describe the methodology followed; the results are discussed in Section 4; finally, we conclude with Section 5, shed some light on this study's limitations, and make suggestions for future research.

2 LITERATURE REVIEW

There is a vast literature on market anomalies, challenging the notion of market efficiency. For some recent surveys on market efficiency and anomalies, see Meier (2014) and Rossi (2015).

Many anomalies have been documented over the years, and some have been proved to have attenuated with time. This may be a result of the market readjusting itself, after the predictable value of such anomalies has been exploited by market participants, a natural consequence of markets becoming more developed and efficient. Other anomalies have persisted, and where traditional finance theory fails to explain them, behavioural finance attempts to find justification for them in psychological factors (De Bondt et al., 2008). Despite having been first documented several decades ago, calendar effects – anomalies that are seasonal in behaviour, or otherwise linked to calendar time – are still the subject of research to this day. As a consequence of being dependent on calendar time, they are costly anomalies to exploit, as strategies devised around calendar effects would necessarily suffer from numerous transactions (French, 1980; Thaler, 1987b). While this might help explain why they have not been simply arbitraged away with time, it makes the research of calendar anomalies even more relevant in recent times, as transaction costs get lower, and opportunities might arise where they were previously non-existent.

On this section, we briefly review some of the existing findings on calendar effects. We highlight some studies that evidence how these effects vary for different countries and market conditions. We also give a summarised introduction to the definition of financial development we employ in this study.

2.1 Day of the Week Effects

Differences in returns throughout the week are frequently documented, most commonly for Mondays and Fridays. Cross (1973) reports that, between 1953 and 1970, the S&P Composite Stock Index had negative returns on 60% of Mondays, and positive on over 60% of Fridays.

While Cross attempts no explanation for the observation, French (1980) hypothesises that unfavourable information released while the market is closed over the weekend may be to blame for low Monday returns, a theory shared by Thaler (1987b). More than a weekend-only effect, French characterizes it as a consequence of regular market-closings, but not occasional ones, as Tuesdays also present negative returns when following a Monday public holiday. Steeley (2001) also attributes the effect to information seasonality: he observes that macroeconomic announcements in the UK usually fall in the middle of the week (Tuesday to Thursday). As there is a brokers' bias towards buy recommendations, this would result in Fridays being dominated by buying activity, and the opposite being true of Mondays.

Lakonishok & Levi (1982) point out a "settlement effect". If a purchase happens on Friday, it will take two extra calendar days for the seller to be paid compared to other weekdays, making it likely that sellers would demand higher compensation on Fridays. Likewise, buyers would be willing to pay more for the extra two days of interest before the payment happens.

Following Phillips-Patrick & Schneeweis (1988)'s research on the US's stock market between 1982 and 1985, there yet is an inverse Monday effect for dividend yields, which could also be behind the Monday low returns.

Jaffe & Westerfield (1985a) observe the same low Monday and high Friday returns for Japan, between 1970 and 1983. They also find a negative effect on returns on Tuesday (also present for Australia between 1973 and 1982, see Jaffe & Westerfield (1985b)), which cannot be completely explained by a "time-zone" effect alone.

2.2 Month of the Year Effects

The most commonly discussed monthly effect in the literature is the so called *January effect*, i.e., the observation of abnormally high returns in January compared to the rest of the year. The abnormal returns are commonly linked to size, as smaller firms exhibit a stronger January effect. Keim (1983) reports that around half of the annual excess return of small firms occurs on the month of January.

Rozeff & Kinney Jr (1976) put forward the accounting information hypothesis for the effect – returns might be influenced by preliminary announcements of companies' previous year's results. Reinganum (1983) finds evidence to support the tax-loss selling selling hypothesis, i.e., that as the end of the fiscal year approaches, large investors sell stocks that have underperformed, seeking to claim a loss for tax purposes. However, he also observes that the effect is still present in firms less likely to be the target of tax-loss selling. Yet an alternative explanation would be "window dressing". Before the end of the year, institutional investors may sell specific stocks to apparent a stronger performance to clients and shareholders, and reinvest in January (Thaler, 1987a).

Jaffe & Westerfield (1985b) find the effect present in Japanese stocks, even though the tax year in Japan begins on April 1st, suggesting that the tax-loss selling hypothesis does not completely explain the January effect. Zhang & Jacobsen (2012) reach similar conclusions for the UK between 1951 and 2009, with a tax year beginning on April 5th. They also find positive effects for April and December. Furthermore, the positive April effect is present even before 1965, when the capital gains tax was implemented in the UK. The positive April and December effects in the UK are also observed by Reinganum & Shapiro (1987), Clare et al. (1995), and Dimson & Marsh (2001). There might yet be a seasonality in the payment of bonuses (for example, year-end bonuses), capital gains realizations, and other such cash inflows that drive investors to buy more securities in certain months (Ritter, 1988). Especially at the end of the year, this would result in an environment biased towards buying behaviour.

Other month effects may be consequence of a broader effect, not related to specific months, but rather to the period they fall on – that is the case of the *Halloween effect*. The Halloween effect is the belief that stock returns are generally lower between May 1st and October 31st. Bouman & Jacobsen (2002) study 37 countries and find support for the existence of a global Halloween effect, especially significant for European countries. For their sample, returns were significantly higher for the months between November and April than for the rest of the year. They find support for the hypothesis that the effect is due to market participants being away during Summer, as they report that vacations length and timing are positively correlated with the occurrence of the Halloween effect. Carrazedo et al. (2016) corroborate their findings for European countries, from 1992 to 2010. Maberly & Pierce (2004) argue, however, that the Halloween "puzzle" can be solved by controlling for outliers. They find that the effect loses significance when excluding major events that had an impact on markets.

2.3 Behavioural Finance and Calendar Effects

Behavioural finance has gained traction in recent years. As traditional finance theory fails to explain certain anomalies and phenomenons, a growing number of scholars have looked for answers in irrational investor behaviour. For some comprehensive reviews of behavioural finance, see Barberis & Thaler (2003) or, more recently, Konstantinidis et al. (2012) and Hirshleifer (2015).

Al-Hajieh et al. (2011) find a positive effect on stock returns for Middle East countries between 1992 and 2007 during the Ramadan period, and attribute it to positive investor sentiment. Similarly, Teng & Liu (2013) hypothesise that positive emotions are responsible for positive returns before holidays for the Taiwan stock market, from 1997 to 2011. Doeswijk (2008) proposes a psychological explanation for monthly seasonality in stock returns: the optimism-cycle hypothesis. As the new year approaches, investors become optimistic, resulting in high returns in the last quarter of the year and the first few months of the following year. However, as the year advances, their attitude inverts, giving way to negative Summer returns. Mental accounting (Thaler, 1999) could also be to blame for positive returns at the beginning of the tax year.

Investors would be more willing to make risky stock purchases with income from tax-refunds, for example, than their regular monthly income. Ahmad & Hussain (2001) find a positive February effect for Malaysia between 1986 and 1996, and relate it to the Chinese New Year being seen by investors as a "focal point". Abu Bakar et al. (2014) find support for the "blue Monday" hypothesis – between 2007 and 2012, the Monday effect loses significance for 20 countries after controlling for negative mood indicators at the beginning of the week, suggesting that patterns in returns throughout the week are related to sentiment patterns among market participants.

2.4 Varying Calendar Effects

Calendar effects are not persistent in all samples. There is a branch of the literature on the subject that relates variations in calendar effects to market stability and efficiency, or to the nature of the markets – whether developed or emerging.

Gu (2003) relates the weakening of the January effect in the US to periods of higher GDP growth and inflation. For this purpose, he develops a power ratio to measure the difference between the January return and the average return of the other months of the year. Urquhart & McGroarty (2014) show that certain calendar effects vary for different market conditions – market crashes, bull or bear markets, market contractions -, consistent with the Adaptive Market Hypothesis. Floros & Salvador (2014) employ a Markov switching model to cash and future returns, and observe that there are generally positive weekly and monthly effects during low volatility periods, that turn into negative effects under high volatility. Kumar (2016) studies twelve currency markets between 1985 and 2014 and shows that both weekly and monthly patterns in returns are stronger for emerging markets than for developed ones, supporting the hypothesis that there is a relationship with countries' development. Balbina & Martins (2002) report that between 1988 and 1996, there is a significant difference in daily returns throughout the week for the Portuguese stock market, that disappears after 1997[1]. Their results suggest that the disappearance of the Day of the Week (DOTW)

[1] 1997 is the year that the Portuguese market went from being internationally considered an emerging market to a developed one.

effects is, at least partially, related to the improvement in financial development.

2.5 Financial Development

Literature on financial development usually defines a single indicator to serve as a proxy for financial development - for example, money supply to GDP (Hassan et al., 2011), private-sector credit to GDP (Ductor & Grechyna, 2015), or market capitalization to GDP (Chakraborty, 2010). A single indicator approach has numerous disadvantages, most strikingly having varying degrees of relevance for different countries, making it inadequate for a cross-country analysis. To mitigate the shortcomings of a single indicator, some works employ more than one definition of financial development, as a robustness check (Anwar & Cooray, 2012; Berdiev & Saunoris, 2016; Yu et al., 2012). Others construct aggregate measures of financial development. Naceur & Ghazouani (2007) develop the SMINDEX, a measure of stock market development, from three indicators: stock market capitalization to GDP, value of stock trades to GDP, and value of stock trades to market capitalization. By using only stock market indicators, however, they restrict their analysis to only 11 countries, as many countries have either non-existent or too recent stock markets. Samargandi et al. (2015) go a different route and develop an index from three banking sector ratios: liquid liabilities to GDP, commercial bank assets to GDP, and private credit to GDP. As their measure disregards stock markets, however, it is also unsuitable for our purposes.

A more recent definition of financial development is the International Monetary Fund (IMF)'s Financial Development (FD) index. The FD index is a database of nine sub-indices, based upon 20 key indicators. It contains information on the degree of depth, access and efficiency of both financial markets and institutions, resulting in an overall measure of financial development (Svirydzenka, 2016). For the purpose of this work, we use the FD index as proxy for the financial development of each country in our sample. Other recent studies employing the FD index as the definition of financial development are, for instance, Dafe et al. (2018), Imamoğlu et al. (2018), Thaler (2018), or Yan et al. (2018).

3 DATA AND METHODOLOGY

3.1 Data Description

As of 2019, the FD index has yearly data available for 183 countries, from 1980 to 2016. As such, our sample period runs from 2nd January 1992 to 30th December 2016, a 25 years-period ending on the last year with data available for the index.

The FD index gathers major indicators from the literature on financial development, and summarizes them into three categories, for both financial markets and institutions: depth, access, and efficiency indicators (Figure 1). The full list of indicators used can be found on Table I. The indicators are normalized and aggregated as a weighted average into each of the sub-indices. The summarized indices have values between 0 and 1, being a relative ranking of financial development across countries in the database. For each country and year, we take the corresponding value of the aggregated index. The FD values for our sample range from 0.116 to 1, corresponding to the lowest (Ukraine, 1998) and highest (Switzerland, 2007) degrees of financial development observed, respectively.

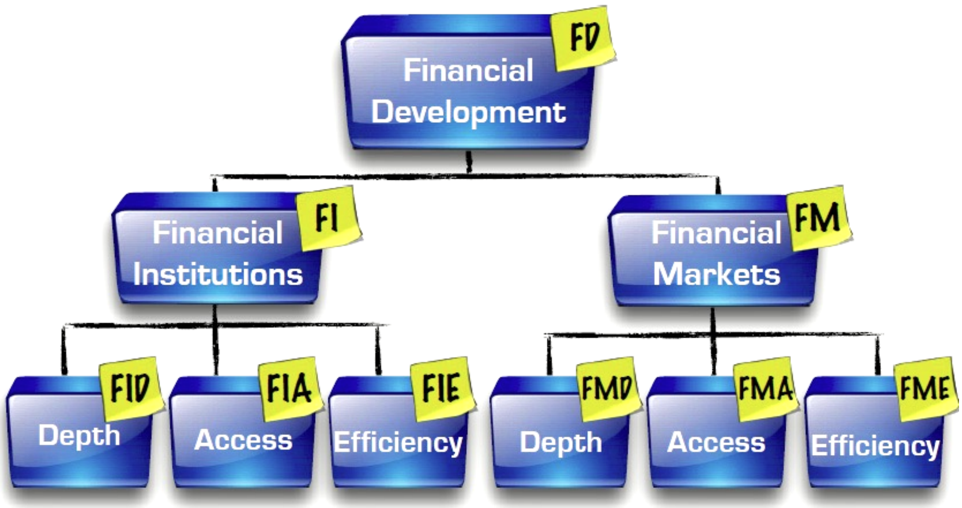

Figure 1: Financial Development Index.
Source: Sahay et al. (2015).

Table I: Key indicators used in the construction of the FD index

Category	Indicator
	Financial Institutions
Depth	Private-sector credit to GDP
	Pension fund assets to GDP
	Mutual fund assets to GDP
	Insurance premiums, life and non-life to GDP
Access	Bank branches per 100,000 adults
	ATMs per 100,000 adults
Efficiency	Net interest margin
	Lending-deposits spread
	Non-interest income to total income
	Overhead costs to total assets
	Return on assets
	Return on equity
	Financial Markets
Depth	Stock market capitalization to GDP
	Stocks traded to GDP
	International debt securities of government to GDP
	Total debt securities of financial corporations to GDP
	Total debt securities of nonfinancial corporations to GDP
Access	Percentage of market capitalization outside of top 10 largest companies
	Total number of issuers of debt (domestic and external, nonfinancial and financial corporations)
Efficiency	Stock market turnover ratio (stocks traded to capitalization)

Source: Svirydzenka (2016).

For our analysis, we examine daily closing prices for 46 country stock indices, retrieved on 16th March 2019 from Bloomberg Terminal. Due to data unavailability, some indices start at a later date. The indices used and their respective start dates can be found on Table II.

Table II: Country indices in the sample and respective start dates

Country	Index	Start date
Argentina	MERVAL Index	02/01/1992
Australia	S&P/ASX 300	01/06/1992
Austria	Wiener Börse Index	09/06/1992
Belgium	BEL 20	02/01/1992
Brazil	Bovespa Index	02/01/1992
Bulgaria	SOFIX	25/10/2000
Canada	S&P/TSX Composite Index	02/01/1992
Chile	IPSA	02/01/1992
China	SSE Composite Index[2]	02/01/1992
Croatia	CROBEX	17/06/2002
Czech Republic	PX-GLOB	03/10/1994
Denmark	OMX Copenhagen 20	02/01/1992
Finland	OMX Helsinki All-Share Index	02/01/1992
France	CAC 40	02/01/1992
Germany	DAX Composite Index	02/01/1992
Greece	Athens Stock Exchange General Index	02/01/1992
Hong Kong	Hang Seng Index	02/01/1992
India	BSE SENSEX	02/01/1992
Indonesia	Jakarta Composite Index	02/01/1992
Ireland	ISEQ All-Share Index	02/01/1992
Italy	FTSE MIB	02/01/1998
Japan	Nikkei 225	06/01/1992
Lithuania	OMX Vilnius	05/01/2000
Mexico	S&P/BMV IPC	20/01/1994
Morocco	Moroccan All-Shares Index	03/01/1995
Netherlands	AEX All-Share Index	02/01/1995
New Zealand	NZX 50 Index	04/01/2001
Nigeria	Nigerian Stock Exchange All-Share Index	05/01/1998
Norway	Olso Børs All-Share Index	02/01/1996
Peru	S&P/BVL Peru General Index	02/01/1992
Philippines	PSE Composite Index	02/01/1992
Poland	WIG	07/01/1992
Portugal	PSI All-Share Index	02/01/1992
Romania	Bucharest Exchange Trading Index	23/09/1997
Russia	MOEX Russia Index	23/09/1997
Singapore	FTSE Straits Times Index	01/09/1999
South Africa	FTSE/JSE Africa All-Share Index	03/07/1995

Continued on next page

[2]Before 21st May 1992, the Shanghai Stock Exchange had a limit of 5% on stocks' daily price movements. The removal of this limit on this date lead to a daily return of over 71%. This observation has been excluded from the sample.

Table II: *Continued from previous page*

Country	Index	Start date
South Korea	Korea Composite Stock Price Index	04/01/1999[3]
Spain	IBEX 35	04/12/1996
Sweden	OMX Stockholm 30	02/01/1992
Switzerland	Swiss All-Share Index	02/07/1998
Thailand	SET Index	02/01/1992
Tunisia	Tunindex	14/04/1999
Ukraine	PFTS Index	13/01/1998
United Kingdom	FTSE All-Share Index	02/01/1992
United States	NASDAQ Composite	02/01/1992

Daily logarithmic returns are computed as follows:

$$R_{it} = ln\left(\frac{P_{it}^{close}}{P_{it-1}^{close}}\right) \tag{3.1}$$

where R_{it} is the daily return on day t for index i, P_{it}^{close} is the closing price on day t of index i, and P_{it-1}^{close} is the closing price on day $t-1$ of index i.

There are four Saturdays and four Sundays of trading for the Indian index, BSE SENSEX, during the sample period: 25th October 1992; 13th November 1993; 10th November 1996; 25th October 2003; 21st October 2006; 17th October 2009; 3rd November 2013; 30th October 2016. All eight dates correspond to the traditional Muharat Trading session[4]. We exclude the daily returns for these dates from the sample, as well as for the corresponding following Mondays.

The final sample is comprised of 256,133 observations of daily returns, and 1,039 observations of yearly FD values. Observations for each country range from 3,572 to 6,349 daily observations. Descriptive statistics can be found on Table III.

[3]Although the index is available since the start of the sample period, we only consider it for our analysis starting on 4th January 1999. Before this date, the trading week for South Korea ran from Monday to Saturday. We have kept this period out of our sample in order to have comparable daily returns across the weekdays for all countries.

[4]An annual event where the market opens one hour for trading, even if it falls on a weekend.

Table III: Descriptive statistics for daily returns and FD for the sample

	Daily Return (%)	FD
Mean	.033	.551
Median	.052	.565
Standard Deviation	.015	.211
Observations	256,133	1,039

3.2 Methodology

We test three null hypothesis, and employ different methodologies to test each:

1. The mean daily return on a given weekday, month, or period[5] is the same as the mean daily return for all days, for all levels of FD;
2. There is no excess nor deficit mean daily return on a given weekday, month, or period compared to the other days, for all levels of FD;
3. There is no relationship between the significance of calendar anomalies in a given country's market and its level of FD.

The methodologies followed are described in the following sub-sections.

3.2.1 One Sample T-Test per Weekday, Month, and Period

It is common place in existing literature to divide the sample into quantiles to observe how the effects vary across groups (see, for example, Keim (1983) and Reinganum (1983)). As such, on a first approach, we divide the sample into four quartiles of FD each year (Figure 2). For each quartile, we employ a one sample t-test to test the first null hypothesis, defined as:

$$H_0 : \mu_i = \mu_0 \tag{3.2}$$

[5] I.e., Summer (May 1st to October 31st) or Winter (November 1st to April 30th).

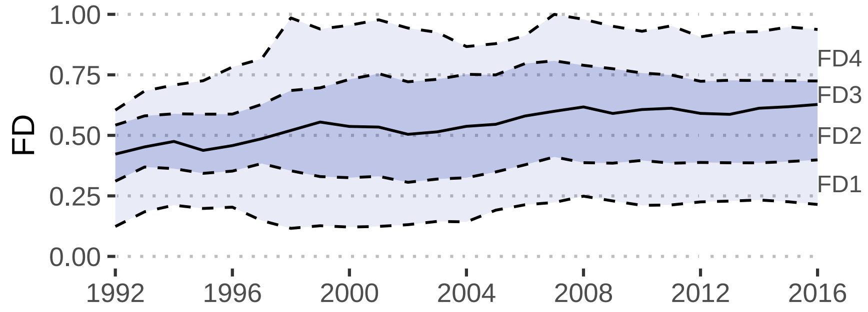

Figure 2: Quartiles of FD over the sample period.

where μ_0 is the global mean daily return for all days, and μ_i is the mean daily return for weekday, month or period i. The t-statistic is defined as:

$$T = \frac{\bar{x}_i - \mu_0}{\frac{s_i}{\sqrt{n_i}}} \tag{3.3}$$

where $\bar{x}_i$, s_i, and n_i are, respectively, the sample mean, the sample standard deviation, and the number of observations for weekday, month, or period i. The confidence interval for $\alpha = 0.05$ is computed as:

$$CI = \bar{x}_i \pm t_{\frac{\alpha}{2}} \frac{s_i}{\sqrt{n_i}} \tag{3.4}$$

where $t_{\frac{\alpha}{2}}$ is the critical value for a two-tailed test, with $\alpha = 0.05$, and $n_i - 1$ degrees of freedom.

If the null hypothesis is rejected, we conclude that the mean daily return for weekday, month, or period i is significantly different from the global mean daily return. We then compare the results of the statistical tests across the quartiles of FD, and observe how they vary.

3.2.2 Linear Regression Models

For the second hypothesis, we employ the pooled OLS method to estimate the coefficients for three models: one for the Day of the Week (DOTW) effects, one for the Month of the Year (MOTY) effects, and one for the Halloween effect. For each of the first two regressions, we isolate the main effects identified by the use of the methodology described in the previous sub-section, and end up with the following models and respective null hypothesis:

$$R_{it} = \beta_0 + \beta_2 D_{2,it} + \beta_6 D_{6,it} + \epsilon_{it} \tag{3.5}$$

$$H_0 : \beta_2 = \beta_6 = 0 \tag{3.6}$$

for the DOTW effects, where β_0 is the expected mean daily return on any given weekday, β_2 and β_6 are the excess mean daily returns on Mondays and Fridays, respectively, and $D_{j,it}$ is a dummy variable that takes the value of 1 if R_{it} occurs on weekday j, and 0 otherwise;

$$R_{it} = \beta_0 + \beta_1 M_{1,it} + \beta_4 M_{4,it} + \beta_{12} M_{12,it} + \epsilon_{it} \tag{3.7}$$

$$H_0 : \beta_1 = \beta_4 = \beta_{12} = 0 \tag{3.8}$$

for the MOTY effects, where β_0 is the expected mean daily return on any given month, β_1, β_4, and β_{12} are the excess mean daily returns on January, April, and December, respectively, and $M_{j,it}$ is a dummy variable that takes the value of 1 if R_{it} occurs on month j, and 0 otherwise; and

$$R_{it} = \beta_0 + \beta_1 H_{it} + \epsilon_{it} \tag{3.9}$$

$$H_0 : \beta_1 = 0 \tag{3.10}$$

for the Halloween effect, as in Bouman & Jacobsen (2002), where β_0 is the expected mean daily return during the Summer period (May 1st to October 31st), β_1 is the excess expected mean daily return during the Winter period (November 1st to April 30th), and H_{it} is a dummy variable that takes the value of 1 if R_{it} occurs during the Winter period and 0 otherwise.

Each model is estimated for each quartile of FD, in a total of twelve regressions. If the null hypothesis is rejected, we conclude that daily returns are significantly different across weekdays, months, or periods. We compare the regressions for each quartile of FD, drawing conclusions on how the several effects vary in significance across the quartiles.

3.2.3 Measuring Calendar Effects

Finally, we test the third and last hypothesis, by developing measures of the degree of calendar anomalies that can be quantified and related to FD. Firstly, we adapt Gu (2003)'s January power ratio to each of the effects previously isolated: the Monday, Friday, January, April, December, and Halloween effects. Unlike Gu (2003), we do not use monthly and yearly returns. Instead, we use the average daily return during the period we are concerned with. The power ratios are defined as:

$$PR_i = \frac{1 + r_i}{1 + r_0} - 1 \tag{3.11}$$

where r_i is the mean daily return on weekday, month, or period i, and r_0 is the mean daily return throughout the entire year.

A positive power ratio stands for a positive effect on daily returns. We compute the power ratios for the six effects for each country and each year, for between 1,027 and 1,039 observations for each ratio. To test whether each of these ratios can be accurately explained by a country's degree of FD, we estimate the following model:

$$PR_i = \gamma_0 + \gamma_i FD_i + \epsilon_i \tag{3.12}$$

and test the null hypothesis: $H_0 : \gamma_i = 0$.

As there is no widely used indicator in existing literature to quantify the overall impact of calendar anomalies for a market, we propose three alternative measures which aggregate all six effects. We name them Calendar Effects Score (CES) A, B, and C.

$\mathbf{CES_A}$ measures the number of significant calendar effects for a given country and in a given year. To construct it, we apply models (3.5), (3.7), and (3.9) to each country and each complete year of observations, and count the number of coefficients that are significant at the 5% level, so that $0 \leq CES_A \leq 6$. $\mathbf{CES_A}$ is a categorial variable, as we are dealing with count data, so we need to follow a GLM approach, rather than an OLS estimation. A Poisson regression model is estimated:

$$log(\lambda_i) = \gamma_0 + \gamma_i FD_i + \epsilon_i \tag{3.13}$$

where λ_i is the mean of CES_{Ai}, and we assume $CES_{Ai} \sim Poisson(\lambda_i)$.

The second and third measures, $\mathbf{CES_B}$ and $\mathbf{CES_C}$, both represent the intensity of the calendar effects measured. The difference between the two lies in the way they are computed, and subsequent interpretations. Both are defined as:

$$CES = \frac{\sum_{i=1}^{6} |\beta_i|}{n} \tag{3.14}$$

where β_i is the value of the coefficient for anomaly i (it takes the value of 0 if the coefficient is not significant at the 5% level). For $\mathbf{CES_B}$, n equals the number of significant coefficients, while for $\mathbf{CES_C}$ $n = 6$. We take the absolute value of the coefficients for each anomaly, to avoid opposite-sign effects cancelling each other out. The indicators are, therefore, interpreted as the absolute anomalous daily return caused by the calendar anomalies for a given country in a given year. **$\mathbf{CES_B}$** gives equal weights to all potential anomalies, and, indirectly, values more strongly the intensity of existing anomalies rather than the number of present anomalies, even if they are few in number. **$\mathbf{CES_C}$**, on the other hand, attributes more weight to the number of existing anomalies. A country with six weak calendar effects, for example, could have the same CES_C as a country with one singular but strong effect, while CES_B would be lower for the former.

For the last two measures, we employ two linear regression models of the same form as (3.12):

$$CES_{Bi} = \gamma_0 + \gamma_{1i} FD_i + \epsilon_i \tag{3.15}$$

and

$$CES_{Ci} = \gamma_0 + \gamma_{1i} FD_i + \epsilon_i \tag{3.16}$$

4 ANALYSIS OF RESULTS

Figure 3 presents summary statistics for daily returns, by quartile of FD and by weekday. Detailed reporting on the one sample t-tests can be found on Table A.I, in the appendix. For a 5% significance level, only Mondays' average daily returns are significantly different from the global average, for all quartiles. Fridays have a significant positive effect for all but the highest quartile. There is also a negative Tuesday effect for the first two quartiles, possibly a reflection of a "time-zone" Monday effect for some countries (Jaffe & Westerfield, 1985b) – from Figure 4 we see that the effect attenuates excluding countries 12 or more hours ahead of New York. There are no noteworthy effects for the other weekdays.

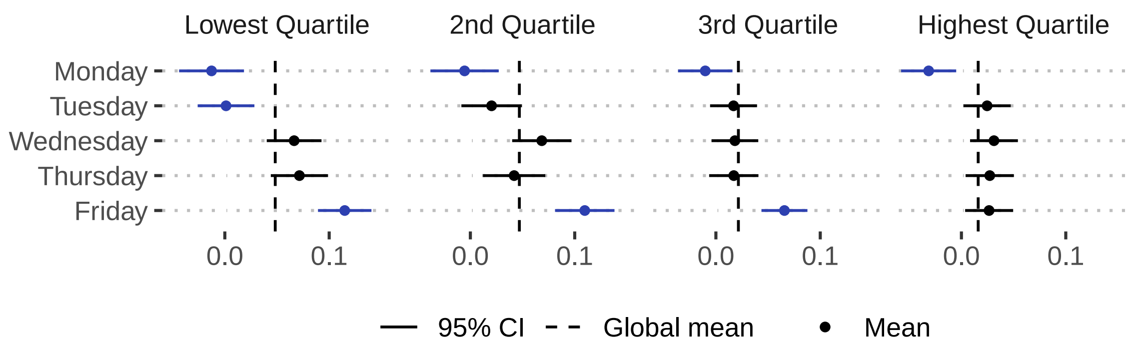

Figure 3: Mean daily return and confidence intervals per weekday and per quartile.

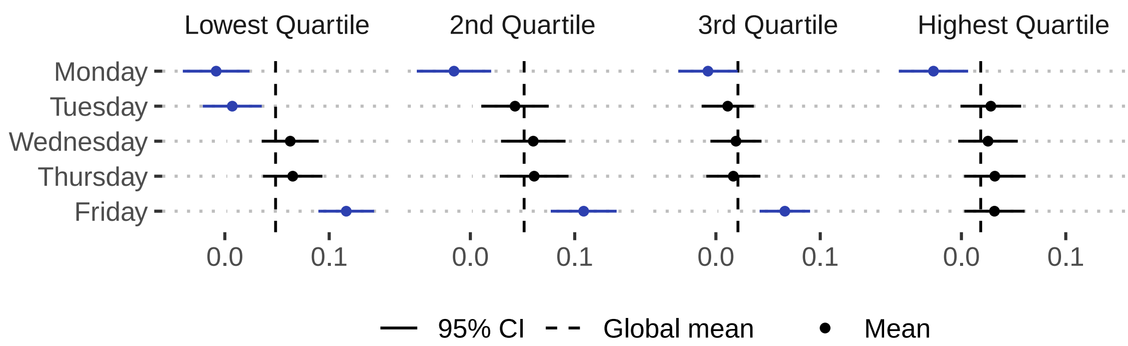

Figure 4: Mean daily return and confidence intervals per weekday and per quartile (excluding countries ahead of New York by at least 12 hours).

If the low Monday returns are caused by a seasonal pattern in market announcements, as is often claimed (see French (1980); Steeley (2001); Thaler (1987b)), they should be independent of financial development. For example, companies releasing news only when the market is closed during the weekend to avoid investor overreaction would most likely be a practice independent of a country's financial development (as defined by the FD index, at least). That would, on the other hand, mean that the high Friday returns were at least partly a consequence of financial development, as they do not persist as the Monday effect does. In this case, the settlement effect would be more likely. Different countries have different settlement cycles, but the tendency is for the number of settlement days to decrease with improvements in development, making the delay less significant. It is also important to take psychological factors into account. Anomalous returns that are the consequence of psychological, irrational behaviour, like the "blue Monday" hypothesis (Abu Bakar et al., 2014), are more likely to be persistent even with improvements in financial development than ones caused by small inefficiencies in financial institutions and markets.

The MOTY effects are reported on Figure 5, and Tables A.II and A.III in the appendix detail the one sample t-test results. There are three positive effects worthy of mention, for the months of January, April, and December. Of these, only the January effects loses its significance for the two highest FD quartiles. As for negative effects, most Summer months consistently have average daily returns significantly lower than the global average, for all quartiles. Figure 7 reinforces the significance of the effect regardless of FD.

The results hint at the January effect gradually disappearing with improved financial development. They also reinforce previous findings that the January effect is stronger for small stocks, as the average market capitalization of firms is likely to be higher for more developed countries. Thus, if the January and size effects really are related, it comes as no surprise that the effect would be more statistically significant for lower levels of FD. Furthermore, the existence of a positive December effect is inconsistent with the tax-loss selling hypothesis.

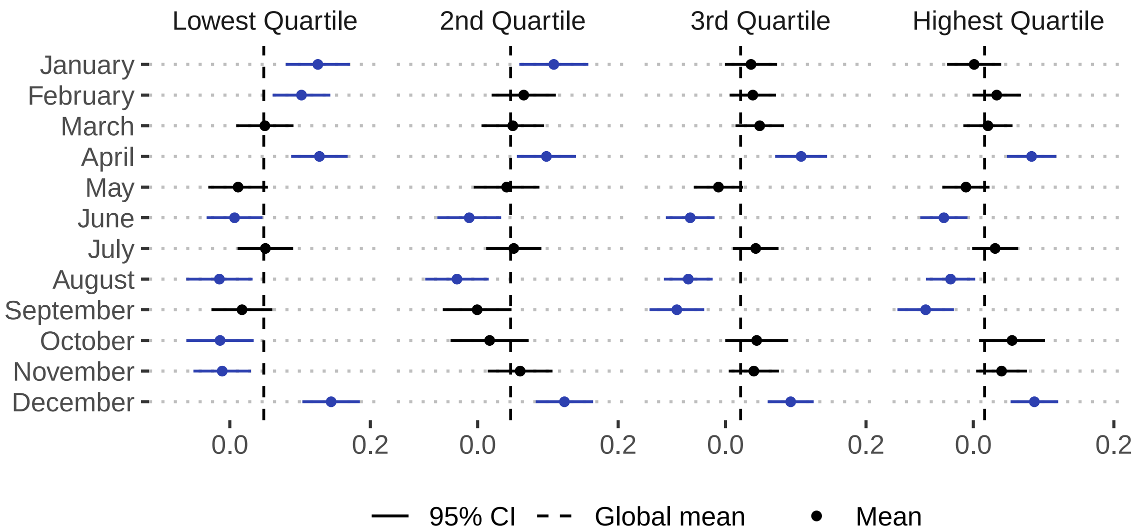

Figure 5: Mean daily return and confidence intervals per month and per quartile.

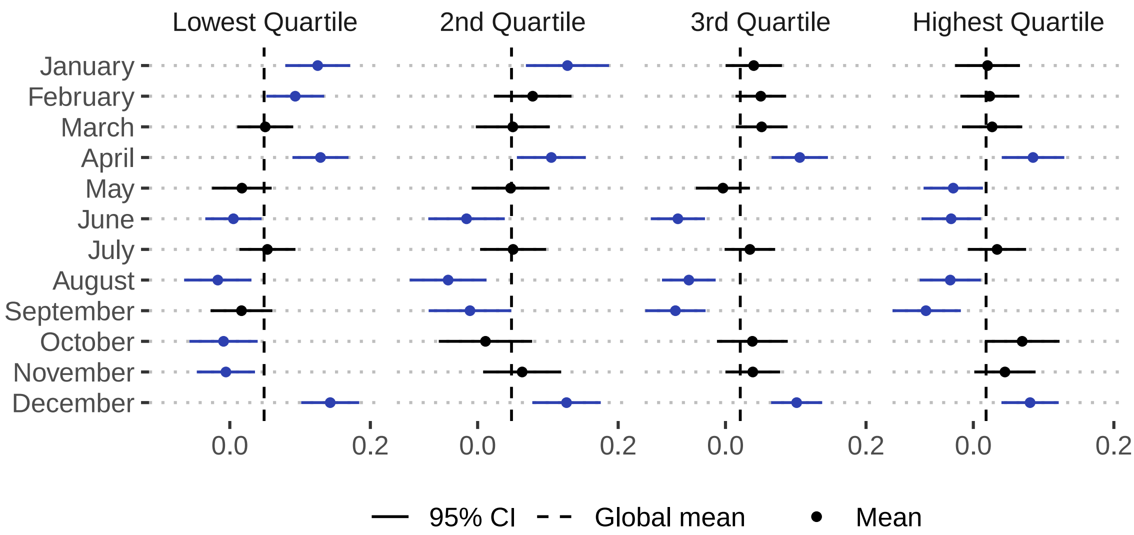

Figure 6: Mean daily return and confidence intervals per month and per quartile (excluding countries with an April tax-year end).

The April effect, however, remains statistically significant regardless of FD, as does the December effect. It may also not be solely a consequence of tax-loss selling, as only eight[6] out of the 46 countries in the sample have an April tax-year end, and the effect persists even when excluding said countries from the analysis (Figure 6). The December effect could be caused by the same abundance in cash inflows at the end of

[6]Canada, Hong Kong, India, Japan, New Zealand, Singapore, South Africa, and the United Kingdom (Source: Central Intelligence Agency (2018)).

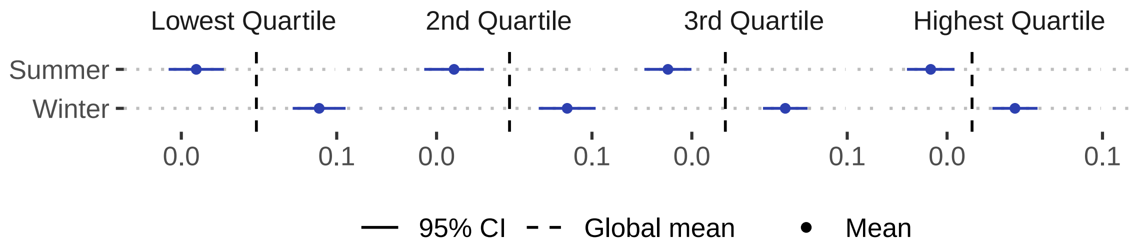

Figure 7: Mean daily return and confidence intervals for the Halloween effect per quartile.

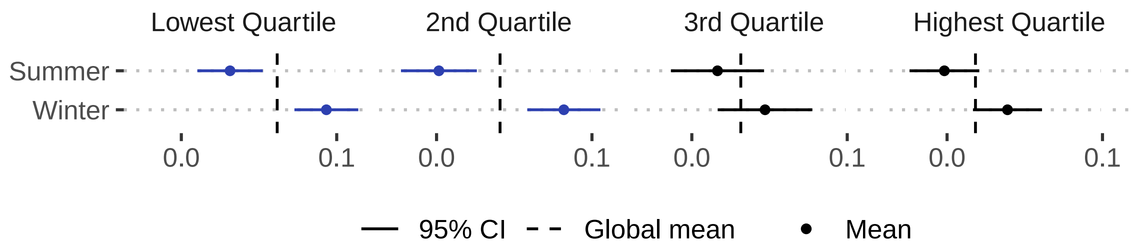

Figure 8: Mean daily return and confidence intervals for the Halloween effect per quartile (excluding European countries).

the year that Ritter (1988) attributes the January effect to.

At an immediate analysis, the Halloween effect does not show any improvement as FD increases either. However, as Bouman & Jacobsen (2002) have noted, it is an anomaly that affects European countries more strongly. Once we exclude them, the effect loses some significance for the higher quartiles (Figure 8). On one hand, if the effect really is connected to the length of Summer vacations, as Bouman & Jacobsen (2002) suggest, it could very well be independent of FD, as annual paid leave days do not vary greatly across countries. Doeswijk (2008)'s optimism-cycle hypothesis also seems more likely an explanation in light of our evidence, as psychological factors cannot be explained away by financial development alone.

Having identified six main calendar effects in our sample, we report the results for the three regressions described on Section 3 on Tables IV to VI. Our previous conclusions hold up: the Friday and January effects lose significance as we move up the quartiles, while the Monday, April, December, and Halloween effects do not.

Table IV: Regression results for the DOTW effects per quartile of FD

$R_{it} = \beta_0 + \beta_2 D_{it,2} + \beta_6 D_{it,6} + \epsilon_{it}$		Estimate	Standard Error	T-statistic
FD1 (lowest)	Intercept (β_0)	.046	.008	
	Monday (β_2)	-.059	.016	-3.612***
	Friday (β_6)	.069	.016	4.218***
	F-statistic			20.38***
	Degrees of freedom			2; 65,308
	Adjusted R^2			.0006
FD2	Intercept (β_0)	.044	.009	
	Monday (β_2)	-.049	.018	-2.785***
	Friday (β_6)	.066	.018	3.764***
	F-statistic			14.39***
	Degrees of freedom			2; 61,910
	Adjusted R^2			.0004
FD3	Intercept (β_0)	.017	.007	
	Monday (β_2)	-.028	.014	-1.994**
	Friday (β_6)	.048	.014	3.499***
	F-statistic			10.44***
	Degrees of freedom			2; 66,616
	Adjusted R^2			.0003
FD4 (highest)	Intercept (β_0)	.028	.007	
	Monday (β_2)	-.059	.014	-4.192***
	Friday (β_6)	-.001	.014	-0.083
	F-statistic			9.253***
	Degrees of freedom			2; 62,287
	Adjusted R^2			.0003

*** and ** indicate statistical significance at the 1% and 5% levels, respectively. Daily returns measured in percent. FD1 to FD4 are quartiles of FD. $H_0 : \beta_2 = \beta_6 = 0$

Table V: Regression results for the MOTY effects per quartile of FD

$R_{it} = \beta_0 + \beta_1 M_{1,it} + \beta_4 M_{4,it} + \beta_{12} M_{12,it} + \epsilon_{it}$		Estimate	Standard Error	T-statistic
FD1 (lowest)	Intercept (β_0)	.022	.007	
	January (β_1)	.104	.023	4.493***
	April (β_4)	.106	.023	4.548***
	December (β_{12})	.123	.023	5.246***
	F-statistic			19.15***
	Degrees of freedom			3; 65,307
	Adjusted R^2			.0008

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Table V: *Continued from previous page*

$R_{it} = \beta_0 + \beta_1 M_{1,it} + \beta_4 M_{4,it} + \beta_{12} M_{12,it} + \epsilon_{it}$		Estimate	Standard Error	T-statistic
FD2	Intercept (β_0)	.027	.007	
	January (β_1)	.082	.025	3.287***
	April (β_4)	.071	.025	2.816***
	December (β_{12})	.097	.025	3.878***
	F-statistic			9.478***
	Degrees of freedom			3; 61,909
	Adjusted R^2			.0004
FD3	Intercept (β_0)	.004	.006	
	January (β_1)	.033	.019	1.676*
	April (β_4)	.104	.020	5.188***
	December (β_{12})	.089	.020	4.495***
	F-statistic			14.60***
	Degrees of freedom			3; 66,615
	Adjusted R^2			.0006
FD4 (highest)	Intercept (β_0)	.003	.006	
	January (β_1)	-.002	.020	-0.103
	April (β_4)	.080	.020	3.973***
	December (β_{12})	.084	.020	4.186***
	F-statistic			10.37***
	Degrees of freedom			3; 62,286
	Adjusted R^2			.0005

*** and * indicate statistical significance at the 1% and 10% levels, respectively. Daily returns measured in percent. FD1 to FD4 are quartiles of FD. $H_0 : \beta_1 = \beta_4 = \beta_{12} = 0$

Table VI: Regression results for the Halloween effect per quartile of FD

$R_{it} = \beta_0 + \beta_1 H_{it} + \epsilon_{it}$		Estimate	Standard Error	T-statistic
FD1 (lowest)	Intercept (β_0)	.010	.009	
	Winter (β_1)	.079	.013	6.289***
	F-statistic			39.56***
	Degrees of freedom			1; 65,309
	Adjusted R^2			.0006
FD2	Intercept (β_0)	.011	.009	
	Winter (β_1)	.073	.014	5.369***
	F-statistic			28.82***
	Degrees of freedom			1; 61,911
	Adjusted R^2			.0004

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Table VI: *Continued from previous page*

$R_{it} = \beta_0 + \beta_1 H_{it} + \epsilon_{it}$		Estimate	Standard Error	T-statistic
FD3	Intercept (β_0)	-.015	.007	
	Winter (β_1)	.076	.011	7.089***
	F-statistic			50.25***
	Degrees of freedom			1; 66,617
	Adjusted R^2			.0007
FD4 (highest)	Intercept (β_0)	-.011	.008	
	Winter (β_1)	.054	.011	5.036***
	F-statistic			25.36***
	Degrees of freedom			1; 62,288
	Adjusted R^2			.0004

*** indicates statistical significance at the 1% level. Daily returns measured in percent. FD1 to FD4 are quartiles of FD. $H_0 : \beta_1 = 0$

Following Gu (2003)'s approach, we compute a power ratio for each of the six effects, as defined by Equation (3.11), per country and year. The results are reported on Table VII.

This approach supports our previous evidence, for the most part. The Friday and January positive power ratios significantly decrease with FD. This time, however, the same can be said about the December effect, for the 5% level. The Halloween effect remains significant and unrelated to FD, while the Monday and April effects do not exhibit statistical significance.

Finally, we report the relationship between FD and each of the three CES measures on Figures 9 and 10, and Table VIII. All three measures have a negative relationship with FD. An increase in FD of one unit (i.e., the difference between the least and the most financially developed countries, according to the index) would result, on average, in a decrease in the number of significant calendar effects of around 92% ($1 - e^{-2.559} = .923$). In other words, while we expect the least financially developed countries to have, on average, between one and two significant calendar effects at the 95% level ($e^{.397} = 1.487$), a country at the opposite end of the index would have no significant calendar effects ($e^{.397-2.559} = .116$). As for the difference in intensity of these effects for different levels of FD, we expect less financially developed countries

Table VII: Regression results for the relationship between FD and the power ratios

Model		Estimate	Standard Error	T-statistic
$PR_{Monday} = \gamma_0 + \gamma_1 FD + \epsilon$	Intercept (γ_0)	.023	.024	0.946
	FD (γ_1)	-.065	.041	-1.573
	F-statistic			2.476
	Degrees of freedom			1; 1,037
	Adjusted R^2			.0014
$PR_{Friday} = \gamma_0 + \gamma_1 FD + \epsilon$	Intercept (γ_0)	.192	.021	9.030***
	FD (γ_1)	-.204	.036	-5.629***
	F-statistic			31.69***
	Degrees of freedom			1; 1,036
	Adjusted R^2			.0287
$PR_{January} = \gamma_0 + \gamma_1 FD + \epsilon$	Intercept (γ_0)	.160	.033	4.894***
	FD (γ_1)	-.225	.056	-4.053***
	F-statistic			16.42***
	Degrees of freedom			1; 1,025
	Adjusted R^2			.0148
$PR_{April} = \gamma_0 + \gamma_1 FD + \epsilon$	Intercept (γ_0)	.033	.029	1.127
	FD (γ_1)	.065	.050	1.295
	F-statistic			1.677
	Degrees of freedom			1; 1,026
	Adjusted R^2			.0007
$PR_{December} = \gamma_0 + \gamma_1 FD + \epsilon$	Intercept (γ_0)	.128	.024	5.292***
	FD (γ_1)	-.089	.041	-2.165**
	F-statistic			4.686**
	Degrees of freedom			1; 1,037
	Adjusted R^2			.0035
$PR_{Halloween} = \gamma_0 + \gamma_1 FD + \epsilon$	Intercept (γ_0)	.045	.009	5.020***
	FD (γ_1)	-.017	.015	-1.099
	F-statistic			1.207***
	Degrees of freedom			1; 1,037
	Adjusted R^2			.0002

*** and ** indicate statistical significance at the 1% and 5% levels, respectively. Power ratios measured in percent. $H_0 : \gamma_1 = 0$

to have, on average, a 0.5% daily anomalous return, as defined by CES_B, or 0.1% daily anomalous return, as defined by CES_C, with both measures converging to 0 as FD increases.

Table VIII: Regression results for the relationship between FD and the CES measures

Model		Estimate	Standard Error	Z-statistic
$log(\lambda_i) = \gamma_0 + \gamma_1 FD + \epsilon$	Intercept (γ_0)	.397	.119	
$CES_{Ai} \sim Poisson(\lambda_i)$	FD (γ_1)	-2.559	.246	-10.399***
	Null Deviance			1031.63
	Degrees of Freedom			1,025
	Residual Deviance			914.77
	Degrees of Freedom			1,024
Model		**Estimate**	**Standard Error**	**T-statistic**
$CES_{Bi} = \gamma_0 + \gamma_{1i} FD_i + \epsilon_i$	Intercept (γ_0)	.477	.030	
	FD (γ_1)	-.506	.052	-9.802***
	F-statistic			96.08***
	Degrees of freedom			1; 1,024
	Adjusted R^2			.0849
$CES_{Ci} = \gamma_0 + \gamma_{1i} FD_i + \epsilon_i$	Intercept (γ_0)	.109	.007	
	FD (γ_1)	-.121	.012	-10.26***
	F-statistic			105.4***
	Degrees of freedom			1; 1,024
	Adjusted R^2			.0924

*** indicates statistical significance at the 1%. CES measured in percent. $H_0 : \gamma_1 = 0$

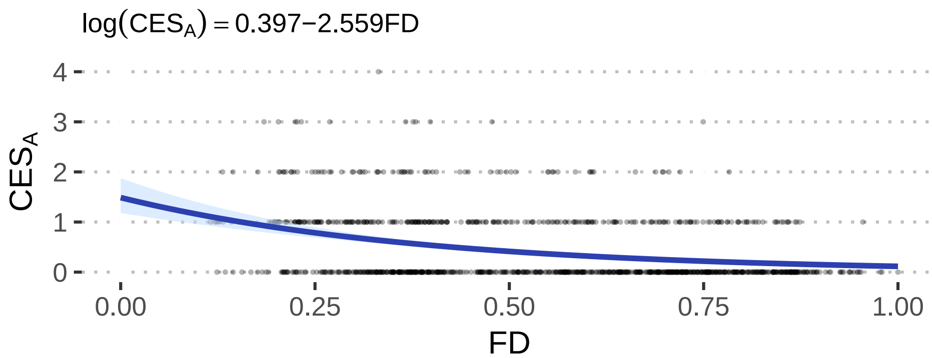

Figure 9: Poisson regression relationship between FD and CES_A.

Analysed together, our results show that not only are there more calendar effects present in less financially developed countries, but, when they exist, they also have a

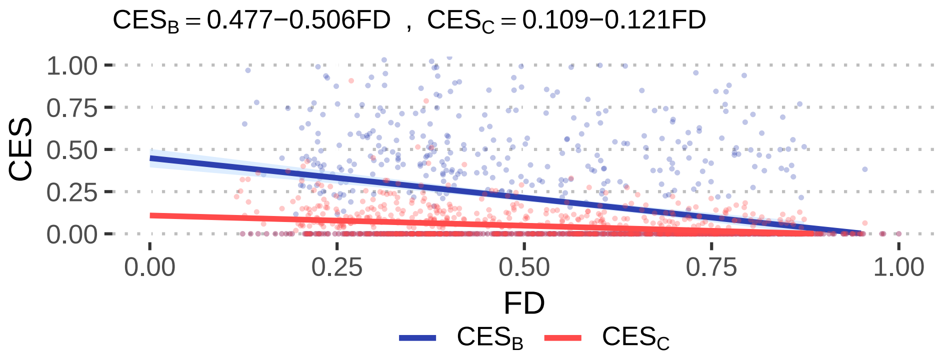

Figure 10: Linear regression relationships between FD and CES_B and CES_C.

higher impact on returns than for the more financially developed countries.

5 CONCLUSIONS

We show that a lack of financial development can be to blame for at least some calendar effects – namely the positive Friday and January effects, and possibly the positive December effect as well. Most of the usual explanations for these anomalies concern inefficiencies that should disappear with financial development, in agreement with our results. In light of our findings, the most likely motive behind the Friday effect would be a settlement effect. With settlement cycles getting shorter for more developed countries, the effect has naturally lost its significance. The January effect, being mostly a small stocks effect, has also disappeared with improvements in financial development, as more developed countries should have a higher average firm market capitalization. Finally, while the one sample t-tests and the linear regression models do not show any relationship between the positive December effect and financial development, the use of a power ratio reveals that the amount of excess return generated during the year that is due to the high December returns decreases with financial development.

On the other hand, other anomalies have withstood our hypothesis. The negative Monday effect, and the positive April and Halloween effects, have remained statistically significant for our entire sample, regardless of the level of financial development, and do not show any weakening. The Monday effect shows no relationship to financial development, despite the disappearance of the Friday effect, hinting at both effects not being related. The low Monday returns cannot be simply a price adjustment movement after the high Friday returns. Our results also make the April effect unlikely to be due to tax-loss selling, as it is present even excluding countries with an April fiscal year-end from the sample. Most puzzling of all, the Halloween effect, although it does weaken excluding European countries from the sample, does not lose any of its significance for the sample as a whole. That it outlives the January effect proves that there is more to the Halloween effect than just being a consequence of January returns (which fall on the Winter period) outperforming the rest of the year. However, of these, only the Halloween effect remains significant even when employing a power ratio approach. The persistent effects might yet be caused by psychological factors, hence their lack of relationship to financial development. This is particularly likely for the Monday and Halloween effects, that might be a consequence of seasonality in investor mood and optimism.

By developing three measures for calendar effects (the CES_A, CES_B, and CES_C measures), our findings show that the less developed countries in our sample have, on average, between one and two significant calendar effects, resulting in around 0.5% absolute daily anomalous return. As they become more financially developed, the anomalies disappear.

As a final note, one of the main reasons why calendar effects are so puzzling, is that some of them persist even when common sense says they should inevitably be arbitraged away. However, as previous literature has pointed out – see French (1980) or Thaler (1987b) –, transaction costs may render these strategies unexploitable. With increasing financial development also come lower transaction fees and, thus, better market efficiency. This is a possible explanation for why more financially developed countries can move away from calendar effects (and possibly other market anomalies as well), while their less developed peers are still affected by them. Only when transaction costs have decreased enough to make strategies based on calendar effects profitable, should they eventually disappear – or revert –, as the market adapts.

While this study focuses on the IMF's FD index, it would be important to test whether the conclusions hold up for different definitions of financial development – like Naceur & Ghazouani (2007)'s SMINDEX, or Samargandi et al. (2015)'s financial development indicator. The results for a study of this nature can only be as accurate as the proxy used, and different proxies may lead to other interpretations. An additional limitation from using the FD index is that data is only available up to 2016. With stock markets' increased volatility in recent months, and stock returns worldwide experiencing a significant downturn at the end of 2018, we may reach interesting conclusions by including the latter half of the 2010's into the analysis, in future research. Finally, with the possibility of some of theses effects being explained by behavioural issues, it would be interesting to regress psychological indicators on our proposed CES measures.

BIBLIOGRAPHY

Abu Bakar, A., Siganos, A., & Vagenas-Nanos, E. (2014). Does mood explain the Monday effect? *Journal of Forecasting*, 33(6):409–418.

Ahmad, Z. & Hussain, S. (2001). KLSE long run overreaction and the Chinese New-Year effect. *Journal of business finance & accounting*, 28(1-2):63–105.

Al-Hajieh, H., Redhead, K., & Rodgers, T. (2011). Investor sentiment and calendar anomaly effects: A case study of the impact of Ramadan on Islamic Middle Eastern markets. *Research in International Business and Finance*, 25(3):345–356.

Anwar, S. & Cooray, A. (2012). Financial development, political rights, civil liberties and economic growth: Evidence from South Asia. *Economic Modelling*, 29(3):974–981.

Balbina, M. & Martins, N. C. (2002). *The analysis of seasonal return anomalies in the Portuguese stock market*. Banco de Portugal.

Barberis, N. & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, 1:1053–1128.

Berdiev, A. N. & Saunoris, J. W. (2016). Financial development and the shadow economy: A panel VAR analysis. *Economic Modelling*, 57:197–207.

Bouman, S. & Jacobsen, B. (2002). The Halloween indicator, "sell in May and go away": Another puzzle. *American Economic Review*, 92(5):1618–1635.

Carrazedo, T., Curto, J. D., & Oliveira, L. (2016). The Halloween effect in European sectors. *Research in International Business and Finance*, 37:489–500.

Central Intelligence Agency (2018). The world factbook. https://www.cia.gov/library/publications/the-world-factbook. [Accessed: 22.05.2019].

Chakraborty, I. (2010). Financial development and economic growth in india: An analysis of the post-reform period. *South Asia Economic Journal*, 11(2):287–308.

Clare, A. D., Psaradakis, Z., & Thomas, S. H. (1995). An analysis of seasonality in the UK equity market. *The Economic Journal*, 105(429):398–409.

Cross, F. (1973). The behavior of stock prices on Fridays and Mondays. *Financial analysts journal*, 29(6):67–69.

Dafe, F., Essers, D., & Volz, U. (2018). Localising sovereign debt: The rise of local currency bond markets in sub-Saharan Africa. *The World Economy*, 41(12):3317–3344.

De Bondt, W. F., Muradoglu, Y. G., Shefrin, H., & Staikouras, S. K. (2008). Behavioral finance: Quo vadis? *Journal of Applied Finance (Formerly Financial Practice and Education)*, 18(2).

Dimson, E. & Marsh, P. (2001). UK financial market returns, 1955–2000. *The Journal of Business*, 74(1):1–31.

Doeswijk, R. Q. (2008). The optimism cycle: Sell in May. *De Economist*, 156(2):175.

Ductor, L. & Grechyna, D. (2015). Financial development, real sector, and economic growth. *International Review of Economics & Finance*, 37:393–405.

Floros, C. & Salvador, E. (2014). Calendar anomalies in cash and stock index futures: International evidence. *Economic Modelling*, 37:216–223.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of financial economics*, 8(1):55–69.

Gu, A. Y. (2003). The declining January effect: evidences from the US equity markets. *The Quarterly Review of Economics and Finance*, 43(2):395–404.

Hassan, M. K., Sanchez, B., & Yu, J.-S. (2011). Financial development and economic growth: New evidence from panel data. *The Quarterly Review of economics and finance*, 51(1):88–104.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics*, 7:133–159.

Imamoğlu, H., Katircioğlu, S., & Payaslioğlu, C. (2018). Financial services spillover effects on informal economic activity: evidence from a panel of 20 European countries. *The Service Industries Journal*, 38(11-12):669–687.

Jaffe, J. & Westerfield, R. (1985a). Patterns in Japanese common stock returns: Day of the week and turn of the year effects. *Journal of financial and quantitative analysis*, 20(2):261–272.

Jaffe, J. & Westerfield, R. (1985b). The week-end effect in common stock returns: The international evidence. *The journal of finance*, 40(2):433–454.

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of financial economics*, 12(1):13–32.

Kohers, G., Kohers, N., Pandey, V., & Kohers, T. (2004). The disappearing day-of-the-week effect in the world's largest equity markets. *Applied Economics Letters*, 11(3):167–171.

Konstantinidis, A., Katarachia, A., Borovas, G., Voutsa, M. E., et al. (2012). From efficient market hypothesis to behavioural finance: Can behavioural finance be the new dominant model for investing. *Scientific Bulletin–Economic Sciences*, 11(2):16–26.

Kumar, S. (2016). Revisiting calendar anomalies: Three decades of multicurrency evidence. *Journal of Economics and Business*, 86:16–32.

Lakonishok, J. & Levi, M. (1982). Weekend effects on stock returns: a note. *The Journal of Finance*, 37(3):883–889.

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

Meier, C. (2014). Adaptive market efficiency: review of recent empirical evidence on the persistence of stock market anomalies. *Review of Integrative Business and Economics Research*, 3(2):268.

Naceur, S. B. & Ghazouani, S. (2007). Stock markets, banks, and economic growth: Empirical evidence from the MENA region. *Research in International Business and Finance*, 21(2):297–315.

Phillips-Patrick, F. J. & Schneeweis, T. (1988). The weekend effect for stock indexes and stock index futures: Dividend and interest rate effects. *Journal of Futures Markets*, 8(1):115–121.

Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects. *Journal of Financial Economics*, 12(1):89–104.

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

Ritter, J. R. (1988). The buying and selling behavior of individual investors at the turn of the year. *The Journal of Finance*, 43(3).

Rossi, M. (2015). The efficient market hypothesis and calendar anomalies: a literature review. *International Journal of Managerial and Financial Accounting*, 7(3-4):285–296.

Rozeff, M. S. & Kinney Jr, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of financial economics*, 3(4):379–402.

Sahay, R., Cihak, M., N'Diaye, P., Barajas, A., Pena, D. A., Bi, R., Gao, Y., Kyobe, A., Nguyen, L., Saborowski, C., et al. (2015). Rethinking financial deepening: Stability and growth in emerging markets. *IMF Staff Discussion Note: Rethinking Financial Deepening-Stability and Growth in Emerging Markets*, 15(8).

Samargandi, N., Fidrmuc, J., & Ghosh, S. (2015). Is the relationship between financial development and economic growth monotonic? evidence from a sample of middle-income countries. *World Development*, 68:66–81.

Seif, M., Docherty, P., & Shamsuddin, A. (2017). Seasonal anomalies in advanced emerging stock markets. *The Quarterly Review of Economics and Finance*, 66:169–181.

Steeley, J. M. (2001). A note on information seasonality and the disappearance of the weekend effect in the UK stock market. *Journal of Banking & Finance*, 25(10):1941–1956.

Svirydzenka, K. (2016). *Introducing a new broad-based index of financial development*. International Monetary Fund.

Teng, C. & Liu, V. (2013). The pre-holiday effect and positive emotion in the Taiwan stock market, 1971–2011. *Investment Analysts Journal*, 42(77):35–43.

Thaler, D. (2018). Sovereign default, domestic banks and exclusion from international capital markets.

Thaler, R. H. (1987a). Anomalies: the January effect. *Journal of Economic Perspectives*, 1(1):197–201.

Thaler, R. H. (1987b). Anomalies: weekend, holiday, turn of the month, and intraday effects. *Journal of Economic Perspectives*, 1(2):169–177.

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral decision making*, 12(3):183–206.

Urquhart, A. & McGroarty, F. (2014). Calendar effects, market conditions and the Adaptive Market Hypothesis: Evidence from long-run US data. *International Review of Financial Analysis*, 35:154–166.

Yan, S., Ferraro, F., & Almandoz, J. (2018). The rise of socially responsible investment funds: The paradoxical role of the financial logic. *Administrative Science Quarterly*, page 0001839218773324.

Yu, J.-S., Hassan, M. K., & Sanchez, B. (2012). A re-examination of financial development, stock markets development and economic growth. *Applied Economics*, 44(27):3479–3489.

Zhang, C. Y. & Jacobsen, B. (2012). Are monthly seasonals real? A three century perspective. *Review of Finance*, 17(5):1743–1785.

Zhang, J., Lai, Y., & Lin, J. (2017). The day-of-the-week effects of stock markets in different countries. *Finance Research Letters*, 20:47–62.

APPENDICES

A. One Sample T-Tests Results

Tables A.I to A.III report the results for the one sample t-tests, per quartile of FD, for $H_0 : \mu_i = \mu_0$, where μ_0 is the global mean daily return for all days, and μ_i is the mean daily return for weekday, month or period i. The t-statistic is defined as $T = \frac{\bar{x}_i - \mu_0}{\frac{s_i}{\sqrt{n_i}}}$, and the confidence interval is computed as $CI = \bar{x}_i \pm t_{\frac{\alpha}{2}} \frac{s_i}{\sqrt{n_i}}$, where $\bar{x}_i$, s_i, and n_i are, respectively, the sample mean, standard deviation, and the number of observations for weekday, month, or period i, and $t_{\frac{\alpha}{2}}$ is the critical value for a two-tailed test.

Table A.I: One sample t-test per weekday and per quartile

	Weekday	Mean	S.D.	T-statistic	95% CI	P-value	Observations
FD1	Monday	-.013	1.794	-3.848	-.044, .018	.000***	12,785
(lowest)	Tuesday	.001	1.595	-3.400	-.026, .028	.001***	13,236
	Wednesday	.067	1.541	1.353	.040, .093	.176	13,266
	Thursday	.072	1.601	1.656	.044, .099	.098*	13,096
	Friday	.121	1.486	5.095	.089, .141	.000***	12,928
FD2	Monday	-.006	1.840	-3.141	-.038, .027	.001***	12,131
	Tuesday	.020	1.657	-1.802	-.009, .049	.072*	12,589
	Wednesday	.068	1.618	1.484	.040, .097	.138	12,492
	Thursday	.042	1.703	-0.329	.012, .072	.745	12,479
	Friday	.110	1.607	4.310	.081, .138	.000***	12,222
FD3	Monday	-.010	1.518	-2.388	-.036, .016	.017**	13,025
	Tuesday	.017	1.336	-0.405	-.006, .039	.686	13,524
	Wednesday	.018	1.331	-0.295	-.004, .041	.768	13,562
	Thursday	.017	1.392	-0.367	-.006, .041	.714	13,329
	Friday	.066	1.291	3.923	. 044, .088	.000***	13,179
FD4	Monday	-.031	1.473	-3.526	-.058, -.005	.000***	11,981
(highest)	Tuesday	.025	1.298	0.740	.002, .047	.459	12,645
	Wednesday	.031	1.316	1.294	.008, .054	.196	12,654
	Thursday	.027	1.326	0.938	.004, .050	.348	12,593
	Friday	.026	1.305	0.891	.004, .049	.373	12,417

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Daily returns measured in percent. FD1 to FD4 are quartiles of FD.

Table A.II: One sample t-test per month and per quartile

	Month	Mean	S.D.	T-statistic	95% CI	P-value	Observations
FD1 (lowest)	January	.125	1.703	3.308	.080, .171	.001***	5,352
	February	.102	1.507	2.559	.061, .143	.011**	5,169
	March	.050	1.546	0.075	.009, .091	.940	5,525
	April	.128	1.486	3.860	.087, .168	.000***	5,247
	May	.012	1.585	-1.690	-.031, .054	.091*	5,362
	June	.007	1.500	-2.049	-.033, .047	.040**	5,476
	July	.051	1.518	0.114	.011, .090	.909	5,669
	August	-.015	1.801	-2.619	-.062, .032	.009***	5,579
	September	.017	1.642	-1.402	-.026, .061	.161	5,533
	October	-.014	1.849	-2.546	-.062, .034	.011**	5,729
	November	-.011	1.544	-2.829	-.052, .030	.005***	5,457
	December	.144	1.507	4.592	.103, .185	.000***	5,213
FD2	January	.108	1.789	2.452	.059, .157	.014**	5,103
	February	.066	1.616	0.801	.020, .111	.423	4,809
	March	.050	1.657	0.135	.005, .095	.893	5,322
	April	.098	1.504	2.373	.056, .140	.018**	4,915
	May	.041	1.702	-0.242	-.006, .088	.809	5,101
	June	-.012	1.662	-2.542	-.057, .033	.011**	5,136
	July	.051	1.475	0.222	.012, .091	.824	5,418
	August	-.029	1.691	-3.312	-.075, .016	.001***	5,379
	September	-.001	1.806	-1.909	-.050, .048	.056*	5,237
	October	.017	2.062	-1.054	-.039, .073	.292	5,286
	November	.060	1.689	0.575	.014, .107	.565	5,155
	December	.124	1.480	3.676	.083, .164	.000***	5,052
FD3	January	.036	1.407	0.779	-.001, .073	.436	5,522
	February	.039	1.221	1.028	.006, .072	.304	5,244
	March	.049	1.327	1.541	.014, .083	.123	5,694
	April	.108	1.358	4.566	.071, .145	.000***	5,187
	May	-.010	1.312	-1.766	-.045, .025	.078**	5,379
	June	-.050	1.314	-4.052	-.085,-.015	.000***	5,509
	July	.043	1.265	1.296	.011, .076	.195	5,823
	August	-.053	1.348	-4.204	-.088,-.018	.000***	5,793
	September	-.069	1.500	-4.572	-.108,-.030	.000***	5,709
	October	.044	1.741	0.999	.000, .089	.318	5,799
	November	.040	1.368	1.031	.005, .076	.303	5,650
	December	.093	1.218	4.262	.060, .126	.000***	5,310
FD4 (highest)	January	.001	1.405	-0.759	-.037, .040	.448	5,124
	February	.033	1.231	0.980	-.001, .068	.327	4,899
	March	.021	1.307	0.264	-.014, .056	.792	5,354

Continued on next page

Table A.II: *Continued from previous page*

	Month	Mean	S.D.	T-statistic	95% CI	P-value	Observations
	April	.083	1.259	3.737	.048, .118	.000***	4,949
	May	-.011	1.229	-1.553	-.044, .023	.121	5,151
	June	-.042	1.236	-3.382	-.076,-.008	.001***	5,200
	July	.031	1.227	0.898	-.002, .064	.369	5,414
	August	-.032	1.310	-2.711	-.067, .003	.007***	5,374
	September	-.068	1.480	-4.090	-.108,-.028	.000***	5,209
	October	.055	1.756	1.634	.008, .102	.102	5,383
	November	.040	1.335	1.307	.004, .076	.191	5,243
	December	.087	1.219	4.105	.053, .121	.000***	4,990

***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Daily returns measured in percent. FD1 to FD4 are quartiles of FD.

Table A.III: One sample t-test for the Halloween Effect per quartile

	Period	Mean	S.D.	T-statistic	95% CI	P-value	Observations
FD1	Summer	.010	1.656	-4.267	-.008, .027	.000***	33,348
(lowest)	Winter	.089	1.552	4.651	.072, .106	.000***	31,963
FD2	Summer	.011	1.741	-3.641	-.008, .030	.000***	31,557
	Winter	.084	1.627	3.972	.066, .102	.000***	30,356
FD3	Summer	-.015	1.425	-4.783	-.031, .000	.000***	34,012
	Winter	.060	1.320	5.275	.046, .074	.000***	32,607
FD4	Summer	-.011	1.388	-3.414	-.026, .005	.001***	31,731
(highest)	Winter	.044	1.296	3.727	.029, .058	.000***	30,559

*** indicates statistical significance at the 1% level. Daily returns measured in percent. FD1 to FD4 are quartiles of FD.

B. Panel Regression Models for the Relationship Between CES and FD

Table A.IV presents an alternative approach to the regressions on Section 4 for the CES_B and CES_C measures. A panel regression approach rather than a pooled OLS analysis allows us to account for individual differences across countries. We employ both Fixed Effects (FE) and Random Effects (RE) models with the 46 countries as individuals, and the yearly obsevations as the time periods. As not all countries have observations for every year (see Table II), we are in the presence of unbalanced panel data.

Table A.IV: Panel regression results for the relationships between FD and CES_B and CES_C

Model		**FE**	**RE**
$CES_{Bi} = \gamma_0 + \gamma_{1i} FD_i + \epsilon_i$	Intercept (λ_0)		.484
			(.036)
	FD (γ_1)	-.772***	-.520***
		(.147)	(.061)
	F/χ-statistic	27.43***	73.68***
	Degrees of freedom	1; 979	1
	Adjusted R^2	-.018	.066
$CES_{Ci} = \gamma_0 + \gamma_{1i} FD_i + \epsilon_i$	Intercept (γ_0)		.110
			(.008)
	FD (γ_1)	-.186***	-.124***
		(.034)	(.014)
	F/χ-statistic	30.59***	81.96***
	Degrees of freedom	1; 979	1
	Adjusted R^2	-.015	.073

*** indicates statistical significance at the 1% level. CES measured in percent.
$H_0 : \gamma_1 = 0$

The conclusions are not too different from the pooled OLS models. However, the explanation power of the regressions has suffered, especially for the fixed effects model, suggesting that, for the purposes of this work, we can neglect individual heterogeneity across countries. Therefore, for the sake of parsimony, we base our analysis on the OLS estimators.

C. CES Measures: Descriptive Statistics and Database

Table A.V presents some summary statistics for the three CES measures developed in Section 4 of this work. Some examples of the measures are reported on Table A.VI.

Table A.V: Descriptive statistics for the CES measures

	CES_A	CES_B	CES_C
Min	.00	.00	.00
Median	.00	.00	.00
Mean	.42	.20	.04
Max	4.00	2.70	.91
Standard Deviation	.68	.36	.08

Table A.VI: CES measures for Portugal (1992-1996)

Year	β_{Mon}	β_{Fri}	β_{Jan}	β_{Apr}	β_{Dec}	β_{Hal}	CES_A	CES_B	CES_C
1992	.128**	.070	-.095	.199**	.134	.164***	3	.164	.082
1993	-.424*	.097	-.287	-.052	.024	-.528***	1	.528	.088
1994	-.041	-.118	.532***	-.167**	-.119	.164	1	.532	.089
1995	-.007	.004	-.262**	.111**	.108	.006	1	.262	.044
1996	.014	-.049	.255***	.038**	.115	.079*	1	.255	.043

***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. CES measured in percent.

The full database can be found online, at https://github.com/psmacedo/ces-database, due to size constraints.