Received: 16 January 2017 | Revised: 10 March 2018 | Accepted: 26 June 2018

DOI: 10.1002/ijfe.1643

RESEARCH ARTICLE

WILEY

European trading volumes on cross-market holidays

Bogdan Batrinca | Christian W. Hesse | Philip C. Treleaven

Department of Computer Science, University College London, London, UK

Correspondence
Bogdan Batrinca, Department of Computer Science, University College London, Gower Street, London WC1E 6BT, UK.
Email: bogdan.batrinca.09@ucl.ac.uk

Funding information
Engineering and Physical Sciences Research Council (EPSRC)

JEL Classification: C32; C52; C58; G12; G15; G17

Abstract

There is anecdotal evidence of reduced trading volume in equity markets when other external markets are not trading. This phenomenon can be called the "cross-market holiday effect," and this study investigates it in detail, providing evidence for the existence of a strong cross-market holiday effect in the pan-European equity markets. The analysis provides an in-depth examination of other aspects like lagged volumes, market capitalization, or multistep ahead modelling. The trading volumes on dates when there is at least one cross-market holiday are on average 8.5% lower than the volumes of the previous period. There are salient effects when the holiday takes place in a dominant market or when most of the European markets are shut. We test whether the lower trading activity on Monday cross-market holidays is a consequence of the weekend effect or whether the Monday bank holidays push down the Monday trading volume. We report a significantly lower volume associated with the Monday bank holidays, and we argue that the weekend effect has an insignificant impact on the Monday volumes where there is at least one regional cross-market holiday.

KEYWORDS

behavioural finance, cross-market holiday effect, European stock market, holiday effect, international market comovement, ridge regression, trading volume

1 | INTRODUCTION

This study investigates the anecdotal evidence of lower trading volume associated with one or more external markets not trading. We propose naming this phenomenon as the "cross-market holiday effect." We test the hypothesis that the trading volume is lower on cross-market holidays than usually. The rationale behind these hypotheses relies on the fact that markets are event-driven and are typically in a rather constant state. However, certain events occur (e.g., expiries, trading holidays, earnings announcement, and news), and markets are consequently transitioning to a different state. It is this event-driven nature that we would like to exploit in this volume analysis. This study considers the impact of cross-market holidays on trading volume and explores this effect among European countries.

The motivation of this study is threefold: first, the cross-market holiday effect has not been investigated sufficiently in the literature, nor has it been examined on European market data; second, the studies on the European equity markets and trading volume are very scarce, with a large majority focusing on the price returns instead; and third, planning a multi-day trade is extremely important for practitioners, and this is why this study proposes a multistep ahead prediction model. An example of a very common use case consists of traders and portfolio managers, who want to size a multi-day order allocation with the aim of minimizing the market impact based on the available liquidity. For example, they could ask how the trading volume would be in a few days' time in the United Kingdom given that it will be the May 1st and the mainland Europe is not trading; they need to have the ability to quantify and forecast the volume trends in order to be able to plan multi-day trades. This practical problem has not yet been properly addressed.

To the best of our knowledge, the cross-market holiday effect has been investigated in only a couple of studies, using data sets from over 10 years ago; one of the studies investigates the effect of U.S. holidays on the European markets' returns and volumes (Casado, Muga, & Santamaria, 2013), whereas the other study explores the cross-market holiday effect on volumes between the United States and Canada (Cheung & Kwan, 1992). It is the first time that such an analysis is performed on the European markets on a huge data set and this is the main contribution of this study. It is the first analysis to employ an accurate trading calendar for more than 20 countries (i.e., covering the United States and the vast majority of the European Union) in order to produce a unified region-wide trading calendar.

We surveyed 80 relevant papers and found that very few studies include European stocks in their analysis. There are 10 studies focusing exclusively on one European country, 16 studies with international data sets including a few European countries, and there are three studies that focus on and cover more European countries; the largest data set is employed in a study on the emerging Central and Eastern European financial markets (Dodd & Gakhovich, 2011), covering 14 European markets for almost 20 years. Moreover, only seven of the surveyed papers include recent market data after 2005, and little attention has been paid to the volume dimension.

The holiday effect consists of rather rare events, but the study is conducted on a comprehensive pan-European data set with sufficient observations (1,343,636 observations). The aim of this study is to introduce a number of in-depth pan-European in-sample analyses for volume prediction in the context of special events, such as the cross-market holidays.

The study consists of two main methodological components: first, we conduct randomization testing in order to explore the existence of the potential cross-market holiday effect and investigate whether the lower volume corresponding to cross-market holidays is in reality caused by the Monday effect or by the Monday bank holidays, because the United Kingdom is the largest market in Europe and its bank holidays fall predominantly on Mondays; we also analyse whether there is a differentiating effect magnitude across small-, mid-, and large-cap stocks; second, based on these hypotheses, we propose a number of predictive models for trading volume in order to assess the out-of-sample performance of a forecasting model based on this effect and the other relevant aspects. It is important to note the rigour associated with the (pairwise) randomization tests to determine the outcome of the various hypotheses based on controlled rearrangements and the novelty of the application of ridge regression on financial time series in this study.

The data analysis consisted of a series of challenges, ranging from unavailable trading calendars to high coefficient variability due to multicollinearity. We constructed from scratch a highly accurate non-trading calendar for the U.S. and the European markets included in this analysis, which allowed us to validate the hypotheses investigated in this study. The scope of this phenomenon is new, and we provide an extensive study of its existence and effect size.

The paper proceeds as follows: Section 2 surveys the relevant literature on calendar effects in order to provide the fundamental knowledge on the relevant calendar effects; Section 3 describes the data sample of this study, including the stock universe, the market data, and the calendar data; Section 4 presents the analytical approach of this paper; Section 5 introduces an examination of the existence of the cross-market holiday effect and other potential drivers of decreased volume using randomization tests; Section 6 provides a methodological outline of the shrinkage methods and proposes a number of volume prediction models using ridge regression, followed by a presentation of the results of the cross-market holiday models and their interpretation, whereas Section 7 provides a brief discussion of the randomization and regression results and a conclusion of this study.

2 | BACKGROUND

We start surveying the finance literature on comovement in international markets in order to motivate the cross-market holiday study. We provide further context to the temporal exogenous variables being investigated in this volume prediction analysis with a review of the behavioural finance literature on a variety of calendar effects. Because most of the calendar effects have been previously studied in conjunction with price returns, the finance literature review concludes with a summary of the empirical findings on the volume–price relation, which will be ultimately used to infer a direct relation between the calendar effects and trading volume.

2.1 | Comovement of returns and volatility in international markets

The analysis of information flow across international markets stems from the previous stock market crashes and the way price changes have diffused throughout international markets. King and Wadhwani (1990) provide empirical evidence for a contagion effect during the crash of October 1987, when investors inferred information from the price changes in other markets, causing the world stock markets to fall uniformly. The authors argue that volatility is positively correlated with the contagion effect magnitude. Similarly, Hamao, Masulis, and Ng (1990) investigated price volatility spillover effects in three international markets, namely, Tokyo, London, and New York. The spillover effect exhibits asymmetry, with a significant spillover effect on the Japanese market and considerably weaker effects on the U.K. and U.S. markets. The spillover effect asymmetry is also shared by the findings of Becker, Finnerty, and Gupta (1990), who found that the open-to-close returns of U.S. stocks from the previous trading day are highly correlated with the current day returns of Japanese stocks, whereas the Japanese market has a minor impact on the U.S. returns, and Eun and Shim (1989), whose nine-market vector autoregression model exhibited a significant transmission of U.S. innovations (or residual returns) to other markets, whereas none of the other eight markets could explain the U.S. price movements. Connolly and Wang (2003) argue that the intraday and overnight return comovement in international equity markets cannot be explained by public information on economic fundamentals; instead, it is rather driven by contagion and trading on private information.

Domestic comovements are found across the U.S. asset classes, that is, the stock, bond, money, and currency markets (Darbar & Deb, 2002).

2.2 | Calendar effects

There is a wide range of studies looking at the calendar effects on prices, with little focus on their effects on trading volume. Therefore, it is important to understand these findings and then combine them with the results of the literature looking at the volume correlation with prices, in order to infer a connection between calendar effects and trading volume. We further extend this and investigate the cross-market holiday effect because there is extremely little literature investigating this hypothesis (i.e., the literature looks at the cross-market holiday effect on trading volume in the United States and Canada only), whose importance is crucial for predicting major liquidity changes.

Calendar effects are market anomalies or economic effects that are related to the calendar. They involve a seeming change in the stock markets' behaviour; their granularity varies from intraday and day-of-the-week effects to turn-of-the-year and multi-year effects. Many calendar effects have vanished or reversed since they were discovered and documented (Dimson & Marsh, 1999). These anomalies have been researched ex post, since their existence is inferred from past empirical data. Therefore, the market inefficiency theories cannot be predicted ex ante due to the data-driven nature of such theoretical studies documenting a calendar effect and the ambiguity of the economic variables interdependencies.

A survey of the most illustrative calendar effects is included below in order to understand the impact of these calendar anomalies on prices and, consequently, on volume. The following review of calendar effects proves that markets have event-driven irregularities. One of the most popular calendar effects being investigated by the behavioural finance literature is the weekend effect. The main literature findings that are synthesized below prove the inconclusiveness of the research on calendar effects, where this study contributes by providing further evidence on the cross-market holiday effect in a pan-European setting.

Noise and outliers are salient features of financial data, making many of the studies on calendar effects prone to biases. Sullivan, Timmermann, and White (2001) argue that the significance of individual calendar effects is weaker when they are evaluated in the context of the full universe containing all the calendar effects and rules (and their interdependencies) than when they are assessed in isolation. Moreover, they draw attention to the potential data mining biases resulting from the common practice of using the same data set to both formulate and test hypotheses.

2.2.1 | Monday effect

The Monday effect (or weekend effect) consists of a lower closing price on Monday than on the previous Friday, as first reported by Cross (1973) and confirmed by other authors (French, 1980; Gibbons & Hess, 1981; Jaffe & Westerfield, 1985; Pettengill, 2003). Moreover, the empirical evidence of Berument and Kiymaz (2001) confirms the lowest returns on Monday and finds a day-of-the-week effect on volatility.

2.2.2 | Holiday effect

The holiday (or preholiday) effect consists of high mean returns on the trading day before a holiday, with a mean of 9 to 14 times the average return during the remaining days of the year (Ariel, 1990). This effect is not related to any other calendar anomaly (Meneu & Pardo, 2004), and its magnitude is related to the level of economic activity and firm size (Liano & White, 1994). Fabozzi, Ma, and Briley (1994) reported that the trading volume of futures contracts is lower than average on the day prior to a holiday. Kim and Park (1994) reported that the holiday effect in the U.K. stock market is independent of the holiday effect in the U.S. stock market. Chan, Khanthavit, and Hugh (1996) found that the effect of cultural holidays is stronger than the effect of state holidays. Chong, Hudson, Keasey, and Littler (2005) show that the preholiday effect has declined in the U.S. and Hong Kong markets, and more significantly in the United States; the period between 1991 and 1997 witnessed a reverse preholiday effect (with negative mean returns), and the subsequent period between 1997 and 2003 marked the elimination of the preholiday effect. A few authors have investigated and confirmed the presence of the holiday effect in the European returns, such as Arsad and Coutts (1997), who investigated the United Kingdom's FT 30 Index over a 60-year time frame; Krämer and Runde (1996) with their study on Germany's DAX Index, where the average return over holidays is more than 10 times larger than the non-holidays average return; Dodd and Gakhovich (2011), who analysed 14 Central and Eastern European markets; or Dumitriu, Stefanescu, and Nistor (2011), who analysed the Romanian market and found abnormal post-holiday returns along with the preholiday high returns. Vergin and McGinnis (1999) reported that the positive preholiday returns have disappeared for large firms and diminished for small firms between 1987 and 1996. Conversely, the hypothesis that the holiday effect has diminished or disappeared is rejected by Brockman and Michayluk (1998), whose results reveal a robust and persistent holiday effect after 1987. Hong and Yu (2009) confirm that the trading volume is lower during the summer because market participants are on holiday. Similarly, Al-Ississ (2010) reported significantly lower trading volume and changes in daily stock returns in 17 Muslim financial markets during the Muslim holy days of Ramadan and Ashoura. However, Bialkowski, Etebari, and Wisniewski (2010) found higher stock returns and no change in the trading volume during Ramadan.

The preholiday effect has been widely studied in an intra-market context, but very little attention has been paid to holidays in a cross-market context. This motivation introduces the review of the literature on the cross-market holiday effect.

2.2.3 | Cross-market holiday effect

Cheung and Kwan (1992) were the first authors to bring the volume dimension into the literature on the transmission of information across international markets. By computing the average Canadian daily volume during U.S. holidays and U.S. trading periods, and computing the ratios of these volume averages, they found evidence that the U.S. trading holidays impact both volatility and trading volume in Canada's Toronto Stock Exchange (TSE); the Canadian trading volume drops when there is a holiday in the United States. Similarly, they investigated the reverse causality, looking at the effect of Canadian holidays on the U.S. market; despite finding a decrease in volumes, this was a significantly less blatant response. Cheung and Kwan's study concludes that the information originating from the United States has a major impact on other markets, whereas the converse might not be valid. Casado et al. (2013) reported a significant U.S. holiday effect on the European markets, with return rates above average and volatility/trading volume below average. The lower volume could be caused by the absence of U.S. institutional investors and a lower macroeconomic information volume with less investor disagreement since the world's largest stock market and economic news source is closed; these factors change the public information flow and the European investor mix. There are significantly positive returns in the European stock markets when there is a holiday on the New York Stock Exchange (NYSE), and their magnitude depends on the sign of the previous day's NYSE closure. They used recent financial data for the European stock market indices ranging from 1991 to 2008 and defined three measures for returns: off-market return (i.e., close-to-open return), intraday return (i.e., open-to-close return), and ordinary return (i.e., close-to-close return), in order to assess the impact of the six U.S. holidays that occur on European trading days and compared the average of the sample return with the average of the returns during NYSE holidays before proceeding to fitting a regression model with dummy variables, the previous day's return, and the ordinary trading volume on Mondays only. The authors decomposed the European returns into off-market returns and intraday returns in order to test whether the NYSE information is not totally reflected in the European prices before the markets shut but found that the previous day's NYSE information is fully incorporated in the European opening prices and therefore it is irrelevant to the cross-market holiday effect. The U. S. holidays that are non-holidays in Europe are

- Labour Day on the first Monday in September;
- Presidents Day on the third Monday in February;
- Memorial Day on the last Monday in May;
- Independence Day on July 4th;
- Thanksgiving Day on the fourth Thursday in November; and
- Martin Luther King Day (since 1998) on the third Monday in January.

On a partially related note, Meneu and Pardo (2004) examined the cross-market preholiday effect. Using the five most traded stocks in the Spanish Stock Exchange, which are also traded on the NYSE and the Frankfurt Stock Exchange, they analysed a preholiday effect in the Spanish market prior to a U.S. or German holiday and found no such effect in their analysis sample. The only significant preholiday effect in the Spanish market was domestic (i.e., prior to Spanish holidays) and not international.

There is research investigating and confirming all of the calendar effects (i.e., the weekend effect, turn-of-the-month, turn-of-the year, and holiday effects) and their persistence (Agrawal & Tandon, 1994; Barone, 1990; Lakonishok & Smidt, 1988; Mills & Coutts, 1995). Other papers report the recent diminishing (or absence) of calendar effects for large-firm stocks starting from the late 1980s (Hansen, Lunde, & Nason, 2005; Pearce, 1996). Many popular anomalies do not hold up in different sample periods (Schwert, 2003).

2.3 | The volume–price relation

The positive correlation between volume and price changes has been extensively studied in the finance literature (Harris & Raviv, 1993; Hong & Stein, 2007). There are two forms that price changes can take in their positive correlation with volume: the magnitude (or absolute value) of the price change, that is, $|\Delta p|$ (Assogbavi & Osagie, 2006), or the price change per se (or the raw price change value), that is, Δp (Karpoff, 1987), where one can define the price change as either the log-price difference or the percentage price change.

3 | DATA SET

This section introduces the data sample retrieval and processing. The study employs a data sample that contains an extensive sample of 2,353 stocks. The financial market data set was complemented by a data set containing a representative temporal exogenous determinant of volume and non-stationarity, namely, bank holidays. The data sample spans from January 1, 2000, to May 10, 2015, and investigates the markets during stable periods but also during the financial crisis of 2007–2008, which motivates a subsequent analysis of structural breaks before and after the crisis.

3.1 | Stock universe

We start from a list of indices, outlined in Table 1 along with their Reuters Identification Codes. The constituent list for each of these European indices is generated and is valid as of May 11, 2015, in order to create an optimal representation of the pan-European market.

We added the largest 42 South African stocks to our pan-European universe for a number of reasons: the

TABLE 1 Market data European indices

RIC	Name	RIC	Name
.STOXX	STOXX Europe 600 EUR Price Index	.PSI20	Euronext Lisbon PSI 20 Index
.FTSE	FTSE 100 Index	.OMXS30	OMX Stockholm 30 Index
.FTMC	FTSE Mid 250 Index	.OBX	Oslo Stock Exchange Equity Index
.FTLC	FTSE 350 Index	.OMXHPI	OMX Helsinki_Pl
.FTSC	FTSE Small-Cap Index	.BFX	BEL 20 Index
.FTAS	FTSE All Share Index	.OMXC20	OMX Copenhagen 20 Index
.GDAXI	Deutsche Boerse DAX Index	.ATG	Athex General Composite Share Price Index
.MDAXI	MDAX Performance Index	.ISEQ	ISEQ Overall Price Index
.SDAXI	SDAX Share Index	.JTOPI	Johannesburg Stock Exchange Top 40 Tradeable Index
.FCHI	CAC 40 Index	.ATX	Austrian Traded Index
.CN20	CAC Next20 Index	.FTMIB	FTSE MIB Index
.CACMD	CAC Mid 60 Index	.MSPE	MSCI International Pan Euro Price Index
.CACS	CAC Small Index	.MCX	MICEX Composite Index
.SSMI	Swiss Market Index	.WIG20	Warsaw SE WIG-20 Single Market Index
.AEX	Amsterdam Exchange Index	.TRXFLDEUPU	Thomson Reuters Europe Index
.IBEX	IBEX 35 Index		

Note. RIC: Reuters Identification Code.

trading of South African stocks is closely connected to the European stocks; South Africa operates on the same time zone as the Eastern Europe, that is, Coordinated Universal Time + 2 hr; and the Johannesburg Stock Exchange is a liquid trading venue. The frequency table of the market data sample in Table 2 shows the stock distribution by country. The country codes are encoded in the two-letter format specified by ISO 3166-1 alpha-2. A stock is assigned to a country based on the exchange this stock is trading at, for example, a Spanish stock trading on the London Stock Exchange is associated with the United Kingdom.

3.2 | Market data

Daily market data containing OHLC (open, high, low, close) prices and end-of-day volume are retrieved from Thomson Reuters using a Visual Basic for Applications (VBA) script that automates the data retrieval. The stocks' daily market data are retrieved and augmented by computing their consolidated volume, that is, the sum of a stock's main exchange trading volume and its volume on multilateral trading facilities. The consolidated volume has been used in this study in order to better reflect the actual volumes. Therefore, any subsequent reference to trading volume in this study indicates the consolidated volume.

The market data were preprocessed to account for missing data or incorrect data. For instance, the constituents of the FTSE MIB index could not be retrieved along with all the other indices' constituents, and, in this instance, manual intervention for data cleansing was required. The stocks whose number of market data available days is less than 100 days have been discarded. The stocks are augmented by metadata that includes exchange location, currency, company market capitalization, economic sector, business sector name, industry/subindustry name, and activity name. The final number of daily observations across all 2,353 stocks is nearly 7.2 million.

3.3 | Construction of the calendar data set

The calendar data consist of the European non-trading calendar for the 21 countries being analysed and for the United States and was laboriously constructed from scratch in order to provide an accurate reflection of the special events occurring in the equity markets. A total number of 3,039 bank holidays are included in the calendar data. Due to data unavailability, half-trading days are not included in this study.

The non-trading calendar contains public holidays and bank holidays when the stock exchanges are closed. The data set covers the same period as the market data and contains the trading holidays for European countries and the United States. The non-trading calendar for the 21 European countries outlined in Table 2 and the United States (as a dominant financial market) was elaborated using multiple sources, ranging from the trading calendar on the exchange websites, and public holidays from www.timeanddate.com, to the empirical trading calendar inferred from this study's daily market data. The rationale of manually constructing the holiday calendar is twofold: first, high accuracy is crucial for identifying the extent to which volume is correlated to cross-market holidays; second, there is no available trading calendar that mirrors the observed activity for the European exchange venues, and there are major differences between the non-trading calendars and the official holiday calendars that are publicly available.

A non-trading calendar comma-separated values (CSV) file was created for each of the trading countries. We started by getting a list of expected trading holidays

TABLE 2 Market data sample country breakdown

Country code	Country name	Stocks	%	Country code	Country name	Stocks	%
AT	Austria	32	1.36	HU	Hungary	4	0.17
BE	Belgium	62	2.63	IE	Ireland; Republic of	43	1.83
CH	Switzerland	104	4.42	IT	Italy	111	4.72
CZ	Czech Republic	5	0.21	NL	The Netherlands	46	1.95
DE	Germany	176	7.48	NO	Norway	69	2.93
DK	Denmark	43	1.83	PL	Poland	65	2.76
ES	Spain	61	2.59	PT	Portugal	18	0.76
FI	Finland	130	5.52	SE	Sweden	158	6.71
FR	France	346	14.70	TR	Turkey	130	5.52
GB	United Kingdom	647	27.50	ZA	South Africa	42	1.78
GR	Greece	61	2.59				

by getting the zero-volume business days for each country. This ensured that the non-trading calendar is accurate from a financial market viewpoint. It is important to distinguish from the public holidays calendar of a country and the non-trading calendar for an exchange venue, because the latter might be owned by an international company (e.g., Euronext), which enforces a different trading calendar, or it might be located in a region with additional holidays, or unforeseeable events might occur (e.g., Hurricane Sandy and September 11th Terrorist Attacks). No external source was able to accurately reflect the trading holidays for the entire study period and necessitated thorough implementation of a non-trading calendar. For the countries with few and potentially illiquid stocks that are listed in Table 3, the expected list of holidays was significantly larger than in reality due to many zero-volume days when the markets are actually open. Therefore, we got the data from the main indices from these countries and cross-checked the expected trading days as the methodology based on zero-volume would output more non-trading dates than the actual number. Additional data cleansing was performed for very few incorrect stocks that were trading during their exchanges' trading holidays.

3.3.1 | Country-specific calendar peculiarity

Each country has its own “hidden” methodology of generating the public holidays calendar. When a public holiday falls on a weekend, it is substituted by the previous trading day in some countries (e.g., New Year's Eve in Austria and Belgium) or the next day in others, or it is not substituted at all. Some other countries have additional “bridge” holidays when a holiday falls on a Tuesday or Thursday, in order to get a 4-day weekend (e.g., Hungary and Poland).

Additional holidays are observed despite not being officially declared as public holidays. It is worth noting that periodic holidays can cease at certain times and others can be introduced. For example, the Swedish National Day started being celebrated from 2005; the Swiss National Day was not a public holiday for a few consecutive years, between 2001 and 2005; Good Friday in Hungary and Czech Republic was observed from 2012 and 2013, respectively; and Christmas Eve is a non-trading day in Ireland until 2005. On the other hand, a few countries like Norway and South Africa have a well-defined periodic structure for their bank holidays, although South Africa has a few one-off holidays for General Elections and Municipal Elections.

Surprisingly, the Greek exchanges are not trading on both catholic and orthodox Easters, apart from the years when they fall on the same date (i.e., 2001, 2004, 2007, 2010, 2011, and 2014) and 2013.

The longest holidays are Turkey's Festival of Sacrifice (or Eid al-Adha) and End of Ramadan (or Eid ul-Fitr).

Despite the fact that May 1st is not a bank holiday in the Netherlands, it is actually observed on the Amsterdam stock exchange after it merged with the Brussels and Paris stock exchanges to form Euronext in 2000; it became a non-trading day since 2002 though. In the Netherlands, May 1st is not an official day due to the Queen's Day, which was a public holiday in its own right until 2013, falling on April 30th. It was replaced in 2014 by the King's Day (falling on April 27th). After joining Euronext, the public holidays in Belgium occurring between May 1st and Christmas Eve became regular trading days on the exchange, starting from 2002. Similarly, the Portuguese trading calendar changed from 2003 after Lisbon joined Euronext in 2002, and the French trading calendar changed from 2001.

3.3.2 | Normalized trading calendar

When constructing each country's calendar from scratch, the postprocessing step ensured that each periodic holiday observation is identified by the same name (i.e., bank holiday normalization). However, slight variations were identified when using the calendar of the European countries and the United States altogether, and we had to define regular expression-based nomenclature transformations so that the alternative names of the various events are mapped to the same holiday concept. Some representative examples from the 56 rules include

- From May Day (except Ireland), Labour Day, Labor Day (except the United States), Workers' Day, Labor and Solidarity Day to May 1st;

TABLE 3 Low liquidity countries

Country	Number of stocks	Main stock index	RIC
Czech Republic	5	Prague Index	.PX
Hungary	4	Budapest Index	.BUX
Portugal	18	Euronext Lisbon PSI20	.PSI20

Note. RIC: Reuters Identification Code.

- From St. Stephen's Day, 2nd Christmas Day, Second Day of Christmas, Synaxis of the Mother of God, Day of Goodwill, and Christmas Day (occurring on 26th December) to Boxing Day;
- From Independence Day to [country name] Independence Day; from Constitution Day to [country name] Constitution Day; from National Day to [country name] National Day;
- From Family Day to Easter Monday;
- From Spring Bank Holiday (UK) and Memorial Day (US) to GB US Spring Bank Holiday/Memorial Day;
- From Pentecost Monday to Whit Monday;
- From Dormition of the Holy Virgin to Assumption of Mary; and
- From Independent Czechoslovak State Day (CZ) and The Ochi day (GR) to CZ GR Independent Czechoslovak State Day/The Ochi day.

In some cases, we are discriminating between two or more holidays that have the same name but are essentially referring to different holiday concepts (e.g., the generic *Independence Day* holiday, which occurs on different dates in the United States, Finland, Poland, Greece, etc.). In other cases, we are aggregating holidays with different names, which refer to the same concept to some extent, ranging from semantically identical holidays (e.g., *Pentecost Monday* and *Whit Monday*) to similar holidays falling on the same date annually (e.g., *Boxing Day*, *Second Christmas Day*, and *St. Stephen's Day*).

The calendar also exhibits additional holidays issued by certain governments. Because these holidays are sparse observations that are not periodic, we appended "Additional" in order to distinguish from the main holiday which they follow.

All of the holidays that are observed exclusively in one country are prefixed by the country code. Early May Bank Holiday is observed in the United Kingdom and Ireland. Table 4 shows all of the normalized bank holidays, both periodic and non-periodic. This bank holiday normalization found 95 unique pan-European non-trading events from 3,039 non-normalized bank holidays.

4 | ANALYSIS APPROACH

In this section, we outline the analytical approach we followed throughout this study, and we outline the methodology of this paper. We start by asking the question whether the cross-market holiday effect is real. Then, we check whether it can be modelled, and we are looking at the feasibility of modelling this effect with the view of predicting using ridge regression, along with additional features (besides the bank holiday-specific indicator variables). Finally, we raise the question of how well the cross-market holiday effect can be modelled the further we go into the future. We investigate how accurate the predictions of the volume are n days ahead of time. The motivation of a multistep ahead analysis is to address a common scenario where portfolio managers and traders would like to size the allocation of a trade prior to a bank holiday, when they typically do not work. Their aim is to gauge the predicted available liquidity while minimising market impact. This is a practical problem that has not been properly addressed.

For each cross-market holiday of every stock, we would like to compare the trading volume on the special event (i.e., "target date" or t_0) with its benchmark volume. The benchmark volume is defined, since the median of the previous 20 trading days' volumes as the median helps dampen the effect of outliers. Besides the default one-step ahead analysis, a multistep ahead forecasting is provided for step size n, ranging from 2 to 6; for example, if $n = 6$, we could use the 20 most recent trading days' volumes up to today in order to predict the impact on the trading volume in 6 days' time. Figure 1 illustrates the lower trading volumes on cross-market holidays, compared with the median of the previous 20 trading days (i.e., benchmark volume) on the logarithmic scale.

The data necessitate further processing in order to compute the relative volume. It is the log-ratio between the t_0 volume on the cross-market holiday and the median of the benchmark volumes, which can be lagged depending on the step size for the step ahead analysis, where $lag = n - 1$.

$$V_{rel} = \log \frac{V_{t0}}{median\ \left(V_{t-lag-1},\ V_{t-lag-2},\ \ldots,\ V_{t-lag-20}\right)}. \quad (1)$$

We are dealing with data that are sparse and there is a limited number of holidays. Consequently, we normalize the analysis data in order to increase the number of observations and find effects that are common to a basket of stocks and a particular event.

The bar charts in Figure 2 show the median cross-market holiday effect, expressed in linear space percentage values, for the trading volume in the United Kingdom, Germany, France, and Switzerland, for each external holiday country. These represent the volume decrease percentage, compared with the benchmark volume.

Table 5 shows the median percentage reduction in volume on cross-market holidays for every pair of countries, expressed in linear space; the columns represent

TABLE 4 Normalized bank holidays

Holiday name	Closed markets	Holiday date observations	Trading observations	Trading stocks	Trading countries
AT Austria National Day	1	10	17,879	2,127	20
All Saints' Day	6	11	19,008	2,132	18
Ascension Day	9	15	20,106	1,832	17
Assumption of Mary	7	13	20,856	2,190	20
BE Belgian National Day	1	1	1,353	1,353	19
Boxing Day	21	12	1,206	130	1
Boxing Day Additional	4	8	11,680	2,236	21
CH Berchtold Day	1	11	18,561	2,246	20
CH Swiss National Day	1	8	15,079	2,232	20
CZ GR Independent Czechoslovak State Day, The Ochi day	2	10	18,543	2,276	19
CZ Jan Hus Day	1	10	18,109	2,143	20
CZ Saints Cyril and Methodius	1	11	19,804	2,200	20
CZ St. Wenceslas Day	1	10	18,275	2,146	20
CZ Struggle for Freedom and Democracy Day	1	10	18,608	2,339	20
CZ Victory in Europe Day	1	12	22,377	2,347	20
Christmas Day	21	11	1,097	130	1
Christmas Eve	16	11	12,069	1,508	12
Corpus Christi	3	15	26,562	2,209	19
DE Day of German Unity	1	2	3,435	2,154	20
DK Ascension Day Additional	1	6	12,435	2,251	20
DK Denmark Constitution Day	1	10	17,411	2,252	20
DK Great Prayer Day	1	16	27,545	2,265	20
ES Assumption of Mary Additional	1	1	1,577	1,577	20
ES Hispanic Day	1	3	4,379	1,636	20
ES Spain Constitution Day	1	4	5,543	1,556	19
GB IE Early May Bank Holiday	2	16	19,044	1,664	20
Easter Monday	20	16	1,755	169	2
Epiphany	6	11	16,805	1,955	17
FI Finland Independence Day	1	11	18,922	2,114	20
FR Bastille Day	1	1	1,159	1,159	19
GB Golden Jubilee Bank Holiday	1	1	1,086	1,086	20
GB Royal Wedding Bank Holiday	1	1	1,512	1,512	20
GB Summer Bank Holiday	1	15	20,043	1,691	21
GB The Queen's Diamond Jubilee	1	1	1,500	1,500	19
GB US Spring Bank Holiday, Memorial Day	3	17	22,559	2,241	21
GR Clean Monday	1	16	28,667	2,292	20
GR Greece Independence Day	1	11	18,999	2,292	20
GR Holy Spirit Monday	1	15	23,115	2,224	20
GR Orthodox Easter Monday	1	10	15,073	2,288	20
GR Orthodox Easter Tuesday	1	2	3,577	2,120	20

(Continues)

TABLE 4 (Continued)

Holiday name	Closed markets	Holiday date observations	Trading observations	Trading stocks	Trading countries
GR Orthodox Good Friday	1	11	17,922	2,292	20
Good Friday	21	16	1,841	178	4
HU 1848 Revolution Memorial Day	1	11	19,502	2,171	20
HU 1848 Revolution Memorial Day Additional	1	5	9,160	2,130	20
HU 1956 Revolution Memorial Day	1	11	20,110	2,340	20
HU 1956 Revolution Memorial Day Additional	1	6	11,456	2,338	20
HU All Saints' Day Additional	1	5	9,381	2,156	20
HU Hungary National Day	1	11	20,556	2,333	20
HU Hungary National Day Additional	1	3	5,687	2,203	20
IE August Bank Holiday	1	1	1,365	1,365	20
IE June Bank Holiday	1	15	24,780	2,252	20
IE October Bank Holiday	1	2	2,845	1,541	20
Immaculate Conception	3	10	18,328	2,317	20
Maundy Thursday	3	16	28,200	2,240	20
May 1st	19	12	6,518	878	6
May 1st Additional	3	9	15,031	2,285	21
Midsummer Eve	2	15	24,377	2,031	19
NL Queen's Birthday	1	1	1,422	1,422	20
NO 17 May Constitution Day (1814)	1	9	15,372	2,131	20
New Year's Day	22	16	5,891	1,517	20
New Year's Day Additional	4	5	8,140	2,301	21
New Year's Eve	18	11	12,240	1,510	13
New Year's Eve Additional	3	5	8,477	2,113	21
PL Poland Constitution Day	1	11	18,155	2,128	20
PL Poland Independence Day	1	10	18,687	2,279	20
PT Carnival/Shrove Tuesday	1	3	4,220	1,550	20
PT Liberty Day	1	3	4,261	1,552	20
PT Portugal Day	1	1	1,520	1,520	20
PT Republic Implantation	1	2	2,841	1,508	20
PT Restoration of Independence	1	1	1,424	1,424	20
SE Sweden National Day	1	8	14,981	2,145	20
TR Commemoration of Ataturk, Youth and Sports Day	1	10	17,305	2,158	20
TR National Sovereignty and Children's Day	1	12	21,599	2,221	20
TR Ramadan Feast	1	41	67,097	2,203	20
TR Sacrifice Feast	1	52	87,713	2,212	20
TR Turkey Republic Day	1	11	19,688	2,215	20
TR Victory Day	1	10	15,826	2,081	20
US September 11th Terrorist Attacks	1	4	5,784	1,542	21
US Independence Day	1	15	27,570	2,326	21
US Labor Day	1	15	27,831	2,333	21

(Continues)

TABLE 4 (Continued)

Holiday name	Closed markets	Holiday date observations	Trading observations	Trading stocks	Trading countries
US Markets closed—Hurricane Sandy	1	2	4,148	2,156	21
US Martin Luther King Day	1	16	29,615	2,351	21
US National Day of Mourning for President Gerald R. Ford	1	1	1,706	1,706	19
US National Day of Mourning for President Ronald Reagan	1	1	1,608	1,608	21
US Presidents Day (Washington's Birthday)	1	16	29,453	2,351	21
US Thanksgiving Day	1	15	28,065	2,350	21
Whit Monday	10	15	21,890	2,112	17
ZA Day of Reconciliation	1	13	24,339	2,310	20
ZA Freedom Day	1	14	25,490	2,309	20
ZA General Elections	1	3	5,736	2,240	20
ZA Heritage Day	1	13	23,653	2,294	20
ZA Human Rights Day	1	12	21,306	2,223	20
ZA Municipal Elections	1	3	5,187	2,052	20
ZA National Women's Day	1	12	21,381	2,164	20
ZA Youth Day	1	12	21,573	2,256	20

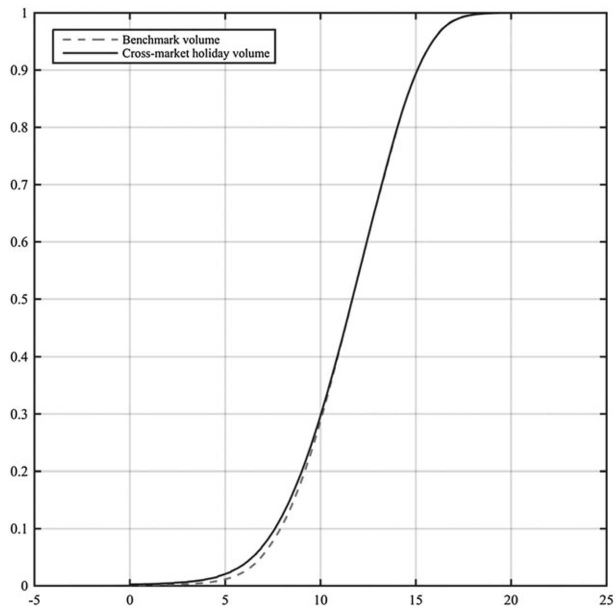

FIGURE 1 Cumulative distributions of the logarithmic volume data for the entire stock universe on cross-market holidays and on the benchmark period

the holiday countries, whereas the rows represent the trading countries.

The cross-market holidays analysis is extended by a further investigation of the discrimination between market capitalization classes. This particular analysis uses a restricted data set for three countries (the United Kingdom, France, and Germany), each with three indices for small-, mid-, and large-cap stocks, although France contains four indices because there are two CAC indices for large-cap indices, as shown in Table 6.

The data analysis starts with an exploration of the cross-market holiday effect using rigorous randomization tests. Once the existence of this phenomenon is confirmed, we build a predictive model for trading volume.

5 | RANDOMIZATION ANALYSIS

In this first part of the analysis, we assess the statistical significance of the existence of the cross-market holiday effect. Then, we examine whether the phenomenon is driven by the Monday effect and whether its impact on the trading volume is different based on the stock market capitalization.

The aim of the randomization (or permutation) tests is to assess whether two vectors X and Y are significantly different. The procedure starts by calculating the observed statistic, which is the difference between the two vector means. If the test is two-tailed, then the observed statistic is the absolute value of this difference. Then, the labels of vectors X and Y are randomized, and the randomized statistic is recomputed in the same manner as the observed statistic, based on the newly randomized vectors. This step is repeated 1,000 times. Eventually, the randomization test checks if the randomized differences are more extreme than the observed data. This allows computing an empirical p value that corresponds to the percentage of times when the observed difference

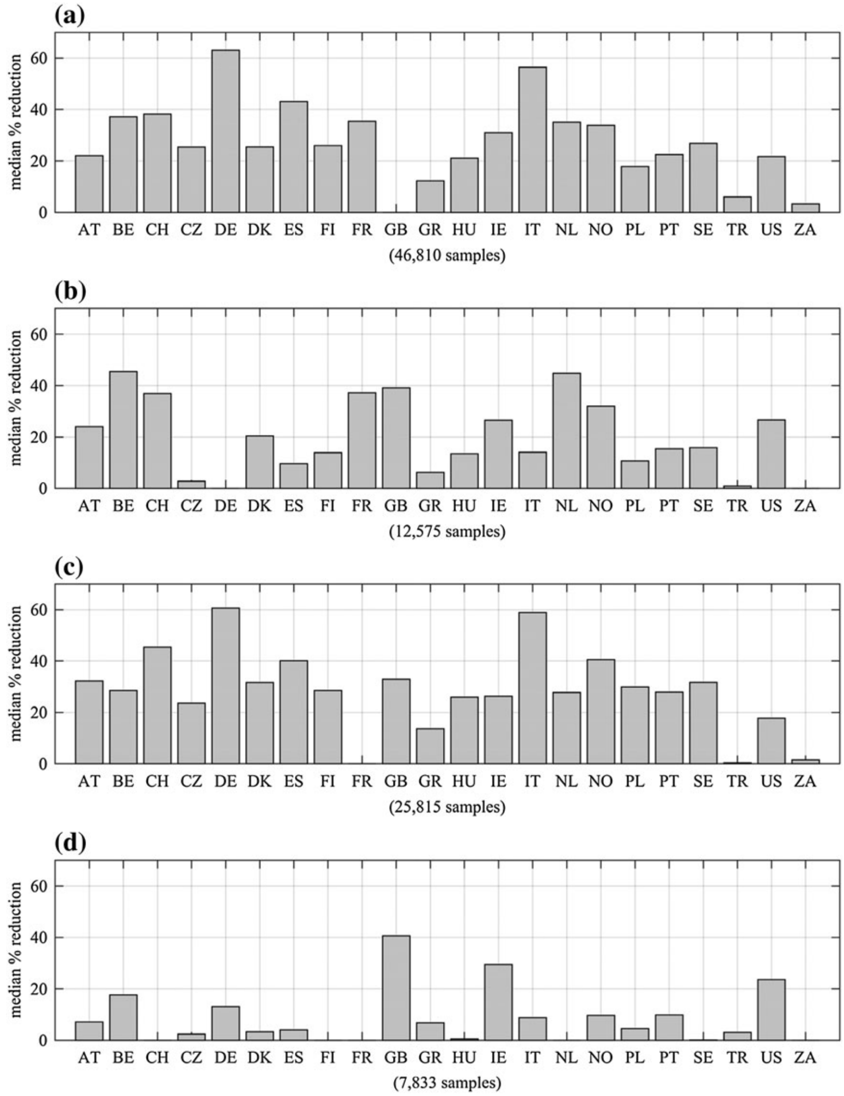

FIGURE 2 Cross-market holiday effect on the trading volume in the United Kingdom, Germany, France, and Switzerland, shown for each external holiday country. (a) Reduction of trading volumes in GB on different holidays; (b) reduction of trading volumes in DE on different holidays; (c) reduction of trading volumes in FR on different holidays; and (d) reduction of trading volumes in CH on different holidays

is larger (for the right-tailed and the two-tailed tests) or smaller (for the left-tailed) than the randomized differences. The significance level for the randomization tests is $\alpha = 5\%$. The null hypothesis is rejected when the empirical p value is less than the significance level.

The cross-market holiday and Monday bank holiday randomization tests involve a pairwise shuffling of labels. In this instance, for each target date, we compute an artificial control date that is conditioned on the original target date. Because the vectors have the same size, we flip a coin for each element and decide whether the elements are to be interchanged.

Throughout these permutation tests, we also investigate the existence of potential structural breaks. We test the validity of structural homogeneity by splitting the data set covering almost 16 years into two folds: The first sample period half is between January 1, 2000, and December 31, 2007, whereas the second sample half covers January 1, 2008, to May 10, 2015. The motivation stems from the financial crisis of 2007–2008, which culminated with the collapse of Lehman Brothers on September 15, 2008.

Three types of randomization tests are performed in order to test a number of aspects regarding the cross-market holidays, such as the differentiated effect magnitude depending on market capitalization or determining whether the Monday bank holidays are the drivers of lower trading volumes on Monday or whether it is the Monday effect that impacts on the trading volume.

5.1 | Cross-market holidays versus control dates

For the randomization between cross-market holidays and their control dates, we defined the target volumes as the relative volume of a stock on the days (i.e., the "target dates") when there is at least on cross-market holiday. For each stock, we iterate each of its unique target dates and compute a pairwise control date such that it is a trading day when there are no cross-market

TABLE 5 Cross-market holiday effect showing the median percentage reduction in volume for each pair of countries, where the rows represent the trading countries and the columns represent the holiday countries

	AT	BE	CH	CZ	DE	DK	ES	FI	FR	GB	GR	HU	IE	IT	NL	NO	PL	PT	SE	TR	US	ZA
AT	0.0	−43.5	21.0	9.0	8.9	3.4	0.0	−2.0	32.9	35.4	9.1	1.5	25.4	0.0	16.4	1.0	10.6	−8.1	−10.0	1.6	24.4	1.5
BE	37.4	0.0	53.9	21.3	68.7	37.4	50.6	32.7	31.1	35.9	14.3	28.4	28.6	65.8	29.4	47.8	32.7	32.8	35.8	1.3	22.9	1.5
CH	7.1	17.7	0.0	2.4	13.1	3.3	4.0	−3.0	−20.7	40.7	6.8	0.5	29.5	8.8	−7.8	9.7	4.5	9.8	0.1	3.1	23.7	−0.2
CZ	19.4	54.4	31.9	0.0	44.8	20.4	26.6	15.2	54.4	43.8	10.9	13.4	33.9	33.8	49.2	23.1	18.4	44.4	23.2	5.4	25.9	12.4
DE	24.1	45.5	36.8	2.8	0.0	20.4	9.5	13.8	37.2	39.1	6.2	13.5	26.5	14.0	44.8	31.9	10.7	15.4	15.8	0.9	26.6	−0.8
DK	3.5	44.0	14.5	10.8	32.4	0.0	14.5	10.9	46.1	30.3	3.8	5.0	24.1	11.8	46.7	27.9	3.9	22.6	9.6	3.9	25.5	6.4
ES	24.1	2.6	26.4	6.7	44.9	19.1	0.0	20.0	26.8	40.6	14.8	17.8	26.0	53.2	17.5	29.1	20.9	12.2	15.5	2.6	25.9	2.3
FI	7.9	42.7	17.5	12.3	14.7	16.8	0.0	0.0	28.8	30.6	6.4	4.3	22.0	0.0	29.1	29.0	4.4	5.9	19.2	0.0	23.1	−2.5
FR	32.2	28.5	45.4	23.6	60.7	31.7	40.1	28.5	0.0	32.9	13.6	26.0	26.3	58.9	27.8	40.5	29.9	27.9	31.7	0.4	17.7	1.5
GB	22.0	37.1	38.2	25.4	63.0	25.4	43.1	26.0	35.4	0.0	12.2	21.1	31.0	56.4	35.0	33.8	17.8	22.5	26.8	6.0	21.7	3.2
GR	14.0	37.6	24.0	18.0	38.3	10.0	25.7	17.6	29.5	20.0	0.0	8.8	18.6	48.6	34.7	16.3	14.5	7.7	19.3	−4.0	11.2	6.5
HU	10.6	83.5	42.2	13.8	71.6	21.9	39.1	10.2	86.0	55.5	1.1	0.0	40.6	47.7	86.0	32.3	6.1	43.5	17.5	4.7	44.5	14.1
IE	30.8	67.0	49.2	26.9	76.9	27.8	50.1	29.8	66.0	70.1	19.4	29.0	0.0	66.9	61.5	45.3	23.3	29.1	33.1	3.0	32.7	7.0
IT	22.2	21.9	19.4	5.2	22.2	8.4	34.4	9.6	18.0	37.3	10.2	15.3	30.9	0.0	20.4	13.5	10.4	28.0	10.3	1.4	21.3	4.5
NL	25.9	23.8	49.7	21.0	76.2	31.3	39.5	26.3	23.1	46.7	10.0	21.4	36.0	70.2	0.0	44.2	18.0	15.5	29.4	3.4	32.7	1.5
NO	−2.4	−7.4	14.7	11.3	−2.1	−4.6	1.0	2.1	−25.0	35.9	1.3	1.3	28.7	−20.9	−38.0	0.0	−0.4	−0.5	1.9	−0.6	26.0	0.2
PL	13.0	15.0	23.1	9.1	38.8	15.3	8.0	3.6	42.0	30.4	9.0	18.5	24.4	40.5	29.3	15.3	0.0	13.5	8.9	−1.2	25.0	5.0
PT	31.1	17.8	37.8	17.2	56.1	29.1	46.6	22.7	24.1	39.3	17.8	25.1	29.7	59.6	25.5	38.8	31.7	0.0	23.2	2.1	26.8	7.9
SE	3.6	−11.2	24.3	11.4	9.8	23.1	−3.6	0.9	3.5	31.0	5.3	8.9	24.3	−6.9	26.0	37.1	2.0	0.7	0.0	0.9	22.1	−1.3
TR	12.5	22.1	20.2	19.8	23.9	17.1	17.6	14.4	23.7	22.1	16.2	13.4	19.4	22.0	23.2	16.6	14.7	16.9	16.5	0.0	18.5	11.9
ZA	18.0	30.4	47.2	29.6	78.2	23.4	48.9	24.8	39.4	43.2	15.0	20.7	31.2	73.7	20.0	34.0	11.2	6.7	26.3	4.9	28.9	0.0

TABLE 6 Market capitalization indices

Index	Country	Small-Cap Index	Mid-Cap Index	Large-Cap Index
FTSE	United Kingdom	FTSE Small-Cap Index	FTSE Mid 250 Index	FTSE 100 Index
DAX	Germany	SDAX Index	MDAX Index	DAX 30 Index
CAC	France	CAC Small Index	CAC Mid 60 Index	CAC 40 Index CAC Next20 Index

holidays, it falls on the same day-of-the-week as the target date, and it is within a +/− 2-month interval relative to the target date. If more than one control dates are found for a given target date, we pick the control date that is closest to the target date (i.e., the control date whose calendar day difference relative to the target date is the lowest). We define the relative trading volume for these control date as the control volumes of the randomization test. Because this is an instance of a pairwise randomization test, each target date has one paired control date. Based on this methodology, we perform a two-tailed and a left-tailed pairwise randomization test. The null hypothesis of the two-tailed test is that the difference of the relative volumes of the dates with cross-market holidays and the dates without cross-market holidays comes from a distribution with mean equal to zero. The left-tailed randomization tests the alternative hypothesis that the relative volume mean on cross-market holidays is less than the mean on dates without cross-market holidays.

The volumes on the cross-market holidays are significantly lower than those on the control dates (i.e., with no cross-market holidays), as shown by the randomization tests' p values in Table 7. This is also valid for the multistep ahead forecasts (n-step ahead analyses for n between 2 and 6; here, the number of target dates becomes 1,343,485–1,343,481). The results are consistent for the two sample period halves. Figure 3 reveals the relative volume cumulative distribution for dates with cross-market holiday (i.e., target dates) and dates with no cross-market holidays (i.e., control dates). The cross-market holidays show a slightly positive skew compared with the control dates. The median of the relative volume change for the dates with cross-market holidays is −8.882%. This relative change is expressed as a percentage on the natural logarithm scale, and, after exponentiation, it corresponds to a reduction of volume in linear space by 8.499% compared with the benchmark volume.

5.2 | Monday bank holidays versus regular Mondays

The target dates for the Monday bank holiday randomization test consist of all of the trading Mondays for a given stock when there is at least one cross-market holiday. The pairwise control dates consist of the closest Monday relative to a target date, falling within a +/− 2-month time interval and having no cross-market holidays. The test randomizes the relative volumes of the target dates and the control dates. We performed a left-tailed test and a two-tailed test and found that the volumes on the cross-market holidays falling on Monday are significantly lower than the volumes of the Mondays with no cross-market holidays, as indicated by the results in Table 8. The results are consistent among the multistep ahead analyses. There are no structural breaks around the financial crisis of 2007–2008, as we observe a significantly lower volume on Monday cross-market holidays throughout the two 7-year time periods. As with the cross-market holiday randomization test, the null hypothesis of the two-tailed test is that the difference of the relative volumes of Mondays with cross-market holidays and Mondays without cross-market holidays comes from a distribution with mean equal to zero. The left-tailed randomization tests the alternative hypothesis that the relative volume mean on Monday cross-market holidays is lower than the mean on Mondays without cross-market holidays.

Figure 4 illustrates the relative volume cumulative distribution for Mondays with cross-market holidays (i.e., target dates) and Mondays with no cross-market holidays (i.e., control dates for the Monday effect).

5.3 | Small versus mid versus large market capitalization

We further investigate whether the cross-market holiday effect might be less conspicuous or even absent in any

TABLE 7 Randomization tests: Cross-market holidays versus control dates

Sample period/s	n-step ahead	Stocks	Target dates	Randomization tail/s	p value	Reject H_0
2000–2007, 2008–2015, 2000–2015	1	2,353	1,343,487	Both	0	Yes
2000–2007, 2008–2015, 2000–2015	1	2,353	1,343,487	Left	0	Yes

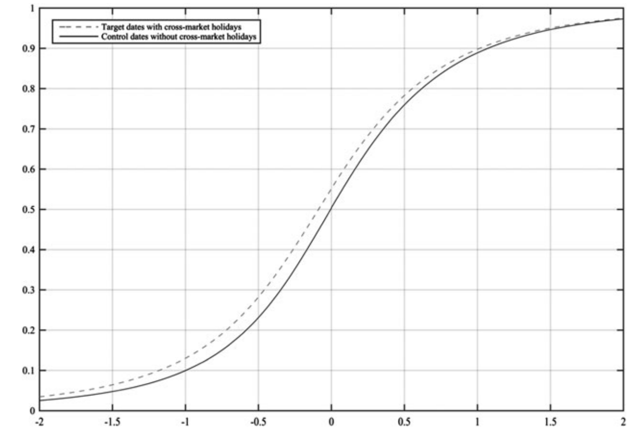

FIGURE 3 Relative volume cumulative distribution for the cross-market holiday target and control dates

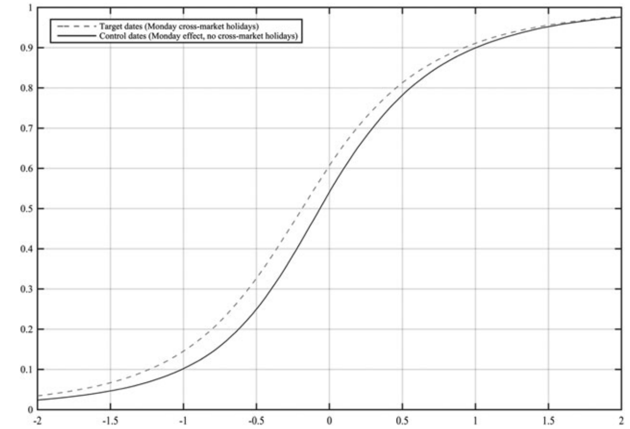

FIGURE 4 Relative volume cumulative distribution for the Monday bank holiday target and their control dates

of the market capitalization classes. The methodology for the randomization test for market capitalization is slightly different from the previous pairwise randomization tests. Given X small-cap stock, Y mid-cap stocks, and Z large-cap stocks, we define the observed test statistic using Equation (2). The test randomizes the stock capitalization classes for vectors X, Y, and Z and recomputes the randomized statistic as the new sum of pairwise absolute differences in means for the market capitalizations. We perform a two-sample absolute value randomization test (i.e., two-tailed) in order to test the null hypothesis that the pairwise market capitalization differences come from the same distribution, that is, that there is a sum of absolute differences that is persistent. We expect the statistic on the structured data to be an extreme value and the shuffled values to be much lower. The test is performed for the main European market capitalization-based indices: FTSE, CAC, and DAX. We test each index individually, and then, we aggregate the three indices and test them altogether.

$$\begin{aligned} Observed\ statistic = &|mean(X) - mean(Y)| \\ &+ |mean(Y) - mean(Z)| \\ &+ |mean(X) - mean(Z)|. \end{aligned} \tag{2}$$

Based on the results of the two-tailed randomization tests in Table 9, we report that FTSE, DAX, and the aggregated indices exhibit a market capitalization-based differentiation of the cross-market holiday effect. The CAC index does not exhibit significant differences across the market capitalization classes. The multistep ahead analyses have identical test outcomes, although the p values increase slightly for the German and French indices, but they support the same null hypothesis rejection decisions.

We find a structural break for the distinctive impact of cross-market holidays on the three market capitalization classes. For example, during 2000–2007, only FTSE and DAX have a significantly different impact based on market capitalization; this is similar to the randomization test performed on the entire sample period, except for the aggregated indices, which do not exhibit a market capitalization differentiation before the financial crisis. In the second period following the financial crisis, FTSE, CAC, and the aggregated indices show a significantly different influence of the cross-market holidays on the market capitalization classes. We report a reverse effect for the DAX and CAC indices following the financial crisis.

Figure 5 shows the cumulative distribution for the relative volume on cross-market holidays for each market

TABLE 8 Randomization tests: Monday bank holidays versus regular Mondays

Sample period/s	*n*-step ahead	Stocks	Target dates	Randomization tail/s	*p* value	Reject H_0
2000–2015	1–6	2,353	424,976	Both	0	Yes
2000–2015	1–6	2,353	424,976	Left	0	Yes
2000–2007	1	1,997	188,740	Both	0	Yes
2000–2007	1	1,997	188,740	Left	0	Yes
2008–2015	1	2,353	234,212	Both	0	Yes
2008–2015	1	2,353	234,212	Left	0	Yes

TABLE 9 Market capitalization randomization tests

Sample period/s	*n*-step ahead	Country	Index/indices RIC	Stocks	*p* value	Reject H_0
2000–2015	1	GB	.FTSC	290	0	Yes
			.FTMC	249	0	Yes
			.FTSE	100	0	Yes
	1	DE	.SDAXI	50	0	Yes
			.MDAXI	50	0	Yes
			.GDAXI	30	0	Yes
	1	FR	.CACS	223	0.088	No
			.CACMD	59	0.088	No
			.FCHI and .CN20	56	0.088	No
	1	Pan-Euro	Pan-Euro Small Cap	563	0	Yes
			Pan-Euro Mid Cap	358	0	Yes
			Pan-Euro Large Cap	186	0	Yes
2000–2007	1	GB	.FTSC	240	0	Yes
			.FTMC	206	0	Yes
			.FTSE	93	0	Yes
	1	DE	.SDAXI	40	0	Yes
			.MDAXI	40	0	Yes
			.GDAXI	30	0	Yes
	1	FR	.CACS	191	0.889	No
			.CACMD	53	0.889	No
			.FCHI and .CN20	54	0.889	No
	1	Pan-Euro	Pan-Euro Small Cap	471	0.12	No
			Pan-Euro Mid Cap	299	0.12	No
			Pan-Euro Large Cap	177	0.12	No
2008–2015	1	GB	.FTSC	290	0	Yes
			.FTMC	249	0	Yes
			.FTSE	100	0	Yes
	1	DE	.SDAXI	50	0.349	No
			.MDAXI	50	0.349	No
			.GDAXI	30	0.349	No
	1	FR	.CACS	223	0.021	Yes
			.CACMD	59	0.021	Yes
			.FCHI and .CN20	56	0.021	Yes
	1	Pan-Euro	Pan-Euro Small Cap	563	0	Yes
			Pan-Euro Mid Cap	358	0	Yes
			Pan-Euro Large Cap	186	0	Yes

Note. RIC: Reuters Identification Code.

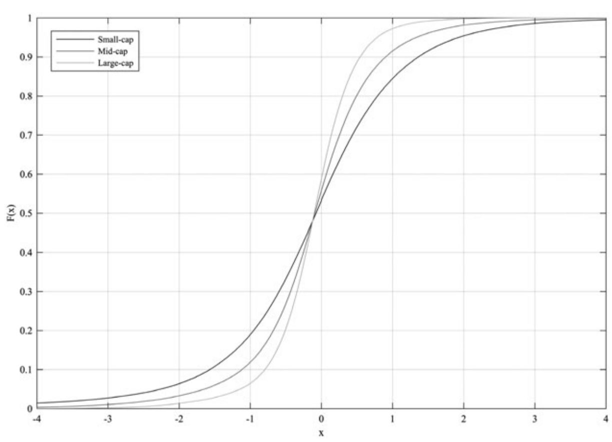

FIGURE 5 Cumulative distribution for the relative volume on cross-market holidays for each market capitalization

capitalization class. Each market capitalization class is computed by aggregating the stocks from the three stratified indices—FTSE, DAX, and CAC. It is important to note that a few stocks, which are constituents of an index, might be left out because of missing trading data, for example, FTSE Mid 250 Index has 250 constituents, whereas the analysis uses 249. The small-cap stocks have a widening cumulative distribution function (CDF) curve, suggesting their high susceptibility to lower volumes caused by cross-market holidays, whereas the mid-cap and the large-cap stocks have a progressively sharper curve.

6 | PREDICTIVE MODELLING

We fit a ridge regression model for each variant of the cross-market holiday effect models. All of these contain a constant term (or intercept), and the dependent variable consists of the relative volume. We reduce the variability and numerical instability of these models by identifying an "appropriate" value for the shrinkage parameter λ, such that it provides the lowest cross-validation mean squared error (MSE) based on the proposed two-section search and it shrinks and stabilizes the coefficients. It is important to note that some coefficients presented in the Results section are very close to zero, but not exactly zero, because ridge regression normalizes the data and therefore the zero indicator variables have a noise in the resulting model. However, the results are straightforward to interpret, because such values are negligible, whereas the real effects are reflected in large coefficient sizes.

6.1 | Ridge regression

Unlike classical variable selection techniques, where variables are assessed in a discrete manner (i.e., they are either kept in the model or excluded), resulting in a reduced model that is interpretable and might have a lower prediction error than the full model, shrinkage (or regularization) methods are more continuous and provide less variability (Hastie, Tibshirani, & Friedman, 2011). Eliminating "non-significant" predictors can result in large prediction biases; ridge regression solves this problem by using small proportions of all the variables, instead of using some variables entirely and none of the other ones that are considered insignificant by the variable selection process (Marquardt & Snee, 1975). This is the rationale of biased estimators and provides our motivation for using ridge regression instead of least squares and variable selection. An improved MSE is achieved at the cost of introducing some bias, while greatly reducing the variance. The bias–variance trade-off balances the following two concepts: increasing the local structure/curvature by making the model more complex and making the coefficients susceptible to high variance by including more terms in the model. The main problem arises when linear regression models contain many correlated variables, and therefore, their coefficients are poorly identified and have high variance. For example, a variable with a large positive coefficient can be cancelled by another variable that is correlated with the former and has a similarly large negative coefficient. Therefore, ordinary least squares (OLS) performs poorly on new data (especially outside the training data region) when the data are ill-conditioned.

This study is based on ridge regression (Hoerl & Kennard, 1970), which is similar to least squares, but the regression coefficients are constrained by imposing a penalty on their size. The ridge coefficients minimize a penalized residual sum of squares (Hastie et al., 2011), outlined in Equation (3), and results in a kind of orthogonal system.

$$\beta^{ridge} = \operatorname{argmin}\left\{\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda\sum_{j=1}^{p}\beta_j^2\right\}. \quad (3)$$

Lambda ($\lambda \geq 0$), which is called the shrinkage/tuning/complexity/regularization parameter and commonly denoted by λ, is the complexity parameter controlling the amount of shrinkage (i.e., the strength of the penalty term). When $\lambda = 0$, the solution is the linear regression estimate. The larger the lambda, the greater the amount of shrinkage, that is, the coefficients are shrunk toward zero and toward each other. If $\lambda = \infty$, then the coefficients are all set to zero and an intercept-only model is obtained. When searching for λ, one balances two ideas, that is, shrinking the coefficients and fitting a linear model.

An important step in performing ridge regression is to generally standardize the input variables before solving Equation (3), because the ridge solutions are not equivariant under scaling of the inputs. This is appropriate whenever the model includes a constant term. Not standardizing the predictors causes ill-conditioning due to the arbitrary origins of the scales on which the predictors lie. Centring the data cancels the non-essential ill-conditioning and reduces the variance inflation in the coefficient estimates. In the particular context of linear models, centring removes the correlation between the intercept and the other terms, whereas scaling allows the equation to be interpreted and used in a straightforward manner (Marquardt & Snee, 1975).

The coefficient of the constant term (i.e., the intercept β_0) is not affected by the penalty term. The rationale is that its penalization would make the ridge process depend on the origin chosen for Y, that is, adding a constant c to each target value y_i would not result simply in a shift of the predictions by the same amount as the constant c (Hastie et al., 2011). Because β_0 is not penalized, one estimates it by the sample mean of the response variables using Equation (4). When the input matrix X is standardized and the linear model contains a constant term, this estimation of β_0 is significantly better than estimating β_0 in the model using least squares (Bertie & Cran, 1985). The other coefficients for the p predictors are estimated by a ridge regression without intercept, using the centred x_{ij}. Therefore, we assume that at this step, centring was performed and that the input matrix X has p columns instead of $p + 1$ columns.

$$\beta_0 \cong \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i. \quad (4)$$

The ridge regression solutions are determined using Equation (5), where I is the $p \times p$ identity matrix. The ridge regression solution is a linear function of y due to the choice of the quadratic penalty X^TX. By adding a positive constant to the diagonal of the penalty X^TX before inversion, the problem becomes non-singular, even if X^TX is not of full rank. This was the main motivation of ridge regression when it was introduced by Hoerl and Kennard (1970).

$$\beta^{ridge} = \left(X^TX + \lambda \mathrm{I}\right)^{-1} X^T y. \tag{5}$$

It is important to conclude that it is a common practice to firstly eliminate an all-constant column in the input matrix X (i.e., the constant term or intercept) and then centre and scale the predictors in order to have mean zero and unit standard deviation, before computing the ridge coefficients. If the predictors have different scales, the shrinking is not fair because the predictors would have different contributions to the penalized term, which is calculated as the sum of squares of all the coefficients. This is the reason why the optimal value of lambda is generally smaller, as it is associated with a smaller sum of squares of the coefficients.

6.1.1 | Identifying λ

The most common technique of determining a good value for the shrinkage parameter is to try various values (e.g., using grid search) and cross-validate the models for each lambda value such that the shrinkage parameter minimizes the MSE. Too little regularization might not be able to solve the numerical instability issues (i.e., matrix singularity), and therefore, the lambda value has to be increased in order to find a threshold above which lambda solves the multicollinearity problem.

Generally, there is an "optimum" value for lambda, and the practical methodology is to explore potential values of λ between 0 and 1 (Marquardt & Snee, 1975), by investigating a range of "admissible" values of λ (i.e., having smaller MSE than the OLS). Another empirical finding of Marquardt and Snee suggests that models without a constant term generally require smaller values of λ (i.e., $\lambda \leq 0.01$) than the models with an intercept.

Introduced by Hoerl and Kennard (1970), the ridge trace is a graphical representation of the coefficients' sensitivity to lambda, plotting each coefficient against the chosen values of λ. The ridge trace is a method of showing the non-orthogonality in two dimensions and illustrates one curve per coefficient; it is advised not to plot the trace for more than 10 coefficients at once in order to provide a meaningful visualization.

The variance of a coefficient is a decreasing function of λ, whereas the bias is an increasing function of λ. As a result, as λ increases, the coefficient MSE (i.e., variance and squared bias) decreases to a minimum and then increases back (Marquardt & Snee, 1975). The main goal is to find a value of λ for a set of coefficients whose MSE is smaller than the OLS solution. Even if increasing λ would also increase the residual sum of squares, we are more interested in finding a "stable" set of coefficients, which will perform well on new observations. The stability we aim to find implies that the coefficients are not sensitive to small changes in the estimation data. Initially, if the predictors are highly correlated, the coefficients will change rapidly for small values of λ up to a point where they stabilize and start changing insignificantly for larger values of λ. The goal is to find the λ values where the coefficients stabilize; there is a range of such equivalent values from a practical viewpoint, because plotting the prediction standard deviation of new data against λ usually exhibits a flat minimum (Marquardt & Snee, 1975). However, this method has been criticized by many researchers for not providing an objective basis of determining λ.

6.2 | Modelling approach

The target date for the cross-market holidays for a particular stock consists of the days when a particular stock is trading (i.e., its exchange country is on a regular business day) and at least one external market (i.e., the U.S. market or one or more European markets) is shut. The variety of target dates for each stock are multiple observations of the cross-market holiday effect and are aggregated into the regression design matrix. The target variable in the regression models is the relative volume and not the raw volume.

We fit the models along with 20 lagged volumes in order to assess whether autoregression improves the volume model in the context of cross-market holidays. Because various stocks with different volume magnitudes are plugged into each regression model, the raw lagged volumes are divided by the median of the benchmark volumes in the same manner as the target relative volume, in order to get the normalized lagged volumes. The reasoning behind the normalization is that stocks are assumed to be different and their lagged volumes need to be normalized in order to account for any differences in magnitude.

The cross-market analyses have two main modelling versions, either as a country-specific regression model, where we fit a separate regression model for each trading country, allowing us to compute the country susceptibility to cross-market holidays, or as a pan-European regression model, where we fit all of the observations across the

European countries in a unified regression model and supply additional indicator variables for the trading country of each stock.

For each stock, we know it is traded in a particular European country and is small-/mid-/large-cap. There are two stock-specific predictor variables, namely, the trading country and the stock capitalization.

The pan-European model allows for the identification of small clusters of countries, for example, the regional effect of the United States on the whole Europe and the effect of the United Kingdom on the mainland Europe. In the pan-European model, we take some variability away off a country's holiday onto the other individual countries (from the country-specific model). The effect of any country onto the region as a whole is relatively constant. The pan-European model could be considered a reduced model assuming a constant effect, although any particular country might be more or less susceptible to holiday effects from other markets. Despite being interesting for measuring each country's holiday susceptibility, the country-specific model does not provide any insights on clustering.

Tenfold stratified cross-validation is applied throughout the analyses of this study, creating random subsamples having roughly equal sizes and roughly the same proportions of observation classes. The class of each observations is defined by encoding each observation's indicator (i.e., binary) variables into a class; for example, an observation in the pan-European cross-market holiday effect model would be encoded by concatenating all the values of the indicator variables (e.g., trading countries, holiday countries, and small-/mid-/large-capitalization flags) into a binary string. This ensures that the model is always trained and tested using subsamples that contain observations from all the classes; furthermore, the representative classes of unbalanced data sets are evenly distributed among the folds. The regression feature matrices are highly sparse, and there can be certain levels that are not represented in one of the cross-validation folds. The cross-validation process returns the 10-fold cross-validation estimate of the MSE. The folds are determined before performing the main analysis, and they are constant across the various analyses in order to ensure consistency across results.

We used ridge regression (L_2 regularization), instead of fitting a linear model and subsequently performing forward feature selection. Employing this shrinkage method was motivated by the fact that it deals well with outliers and collinearity, unlike multiple linear regression, which struggles with numerical instability issues, that is, the design matrix singularity.

The methodology for identifying the value of the ridge parameter λ consists of a two-section search, that is, grid search, followed by the bisection method. Because too little regularization causes numerical instability, it is important to find the minimum value of the shrinkage parameter where the regression matrix becomes non-singular. In the first stage, the grid search iterates 21 possible values of λ in log-space, ranging from -10 to 10 (with a step size of 1). For each of this values, the grid search fits a ridge regression and computes the average cross-validation MSE. Eventually, grid search returns the logarithmic value of λ that minimizes the cross-validation MSE. The second stage performs the bisection method for the adjacent logarithmic values of the λ identified by the grid search. Therefore, we use the previous and the next values relative to the identified λ and start performing the bisection method, where the grid search optimal λ value is the initial midpoint. We iteratively bisect the interval, by performing cross-validation for the two given endpoints of the interval. The interval midpoint successively substitutes the endpoint whose cross-validation MSE is the largest. The process continues unless any of the following criteria fails:

- Minimum delta (i.e., lambda relative change): 0.1;
- Minimum error relative change: 10^{-11}; and
- Maximum number of iterations: 20.

This two-section search is illustrated in Figure 6, where the function between log-space ridge parameters and the cross-validation MSE exhibits a convex interval. Within this convex function, the red circle markers indicate the minimum cross-validation MSE among the search values for λ. The figure contains six illustrative examples of the identification of the regularization parameter for six country-specific models.

If the independent variables have different scales, then the shrinking is not fair. That is because the penalized term is the sum of squares of all the coefficients, and therefore, the predictors will have different contributions to the penalized terms. Hence, the ridge regressions in this study are fit without a constant term, and the predictors are centred and scaled to have zero means and unit variance. Finally, the coefficients are restored to the scale of the original data, and the constant term is estimated by the sample mean of the response variables.

Ridge regression imposes a penalty on the size of coefficients, shrinking them toward zero and toward each other.

6.3 | Models outline

Twelve model variations are fit in this study, and their feature sets are outlined in Table 10. The words in italics in the feature names on the left-hand side column are

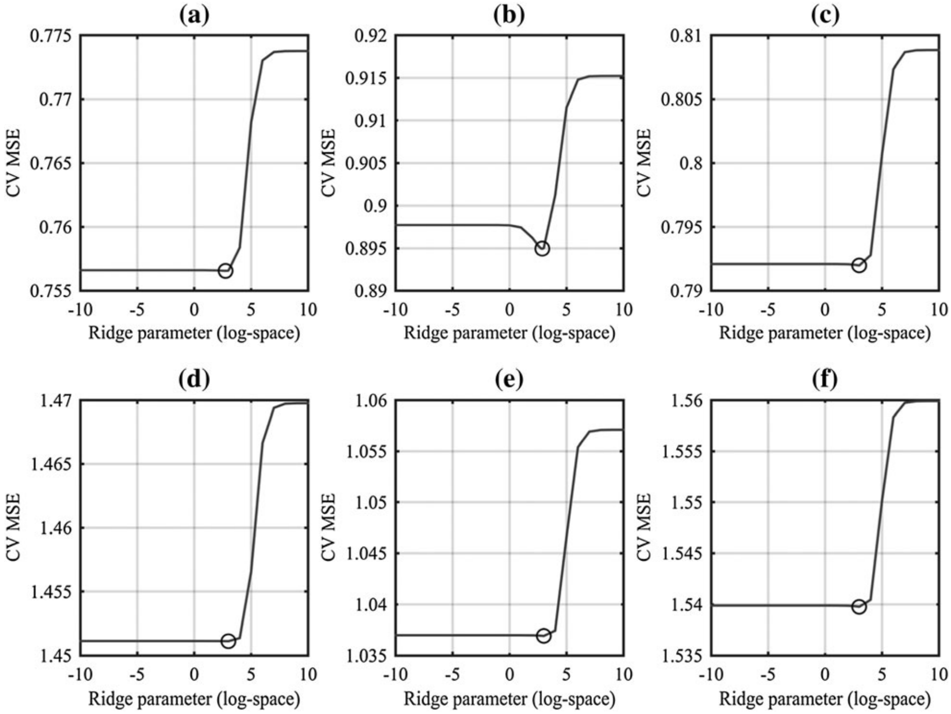

FIGURE 6 Shrinkage parameter versus cross-validation mean squared error (MSE). (a) AT; (b) CZ; (c) DK; (d) FI; (e) NO; and (f) PL

generic names, and multiple features would exist based on this template feature name depending on the data sample. For example, "Trading *country code*" would be substituted by "Trading GB," "Trading DE," "Trading FR," and so forth. Moreover, the predictor "20 lagged normalized volumes" represents 20 distinct features, and similarly, the predictor "*Small-/mid-/large*-cap" corresponds to three features.

6.4 | Holiday country and holiday breakdown models

The first class of models refers to the "holiday country" models, where the holiday calendar and holiday features correspond to each of the countries in our data set. The aim of this model class is to determine the cross-market holiday effect of each non-trading market, and therefore, it has 22 "holiday *country*" predictors.

Unlike the holiday country models, the second class of models treats the U.S. and pan-European holidays as a globally unified feature set, and it is called "holiday breakdown." Here, we are interested in finding the cross-market holiday effect of individual holidays. These models include 95 distinct "holiday *name*" predictors, reflecting the pan-European normalized bank holidays occurring during the study period of over 15 years. These are either periodic holidays, typically occurring on an annual basis, or non-periodic holidays, which are one-off events such as the United Kingdom's Royal Wedding and Diamond Jubilee or the United States's National Day of Mourning for President Gerald R. Ford and National Day of Mourning for President Ronald Reagan.

Each of the two model classes is further split into two model types: country-specific and pan-European.

For the "country-specific" models, a model is fit for each of the 21 trading markets, and the aim is to identify

TABLE 10 Regression models—Feature sets

	Holiday country								**Holiday breakdown**			
	Country-specific				**Pan-European**				**Country-specific**		**Pan-European**	
Intercept	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Trading *country code*					✓	✓	✓	✓			✓	✓
Holiday *country code*	✓	✓	✓	✓	✓	✓	✓	✓				
Holiday *name*									✓	✓	✓	✓
20 lagged normalized volumes	✓	✓			✓	✓			✓		✓	
Small-/mid-/large-cap	✓		✓		✓		✓					

country-to-country holiday effects, while allowing for a better interpretation of a country's susceptibility to the cross-market holiday effect. Because of the highly sparse data, this model is trained on the entire stock universe for a given country, because a stock-specific model would be impractical. For each country-specific regression model, we compute the country susceptibility to cross-market holidays by averaging the non-zero regression coefficients of the "holiday *country code*" predictors. Using this regression model, one can quantify the magnitude of the cross-market holiday effect among various clusters. For instance, the Swedish holidays' effect is different in magnitude on the U.K. trading volume than the U.S. holidays' effect on the U.K. trading volume.

Unlike the country-specific models, only one unified pan-European model is fit in the "pan-European" model types. The proposed pan-European models are fit similarly to the country-specific models, and, unlike the country-specific models, they include all the trading countries in one single model, having additional "trading *country code*" indicator variables for each stock's exchange country. Here, the focus is on the regional effect of each non-trading country, and we rank the cross-market holiday effect strength of a holiday country within a pan-European context based on the regression coefficients.

We report a concordant negative correlation between trading volume and cross-market holidays. The effect sizes are outlined in this section.

6.4.1 | Holiday country models

The regression coefficients for the cross-market holiday model are summarized in Table 11 for the country-specific model and in Table 12 for the pan-European model; the predictors whose coefficients are included in these tables are a subset of the entire feature set, and only the relevant variables have been included due to space constraints. The pan-European model is fit for a shrinkage parameter whose log-value is 2.96387 and has 1,343,636 observations and a CV MSE of 0.94049.

The results in Table 11 raise concerns regarding the Monday effect driving the "Holiday *country code*" coefficients. This motivates the Monday bank holiday randomization test in order to identify which effect is driving Monday volumes. It is important to mention that the

TABLE 11 Country-specific holiday country model

Trading country	Observations	CV MSE	Log shrinkage parameter	Intercept	Holiday DE	Holiday FR	Holiday GB	Holiday US	Country susceptibility
AT	16,746	0.67252	2.75	0.00	−0.18	−0.39	−0.39	−0.20	−0.06
BE	39,984	0.69772	2	0.12	0.01	−0.25	−0.25	−0.27	−0.14
CH	62,070	0.60541	2.5	0.03	−0.18	0.22	0.22	−0.23	−0.05
CZ	2,629	0.78933	2	−0.11	0.03	−0.17	−0.17	−0.02	−0.03
DE	102,500	0.57447	2	0.11		−0.35	−0.35	−0.29	−0.12
DK	25,861	0.68383	2.75	0.02	0.01	−0.31	−0.31	−0.23	−0.05
ES	34,052	0.32781	2	0.05	−0.11	−0.25	−0.25	−0.25	−0.09
FI	70,830	1.32237	2.75	0.02	−0.10	0.12	0.12	−0.20	−0.06
FR	219,181	1.33236	2.942382813	0.06	0.03			−0.14	−0.10
GB	364,239	1.07827	2.75	0.06	−0.49	0.68	0.68	−0.26	−0.05
GR	36,762	0.91295	2	−0.05	0.06	0.21	0.21	−0.04	−0.02
HU	2,743	0.41961	2	−0.04	−0.44	−0.61	−0.61	−0.36	−0.09
IE	18,619	1.99832	2	0.06	−0.79	0.29	0.29	−0.31	−0.12
IT	62,361	0.37758	2	0.03	−0.09	−0.04	−0.04	−0.18	−0.07
NL	30,980	0.38703	2	0.13	−0.39	0.44	0.44	−0.40	−0.08
NO	31,060	0.94061	2.75	−0.03	0.09	0.41	0.41	−0.19	0.02
PL	28,956	1.39764	2.75	−0.02	−0.32	0.04	0.04	−0.20	−0.03
PT	10,319	0.70198	2	0.06	−0.07	0.15	0.15	−0.28	−0.10
SE	83,880	0.69879	2	0.02	0.01	0.08	0.08	−0.19	−0.06
TR	74,946	0.57264	1	−0.05	−0.16	−0.57	−0.57	−0.06	−0.01
ZA	24,918	0.49736	2	0.07	−0.44	−0.05	−0.05	−0.30	−0.11

TABLE 12 Pan-European cross-market holiday model (selected trading and holiday countries exhibited)

Predictor	Coefficient	Predictor	Coefficient	Predictor	Coefficient	Predictor	Coefficient
intercept	0.04	trading_GR	0.04	holiday_AT	−0.04	holiday_HU	−0.09
trading_AT	−0.01	trading_HU	−0.06	holiday_BE	−0.04	holiday_IE	−0.03
trading_BE	−0.03	trading_IE	−0.07	holiday_CH	−0.09	holiday_IT	−0.23
trading_CH	−0.01	trading_IT	−0.01	holiday_CZ	−0.10	holiday_NL	0.22
trading_CZ	−0.04	trading_NL	−0.02	holiday_DE	−0.28	holiday_NO	−0.16
trading_DE	−0.01	trading_NO	0.00	holiday_DK	−0.06	holiday_PL	−0.04
trading_DK	0.01	trading_PL	0.00	holiday_ES	−0.03	holiday_PT	0.03
trading_ES	−0.02	trading_PT	−0.03	holiday_FI	0.04	holiday_SE	−0.03
trading_FI	0.01	trading_SE	0.00	holiday_FR	0.51	holiday_TR	−0.02
trading_FR	−0.01	trading_TR	0.11	holiday_GB	−0.26	holiday_US	−0.21
trading_GB	0.00	trading_ZA	−0.03	holiday_GR	−0.02	holiday_ZA	0.00

U.K. holidays typically fall on a Monday. The randomization test indicated that the volumes on Monday cross-market holidays are significantly lower than the volumes on regular Mondays, with no cross-market holidays. Therefore, we argue that the cross-market holidays are the main driver of lower Monday volumes and we dispute the role of the weekend effect with regard to lower Monday volumes.

The countries with the highest susceptibility to the cross-market holiday effect are Belgium, Spain, France, Hungary, the Netherlands, Portugal, and South Africa, as indicated by the relatively high negative coefficients in Table 11.

The trading *country code* coefficients of the pan-European model are low, close to zero. However, the holiday *country code* predictors, such as Germany, the United Kingdom, Italy, and the United States, exert a strong impact on the trading activity. There are a couple of unexplained positive coefficients for holiday countries such as France and the Netherlands.

Figure 7 shows the distribution of relative volume for the two holiday countries whose coefficients are positive (i.e., France and the Netherlands) and for two other countries (i.e., the United Kingdom and the United States) exerting a clear subduing effect on the other pan-European trading countries, along with the distribution of all the pan-European stocks' relative volume on any cross-market holiday. The relative volumes on French and Dutch holidays are still slightly positively skewed, and we cannot conclude that these countries have a positive impact on the other markets' trading volume.

6.4.2 | Holiday breakdown models

The holiday breakdown models present a set of salient holidays that tend to generally drive the regional trading volume lower. There are two models fit for this model class: the country-specific model, whose results are shown in Table 13 for the regional/global holidays and in Table 14 for the significant country-specific holidays, and the pan-European model, outlined in Table 15 for the regional/global holidays and in Table 16 for the country-specific holidays. These tables contain a small subset of relevant holidays (out of the 95 normalized holidays), excluding other features, such as the lagged normalized volumes.

The May 1st bank holiday is observed in most of Europe's markets, and it is very salient in the few countries that are trading on May 1st: Denmark (−0.65), the United Kingdom (−0.37), Ireland (−1.03), the Netherlands (−0.33), and Turkey (−0.26). Turkey is the only country trading on the Christmas Day (−0.23) and Boxing Day (−0.16), and therefore, these Christian holidays drive the volume lower as the rest of Europe is not trading. Similarly, the Catholic Easter holidays (i.e., Good Friday and Easter Monday) have a strong impact in Greece and Turkey. Hungary experiences low volumes caused by Good Friday only. The New Year's Eve has a strong effect (with coefficients close to −1) in Belgium, Czech Republic, Spain, France, the United Kingdom, Greece, Ireland, the Netherlands, and South Africa.

The Early May Bank Holiday is observed in the United Kingdom and Ireland, where this bank holiday substitutes the generally observed May 1st across the other European countries. Therefore, the Early May Bank Holiday, along with other country-specific holidays from the United Kingdom, Germany, France, and the United States, have a generally strong negative impact on the other European markets. These holidays include one-off holidays (i.e., single occurrence bank holidays issued by the governments for certain reasons), for example, the Queen's Diamond Jubilee.

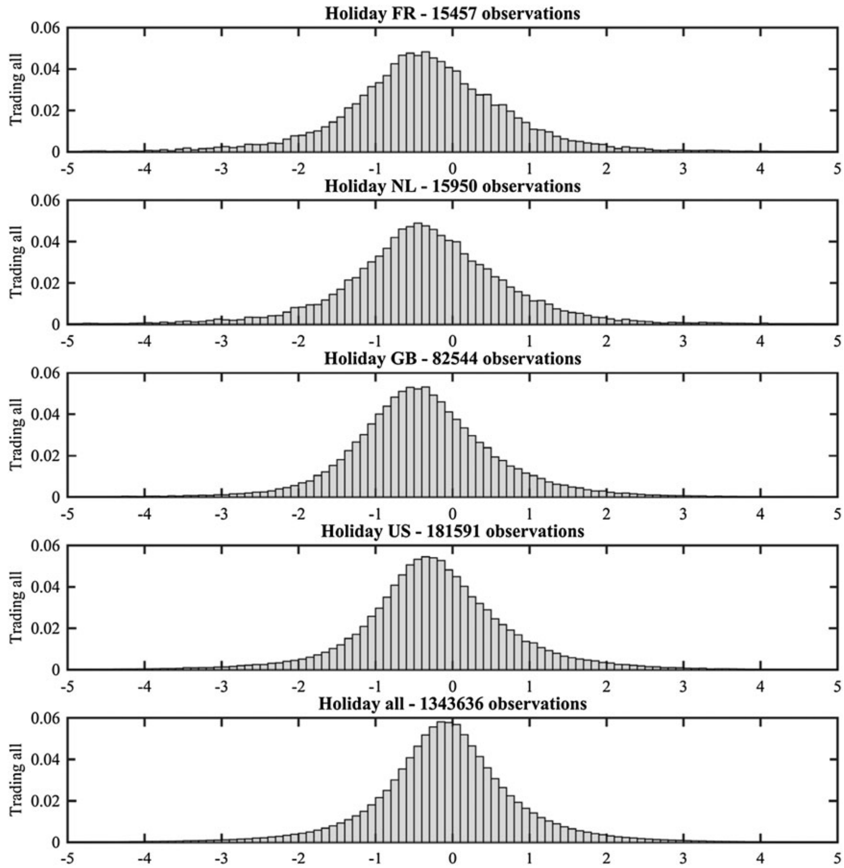

FIGURE 7 Relative volume distribution for the pan-European stocks trading on cross-market holidays occurring in France, the Netherlands, the United Kingdom, the United States, and, eventually, in any country

Some countries exhibit incredibly low volumes associated with the Christmas Eve, which is certainly caused by the fact that most of the trading markets on the Christmas Eve have a half-trading day schedule and therefore the volume is significantly lower. These countries include Belgium (−1.52), Spain (−1.40), the United Kingdom (−1.92), Ireland (−3.26), the Netherlands (−1.80), Poland (−2.29), Portugal (−1.70), and South Africa (−1.95).

Table 15 shows the significant regional/global holidays for the pan-European model, which has 1,343,636 observations, CV MSE 0.93182, and shrinkage parameter 2 (log-space). The "trading *countryCode*" coefficients are very low (close to zero). Some notable regional/global cross-market holidays include Boxing Day (both the main day and the additional day), Christmas Day, Good Friday, Easter Monday, May 1st, New Year's Eve (both the main day and the additional day), Christmas Eve, Whit Monday, Ascension Day, Assumption of Mary, All Saints' Day, and the additional day for the New Year's Day. The additional days are issued by certain countries, especially as "bridge holidays" (i.e., when the main holiday falls on a Thursday or on a Tuesday, and the governments transform the in-between Friday or Monday into a bank holiday in order to have a 4-day break, including the weekend).

Table 16 shows country-specific holidays that exhibit a strong impact to the pan-European trading volume. Unlike the regional/global holidays outlined in Table 15 , which are usually bank holidays in most of the European countries, the magnitude of the country-specific holidays is incredibly high because these are official bank holidays in only one or two countries, whereas the other markets are trading on these days. Important country-specific holidays are identified mainly from the United Kingdom (e.g., Early May Bank Holiday, Spring Bank Holiday, or Summer Bank Holiday) and the United States (e.g., Memorial Day, Independence Day, Labor Day, or Presidents Day), including some one-off holidays with conspicuous effects on the trading volume, for example, Golden Jubilee, Diamond Jubilee, Royal Wedding, Hurricane Sandy, and National Day of Mourning for President Ronald Reagan.

6.5 | Volume autoregression

All of these models are fit with and without 20 lagged normalized volumes in order to determine whether the volume autoregression is improving the volume prediction. Strong volume autoregression is observed across the model variants. Fitting the models with 20 lagged normalized volumes considerably outperforms the models without lagged volumes. The lower MSE achieved by the models trained with lagged volume is outlined in Table 17, where we show the cross-validation MSE for

TABLE 13 Country-specific holiday breakdown model—Selected regional/global holiday features

Country	Observations	CV MSE	Log shrinkage parameter	Intercept	New Year's Day	Boxing Day	Christmas Day	Good Friday	Easter Monday	May 1st	New Year's Eve	Country susceptibility
AT	16,746	0.67	2.94434	−0.03	−0.13	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.03
BE	39,984	0.67	1.91064	0.11	−0.19	−0.02	−0.02	−0.02	−0.02	−0.02	−0.97	−0.21
CH	62,070	0.59	2.00000	0.08	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.15
CZ	2,629	0.78	2.84717	−0.15	0.10	−0.01	−0.01	−0.52	−0.01	−0.01	−1.17	−0.02
DE	102,500	0.57	2.00000	0.08	−0.15	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.13
DK	25,861	0.68	2.00000	0.06	0.09	0.00	0.00	0.00	0.00	−0.65	0.00	−0.08
ES	34,052	0.32	1.93750	0.08	−0.33	−0.01	−0.01	−0.01	−0.01	−0.01	−0.75	−0.16
FI	70,830	1.32	2.95752	0.01	−0.11	0.00	0.00	0.00	0.00	0.00	0.00	−0.04
FR	219,181	1.31	2.00000	0.09	−0.11	−0.02	−0.02	−0.02	−0.02	−0.02	−0.81	−0.17
GB	364,239	1.06	2.00000	0.05	−0.01	−0.01	−0.01	−0.01	−0.01	−0.37	−1.27	−0.12
GR	36,762	0.90	2.00000	0.10	−0.25	−0.01	−0.01	−0.25	−0.49	−0.01	−0.56	−0.12
HU	2,743	0.41	2.00000	−0.06	0.14	−0.01	−0.01	−1.90	−0.01	−0.01	−0.34	−0.06
IE	18,619	1.96	2.75000	−0.08	−0.02	−0.02	−0.02	−0.02	−0.02	−1.03	−1.34	−0.10
IT	62,361	0.37	2.00000	0.04	−0.17	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.11
NL	30,980	0.38	2.00000	0.06	0.05	−0.03	−0.03	−0.03	−0.03	−0.33	−1.10	−0.14
NO	31,060	0.93	2.87500	0.00	−0.15	0.00	0.00	0.00	0.00	0.00	0.00	−0.06
PL	28,956	1.38	2.99561	−0.03	−0.15	−0.01	−0.01	−0.01	−0.01	−0.01	−0.20	−0.07
PT	10,319	0.69	2.50000	−0.06	−0.18	−0.01	−0.01	−0.01	−0.01	−0.01	−0.43	−0.06
SE	83,880	0.68	2.50000	0.01	−0.07	0.00	0.00	0.00	0.00	0.00	0.00	−0.06
TR	74,946	0.55	2.00000	0.04	1.64	−0.16	−0.23	−0.30	−0.20	−0.26	−0.16	−0.06
ZA	24,918	0.47	2.00000	0.00	−0.39	−0.01	−0.01	−0.01	−0.01	−0.01	−1.20	−0.11

TABLE 14 Country-specific holiday breakdown model—Selected country-specific holiday features

Country	GB Spring Bank Holiday, US Memorial Day	GB IE Early May Bank Holiday	DE Day of German Unity	FR Bastille Day	GB Summer Bank Holiday	GB The Queen's Diamond Jubilee	US Independence Day	US Labor Day	US Martin Luther King Day	US Presidents Day/Washington's Birthday
AT	−0.41	−0.21	−0.10	−0.36	−0.28	−0.44	−0.25	−0.21	−0.17	−0.20
BE	−0.47	−0.29	−0.12	−0.23	−0.39	−0.28	−0.46	−0.23	−0.17	−0.31
CH	−0.62	−0.37	−0.19	0.17	−0.46	−0.19	−0.37	−0.33	−0.09	−0.40
CZ	−0.32	0.05	0.33	−0.01	−0.35	−0.05	−0.02	−0.25	0.11	−0.14
DE	−0.55	−0.30	−0.01	−0.02	−0.49	−0.20	−0.38	−0.31	−0.20	−0.32
DK	−0.54	−0.18	0.19	0.04	−0.34	0.00	−0.39	−0.24	−0.21	−0.38
ES	−0.56	−0.39	−0.09	−0.15	−0.53	−0.29	−0.40	−0.29	−0.27	−0.36
FI	−0.40	−0.17	−0.17	0.22	−0.30	−0.26	−0.45	−0.11	−0.16	−0.22
FR	−0.39	−0.24	−0.21	−0.02	−0.27	−0.29	−0.39	−0.02	−0.03	−0.27
GB	−0.20	−0.01	−0.05	0.03	−0.01	−0.01	−0.33	−0.28	−0.11	−0.36
GR	−0.31	−0.09	−0.29	−0.05	−0.22	0.13	−0.40	−0.23	−0.07	−0.35
HU	−0.66	−0.25	−0.32	−0.28	−0.65	0.04	−0.47	−0.30	−0.59	−0.46
IE	−1.20	−0.02	0.01	−0.25	−1.00	−0.75	−0.20	−0.26	−0.07	−0.29
IT	−0.42	−0.25	−0.20	0.08	−0.38	−0.40	−0.36	−0.19	−0.11	−0.22
NL	−0.74	−0.40	−0.06	−0.06	−0.54	−0.42	−0.51	−0.32	−0.23	−0.37
NO	−0.52	−0.22	−0.12	0.38	−0.34	−0.26	−0.38	−0.15	−0.14	−0.29
PL	−0.30	−0.12	−0.45	−0.31	−0.32	−0.30	−0.24	−0.21	−0.10	−0.18
PT	−0.37	−0.29	−0.08	0.40	−0.36	−0.29	−0.27	−0.12	−0.04	−0.27
SE	−0.47	−0.14	−0.02	0.09	−0.26	−0.47	−0.37	−0.18	−0.13	−0.16
TR	−0.17	−0.16	−0.68	−0.68	−0.32	0.29	−0.12	−0.23	−0.12	−0.02
ZA	−0.56	−0.37	−0.15	−0.29	−0.55	−0.29	−0.42	−0.35	−0.06	−0.35

TABLE 15 Pan-European cross-market holiday breakdown model—Full candidate feature set (selected regional/global holiday features exhibited)

Holiday	Coefficient	Holiday	Coefficient
Boxing Day	−0.33	Whit Monday	−0.39
Christmas Day	−0.42	Ascension Day	−0.43
Good Friday	−0.42	Assumption of Mary	−0.26
Easter Monday	−0.34	All Saints' Day	−0.22
May 1st	−0.37	Boxing Day (Additional Day)	−0.40
New Year's Eve	−0.94	New Year's Day (Additional Day)	−0.21
Christmas Eve	−1.51	New Year's Eve (Additional Day)	−0.43

TABLE 16 Pan-European cross-market holiday breakdown model—Significant country-specific holidays extracted from the full candidate feature set

Holiday	Coefficient	Holiday	Coefficient
(GB, US) Spring Bank Holiday, Memorial Day	−0.45	(PL) Poland Independence Day	−0.23
(GB, IE) Early May Bank Holiday	−0.24	(PT) Portugal Day	−0.27
(DE) Day of German Unity	−0.17	(US) Independence Day	−0.36
(GB) Golden Jubilee Bank Holiday	−0.33	(US) Labor Day	−0.22
(GB) Royal Wedding Bank Holiday	−0.21	(US) Markets Closed (Hurricane Sandy)	−0.24
(GB) Summer Bank Holiday	−0.38	(US) National Day of Mourning for President Ronald Reagan	−0.33
(GB) The Queen's Diamond Jubilee	−0.25	(US) Presidents Day (Washington's Birthday)	−0.29

TABLE 17 Pan-European models—Comparison of the presence and absence of the lagged volumes

Model	Lagged volumes	Observations	CV MSE	Shrinkage parameter (in logarithmic space)
Pan-European holiday country	Yes	1,343,636	0.94049	2.96386
	No	1,343,636	1.04997	3
Pan-European holiday breakdown	Yes	1,343,636	0.93182	2
	No	1,343,636	1.03797	2

Note. MSE: mean squared error.

the two pan-European models, fit with and without lagged volumes. These one-step ahead models are fit for the entire sample period of the study.

6.6 | Market capitalization

The holiday country models provide a market capitalization variant, where we further investigate a potential relationship between the cross-market holiday effect and the market capitalization of the stocks. Using only the constituents of the FTSE, DAX, and CAC market capitalization-stratified indices, we can discriminate between small-, mid-, and large-cap stocks.

Figure 8 illustrates the relative trading volume for the three capitalization indices in each column panel: the United Kingdom's FTSE in (a), Germany's DAX in (b), and France's CAC in (c). Each of the rows corresponds to a market capitalization class, with large-cap in the top row, mid-cap in the middle row, and small-cap in the bottom row.

The cross-market holiday models have been enhanced with three indicator variables for the market capitalization class. The country-specific and pan-European models constantly underperform when the market capitalization is included. For example, consider the two variants of the pan-European holiday country model in Table 18. The CV MSE grows from 1.05 to 1.22 when the market capitalization indicator variables are added to the model, and only the market capitalization-stratified observations are considered. The coefficients for the small-/mid-/large-cap indicator variables are provided for the three countries, along with the cross-market holiday effect

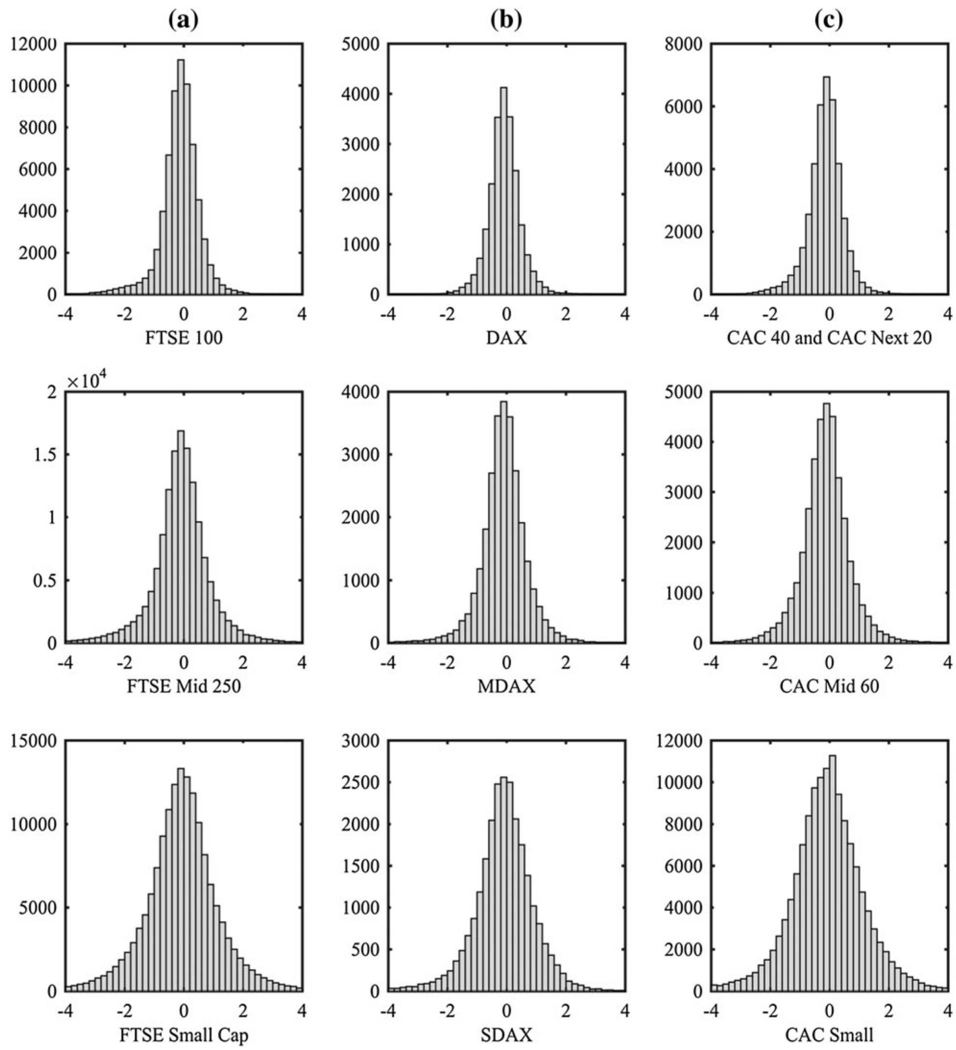

FIGURE 8 Relative volume distribution for the individual market capitalization-stratified stocks. (a) GB; (b) DE; and (c) FR

TABLE 18 Country-specific cross-market holiday model with market capitalization—Reduced feature set (selected market capitalization features exhibited)

Model	Country	Market cap indicators	Observations	CV MSE	Small-cap coefficient	Mid-cap coefficient	Large-cap coefficient	Index susceptibility
Pan-European holiday country	—	No	1,343,636	1.04997	—	—	—	—
	—	Yes	650,957	1.22052	0.00431	0.00172	−0.00916	—
Country-specific holiday country	United Kingdom	Yes	361,510	1.15396	0.01452	0.00051	−0.02464	−0.04966
	Germany	Yes	74,679	0.63508	−0.01422	−0.00379	0.01947	−0.13188
	France	Yes	214,768	1.51558	−0.00698	0.01075	0.00047	−0.10024

Note. MSE: mean squared error.

susceptibility for FTSE, DAX, and CAC. FTSE is the less susceptible index among these.

6.7 | Multistep ahead prediction

Besides the default one-step ahead models introduced so far (i.e., $n = 1$), additional n-step ahead analyses are conducted for step sizes ranging from 2 to 6 days for a subset of models, based on the findings from the one-step ahead models, that is, the model variations whose CV MSE is minimal. The motivation for a multistep ahead prediction stems from the real-world scenario where traders could plan their portfolios by predicting a cross-market holiday effect on a stock's trading volume given

TABLE 19 Comparison of MSE between the one-step ahead model and multistep ahead models

Model	Observations	Cross-validation MSE 1-step ahead	2-step ahead	3-step ahead	4-step ahead	5-step ahead	6-step ahead
Pan-European holiday country	1,343,636	0.94049	1.00390	1.03766	1.06146	1.07983	1.09700
Pan-European holiday breakdown	1,343,636	0.93182	0.99275	1.02501	1.04818	1.06608	1.08266

Note. MSE: mean squared error.

its exchange country. If we want to predict a cross-market holiday effect n days in advance, then we compute the median of the benchmark volumes between $(t - n)$ and $(t - 20 - n)$ and compare it against the volume on the cross-market holiday (i.e., V_0) in order to train the model.

The models exhibit a constant trend of increasing the MSE between the one-step ahead model and the multi-step ahead models, where the largest step becomes 6 days (i.e., six-step ahead model). However, the models and their coefficients perform rather similarly. The cross-validation MSE is directly proportional with the step ahead size, as outlined in Table 19. The error increases progressively once the step size is increased due to the lack of more recent data.

7 | DISCUSSION

This study investigates the anecdotal evidence of lower volumes associated with external markets not trading. This phenomenon was described as the "cross-market holiday effect" in this study, where we examine it in the European equity markets using a comprehensive pan-European stock universe. It is the first study to investigate the cross-market holiday effect within Europe, and it probably has the largest data set employed by any study on the European equity markets and the most accurate European and U.S. trading calendar spanning almost 16 years. As far as we are aware, there are only two studies on the cross-market holiday effect (Casado et al., 2013; Cheung & Kwan, 1992), despite its popularity among finance professionals. The study proposes a novel methodology, consisting of ridge regression applied to finance time series. This is complemented by the initial randomization tests, which provide rigour to our investigation of the phenomenon existence.

Throughout the in-sample analyses, we report compelling evidence of volume autoregression. The empirical results strongly support the existence of a negative cross-market holiday effect in the European markets. The relative trading volume is significantly lower on cross-market holidays. On average, the volume is reduced by 8.5% compared with the volume of the benchmark period. We investigated whether these results are caused by the fact that most of the holidays fall on a Monday in the United Kingdom (i.e., Europe's largest market) and it could possibly be the Monday effect driving down the volumes. The results of the randomization test confirm that the lower trading activity is associated with the cross-market holidays. We do not debate whether the Monday effect itself exists (observed as a day-of-the-week effect and not as a Monday bank holiday effect), but we provide evidence that this study's lower volumes on Mondays having at least one regional cross-market holiday are caused by the cross-market holidays. This provides a recommendation for other researchers to take this study further and investigate the Monday effect on the European liquidity.

Based on the precise trading calendar of this study for the European countries and the United States, we observe some strong country susceptibility levels for a few countries (e.g., Belgium, Spain, France, Hungary, the Netherlands, Portugal, and South Africa). There are strong cross-market holiday effects originating from large markets (e.g., the United States, the United Kingdom, Germany, or Italy), which tend to have a salient effect (in the form of negative coefficients, meaning a subduing effect on the trading volume) across all the other countries, although French holidays exhibit a reverse pan-European cross-market holiday effect, resulting in a regional trading volume increase. Our findings corroborate the results of Casado et al. (2013). We believe that the significantly lower volumes observed when other large markets are shut down are evidence of the contagion between different markets, where liquidity and information can be transmitted across international markets. Potential causes of this cross-market holiday effect include the reduction in news output and lack of public information originating from large markets (in the form of macroeconomic news and stock market data), the absence of institutional investors originating from the closed markets, the reduction in investor disagreement as a result of lower information volume, and the increase in the ratio of noise traders to sophisticated traders caused by the absence of traders from large markets. A common consequence of lower trading volumes is the increase in price movements because it is easier for the prices to move more quickly than when the volume is higher.

The study presents a number of interesting holidays that exert a strong influence on the liquidity of the European markets. After normalizing the U.S. and the pan-European trading calendar, we find that certain periodic (e.g., New Year's Eve, Christmas Day, Boxing Day, May 1st, Easter Monday, and Good Friday) and non-periodic (e.g., the United Kingdom's Golden Jubilee, the Queen's Diamond Jubilee, and the Royal Wedding) bank holidays have a blatant effect on volumes. Strong lower volumes are observed on May 1st in Denmark, the United Kingdom, Ireland, the Netherlands, and Turkey. The Christmas holidays (i.e., Christmas Day and Boxing Day) have a significant impact on the Turkey market, when the rest of Europe is not trading. Similarly, catholic Easter holidays (i.e., Good Friday and Easter Monday) cause a volume drop in Greece and Turkey. The most noticeable holidays that are subduing the trading volume in the pan-European markets originate from the United Kingdom (e.g., Early May Bank Holiday, Spring Bank Holiday, or Summer Bank Holiday), followed by the United States (e.g., Memorial Day, Independence Day, Labor Day, or Presidents Day), whose holidays have a slightly lower intensity on the European volume than the United Kingdom. A few other country-specific holidays are reported to affect the volume, for example, Day of German Unity, Poland Independence Day, and Portugal Day.

The model accounts for a potentially differentiated effect by market capitalization, but the cross-market holiday effect persists across small-, mid-, and large-cap stocks. We also find a structural break around the financial crisis of 2007–2008 for the market capitalization-based impact of cross-market holidays, where the effect reversed for a couple of indices.

This prediction can also be made in advance of the cross-market holidays using multistep ahead forecasting, based on a stock's past volumes and the volume levels during the previous cross-market holidays originating from the same country. Having an accurate trading calendar and anticipating a cross-market holiday could predict the trading volume in the run-up to the cross-market holiday. The findings of this study propose a framework for traders and hedge fund managers for planning their portfolios in advance, in order to predict their positions and profits during the cross-market holidays by knowing how much more or less the trading volumes are expected to be.

ACKNOWLEDGEMENT

This research has been funded by the Engineering and Physical Sciences Research Council (EPSRC) UK.

ORCID

Bogdan Batrinca http://orcid.org/0000-0002-5281-0457
Christian W. Hesse http://orcid.org/0000-0003-4719-2153
Philip C. Treleaven http://orcid.org/0000-0001-8803-8297

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How to cite this article: Batrinca B, Hesse CW, Treleaven PC. European trading volumes on cross-market holidays. *Int J Fin Econ*. 2018;23:675–704. https://doi.org/10.1002/ijfe.1643