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Highlights

- A new approach to test for financial contagion
- It accounts for the existence of day-of-the-week effects in return spillovers and contagion
- We analyse contagion from the US to European countries during the 2007-9 crisis
- Contagion varies across weekdays and countries

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Day-Of-The-Week Effects in Financial Contagion

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Abstract

We propose a new approach to test for financial contagion, which accounts for the existence of day-of-the-week effects in stock returns. For a set of European markets, we provide evidence that contagion effects from the U.S. during the 2007-9 financial crisis varied across days of the week.

Keywords: Financial contagion; day-of-the-week effect; financial crisis.

JEL Classification: F30, G15

1 Introduction

Methods to empirically identify financial contagion between stock markets have been developing independently of the burgeoning literature on the behavioural forces behind anomalies such as the day-of-the-week effect. This paper seeks to bring together these previously disparate strands of the finance literature to provide a more accurate empirical identification strategy for financial contagion where day-of-the-week effects prevail.

With regards to these strands of the literature, there exist a wealth of studies into causes, channels, and implications of financial contagion across markets (see Forbes, 2012, for a review). Despite disagreement on what constitutes contagion,¹ most authors currently apply the definition proposed by Forbes and Rigobon (2001), whereby contagion arises with a significant increase in comovements between stock markets following a shock to one of them. This is usually operationalised by estimating models which employ daily or weekly (e.g., Baur, 2012) returns data and which assume identical comovements across weekdays. The literature employs diverse empirical methods to test for the existence of contagion, including conditional probabilities (e.g., Eichengreen, et al., 1996, Hartmann, et al., 2004),

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¹ The World Bank (2016) operates with three different definitions of financial contagion, for instance. Further, Pericoli and Sbracia (2003) review the relevant literature and pinpoint five definitions of contagion, whereas Forbes (2012) identifies eleven distinctive definitions of contagion.

correlation coefficients (e.g., Brière et al., 2012, Forbes and Rigobon, 2001, Kim et al., 2015, King and Wadhvani, 1990, Sohel Azad et al., 2015, Støve et al., 2014, Wang et al., 2017), single regression and VAR-based approaches (e.g., Baur and Schulze, 2005, Blatt et al., 2015, Climent and Meneu, 2003, Rigobon, 2003, Samarakoon, 2017), multivariate GARCH models (e.g., Bonga-Bonga, 2018, Dungey et al., 2015, Hamao et al., 1990, Mollah et al., 2016), copulas (e.g., Jayech, 2016, Philippas and Siriopoulos, 2013, Rodriguez, 2007), quantile regressions (e.g., Baur and Schulze, 2005, Caporin et al., 2018, Ye et al., 2017), and other approaches² The overwhelming majority of studies in this area report empirical evidence broadly in support of the hypothesis that contagious spillovers between markets exist, for a variety of crisis episodes, countries, data frequencies, etc. (with Forbes and Rigobon, 2002, who argue against the prevalent existence of contagion, being one of the few and maybe the most prominent exception). The common methodological feature of these approaches is that they assume a constant level of comovements between markets across the days of the week, and hence ignore potential weekday effects in return spillovers and contagion.

For the other strand of the literature, the number of studies that have been devoted to calendar effects in stock returns (see Dzhavarov and Ziemba, 2010, for a review) is legion. One of the earliest and most prominent phenomena is the Monday effect, whereby returns on Mondays were found to be significantly lower than on other weekdays. Subsequent studies demonstrated systematic effects for other weekdays, most notably Fridays, while others have suggested that the Monday effect has either disappeared, reversed or migrated to other weekdays (see Pettengill, 2003, for a literature survey).

² For instance, Bae, et al. (2003) propose a new measure of coexceedance based on the extreme value theory, Jin (2016) employs the Hurst exponent approach, Berger (2015) proposed a Wavelet-based approach, Mandilaras and Bird (2010) use a Markov-switching analysis of contagion, and Glasserman and Young (2015) analyse contagion using a network modelling approach.

In this paper, we propose a model of contagion which accounts for day-of-the-week effects. We postulate that any conclusions on the existence and severity of financial contagion derived in the existing literature may be misleading or incomplete, as current testing approaches fail to account for the existence of weekday effects in return spillovers. Firstly, if contagion occurs only on specific weekdays, any approach treating all weekdays equally may fail to identify those contagious but infrequent days. Additionally, even if we do detect contagion by treating all weekdays as identical, a model which accounts for day-of-the-week effects in contagion, as proposed here, will generate a fuller picture of when exactly the contagion risk is most severe.

Why would one assume that spillovers and contagion can differ across weekdays? And could these weekday effects in spillovers, and contagion, vary across countries? We posit that factors leading to the day-of-the-week effect in returns can also lead to uneven occurrences of contagion across weekdays and countries, as they either generate weekday patterns in the sign and strength of shocks transmitted abroad, or in the susceptibility of markets to return spillovers from abroad. For instance, short-sellers have been argued to cause the weekend effect (Chen and Singal, 2003). To the extent that these short-selling transactions are executed by foreign investors, the flow of information across borders they facilitate (i.e., spillovers) should also be expected to display seasonal, weekday patterns. In addition, the differences in intensity of short-selling activities in different economies (e.g. due to local restrictions on short-selling during the crisis) would be expected to result in differences of how countries generate spillovers and are susceptible to spillovers and contagious shocks originating abroad.³

³ Indeed, studies such as Beber and Pagano (2013) document cross-country differences in short-selling restrictions introduced in the wake of the 2007-9 financial crisis, in terms of their timing, stringency, and assets affected. Jain et al. (2013) demonstrate that national short-selling restrictions can affect trading patterns not only in domestic but also in foreign markets.

Another potential reason for weekday effects in returns cited in the literature is the ‘blue Monday’ effect (Rystrom and Benson, 1989), whereby investors are exposed to more bad news over weekends and their subdued sentiment leads to stronger selling pressure and depressed prices on Mondays. One would expect that markets’ sensitivity to news originating abroad, i.e., spillovers, will vary in their intensity as foreign news will interact with the domestic blue Monday effect of varying intensity, depending on the country considered. Equally, even in absence of the domestic blue Monday effect, a market could exhibit lower Monday returns imported from abroad, via spillovers, where that effect is pronounced. In addition, we would expect a strengthening of the blue Monday effect following the crisis outbreak, possibly combined with an increase in the number of negative news releases during the crisis, and the surge in the number of investors taking a short view due to liquidity needs during the 2007-9 financial turmoil period. Hence, weekday seasonality in spillovers would have changed following the crisis outbreak.

Moreover, announcements of macro-economic data take place on different weekdays in different countries, and those announcements have been documented to affect asset prices (e.g., Birz and Lott Jr, 2011, Flannery and Protopapadakis, 2002), generating stronger price movements on announcements days. Again, we hypothesize that news originating abroad will interact with those domestic announcement effects, the latter being of various intensity across countries. Hence, we could observe country-specific weekday effects in return spillovers and contagion. Equally, even in absence of domestic announcement effects these could be carried over from an important foreign market in form of spillovers being more intensive on foreign announcement days.

Interestingly, the literature does recognise that spillovers and contagion may be stronger for negative or positive return shocks (e.g., Bae, et al., 2003); we argue that there can

be weekday-related patterns to these shocks, resulting in weekday effects in spillovers and contagion.

The remainder of this paper is organised as follows: Section 2 presents our data and the methodology to identify day-of-the-week effects in financial contagion, Section 3 discusses empirical results, and Section 4 concludes.

2 Data and methodological framework

We employ stock market index data from eleven European countries (Austria, Denmark, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, Switzerland, the U.K.) and the U.S. Daily index values, denominated in local currencies,⁴ constitute a synchronized dataset of 16:00GMT market prices, and are obtained from DataStream for the period from 29th July 2004 until 27th March 2009: the start of the sample is consistent with the tightening in the U.S. monetary policy and its end corresponds to the end-date of the financial crisis as in Baur (2012). Our sample is also divided into pre-crisis and crisis sub-periods, delineated by the start of the crisis period on 6th August 2007 as determined in Baur, 2012.

Our baseline contagion model does not differentiate among days of the week. It allows for testing for contagion effects from the U.S. to European equity markets and operationalises the Forbes and Rigobon, (2001) definition of shift-contagion as a significant increase in comovements between markets following a shock to one market (the U.S. in our study):

$$R_{i,t} = \alpha_i + \alpha_i^* D_c + \beta_i R_{US,t} + \beta_i^* R_{US,t} D_c + \varepsilon_{i,t} . \quad (1)$$

$R_{i,t}$ represents stock returns of European country i , in this case daily returns, and $R_{US,t}$ represents returns of the U.S. market, both in local currencies at contemporaneous time t . D_c is the crisis dummy equal to one during the crisis period and zero pre-crisis. α_i is the

⁴ The Euro for all countries except for Denmark (Krona), Switzerland (Franc), and the UK (Pound).

constant term and β_i captures spillovers from the U.S. to country i pre-crisis. Contagion during the crisis period is identified by β_i^* being significantly positive.

One of the drawbacks of approaches represented by (1) is that they average out spillover and contagion effects across the days of the week. Accordingly, models such as (1) may not detect contagion if there is an increase in spillovers only during particular days of the week but this is offset by a decline during other days of the week, hence potentially concealing the day-specific contagion effect. Another issue arises when (1) shows evidence of contagion during the crisis period (therefore, necessarily, existence of contagion across all days of the week, on average), but where in reality contagion only occurs on particular days of the week, a phenomenon which would remain undetected when using (1).

Our innovation consists of allowing those spillovers and therefore potential contagious effects to differ across days of the week. In our model, both the day-of-the-week effects and spillover effects are combined:

$$R_{i,t} = \alpha_i + \alpha_{i,DOW} D_{DOW} + \beta_i R_{US,t} + \beta_{i,DOW} D_{DOW} R_{US,t} + \left(\alpha_i^* + \alpha_{i,DOW}^* D_{DOW} + \beta_i^* R_{US,t} + \beta_{i,DOW}^* D_{DOW} R_{US,t} \right) D_c + \varepsilon_{i,t} \quad (2)$$

$R_{i,t}$, $R_{US,t}$ and D_c are defined as previously. α_i denotes the intercept on Mondays and $\alpha_{i,DOW}$ is a vector of intercepts for remaining days of the week, relative to Mondays ($\alpha_{i,DOW} = (\alpha_{i,Tu}, \alpha_{i,We}, \alpha_{i,Th}, \alpha_{i,Fr})$), and analogously for $\alpha_{i,DOW}^*$, $\beta_{i,DOW}$, and $\beta_{i,DOW}^*$. D_{DOW} is a column vector of dummy variables ($D_{DOW} = (D_{Tu}, D_{We}, D_{Th}, D_{Fr})'$) which each take the value of one on their specific day of the week and zero otherwise. Parameters with asterisks indicate effects additionally observed during crisis, as compared to pre-crisis, period.

In (2), the parameter β_i captures pre-crisis spillovers from the U.S. to country i on Mondays, as $D_{DOW} = 0$ for Mondays and $D_c = 0$ pre-crisis. Monday spillovers during the crisis ($D_c = 1$) are measured by $(\beta_i + \beta_i^*)$. Hence, contagion on Mondays, defined as an increase in spillovers, would be captured by β_i^* being significantly positive. Next, denote

$\beta_{i,WD} = \{\beta_{i,Tu}, \beta_{i,We}, \beta_{i,Th}, \beta_{i,Fr}\}$. For Tuesdays to Fridays, spillovers pre-crisis are captured by $(\beta_i + \beta_{i,WD})$, as $D_{DOW} = 1$ for non-Mondays (for example, on Tuesdays, the average spillovers pre-crisis are denoted by $(\beta_i + \beta_{i,Tu})$). During the crisis, non-Monday spillovers are measured by $(\beta_i + \beta_{i,WD} + \beta_i^* + \beta_{i,WD}^*)$, hence contagion on non-Mondays will be identified if non-Monday spillovers are significantly higher during the crisis than pre-crisis, i.e., $(\beta_i^* + \beta_{i,WD}^*) > 0$.

This leads us to the main focus of this paper: we will define the day-of-the-week effect in *contagion* (i.e., contagion during the crisis period differs significantly across weekdays) if either there was contagion on Mondays ($\beta_i^* > 0$) and spillovers changed significantly on any remaining weekday ($\beta_{i,WD}^* \neq 0$), or there was no contagion on Mondays ($\beta_i^* \leq 0$) but spillovers changed significantly on any remaining weekday such that the resulting non-Monday effect ($\beta_i^* + \beta_{i,WD}^*$) is significantly positive (positivity assures existence of contagion on a non-Monday).

3 Empirical Results

Tests for stationarity (unreported to conserve space) indicate that all (natural) log indices are non-stationary but logarithmic returns, calculated as the difference of the log indices, are stationary. Further, we find no evidence of cointegration between the log indices of the U.S. and each European market. As the estimated residuals from models (1) and (2) show evidence of heteroscedasticity, we model their conditional heteroskedasticity by employing the Glosten, et al., 1993, or GJR, variant of the GARCH(1,1) model, as it also captures asymmetries in volatility resulting from positive versus negative shocks (OLS estimates might yield inefficient inference, as demonstrated in Hamilton, 2010)). Further, due to non-normality of residuals, we model them as following a t -distribution (GED specification is also considered but yields inferior empirical fit), and the residuals are tested for autocorrelation: in

cases where it is found, the errors are modelled as an ARMA process of an appropriate order. Lastly, we test whether using a GJR-GARCH specification fully captures the ARCH effects in residuals by applying Engle's LM ARCH test to the resulting standardised residuals. This test finds no remaining ARCH effects.

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Table 1. Estimation results

	Austria	Denmark	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain	Switzerland	UK
Panel A: Estimates of selected parameters from model (1)											
β_i	.75046*** (16.35)	0.02657 (1.50)	.97535*** (33.74)	1.0651*** (35.92)	.66186*** (18.37)	.77138*** (27.14)	.88473*** (34.20)	.32647*** (12.17)	.8029*** (29.38)	.74924*** (25.83)	.62688*** (22.30)
β_i^*	.16416*** (2.94)	.76847*** (23.20)	-0.06632 (-1.94)	-0.29573 (-8.03)	0.011255 (0.25)	0.02375 (0.71)	-0.02007 (-0.58)	.18166*** (5.61)	0.00499 (0.15)	0.02834 (0.80)	.1782*** (4.82)
Panel B: Estimates of selected parameters from model (2)											
β_i	.43848*** (4.06)	0.11879*** (-6.43)	.980926*** (12.35)	1.076843*** (13.32)	.547689*** (5.42)	.7649304*** (9.58)	.909981*** (12.53)	.459642*** (6.70)	.82934*** (11.76)	.761135*** (10.34)	.577952*** (8.19)
$\beta_{i,Tu}$	.407851*** (2.65)	-.09414*** (-2.65)	0.153593 (1.45)	0.101766 (0.94)	0.068779 (0.52)	0.102806 (0.94)	0.109096 (1.08)	-.233798** (-2.43)	0.074445 (0.74)	0.132607 (1.20)	0.048328 (0.50)
$\beta_{i,We}$	.3203197** (2.33)	-.0722499** (-2.29)	-0.12453 (-1.30)	-0.07787 (-0.83)	0.058614 (0.48)	-0.02279 (-0.24)	-0.12565 (-1.45)	-0.12303 (-1.48)	-0.07673 (-0.91)	-0.05114 (-0.56)	0.041604 (0.48)
$\beta_{i,Th}$	.398464*** (2.59)	-.10183*** (-2.64)	0.03205 (0.32)	0.052287 (0.50)	0.200488 (1.48)	0.058621 (0.56)	-0.00215 (-0.02)	-0.1166 (-1.30)	-0.02713 (-0.29)	-0.02663 (-0.28)	.182259* (1.93)
$\beta_{i,Fr}$	.37438*** (2.74)	-.10776** (-2.06)	-0.00984 (-0.10)	-0.0585 (-0.58)	0.196359 (1.58)	-0.05526 (-0.58)	-0.02988 (-0.33)	-.17438** (-1.98)	-0.04202 (-0.46)	-0.02278 (-0.24)	-0.06476 (-0.72)
β_i^*	.4199*** (3.34)	.70661*** (11.60)	-0.10483 (-1.09)	-.253793 (-2.68)	0.062837 (0.54)	0.045004 (0.52)	-0.03381 (-0.40)	-0.08026 (-1.06)	-0.07384 (-0.89)	0.024387 (0.30)	.1433326* (1.74)
$\beta_{i,Tu}^*$	-0.22236 (-1.19)	.34151*** (3.92)	-0.01608 (-0.13)	-0.068 (-0.52)	-0.00665 (-0.04)	-0.02646 (-0.21)	-0.01168 (-0.10)	.444667*** (3.97)	0.055048 (0.46)	-0.05691 (-0.42)	0.177326 (1.47)
$\beta_{i,We}^*$	-0.24738 (-1.49)	0.02731 (0.28)	0.126089 (1.08)	-0.068 (-0.41)	0.164526 (1.13)	0.025283 (0.23)	0.094846 (0.89)	.2287566** (2.36)	0.151922 (1.42)	0.002463 (0.02)	0.032289 (0.30)
$\beta_{i,Th}^*$	-0.28978 (-1.54)	0.06699 (0.60)	-0.03204 (-0.25)	-0.11575 (-0.89)	-0.17735 (-1.07)	-0.12599 (-1.01)	-0.03772 (-0.30)	.294565*** (2.64)	0.031731 (0.27)	-0.01248 (-0.11)	-0.06286 (-0.51)
$\beta_{i,Fr}^*$	-.38843** (2.35)	-0.05218 (-0.52)	0.026607 (0.23)	-0.00068 (-0.01)	-0.1756 (-1.21)	-0.003 (-0.03)	-0.0222 (-0.20)	.355591*** (3.46)	0.107362 (0.99)	0.00006 (0.00)	0.083387 (0.79)

Note: This table present estimates of parameters from (1) and (2) estimated with a GJR-GARCH (1,1) model for the residuals. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively. All tests are double-sided except those for β_i^* which are one sided (>0). t -statistics are in parentheses.

Relevant estimation results from the baseline model (1) are shown in Table 1, Panel A.⁵ There are positive ($\beta_i > 0$) and significant spillovers from the U.S. during the pre-crisis period for all countries but Denmark in our sample. Following the outbreak of the 2007-9 financial crisis, there are contagion effects from the U.S. to Austria, Denmark, Portugal, and the UK, as β_i^* is significantly positive. For Ireland, Italy, Netherlands, Spain and Switzerland, there is no significant effect of the crisis on spillovers from the U.S. We also observe (statistically significantly) weaker spillovers (decoupling) during the crisis period, relative to the pre-crisis, for France and Germany.

Relevant estimation results for (2) are presented in Table 1, Panel B. Pre-crisis, spillovers from the U.S. were a rather constant feature across countries and days of the week: Monday spillovers (β_i) are positive and significant for all countries, and they tend to remain at a constant level across the week, as $\beta_{i,WD}$ parameters are mostly insignificant, except for a few exceptions affecting only four countries (Austria, Denmark, Portugal, and the U.K.). Hence, the overall evidence is not overwhelmingly supportive of the notion that *pre-crisis* spillovers from the U.S. varied in intensity across days of the week.

Following the crisis outbreak, there is some evidence of financial contagion from the U.S. Recall that our baseline model (1) detected contagion from the U.S. for Austria, Denmark, Portugal, and the UK. Model (2) allows for a deeper insight into the nature of this phenomenon, and how this might differ dependant on the day of the week. Firstly, estimation results from model (2) confirm that U.S. spillovers have had a stronger effect on each of these countries, on some days of the week. For Austria, Mondays suffered from contagious impact from the U.S., as $\beta_i^* > 0$, and this effect persisted unchanged until Thursday, as $\beta_{i,Tu}^*$ to $\beta_{i,Th}^*$ are not significant. However, contagion was significantly lower on Fridays compared to Mondays. For Denmark, contagion was present across days of the week, even being

⁵ Other results are not shown to conserve space.

significantly stronger on Tuesdays than on Mondays. In the UK, contagion appears to have had a similar effect on each day of the week, whereas in Portugal, it was absent on Mondays but significantly higher on remaining days of the week.⁶ For remaining countries, the result of no contagion, on average, from model (1) is not rejected for any weekday by model (2), i.e., although theoretically possible, we do not observe in our sample any case where contagion would prevail only on some weekdays but would be undetected when estimated for all weekdays treated as identical (as in model (1)).⁷

Overall, our model (2) gives a more detailed and accurate picture of financial contagion, as it reveals that in countries for which contagion was found it was not a time-invariant phenomenon but rather varying in intensity across days of the week. These weekday patterns are not universal and differ across countries, possibly driven by factors discussed in the Introduction (differences across countries in short-selling intensity and restrictions, in liquidity needs of market participants, in concentration of news announcements on specific weekdays, etc.).

4 Conclusions

This paper explores the existence of day-of-the-week effects in contagion from the U.S. for eleven European countries before and during the 2007-9 financial crisis using synchronised daily stock-price data. The baseline model, which represents methodologies prevailing in the literature, indicates existence of contagion effects in four countries: Austria, Denmark, Portugal and U.K. However, our day-of-the-week model reveals that those countries did not experience contagion consistently across days of the week; rather, excess co-movements

⁶ The resulting non-Monday parameters, $(\beta_i^* + \beta_{i,WD}^*)$, are all positive and significant (results not reported but available on request).

⁷ When prices of stocks in countries outside the Eurozone, i.e., Denmark, Switzerland, and the UK, are denominated in Euros rather than local currencies, the results regarding the existence and weekday patterns generally remain. However, our main analysis utilises stock prices denominated in local currencies, as, e.g., Mink (2015) demonstrated that prices denominated in foreign currencies can be driven by movements in the exchange rates and lead to biased inference about the existence of contagion.

occurred with various intensity across weekdays. Our model has the potential to disclose otherwise unobserved contagious effects. In addition, it can offer a more detailed picture of contagious episodes for those countries for which contagion could be identified using a more traditional approach (which does not allow for spillovers and contagion to vary across days of the week).

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