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**Hong Li, Shamim Ahmed and
Thanaset Chevapatrakul**

Produced By:

Centre for Finance, Credit and
Macroeconomics
School of Economics
Sir Clive Granger Building
University of Nottingham
University Park
Nottingham
NG7 2RD

Tel: +44(0) 115 951 4763

Fax: +44(0) 115 951 4159

suzanne.robey@nottingham.ac.uk

Volatility spillovers across European stock markets around the Brexit referendum

Hong Li*

Shamim Ahmed[†]

Thanaset Chevapatrakul[‡]

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Abstract

The vote of the people of the United Kingdom to leave the European Union following the referendum on June 23, 2016, created tremendous uncertainty in the financial markets. This paper documents the stock market interdependence across four major European markets around this rare and unique event. We uncover the characteristics of the volatility spillover dynamics across France, Germany, Switzerland and the United Kingdom using intraday data at 15-minute intervals. Specifically, we quantify four types of volatility spillover measures: total (non-directional) spillovers, gross directional spillovers, net directional spillovers, and net pairwise spillovers. Our results point to considerable interdependence among the four stock markets. We find that France and Germany were in general the net volatility transmitters to others, while Switzerland and the United Kingdom the net receivers from others during January 4, 2016 to September 30, 2016. Around the day of the Brexit referendum, France and the United Kingdom appear to be net transmitters, while Germany and Switzerland net receivers. Our empirical analysis uncovers important information regarding stock market interdependence, which will be beneficial to both policymakers and practitioners.

JEL Classification: C31, C53, D53, and G15.

Keywords: Market risk, Stock market, Spillover effect, Vector autoregression, and Variance decomposition.

*Nottingham University Business School, University of Nottingham, Nottingham, NG8 1BB, United Kingdom; hong.li@nottingham.ac.uk.

[†]Corresponding author. Nottingham University Business School, University of Nottingham, Nottingham, NG8 1BB, United Kingdom; shamim.ahmed@nottingham.ac.uk. Tel.: +44 (0) 115 823 2359. Fax: +44 (0) 115 846 6667.

[‡]Nottingham University Business School, University of Nottingham, Nottingham, NG8 1BB, United Kingdom; thanaset.chevapatrakul@nottingham.ac.uk.

“Biggest setback in EU’s history plunges bloc into new era of crisis and uncertainty”

– Financial Times¹

1. Introduction

The United Kingdom has chosen to leave the European Union (EU) through a historic referendum on June 23, 2016, the so-called Brexit referendum.² This withdrawal from the longstanding EU membership, which expected to take place some time in 2019, has increased uncertainty for businesses and households across Europe to an elevated level in the coming years. In fact, many academics and practitioners started expressing their grave concerns as early as in January 2016 when the discussion for a possible in-out EU referendum got momentum in the political atmosphere of the United Kingdom.³ After the referendum, policymakers and business communities including bankers, portfolio managers, and investors are in search for strategies to efficiently deal with the uncertain economic and financial environments on the way. But any such effort also requires a good understanding of the interdependence dynamics of the financial markets in concern. This is due to the fact that the existing financial links with the United Kingdom play an important role in the rest of the European economies and vice versa.

To date, a large number of reports and news articles have been published in regard to the likely pros and cons associated with the EU referendum.⁴ However, to the best of our knowledge, there is hardly any empirical study that looks into the interdependence patterns, in terms of return volatility transmissions, of the financial markets across major European countries since the time official talks to holding a referendum got the full impetus in the United Kingdom. A significant strand of literature has shown that in times of major economic and/or political events, stock market volatility, which is one proxy for uncertainty, increases dramatically and spills over across markets at levels depending on the strength of cross-market linkages (see, among others, [Forbes and Rigobon \(2002\)](#), [Bloom \(2009\)](#), [Diebold and Yilmaz \(2009, 2012\)](#), and references therein).⁵ Financial decisions may be altered and/or delayed due to return volatility spillovers. Hence, measuring and monitoring the developments of spillovers of volatility shocks can provide insightful information on the financial market interdependence dynamics, which are crucial for investment and asset allocation decisions, security pricing, and risk management.

¹ “A bad day for Europe: Brexit stuns EU leaders” by Guy Chazan, *Financial Times*, June 24, 2016.

² The referendum results show that 51.90% participants voted in favor of leaving the EU, while 48.10% voted in favor of remaining as a member state of the EU. For more details, see <http://www.electoralcommission.org.uk/>.

³ We use the terms “Brexit referendum” and “EU referendum” interchangeably in this paper.

⁴ See, for example, “BREXIT: the impact on the UK and the EU” published by the Global Counsel at <https://www.global-counsel.co.uk/analysis/special-report/brexit-impact-uk-and-eu>.

⁵ The stock market volatility shocks are highly correlated with other proxies for uncertainty such as the cross-sectional spread of firm- and industry-level earnings and productivity growth (see [Bloom \(2009\)](#)).

Motivated by such considerations, the aim of this paper is to systematically examine the nature and intensity of the volatility spillover dynamics both within and across four major stock markets in Europe, comprising France, Germany, Switzerland and the United Kingdom, over the sample period between January 4, 2016 and September 30, 2016. We employ the shock spillover measurement framework popularized by [Diebold and Yilmaz \(2012\)](#) to the intraday data at 15-minute intervals.⁶ The empirical framework, based on a generalized vector autoregression (VAR) system, enables us to effectively quantify total (non-directional) spillovers, gross directional spillovers, net directional spillovers, and net pairwise spillovers.⁷ In particular, we perform a full-sample (static) analysis uncovering average or unconditional spillovers and a rolling-sample (dynamic) analysis characterizing conditional spillovers both within and across stock markets. Finally, to deepen our understanding of the volatility spillover dynamics during the above baseline sample period, we extend the empirical analysis using intraday data of the same four stock markets covering the period from January 2, 2015 to September 30, 2015.

Our paper makes two important contributions to the existing literature on financial market integration and volatility spillovers. First, we uncover both the time-varying patterns of volatility spillovers and the extent to which volatility shocks transmitted across four major stock markets in Europe around the period when economic and financial uncertainties remained high. More so, we compare the empirical findings for the baseline sample period to that of the similar time period a year ago. Second, we analyze the intraday total (non-directional), gross directional, net directional, and net pairwise spillovers, which are beneficial for better understanding the financial market dynamics given an unprecedented surge in electronic and automated trading over the last few years. Taken together, our empirical analysis conveys valuable information for policymakers, practitioners, and financial institutions faced with the daunting tasks of designing asset allocation and risk management strategies to cope with the uncertainty evolving from the EU referendum. Said differently, the empirical analysis in this paper may add to the information required for better modeling and forecasting stock market dynamics and reducing financial and systemic risk.

We find a host of interesting results. Our full-sample (static) analysis of intraday unconditional spillovers shows that the stock markets in France and Germany have been the net volatility transmitters to others over the baseline sample period. On the other hand, the stock

⁶ The rationale for considering the 15-minute sampling frequency is to strike a balance between measurement error and microstructure noise (e.g., due to bid-ask bounce), while calculating intraday (realized) volatilities of stock markets used in the empirical estimation. Moreover, recent advances in computer technologies and information processing enable participants in financial markets to respond fairly quickly to news, shocks, and macroeconomic announcements. As a result, measuring volatility based on daily observations may ignore important information regarding intraday price dynamics.

⁷ The use of intraday data in a VAR system is not uncommon in the literature (see [Engle, Ito, and Lin \(1990\)](#)).

markets in Switzerland and the United Kingdom have been the net volatility receivers from others. Importantly, while France turns out to be the largest net transmitter of volatility to others, the United Kingdom appears to be the largest net volatility receiver from others. We find that the highest pairwise directional volatility spillover is from France to Germany, while the lowest pairwise spillover is from the United Kingdom to Switzerland. Moreover, the total volatility spillover index points that, on average, roughly two-fifth of the intraday volatility forecast error variance in all four European stock markets comes from shock spillovers. This level of return volatility spillovers in turn suggests considerable interdependence among our four stock markets.

The rolling-sample (dynamic) analysis of intraday conditional volatility spillovers also confirms the empirical findings based on a full-sample (static) analysis. We observe that the total volatility spillover index fluctuates significantly between 23% and 52% over the baseline sample period. The stock markets in France and Germany were largely a net volatility transmitter to others. But the stock markets in Switzerland and the United Kingdom were by and large a net volatility receiver from others. Importantly, around the day of the EU referendum on June 23, 2016, both France and the United Kingdom (Germany and Switzerland) were a net volatility shock transmitter (receiver) to others (from others).

A comparison of the intraday volatility spillover dynamics of our four stock markets over the baseline sample period to that of the period between January 2, 2015 and September 30, 2015, shows two stark differences. First and most importantly, the United Kingdom was at both the giving and receiving ends of the net volatility transmissions, with roughly half of the time altogether at each end during the period between January 2, 2015 and September, 30, 2015. Second, the intraday total volatility spillover index remained mostly within the range between 20% and 30%. But in line with our baseline empirical findings above, Germany (Switzerland) generally appears to be a net transmitter (receiver) of intraday volatility to others (from others). France also turns out to be largely a net transmitter of volatility to others for a significant amount of time altogether, though the pattern of spillovers is not as clear as that observed for our baseline sample period.

The papers closest to ours include [Diebold and Yilmaz \(2009, 2012\)](#). The common finding of these papers is that the cross-market volatility spillovers increase substantially following crises. Our empirical findings are largely in line with these studies, though we focus on the intraday volatility spillovers among four major European stock markets around the time of the Brexit referendum. Another recent paper, that to some extent, related to ours is [Baele \(2005\)](#).⁸ The

⁸ Important earlier papers on volatility spillovers across markets include [Engle, Ito, and Lin \(1990\)](#), [Hamao, Masulis, and Ng \(1990\)](#), [Lin, Engle, and Ito \(1994\)](#), [Karolyi \(1995\)](#), and [Bekaert and Harvey \(1997\)](#).

author shows that stock market development, increased trade integration, and low inflation contribute to the substantial increase in volatility spillovers from the aggregate EU and US market to 13 local Western European stock markets during the 1980s and 1990s.

The remainder of this paper is organized as follows. Section 2 outlines the econometric framework to quantify both the total and directional volatility spillovers. Section 3 describes the stock market index data and summarizes the substantive empirical results. Finally, Section 4 concludes. Some robustness results as well as additional analyses to facilitate comparison with the baseline empirical findings are delegated to the Appendix at the end of this paper.

2. Econometric framework

We follow the econometric approach introduced by [Diebold and Yilmaz \(2012\)](#) to measure both the total (non-directional) and directional volatility spillovers within and across major European stock markets. In particular, the spillover analysis involves computing the forecast error variance decompositions from a generalized VAR framework developed by [Koop, Pesaran, and Potter \(1996\)](#) and [Pesaran and Shin \(1998\)](#). It is important to emphasize that a generalized VAR system enables us to obtain the forecast error variance decompositions, which are invariant to the ordering of the variables of interest.⁹ To illustrate the methodology of [Diebold and Yilmaz \(2012\)](#), consider a covariance stationary N -variable VAR(p) system in standard form given by

$$\mathbf{x}_t = \sum_{i=1}^p \Phi_i \mathbf{x}_{t-i} + \varepsilon_t, \quad (1)$$

where $\varepsilon_t \sim (\mathbf{0}, \Sigma)$. The vector moving average representation of equation (1) is

$$\mathbf{x}_t = \sum_{i=0}^{\infty} \mathbf{A}_i \varepsilon_{t-i}, \quad (2)$$

where the $N \times N$ coefficient matrices \mathbf{A}_i can be obtained using the recursive relations $\mathbf{A}_i = \Phi_1 \mathbf{A}_{i-1} + \Phi_2 \mathbf{A}_{i-2} + \dots + \Phi_p \mathbf{A}_{i-p}$, with \mathbf{A}_0 being an $N \times N$ identity matrix and $\mathbf{A}_i = \mathbf{0}$ for $i < 0$. The dynamics of the VAR system can be uncovered by the moving average coefficients. Specifically, the spillover analysis relies on the so-called variance decompositions, which are in fact transformations of the moving average coefficients (see [Enders \(2014, Chapter 5\)](#) for more details). The variance decompositions, introduced by [Sims \(1980\)](#), show us the proportion of the H -step-ahead error variance in forecasting variable x_i that is accounted for by the shocks

⁹ Throughout this paper, we refer to [Koop, Pesaran, and Potter \(1996\)](#) and [Pesaran and Shin \(1998\)](#) for a generalized VAR approach.

to variable x_j , $\forall j \neq i$, for each i in the VAR system.¹⁰

Often, the computation of variance decompositions proceeds by orthogonalizing the shocks in the VAR system (Diebold and Yilmaz (2014, 2016)). A widely used identification scheme based on the Cholesky factorization achieves this orthogonality condition (see Sims (1980)). However, a drawback of the Cholesky factor orthogonalization is that the resulting variance decompositions can be sensitive to the ordering of the variables in the VAR system. To circumvent this shortcoming, Diebold and Yilmaz (2012) resort to a generalized VAR framework, which departs from orthogonalizing the shocks. Instead, the framework allows for correlated shocks but simultaneously accounts for them by using the historically observed distribution of the errors ε_t , under a multivariate normality assumption.

Accordingly, the cross variance shares or spillovers can be defined as the proportions of the H -step-ahead error variances in forecasting variable x_i that are due to shocks to variable x_j , for $i, j = 1, 2, \dots, N$, such that $i \neq j$. More precisely, the contribution of variable x_j to variable x_i 's H -step-ahead generalized forecast error variance is obtained as

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \mathbf{A}_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \mathbf{A}_h \Sigma \mathbf{A}_h' e_i)}, \quad (3)$$

where $H = 1, 2, \dots$, and σ_{jj} is the standard deviation of the error term for the j th equation, e_i is the selection vector with one as the i th element and zeros elsewhere, \mathbf{A}_h is the coefficient matrix multiplying the h -lagged error vector ε in the infinite moving average representation of the generalized (i.e., non-orthogonalized) VAR system, and Σ is the variance-covariance matrix of the error vector in the generalized VAR system. Since the shocks to each variable are not orthogonalized, the sum of the elements in each row of the generalized variance decomposition matrix is not necessarily equal to one (i.e., $\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$). Hence, each entry of the variance decomposition matrix is normalized by the row sum as

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}. \quad (4)$$

It is important to note that $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$, by construction. The

¹⁰ Since the variables of interest in our case are stock markets' volatilities, described in Section 3.1, we use the terms "variable" and "stock market" interchangeably in this section.

total (i.e., system-wide) volatility spillover index is then constructed as

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100, \quad (5)$$

which quantifies the contribution of transmissions of volatility shocks across all variables to the total generalized forecast error variance. Essentially, the index allows us to distill the various directional volatility shock spillovers into a single number.

Now using the normalized elements of the generalized variance decomposition matrix, the directional volatility spillovers received by stock market i from all other stock markets j can be measured as follows:

$$S_{i \leftarrow \bullet}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100. \quad (6)$$

Likewise, the directional volatility spillovers transmitted by stock market i to all other stock markets j can be obtained as

$$S_{i \rightarrow \bullet}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ji}^g(H)}{N} \times 100. \quad (7)$$

The gross directional spillovers, defined above, can also be used to quantify the net directional spillover from stock market i to all other stock markets j . In particular, the net directional volatility spillover from market i to all other markets j can be simply measured as follows:

$$S_i^g(H) = S_{i \rightarrow \bullet}^g(H) - S_{i \leftarrow \bullet}^g(H). \quad (8)$$

Finally, the difference between the gross volatility shocks transmitted from stock market i to stock market j and those transmitted from stock market j to stock market i provides the net pairwise volatility spillover between markets i and j . The quantity is given by

$$\begin{aligned}
S_{ij}^g(H) &= \left(\frac{\tilde{\theta}_{ji}^g(H)}{\sum_{i,k=1}^N \tilde{\theta}_{ik}^g(H)} - \frac{\tilde{\theta}_{ij}^g(H)}{\sum_{j,k=1}^N \tilde{\theta}_{jk}^g(H)} \right) \times 100 \\
&= \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \right) \times 100.
\end{aligned} \tag{9}$$

Note that there are $(N^2 - N)/2$ net pairwise volatility spillover measures in the above p^{th} -order N -variable generalized VAR system.

3. Empirical results

In this section, we begin by describing the data that we use to empirically quantify the intraday volatility spillovers both within and across the representative stock markets in Europe. Subsequently, we carry out a full-sample (static) analysis of average or unconditional spillovers followed by a rolling-sample (dynamic) analysis of conditional spillovers.

3.1 Data analysis

Our data consist of four local-currency stock market indexes in France, Germany, Switzerland, and the United Kingdom at 34 15-minute intervals during the trading day hours. More precisely, the indexes that we utilize to represent stock markets in the above European countries are the CAC 40 Index, the DAX 30 Index, the SMI, and the FTSE 100 Index, respectively. Table 1 lists the opening and closing times for the four markets in both local time and the United Kingdom time (i.e., Greenwich Mean Time (GMT)). A notable feature of these stock markets is that they open and close at the same GMT.¹¹ Since our primary objective is to study the intraday volatility spillovers among four markets from the time the United Kingdom has announced a referendum on whether to remain in the EU, the baseline sample spans a nine-month period starting from January 4, 2016 and ending to September 30, 2016. But to comprehend the main empirical findings in greater details, we extend the spillover analysis using intraday (i.e., 15-minute interval) data of the same four stock market indexes covering the sample period from January 2, 2015 to September 30, 2015.

We compute intraday volatility of a given stock market i at time t , denoted by $\tilde{\sigma}_{it}^2$, as the squared 15-minute log return on the respective market index. Consistent with the common practice in the literature, we convert all returns calculated in local currencies into US dollars

¹¹ To ease exposition, we plot all figures pertaining to volatility and volatility spillover dynamics against GMT.

using the daily historical spot exchange rates and exclude overnight returns (see, among others, [Bekaert and Harvey \(1997\)](#) and [Engle and Sokalska \(2012\)](#)).^{12,13} Finally, we work with log volatilities (i.e., $\ln(\hat{\sigma}_{it}^2)$) to measure both the total (non-directional) and directional volatility spillovers from a generalized VAR framework described in Section 2.¹⁴ Tables 2 and A1 (in the Appendix) provide basic descriptive statistics for the intraday log volatilities over the periods from January 4, 2016 to September 30, 2016 and from January 2, 2015 to September 30, 2015, respectively. But to provide an overview of the time-series evolution of four stock markets' volatilities in Figures 1 and A2 (in the Appendix), we resort only to volatilities measured as the annualized absolute 15-minute log return in percent (i.e., $\hat{\sigma}_{it} = [100\sqrt{34 \times 252}] \times |r_{it}|$). The data on stock market indexes come from the Bloomberg Terminal provided by Bloomberg LP. The exchange rate data are sourced from the World Markets PLC/Reuters via Datastream.

A cursory look at Figure 1 reveals that: (1) all four stock markets have experienced relatively high levels of intraday volatilities during January to March 2016 and again during June to July 2016; (2) France and Germany have been the most volatile stock markets over the first nine months in 2016 followed by the United Kingdom and Switzerland; (3) there have been a number of occasions in each stock market when intraday volatility displayed huge jumps; and (4) only Switzerland and the United Kingdom have experienced their highest levels of volatilities on June 24 (at 8:30 am), that is, the day following the Brexit referendum on June 23, 2016.

We now elaborate on the observed volatility dynamics of each stock market in Figure 1. Starting with France, we find that intraday volatility, as measured by the annualized absolute 15-minute log return, remained higher than 20% in most of the time and climbed as high as 227% on March 10 (at 12:45 pm), 2016. In fact, a value of 227% is the highest among all four stock markets over the baseline sample period. On March 10, 2016, the European Central Bank (ECB) announced undertaking a number of monetary policy measures including lowering the interest rate on the main refinancing operations of the Eurosystem by 5 basis points to 0% effective from March 16, 2016. The jump in volatility during the day of the ECB's expansionary policy announcement has also been observed in other stock markets. For example, intraday volatilities of stock markets in Germany, Switzerland, and the United Kingdom increased, respectively, to 138% (the highest level over the sample period for Germany's stock market), 99%, and 80% on

¹² The use of US dollar denominated return volatilities facilitates the comparison across countries, while eliminating the impact of exchange rates. In an unreported empirical exercise, we also investigate the average and dynamic volatility spillovers among four stock markets using the time-series of intraday volatilities measured as the squared 15-minute local-currency log return and find the results nearly identical to those based on US dollar denominated return volatilities. These are excluded in this paper but available upon request.

¹³ Inclusion of overnight return volatilities in the spillover analysis yields results qualitatively similar to those reported in Sections 3.2 and 3.3. To conserve space, these are omitted in this paper.

¹⁴ Volatilities tend to be asymmetrically distributed with a positive skewness. Hence, taking natural logarithms of (realized) volatilities induces approximate normality, as emphasized in [Andersen, Bollerslev, Diebold, and Labys \(2003\)](#).

the same day. Also there were a number of occasions in France when volatility soared above the 100% level. These occurred on February 3 (113% at 15:00 pm), June 24 (166% at 8:15 am), and July 8 (123% at 13:30 pm), 2016. During February 3 and 10, 2016, most investors dumped stocks in Societe Generale, due to a growing fear of an imminent European banking crisis, triggered by the release of gloomy reports that the French bank failed to meet analyst income targets in its latest quarterly results. But on July 8, 2016, there was a release of confidence boosting information that 287,000 jobs were created during the month of June, 2016, in the US.

The stock market in Germany also experienced volatility higher than the 20% mark in most of the time over the baseline sample period. Furthermore, there were a number of days in Germany when intraday volatility increased significantly to above 100%. These include February 8 (126% at 9:00 am), February 9 (103% at 8:15 am and 101% at 14:30 pm), March 10 (135% at 8:15 am), April 11 (102% at 8:45 am), and July 8 (106% at 13:30 pm), 2016. In the first-half of February 2016, a series of gloomy news related to the weakening financial health of Germany's flagship bank Deutsche was released. Importantly, intraday volatility on June 24 (at 9:45 am), 2016, increased to 92%, which was lower than the level of volatility observed in many other occasions in Germany over the sample period.

In Switzerland, the stock market went through periods of high intraday volatility during January to March 2016 and June to July 2016. Especially, during the first-half of February 2016, volatility fluctuated widely between 25% and 100% following the disappointing earnings releases by Credit Suisse, UBS AG, and Zurich Insurance Group Ltd., and the publication of statistic showing a rise in Swiss unemployment rate to 3.80% for January 2016. With a few exceptions, volatility during April to May 2016 and again during August to September 2016 remained relatively low and hovered around the 10% level. However, intraday volatility on June 24 (at 8:30 am), 2016, was elevated to 111% — the highest over the sample period. We find that the stock market in Switzerland has been the least volatile compared to the observed volatility dynamics of the stock markets in France, Germany, and the United Kingdom.

The stock market in the United Kingdom was also volatile during the first three months in 2016 followed by a relatively tranquil period during April to May 2016. Intraday volatility picked up again in June and continued to remain high till the end of July 2016. Over these short periods, a series of events took place both in political and financial arenas, which likely steered the volatility dynamics in the stock market. In the political arena, the campaign for a EU referendum got momentum as early as in January 2016. On February 20, 2016, the government announced that the referendum would take place on June 23, 2016. Huge jumps in volatility can be observed on February 9 (91% at 8:15 am), June 24 (143% at 8:30 am and 129% at 14:30

pm), June 30 (101% at 16:00 pm), July 14 (95% at 12:00 pm), and August 4 (100% at 12:00 pm), 2016. On June 30, 2016, after an initial slump in the first two trading days following the Brexit referendum on June 23, the FTSE 100 Index recorded its best weekly performance since December 2011. Some of the reasons that might have contributed to the rebounding of the stock market at that time include: (1) a growing belief that Article 50, the mechanism to trigger the United Kingdom leaving the EU, would not be triggered for months;¹⁵ and (2) comments from the Bank of England’s Governor, Mark Carney, hinting at further cuts in the bank rate in the summer of 2016. Later, on July 14, 2016, the Bank of England’s Governor also suggested a need for restarting quantitative easing to restore economy-wide confidence following the Brexit referendum. On August 3, 2016, the Bank of England lowered the bank rate to 0.25% and announced several stimulus monetary policy measures including an expansion of the asset purchase scheme for the United Kingdom Government bonds amounting to 60 billion pounds.

Finally, to get a glimpse of the intraday volatility dynamics over the same period a year ago (i.e., from January 2, 2015 to September 30, 2015), we focus on Figure A2 in the Appendix. Consistent with our baseline sample period, France and Germany have been the most volatile markets followed by the United Kingdom and Switzerland. Moreover, all four stock markets went through relatively high levels of volatilities in January and August 2015. Especially, volatilities in France, Germany, and the United Kingdom climbed, respectively, to 232%, 162%, 122% on August 24 (at 14:00 pm), 2015. These levels of volatilities, following a jittery outlook of economic slowdown in China, were the highest for the respective stock markets over the entire sample period. With the exception in January and August 2015, volatility remained very low throughout the sample period in Switzerland. However, on January 15, 2015, the stock market in Switzerland experienced a remarkably huge jump in volatility to 520% following the sudden lifting of a three-year-old cap on the Swiss franc (i.e., 1.20 CHF/euro) by the Swiss National Bank. This event threw major stock markets across the world into turmoil, for a while, as well. For example, intraday volatilities in France, Germany, and the United Kingdom increased significantly to 128%, 141%, and 90%, respectively, on January 15 (at 9:45 am), 2015.

3.2 Full-sample volatility spillover analysis

In this sub-section, we specifically focus on the full-sample (static) analysis characterizing the average or unconditional intraday volatility spillovers within and across the four stock

¹⁵ The Article 50 of the Treaty on EU allows any member state to notify its withdrawal from the Union in accordance with its own constitutional requirements and obliges the EU to try to negotiate a withdrawal agreement with that member state.

markets.¹⁶ Table 3 summarizes both the total (non-directional) and directional spillovers during our baseline sample period. We find that the gross directional volatility spillovers from other stock markets (the rightmost column in Table 3) to the stock markets in France and Germany are relatively high at 43.26% and 41.98%, respectively. The corresponding values for Switzerland and the United Kingdom are, respectively, 32.11% and 31.78%. In contrast, the gross directional volatility spillovers from the stock market in France to other stock markets (the bottom row in Table 3) is also high at 47.51%, followed by 43.64% from Germany, 29.17% from Switzerland, and 28.81% from the United Kingdom to others. We learn from Table 3 that the highest pairwise directional volatility spillover is from France to Germany (22.22%), whereas the lowest pairwise spillover is from the United Kingdom to Switzerland (8.01%). In return, the pairwise volatility spillover from Germany to France is 21.32% and from the United Kingdom to Switzerland is only 8.27%. These levels of pairwise unconditional volatility spillovers between France and Germany (the United Kingdom and Switzerland) are indicative of a somewhat moderate (weak) ties between the two countries' respective stock markets.

As for the net directional volatility spillovers (the bottommost row in Table 3), we notice that, on average, France and Germany are the net volatility transmitters to others, while Switzerland and the United Kingdom are the net receivers of volatilities from others. More precisely, the stock market in France is the largest net volatility transmitter ($47.51 - 43.26 = 4.25\%$), while the United Kingdom is the largest net volatility receiver ($29.17 - 31.78 = -2.97\%$) during January 4, 2016 to September 30, 2016. Furthermore, the total (non-directional) volatility spillover index (the bottom-right boldfaced entry in Table 3) indicates that, on average, 37.28% (i.e., $[149.13/400] \times 100$) of the intraday volatility forecast error variance in all four stock markets comes from spillovers. This in turn suggests the existence of a considerable degree of interdependence among our four markets.

Table A2 in the Appendix presents the unconditional intraday volatility spillovers during January 2, 2015 to September 30, 2015. Some key features deserve highlighting. Consistent with our baseline empirical findings above, France and Germany are the net volatility transmitters to other stock markets, while Switzerland and the United Kingdom are the net receivers from others. Nevertheless, the total (non-directional) and directional spillovers during our baseline sample period are higher than those observed for the period between January 2, 2015 and

¹⁶ The intraday spillover results, reported in this paper, are obtained from fourth-order VARs and generalized variance decompositions of 10-step-ahead (i.e., 15-minute $\times 10 = 2.5$ hours) volatility forecast errors. But to check the robustness of our empirical results, we also compute the total volatility spillover index separately for VAR orders of 2 to 6 and forecast horizons of 8 to 15 steps and plot the resulting time-series of minimum, maximum, and median values in Figure A1 of the Appendix. We find that the total spillover plot is sensitive neither to the choice of the order of the VAR system nor to the choice of the forecast horizon. Figure A8 in the Appendix shows similar sensitivity analysis for the sample period between January 2, 2015 and September 30, 2015.

September 30, 2015. Besides, the stock market in Germany appears to be the largest net volatility shock transmitter ($36.34 - 33.56 = 2.78\%$) to others, while the stock market in Switzerland seems to be the largest net volatility shock receiver ($16.84 - 21.26 = -4.42\%$) from others. It is worth mentioning that the level of net volatility spillovers transmitted by the United Kingdom to others is -0.34% compared to -2.97% for the baseline sample period.

3.3 Rolling-sample volatility spillover analysis

The preceding full-sample (static) analysis enables us to empirically comprehend the “average” or “unconditional” patterns of intraday spillovers. However, it is silent about the evolution of time-varying volatility spillovers across stock markets as well as within a stock market. In this sub-section, we provide a dynamic (conditional) analysis of total (non-directional) spillovers, gross directional spillovers, net directional spillovers, and net pairwise spillovers using 200-observation rolling samples for our baseline period, January 4, 2016 to September 30, 2016.^{17,18} An advantage of the dynamic (rolling-sample) analysis is that it helps us to understand the developments in the financial markets over time (Diebold and Yilmaz (2016)).

3.3.1 Total volatility spillovers

Figure 2 plots the rolling-sample total (non-directional) volatility spillovers. Each point in this figure corresponds to equation (5). We observe that the intraday total spillover index evolves largely in a cyclical manner, while confining itself within a wide range between 23% and 52%. More so, the index climbed to its highest peak at 52% on February 10 (at 16:00 pm) and again on February 11 (at 9:00 am), 2016, following the release of a series of news related to the gloomy near-term outlook of heavy-weight financial institutions, such as Societe Generale, Deutsche Bank, Credit Suisse, UBS AG, and Zurich Insurance Group Ltd., in France, Germany, and Switzerland. Apart from these days, there were a number of days between January and March 2016 and again in June 2016 when the spillover index surged above the 45% mark. Some of them worth mentioning include: (1) January 25 (50% at 12:45 pm and 49% at 13:30 pm), following the ECB’s monetary policy decision on January 21 to maintain the interest rates on the main refinancing operations, the marginal lending facility, and the deposit facility at 0.05%, 0.30% and -0.30% , respectively; (2) March 10 (48% at 16:30 pm) and March 11 (48% at 8:30

¹⁷ The choice of a 200-observation rolling estimation window follows from Diebold and Yilmaz (2009, 2012, 2016). But for robustness checks, we also perform the rolling-sample (dynamic) analysis using 400- and 600-observation rolling windows and find the time-series plots of the total (non-directional) and directional volatility spillovers qualitatively identical, though a bit smoother, to those reported in this sub-section. For brevity, these results are omitted in this paper.

¹⁸ We also calculate the total and directional volatility spillovers using 200-observation rolling samples covering the period from January 2, 2015 to September 30, 2015. These results are provided in the Appendix.

am and 46% at 13:00 pm), again following the policy announcement on March 10 by the ECB; and (3) the week following the EU referendum in the United Kingdom on June 23, 2016. More precisely, the total volatility shock spillover index increased sharply from 33% on June 22 (at 15:00 pm) to 47% on June 28 (at 13:30 pm). But the index plummeted significantly to its lowest trough at 23% on August 15 (at 16:00 pm), 2016. Overall, the intraday dynamics of the total spillover index point to considerable interdependence among our four stock markets in Europe.

Comparing the intraday total volatility spillover plot for the baseline sample period to that for the period between January 2, 2015 and September 30, 2015 in Figure A3 of the Appendix, we learn several stark differences. First, the total spillover index stayed within the 20%–30% range in most of the time, whereas the index during the baseline sample period fluctuated mostly within a higher range between 30% and 40%. Especially, it has been markedly higher during January to March 2016. Second, the index followed a sharp declining trend over the first three months of 2015 and then an upward trend with several short cycles from April to the end of September 2015. Third, the total volatility spillover index fell as low as 9% on February 25 (at 13:15 pm) and rose as high as 46% on September 25 (at 8:15 am), 2015.

3.3.2 Gross directional volatility spillovers

We now briefly assess the time-varying nature and magnitude of the gross directional volatility spillovers for our four stock markets over the baseline sample period. Figure 3 plots the rolling-sample intraday directional spillovers received by each stock market from other three markets.¹⁹ One of the first things that we notice is that the volatility shock spillovers in each stock market from other three stock markets vary significantly over the entire baseline sample period. Both France and Germany lead the way by receiving volatility spillovers in the range between 30% and 50% from others in most of the time, followed by Switzerland and the United Kingdom where volatility spillovers from other three stock markets fluctuate mostly between 20% and 40%. Interestingly, gross directional volatility spillovers to the United Kingdom’s stock market from other three markets increased to 37% on June 28 (at 16:00 pm) after the Brexit referendum on June 23, 2016. However, this level of volatility shock transmission is noticeably lower than the corresponding levels for stock markets in France (57%), Germany (51%), and Switzerland (48%) around the same time.

Figure 4 presents the time-series of intraday directional volatility spillovers transmitted by each of the four stock markets to other three markets. Similar to those in Figure 3, the shock spillover dynamics also vary considerably over the baseline sample period. In particular, we

¹⁹ Each point of the time-series plots in Figure 3 corresponds to equation (6), whereas each point of the plots in Figure 4 corresponds to equation (7).

observe that the gross directional volatility spillovers separately from France and Germany to others remain significantly high, within a wide range between 30% and 60%, in most of the time. On the other hand, volatility spillovers separately from Switzerland and the United Kingdom to others remain mostly within the 20%–40% band. The gross spillovers from the United Kingdom to others stayed above 37% throughout the week following June 23, 2016.

In the Appendix, Figures A4 and A5 plot the gross directional volatility spillover dynamics for the period between January 2, 2015 and September 30, 2015. It appears that the gross volatility spillovers from (to) each stock market to (from) other three markets are generally lower than those observed over our baseline sample period. We also notice that the gross directional spillovers received separately by France, Germany, and the United Kingdom from others follow a declining trend in the first three months and an upward trend in the next six months in 2015. Similar downward and upward trends are also observable when looking at the gross directional volatility spillovers transmitted separately by France, Germany, and the United Kingdom to others.

3.3.3 Net directional volatility spillovers

One of the most interesting components of the spillover analysis that shapes our understanding of the volatility shock transmissions is the time-varying net spillovers. In Figure 5, we plot the rolling-sample intraday net directional volatility spillovers from each of the four stock markets to others. Said differently, each point in Figure 5 corresponds to equation (8), which is the difference between the gross volatility shocks transmitted to (i.e., equation (7)) and those received from all other stock markets (i.e., equation (6)) in concern. A closer look at the time-series plots reveals several interesting facts for the baseline sample period. Starting with France, we notice that the stock market predominantly has been at the giving end of the intraday net volatility transmissions. The net directional spillovers to other three stock markets reached its highest peak at 13.10% on February 9 (at 9:45 am), 2016. Note that most investors around that time dumped stocks in Societe Generale due to its disappointing near-term financial outlook. The net volatility shock transmissions to other three stock markets stayed between 1% and 5% in the following week before jumping markedly to 11.30% on February 24 (at 9:15 am), 2016. After the policy rate announcement by the ECB on March 10, the net volatility spillovers from France to others surged again to 11% on March 11 (at 8:15 am), 2016. We learn that this magnitude of net directional shock spillover has been the highest across all four stock markets on that day. There were a handful number of days, when France received net volatility spillovers from others as well. Importantly, the net directional volatility spillovers to

other stock markets entered the negative territory on June 3 (at 9:00 am) and stayed there for a little while before reverting back to the positive territory on June 10 (at 14:45 pm), 2016. Throughout the second-half of June 2016, the net volatility spillovers from France to others stayed positive. In fact, net spillovers to others reached as high as 12.90% on June 22 (at 10:15 am) and 12.80% on June 24 (at 11:45 am), 2016. These are the days immediately before and after the EU referendum in the United Kingdom.

The dynamic behavior of the net directional volatility spillovers from the stock market in Germany to other three stock markets is slightly different from that observed in France. Even though Germany has been at the giving end of the net volatility shock transmissions for a significant amount of time altogether, each episode in the net positive transmission territories was relatively shorter. The net directional volatility spillovers to other stock markets stayed mostly in the range between 0% and 5%, though climbed as high as 11.10% on February 15 (at 14:15 pm), 2016, following a series of news disclosing Deutsche Bank's troubled financial position. Following the announcement by the United Kingdom Government on February 20 for an in-out EU referendum to be held on June 23, 2016, the net spillovers from Germany to others turned negative for a while. We also learn from the respective time-series plot in Figure 5 that the net volatility spillovers to other three stock markets remained negative during June 21 (from 9:30 am) to June 28 (till 15:30 pm). Specifically, the net spillovers to others declined markedly to -8% on June 24 (at 14:15 pm), the day after the Brexit referendum. In other words, Germany turned into a net receiver of volatility shocks from others around that time. However, the net directional spillovers from the stock market in Germany to other three stock markets reached its lowest level at -11.50% on September 5 (at 13:00 pm), 2016, following the release of disappointing data on the country's manufacturing sector.

We notice that Switzerland was at the receiving end of the intraday net volatility shock transmissions in most of the time over the entire baseline sample period. The longest episode during which the net volatility spillovers from the stock market in Switzerland to others remained negative was from January to mid-March 2016. Another noteworthy episode when the net spillovers to others remained in the negative territory was from June 8 to July 7, 2016. Especially, in the week following the EU referendum in the United Kingdom, the net directional volatility spillovers from the stock market in Switzerland to other three stock markets stayed below the -10% mark and reached as low as -16.40% on June 27 (at 11:15 am), 2016. We find that a level of -16.40% net directional spillovers to others was the lowest from Switzerland over the baseline sample period. On the other extreme, the net spillovers from Switzerland to others increased to the highest level at 16.70% on June 3 (at 16:00 pm), 2016, following the release of

the lower-than-expected job data for May by the US Labor Department.

The United Kingdom was also at the receiving end of the net volatility transmissions in most of the time — a feature very similar to that observed for Switzerland. We notice that the net directional spillovers to others turned positive around the day of the EU referendum date announcement on February 20, 2016. In particular, net volatility spillovers from the stock market in the United Kingdom increased to 7.40% on February 22 (at 14:30 pm), 2016. As expected, the net spillovers to others remained positive from the period between June 22 and July 4, 2016. Throughout the week following the Brexit referendum on June 23, the net directional volatility shock spillovers from the stock market in the United Kingdom to other three stock markets stayed above the 10% mark and reached the highest peak at 15% on June 27 (at 11:15 am), 2016. On the other hand, the net volatility shock spillovers from the United Kingdom to others reached the lowest level at -13.20% on July 7 (at 10:15 am), 2016.

In summary, we find that each of the four stock markets has been at both the receiving and giving ends of the intraday net volatility shock transmissions for some time. France and Germany appear to be largely a net transmitter of volatility shocks to others, though the pattern and magnitude of shock spillovers are more pronounced in France. On the other hand, Switzerland and the United Kingdom by and large seem to be a net receiver of volatility from others over the baseline sample period. Furthermore, the stock markets in France and the United Kingdom (Germany and Switzerland) were a net transmitter (receiver) of volatility shocks to others (from others) around the day of the EU referendum on June 23, 2016.

Interestingly, the intraday net directional volatility spillover plots in Figure A6 of the Appendix reveal somewhat different facts. Over the sample period between January 2, 2015 and September, 30, 2015, the United Kingdom was at both the giving and receiving ends of the net volatility shock transmissions, with roughly half of the time altogether at each end. In addition, each episode of net positive (net negative) spillovers to others was much shorter. Consistent with our preceding baseline empirical findings, Germany (Switzerland) predominantly appears to be a net transmitter (receiver) of intraday volatility to others (from others). The stock market in France also appears to be largely a net transmitter of volatility shocks to others for a significant amount of time altogether, though the volatility shock spillover pattern is not as dominant as that observed over the baseline sample period.

3.3.4 Net pairwise volatility spillovers

In this sub-section, we aim to provide a detailed (conditional) analysis of the net volatility shock spillover dynamics between two stock markets. Figure 6 presents the rolling-sample

intraday net volatility spillovers for each pair of markets in concern, where each point of the time-series plots corresponds to equation (9). It can be clearly observed that the net volatility shock spillovers from the stock market in France to Germany's stock market were positive during majority of the days over our baseline sample period. More so, the net pairwise spillovers fluctuated between 0% and 5% in those days. A notable exception to this general observation took place on June 24, 2016 (i.e., the day following the EU referendum), when the net volatility spillovers from France to Germany remained above the 5% level throughout the day and reached as high as 5.19% (at 12:00 pm). On the contrary, there have not been many days in France when the net pairwise spillovers to the stock market in Germany turned negative (i.e., on the net, intraday volatility shocks spilled from Germany to France). The net pairwise spillovers to Germany's stock market recorded its lowest level at -2.93% on June 10 (at 13:00 pm), 2016. Around that time, many investors in the Eurozone shifted their investments from stocks to corporate bonds following the ECB's decision to expand its asset purchasing program.

Looking at the net volatility spillovers from France to the United Kingdom, we find the dynamic spillover pattern largely similar to that from France to Germany. In particular, the intraday net spillovers from France to the United Kingdom mostly remained within the range between 0% and 5%. But some episodes of net positive spillovers from France to the United Kingdom were slightly longer. Importantly, the net pairwise spillovers from France climbed to the highest peak at 6.53% on March 11 (at 8:15 am) after the press release of the ECB's monetary policy stance on March 10, 2016. To the contrary, there were net volatility shock spillovers from the United Kingdom to France in handful number of days. One of such occurrences include February 22, which was the trading day following the EU referendum date announcement on February 20, 2016, in the United Kingdom. Another example is the two weeks following the referendum on June 23, 2016. In fact, the net spillovers from France to the United Kingdom reached as low as -4.55% on June 29 (at 12:00 pm), 2016.

We also find that the overall pattern of the net volatility shock spillovers from France to Switzerland is largely similar to that from France to Germany as well as from France to the United Kingdom. Two observations worth highlighting. First, the duration of some episodes of net positive spillovers from France to Switzerland were much longer. Second, the net pairwise volatility spillovers from France's stock market remained below -2.50% in the first week of June 2016 and reached as low as -7.49% on June 3 (at 16:00 pm), 2016. In the following week, the net pairwise spillovers to Switzerland started to increase rapidly and stayed above the 5% level throughout the second-half of June 2016. The net volatility spillover from France to Switzerland reached sizeably high to 7.78% on June 24 (at 12:45 pm), 2016, which was the highest absolute

level of net spillovers between any two stock markets on that day. Taken together, all of the above mentioned volatility shock spillover dynamics substantiate the time-varying pattern of the intraday net directional spillovers from France’s stock market to other stock markets in Germany, Switzerland, and the United Kingdom, as presented in Figure 5.

Now focusing on the net volatility spillovers from the United Kingdom to Germany, we see that the net pairwise spillovers were negative in most of the days. In other words, volatility shocks, on the net, spilled from Germany to the United Kingdom mostly. As expected, the net volatility spillovers from the United Kingdom to Germany in the last week of June 2016 stayed above 2.50% and reached markedly high to 6.75% on June 27 (at 12:15 pm), 2016. The net pairwise volatility spillovers to Germany reached its lowest level at -7.74% on August 23 (at 14:45 pm), 2016. We also learn from Figure 6 that the dynamic behavior of the net volatility shock spillovers from the United Kingdom to Switzerland is strikingly different from that of the United Kingdom-Germany pair. In particular, there were net positive spillovers from/to the United Kingdom to/from Switzerland in about half of the time altogether over our baseline sample period. We find that during June 6 to July 4, 2016, the net volatility shock spillovers from the United Kingdom to Switzerland stayed positive and reached as high as 5.44% on June 27 (at 11:15 am), 2016. Note that the net pairwise spillovers from the United Kingdom to Switzerland reached its level highest at 7.08% on May 10 (at 14:30 pm), 2016. On the other hand, the net pairwise spillovers to Switzerland’s stock market reached the lowest level at -8.72% on August 25 (at 9:45 am), 2016.

We learn from Figure 6 that the net volatility shock spillovers from Germany to Switzerland were positive in most of the days over the baseline sample period. The net pairwise volatility spillovers to Switzerland reached the lowest level at -8.33% on September 5 (at 13:15 pm), while the highest peak at 7.40% on September 12 (at 10:45 am), 2016. During September 5 to 12, 2016, a series of news related to the poor performance of Germany’s economy came out. Furthermore, there were net positive spillovers from Germany to Switzerland around the EU referendum on June 23, 2016. In sum, the aforementioned intraday net volatility shock transmissions by and large identify both Switzerland and the United Kingdom as a net receiver of volatility from others, whereas both France and Germany as a net transmitter of volatility to others over the baseline sample period (see also Figure 5).

Figure A7 in the Appendix plots the rolling-sample intraday net pairwise volatility spillovers of stock markets for the period between January 2, 2015 and September 30, 2015. Overall, the net pairwise spillover dynamics affirm the observations in Figure A6 of the Appendix that: (1) both France and Germany were largely a net transmitter of volatility to others; (2) Switzerland

was a net receiver of volatility from others in most of the time; and (3) the United Kingdom was at both the giving and receiving ends of volatility shock transmissions.

4. Conclusion

The EU referendum in the United Kingdom on June 23, 2016, has been one of the biggest events, after the global financial crisis of 2007–2008, that increased uncertainty tremendously in the coming years. Policymakers and practitioners including investors are keenly interested in knowing the consequences associated with this event, while seeking strategies for coping with the undesirable outcomes effectively. Against this backdrop, our paper empirically examines the nature and extent of the volatility spillover dynamics within and across four major stock markets in Europe, comprising France, Germany, Switzerland and the United Kingdom, over the period between January 4, 2016 and September 30, 2016. By utilizing a 15-minute intraday data to the econometric framework of [Diebold and Yilmaz \(2012\)](#), we find a host of interesting results. In particular, a full-sample (static) analysis of intraday average or unconditional spillovers clearly reveals that France and Germany have been the net transmitters of volatilities to others. On the other hand, Switzerland and the United Kingdom have been the net receivers of volatilities from others. Interestingly, the stock market in France appears to be the largest net volatility transmitter to others, while the stock market in the United Kingdom seems to be the largest net volatility receiver from others. Besides, the total (non-directional) volatility spillover index suggests that, on average, nearly a two-fifth of the intraday volatility forecast error variance in four stock markets comes from shock spillovers.

Our rolling-sample (dynamic) analysis of intraday conditional volatility spillovers also confirms the above empirical findings. The total (non-directional) volatility spillover index varies greatly over the sample period. The stock markets in France and Germany were largely a net volatility transmitter to others. In contrast, the stock markets in Switzerland and the United Kingdom were by and large a net receiver of volatility from others over the baseline sample period. It is important to highlight that both France and the United Kingdom (Germany and Switzerland) were a net volatility transmitter (receiver) to others (from others) around the day of the Brexit referendum on June 23, 2016.

Finally, a comparison of the intraday volatility spillover dynamics of our four stock markets over the period between January 2, 2015 and September 30, 2015 to that of the period between January 4, 2016 and September 30, 2016, reveals one stark difference. In particular, the United Kingdom was at both the giving and receiving ends of the net volatility transmissions, with roughly half of the time altogether at each end during the sample period between January 2,

2015 and September, 30, 2015. But consistent with our baseline findings for the nine months period in 2016, Germany (Switzerland) mainly appears to be a net transmitter (receiver) of intraday volatility to others (from others). Moreover, the stock market in France turns out to be largely a net volatility transmitter to others for a significant amount of time altogether. Nevertheless, the intraday volatility shock spillover pattern for France's stock market is not as obvious as that observed over the sample period for 2016. In sum, our empirical findings on cross-market volatility transmissions provide valuable implications for policymakers, academics, and market practitioners including traders and fund managers. However, we remain agnostic as to how intraday volatility shocks spilled over among four stock markets in concern.

Appendix

See Tables [A1–A2](#) and Figures [A1–A8](#).

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Table 1
Stock markets and trading hours

The table reports the stock market indexes used in the empirical analysis. Opening and closing times for each market are shown in both local time and the United Kingdom time (i.e., Greenwich Mean Time).

Market	Index	Local time		United Kingdom time	
		Opening time	Closing time	Opening time	Closing time
France	CAC 40	09:00	17:30	08:00	16:30
Germany	DAX 30	09:00	17:30	08:00	16:30
Switzerland	SMI	09:00	17:30	08:00	16:30
United Kingdom	FTSE 100	08:00	16:30	08:00	16:30

Table 2
Descriptive statistics of log volatilities

The table reports descriptive statistics of four stock markets' log volatilities used in the intraday volatility spillover analysis. For each stock market, intraday (realized) volatility is computed as the squared 15-minute log return on the respective market index. All returns are calculated in US dollars and overnight returns are excluded. The sample period covers data from January 4, 2016 to September 30, 2016. See also notes to Table 1.

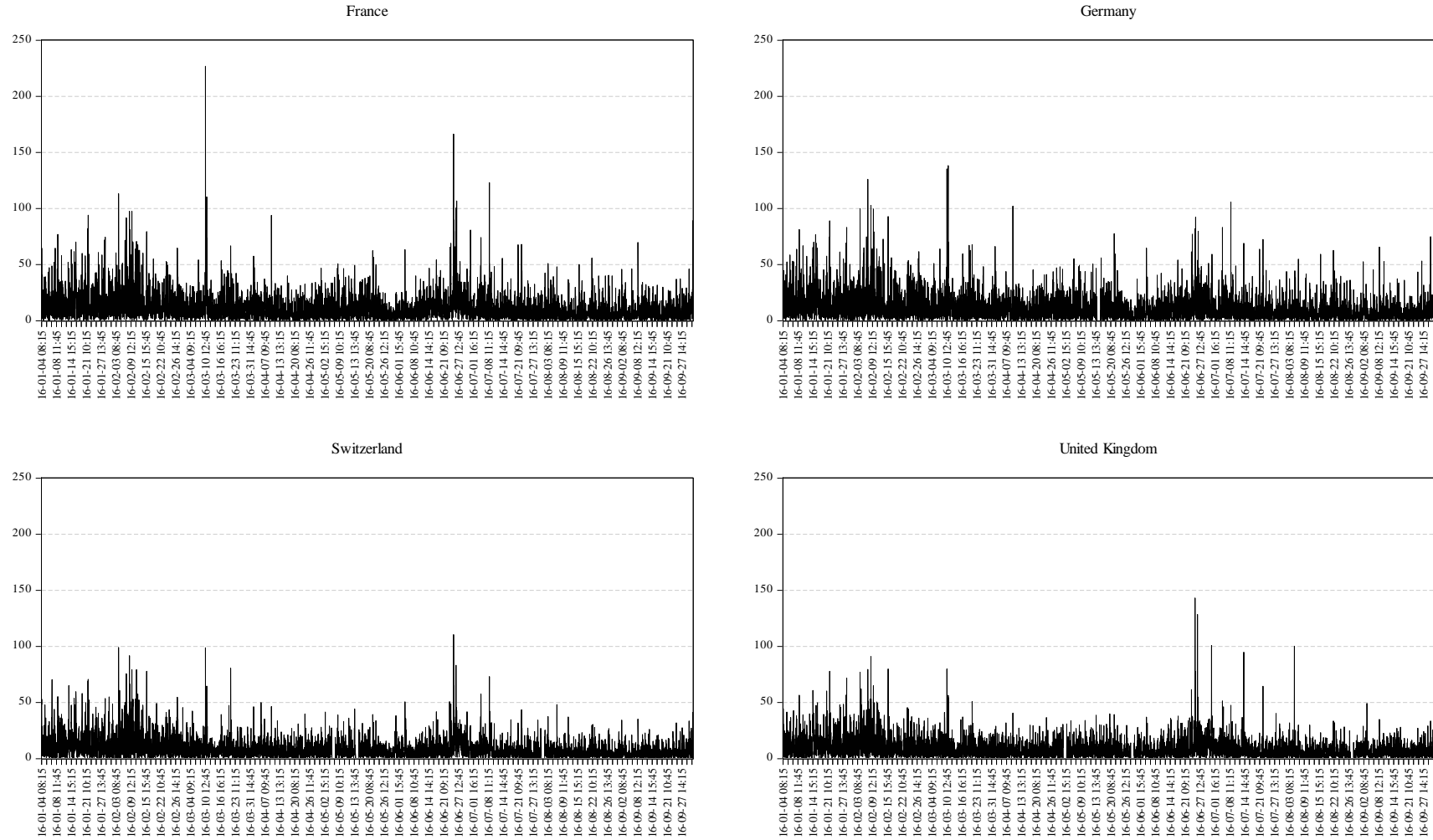
	France	Germany	Switzerland	United Kingdom
Mean	−14.36	−14.43	−14.90	−14.84
Median	−13.99	−14.05	−14.54	−14.49
Std. dev.	2.39	2.42	2.38	2.35
Minimum	−26.07	−27.76	−27.22	−26.90
Maximum	−7.42	−8.41	−8.86	−8.34
Skewness	−1.06	−1.01	−0.99	−1.06
Kurtosis	4.97	4.89	4.71	4.99
Observations	6562	6562	6562	6562

Table 3
Full-sample volatility spillovers

The table reports the full-sample (unconditional) intraday volatility spillovers (in %) for four stock markets. The spillover measures, introduced by [Diebold and Yilmaz \(2012\)](#), are based on a fourth-order vector autoregression system and generalized variance decompositions of 10-step-ahead (i.e., 2.5 hours) volatility forecast errors. The ij -th element of the upper-left 4×4 submatrix shows the estimated contribution to the forecast error variance of stock market i coming from shocks to stock market j . The rightmost column, denoted by FROM, is equal to the off-diagonal row sums and shows the directional volatility spillovers received by stock market i from all other stock markets j . The bottom row, denoted by TO, is equal to the off-diagonal column sums and shows the directional volatility spillovers transmitted by stock market j to all other stock markets i . The bottommost row, denoted by NET, is equal to the difference between the TO and FROM and shows the net directional volatility spillovers. The bottom-right element (in boldface) shows the total (non-directional) spillover index (in %), which is approximately the grand total of the off-diagonal column sums (or row sums) relative to the grand total of the column sums including diagonal elements (or the row sums including diagonal elements). See also notes to [Tables 1](#) and [2](#).

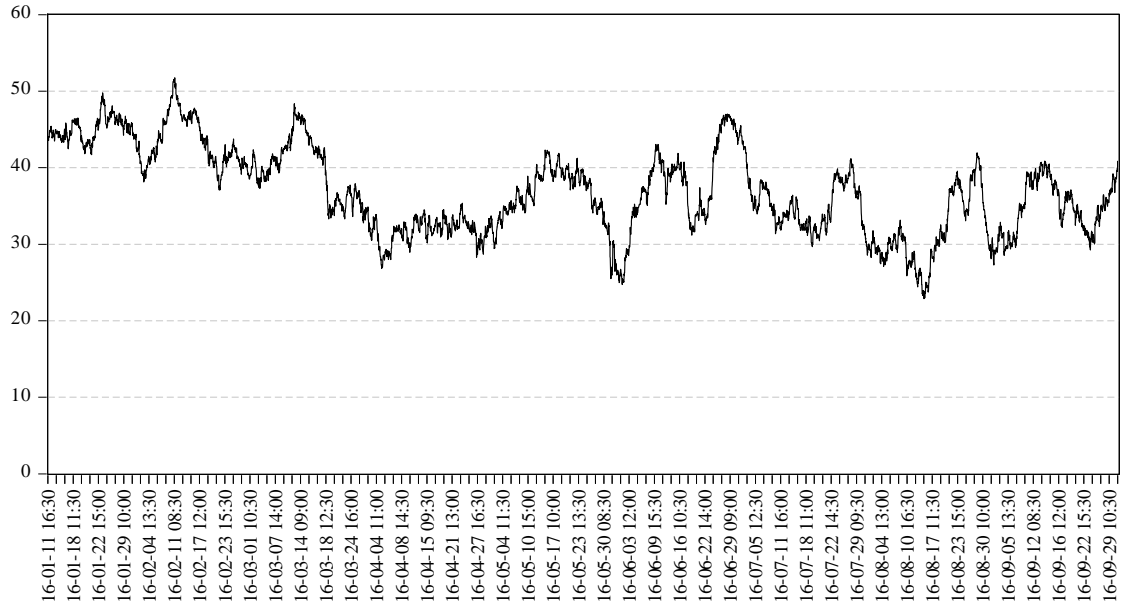
	France	Germany	Switzerland	United Kingdom	FROM
France	56.74	21.32	10.77	11.17	43.26
Germany	22.22	58.02	10.13	9.63	41.98
Switzerland	12.50	11.60	67.88	8.01	32.11
United Kingdom	12.79	10.72	8.27	68.22	31.78
TO	47.51	43.64	29.17	28.81	37.28
NET	4.25	1.66	-2.94	-2.97	

Figure 1
Stock market volatilities



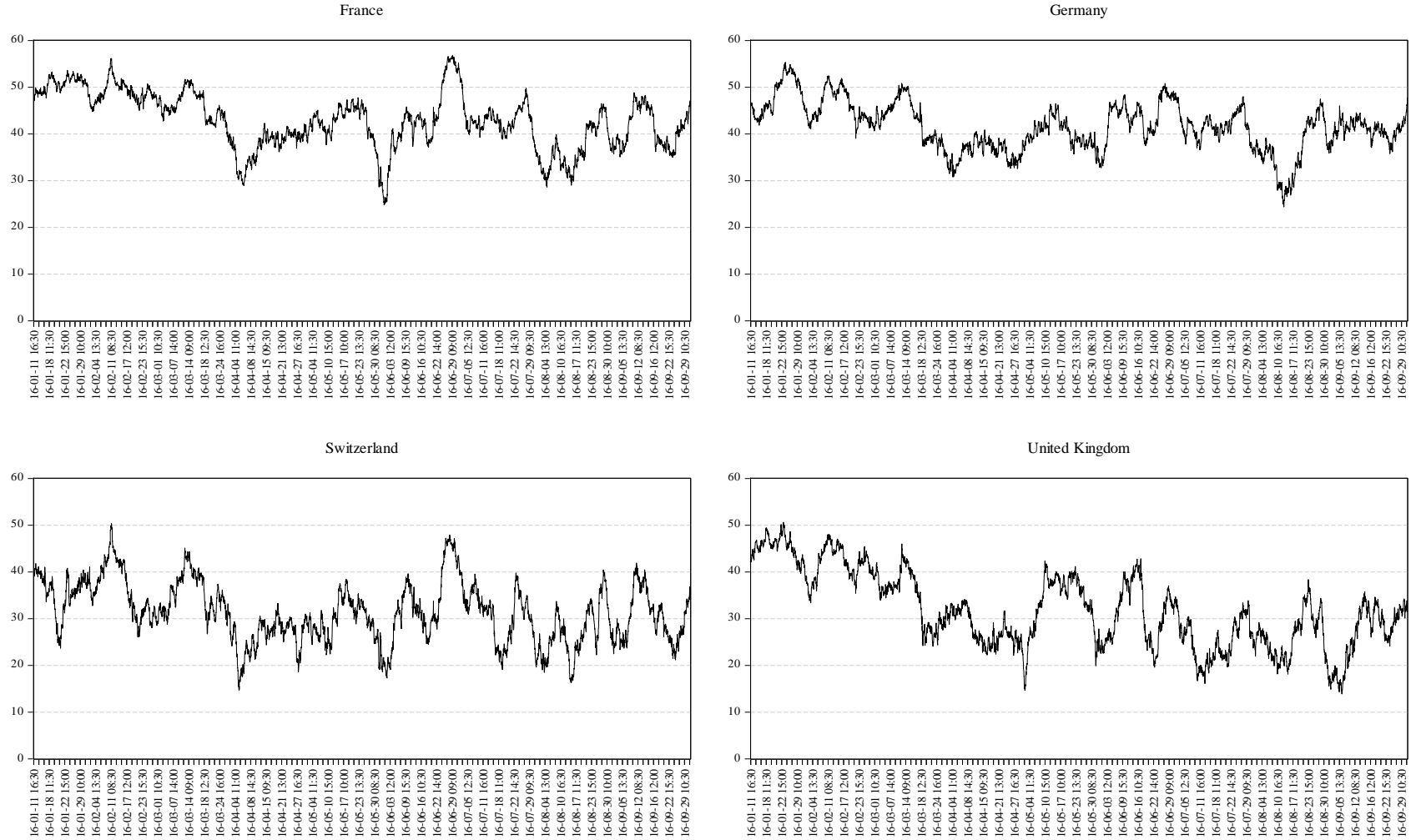
The figure plots the four stock markets' intraday volatilities measured as the absolute 15-minute log return (annualized %). The sample period covers data from January 4, 2016 to September 30, 2016. All returns are calculated in US dollars and overnight returns are excluded. See also notes to Table 1.

Figure 2
Total volatility spillovers



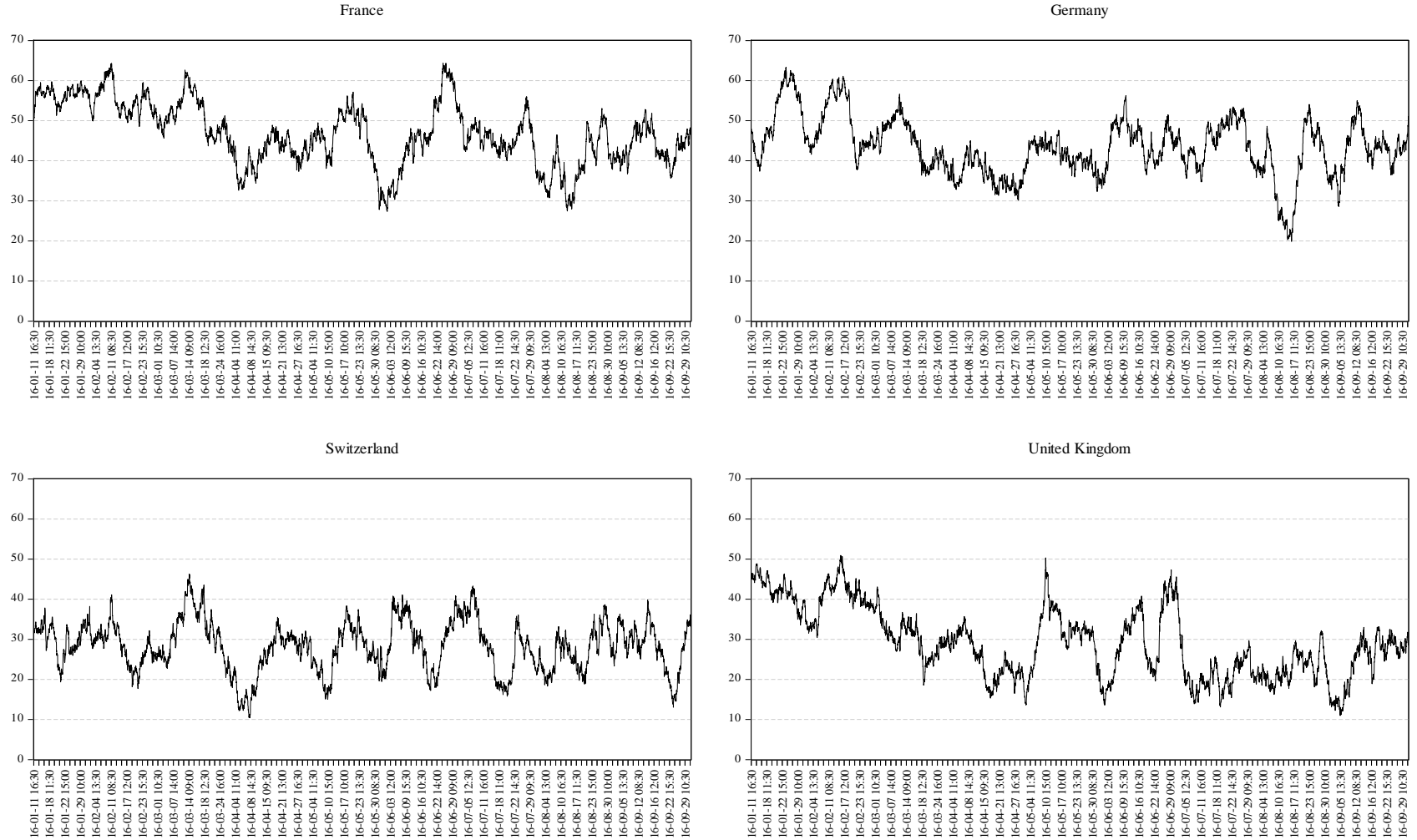
The figure plots the intraday total (non-directional) volatility spillovers (in %) for four stock markets using 200-observation rolling sample window. The forecast horizon for the underlying generalized variance decompositions is 2.5 hours (i.e., 10-step-ahead). See also notes to Tables [1](#) and [2](#).

Figure 3
Directional volatility spillovers received



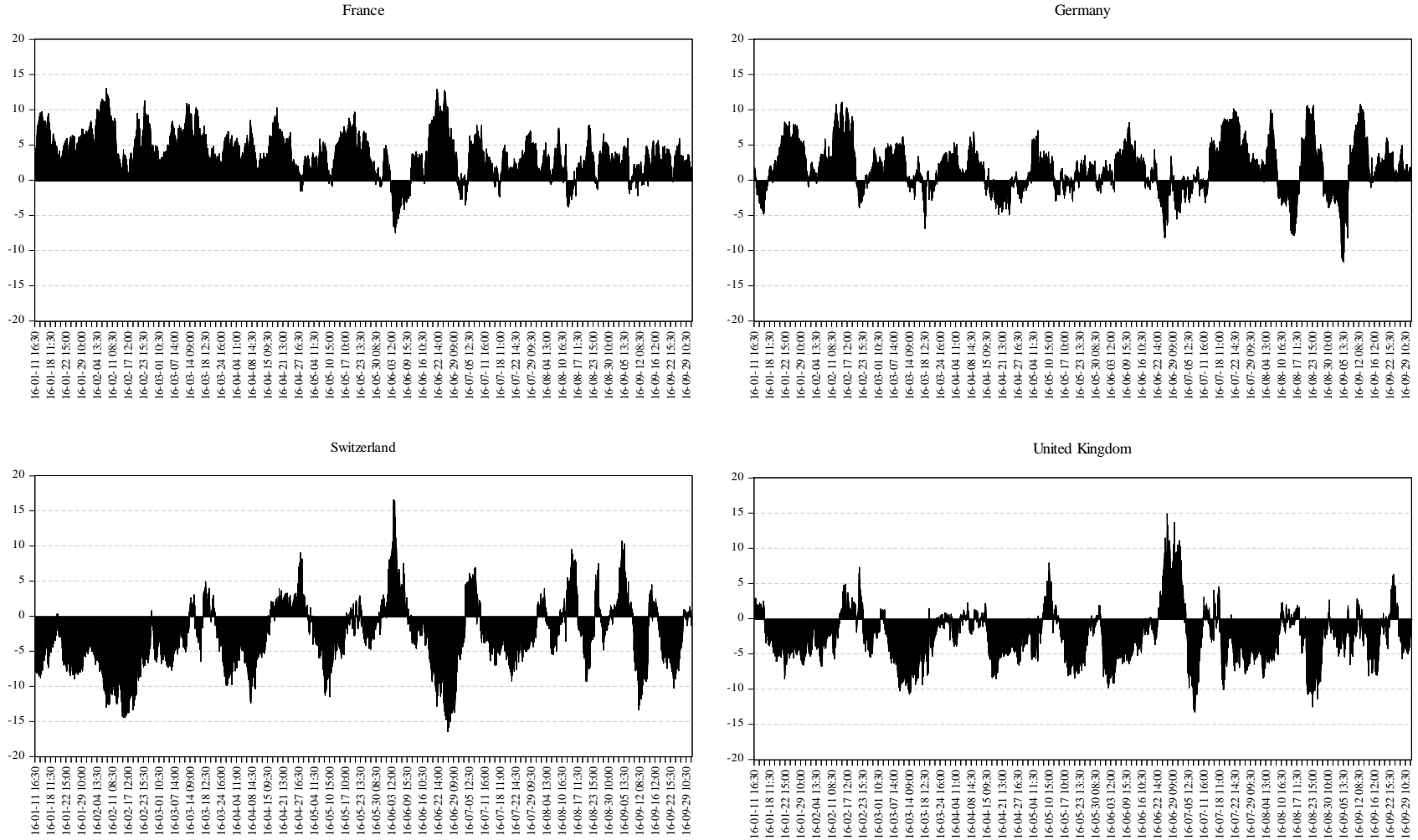
The figure plots the intraday directional volatility spillovers (in %) received by stock market i from all other stock markets j . See also notes to Tables 1 and 2 and Figure 2.

Figure 4
Directional volatility spillovers transmitted



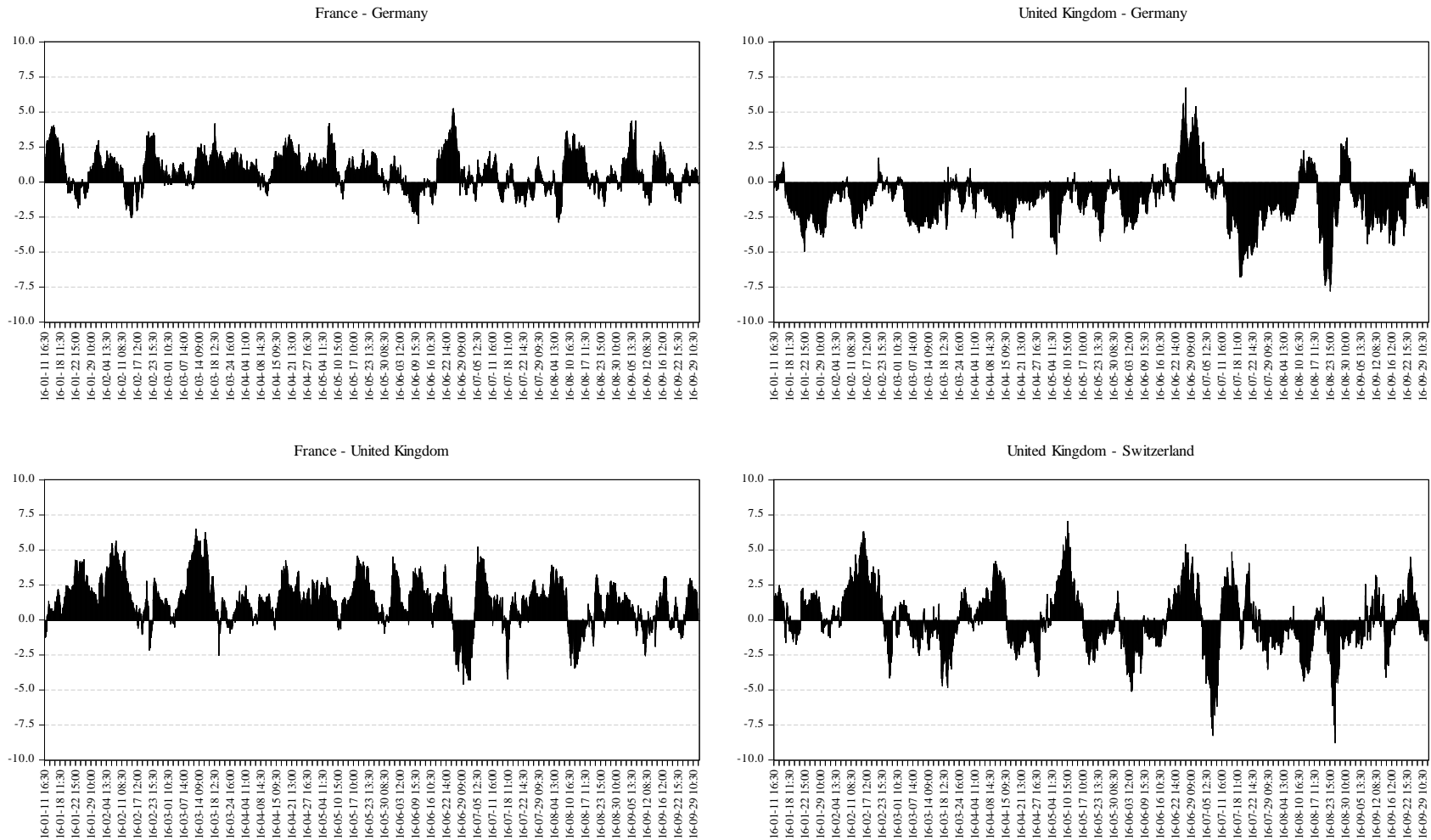
The figure plots the intraday directional volatility spillovers (in %) transmitted by stock market i to all other stock markets j . See also notes to Tables 1 and 2 and Figure 2.

Figure 5
Net directional volatility spillovers



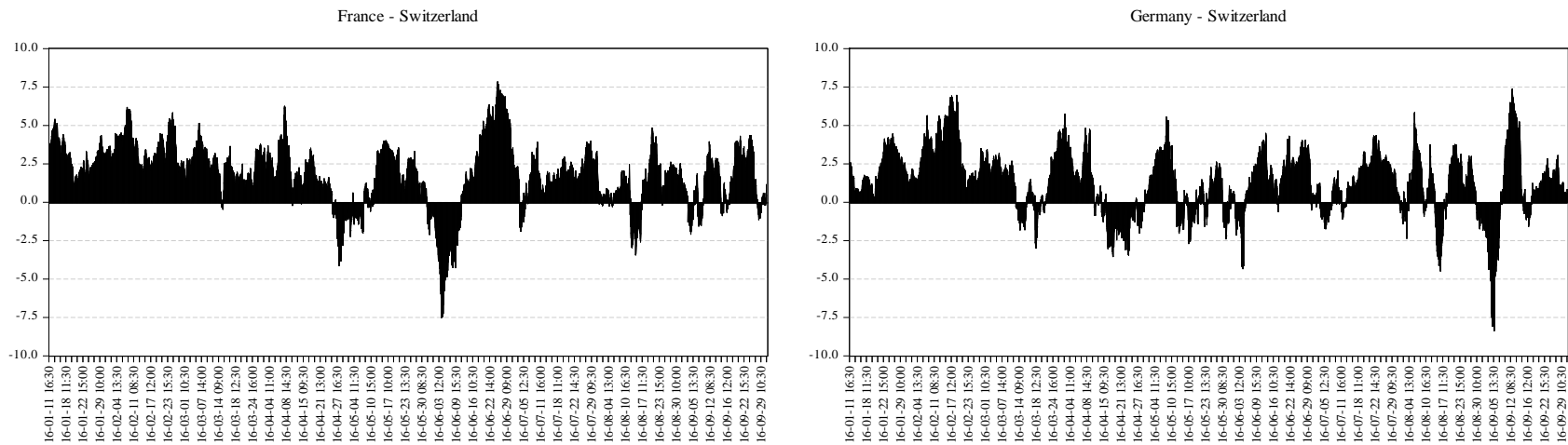
The figure plots the intraday net directional volatility spillovers (in %) from stock market i to all other stock markets j . See also notes to Tables 1 and 2 and Figure 2.

Figure 6
Net pairwise volatility spillovers



(Continued)

Figure 6 – *Continued*



The figure plots the intraday net pairwise volatility spillovers (in %) between markets i and j . See also notes to Tables 1 and 2 and Figure 2.

Table A1
Descriptive statistics of log volatilities: January 2, 2015 to September 30, 2015

The table reports descriptive statistics of four stock markets' log volatilities used in the intraday volatility spillover analysis. See also notes to Tables 1 and 2.

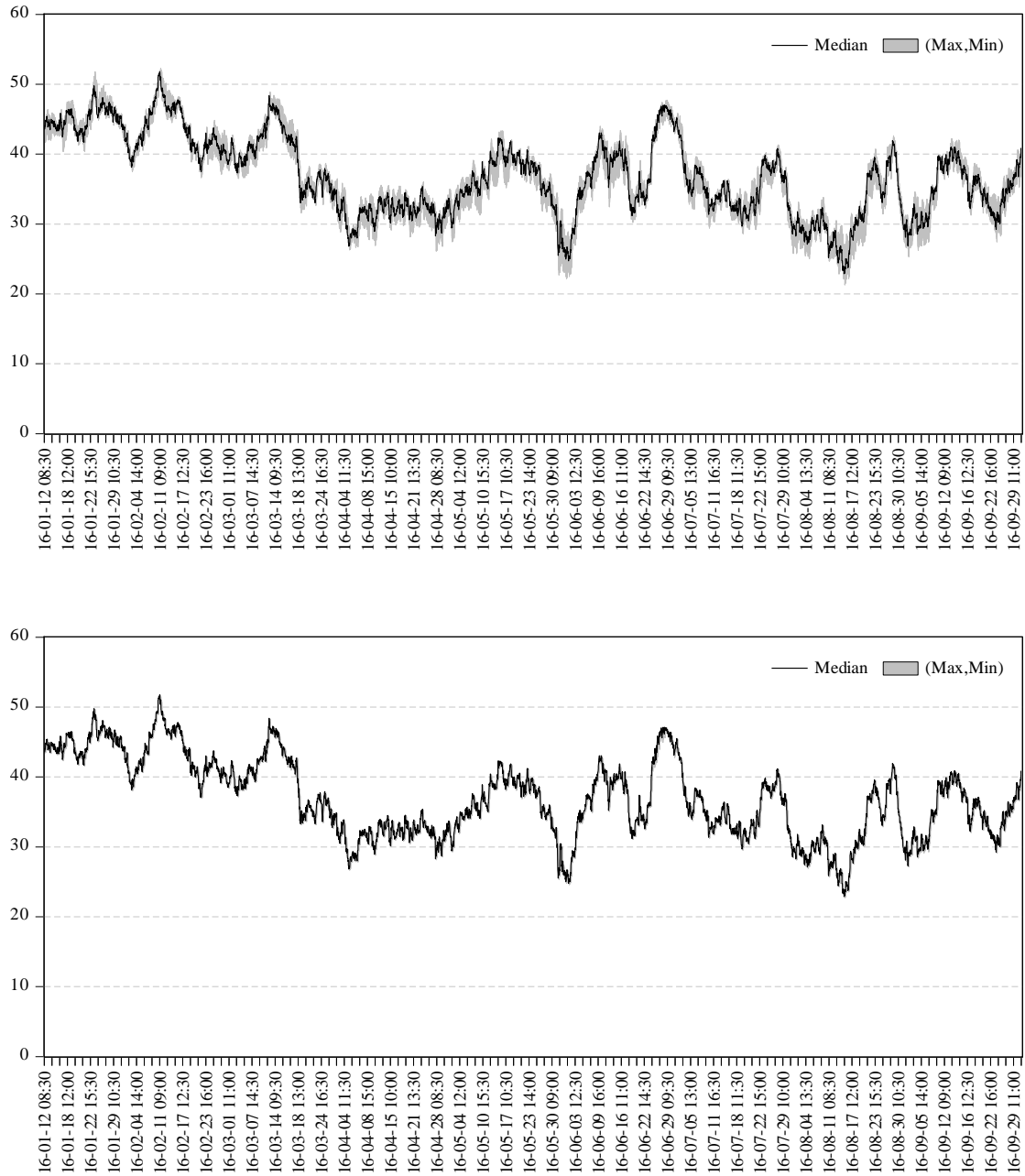
	France	Germany	Switzerland	United Kingdom
Mean	−14.26	−14.21	−14.92	−14.96
Median	−13.85	−13.81	−14.50	−14.61
Std. dev.	2.37	2.39	2.40	2.39
Minimum	−26.35	−27.98	−27.52	−26.93
Maximum	−7.37	−8.09	−5.76	−8.66
Skewness	−1.14	−1.18	−1.02	−1.15
Kurtosis	5.19	5.54	5.03	5.36
Observations	6528	6528	6528	6528

Table A2
Full-sample volatility spillovers: January 2, 2015 to September 30, 2015

The table reports the full-sample (unconditional) intraday volatility spillovers (in %) for four stock markets. See also notes to Tables 1–3.

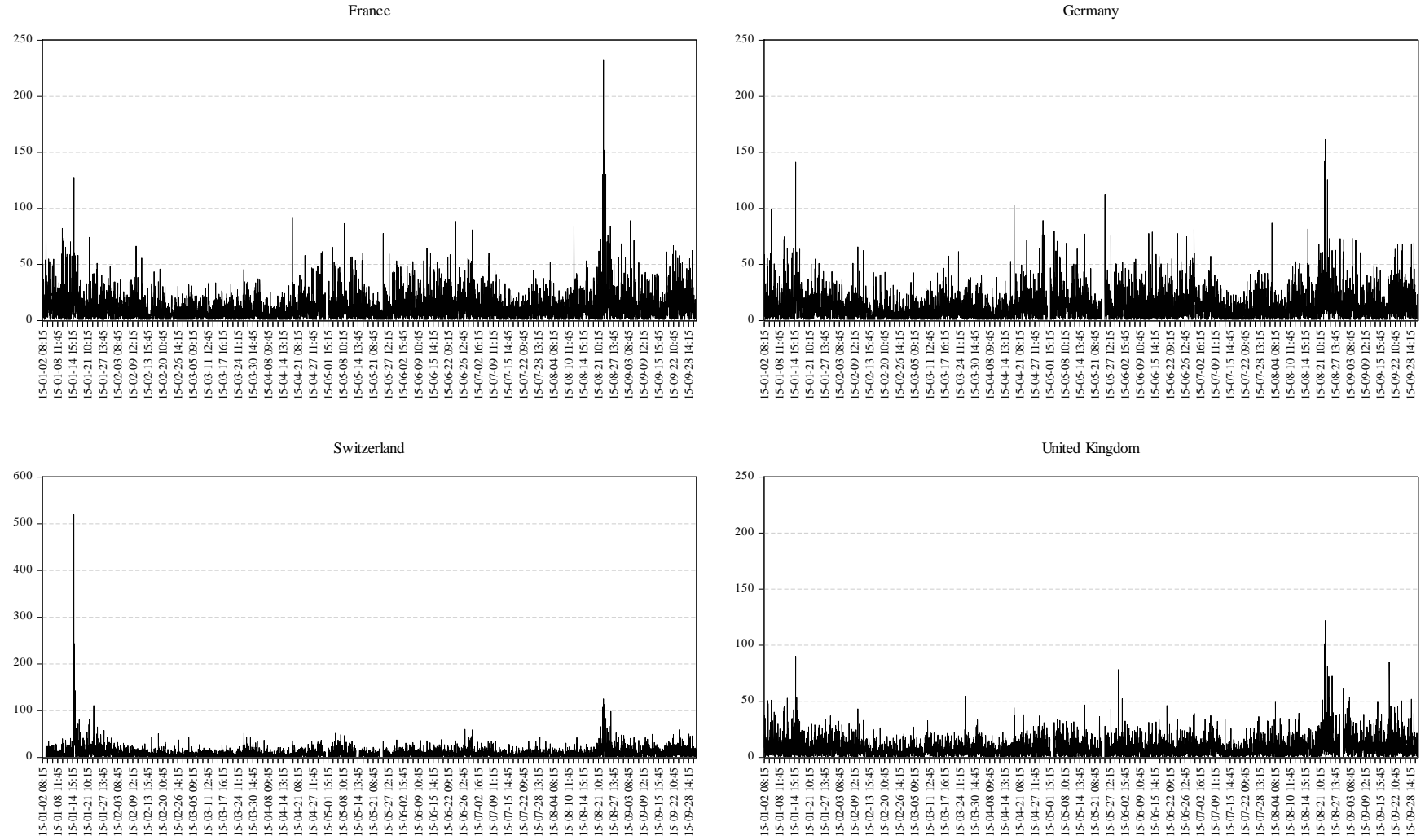
	France	Germany	Switzerland	United Kingdom	FROM
France	65.16	20.71	5.77	8.36	34.84
Germany	20.60	66.44	5.58	7.38	33.56
Switzerland	7.03	7.30	78.74	6.93	21.26
United Kingdom	9.19	8.33	5.49	76.99	23.01
TO	36.82	36.34	16.84	22.67	28.17
NET	1.98	2.78	−4.42	−0.34	

Figure A1
Sensitivities of the total volatility spillover index



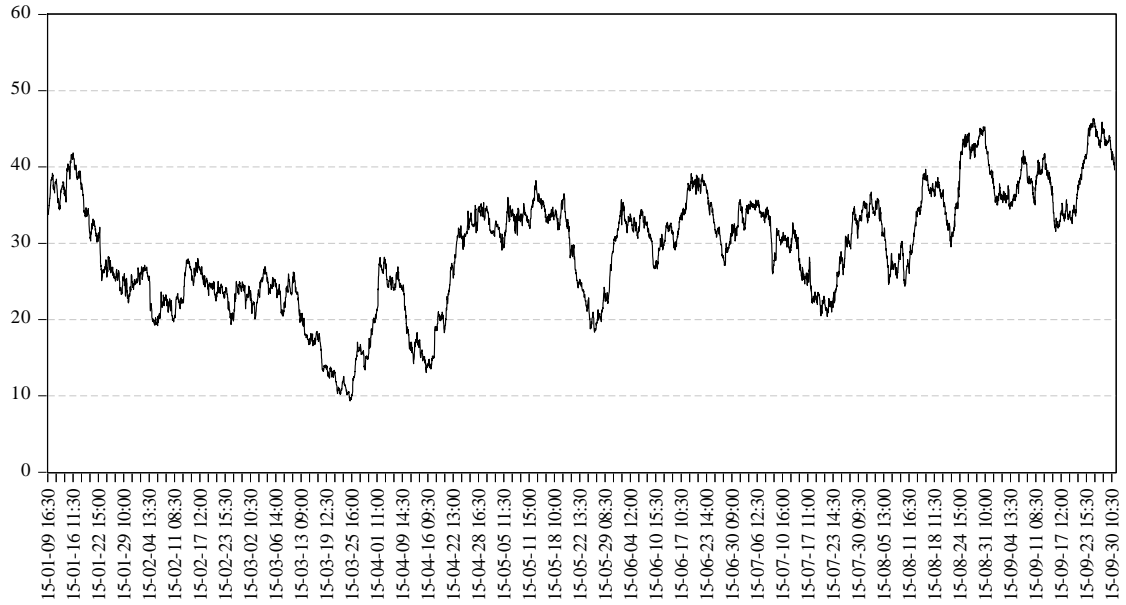
The figure shows sensitivities of the intraday total (non-directional) volatility spillover index (in %) to the lag structure of the generalized vector autoregression (VAR) system and to the forecast horizon. The upper panel plots the time-series of intraday maximum, minimum, and median values of the index for VAR orders of 2 to 6. The lower panel plots the time-series of intraday maximum, minimum, and median values over 8- to 15-step-ahead forecast horizons. In both panels, the rolling estimation window length is 200 observations. See also notes to Tables 2 and 3.

Figure A2
Stock market volatilities: January 2, 2015 to September 30, 2015



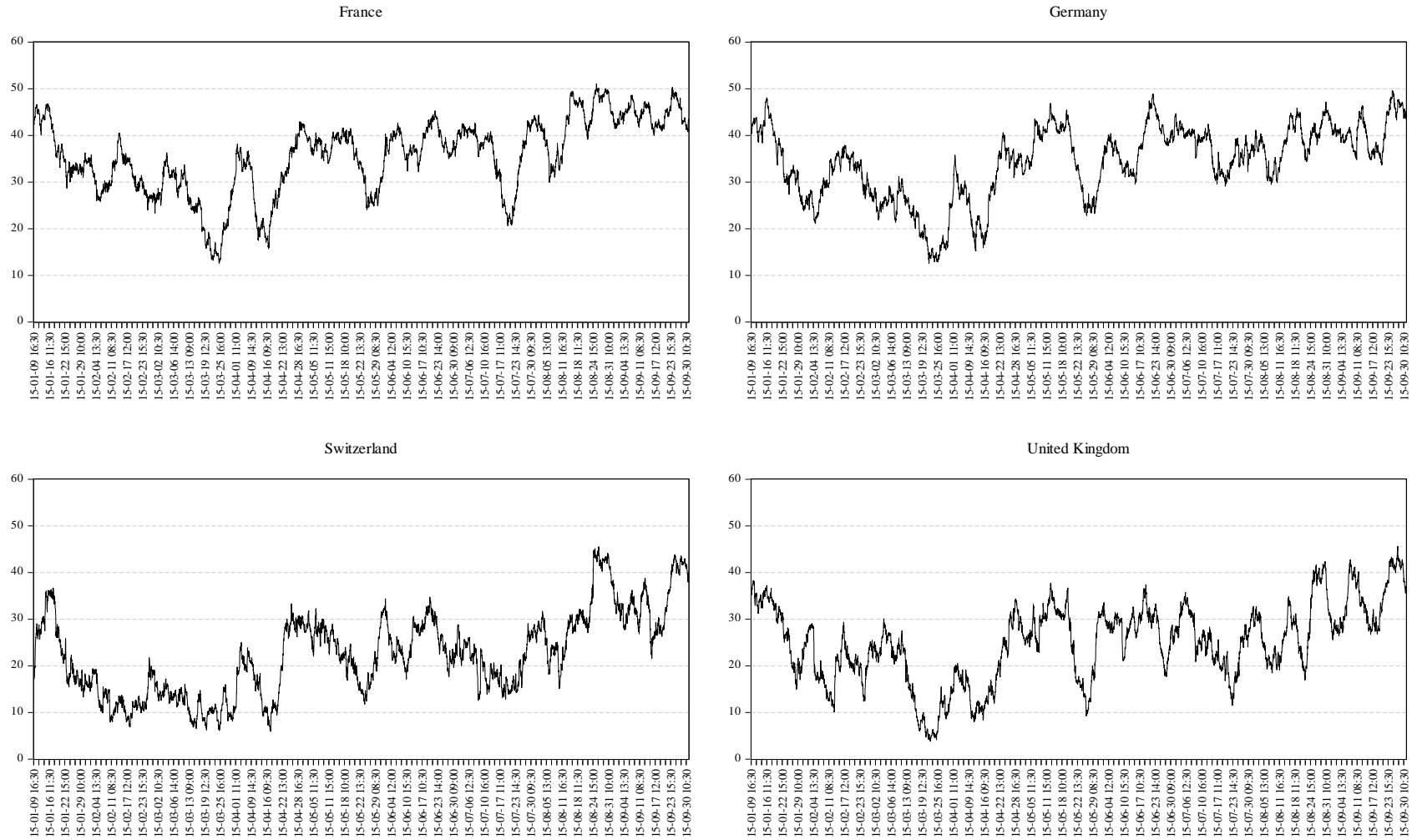
The figure plots the four stock markets' intraday volatilities measured as the absolute 15-minute log return (annualized %). See also notes to Table 1 and Figure 1.

Figure A3
Total volatility spillovers: January 2, 2015 to September 30, 2015



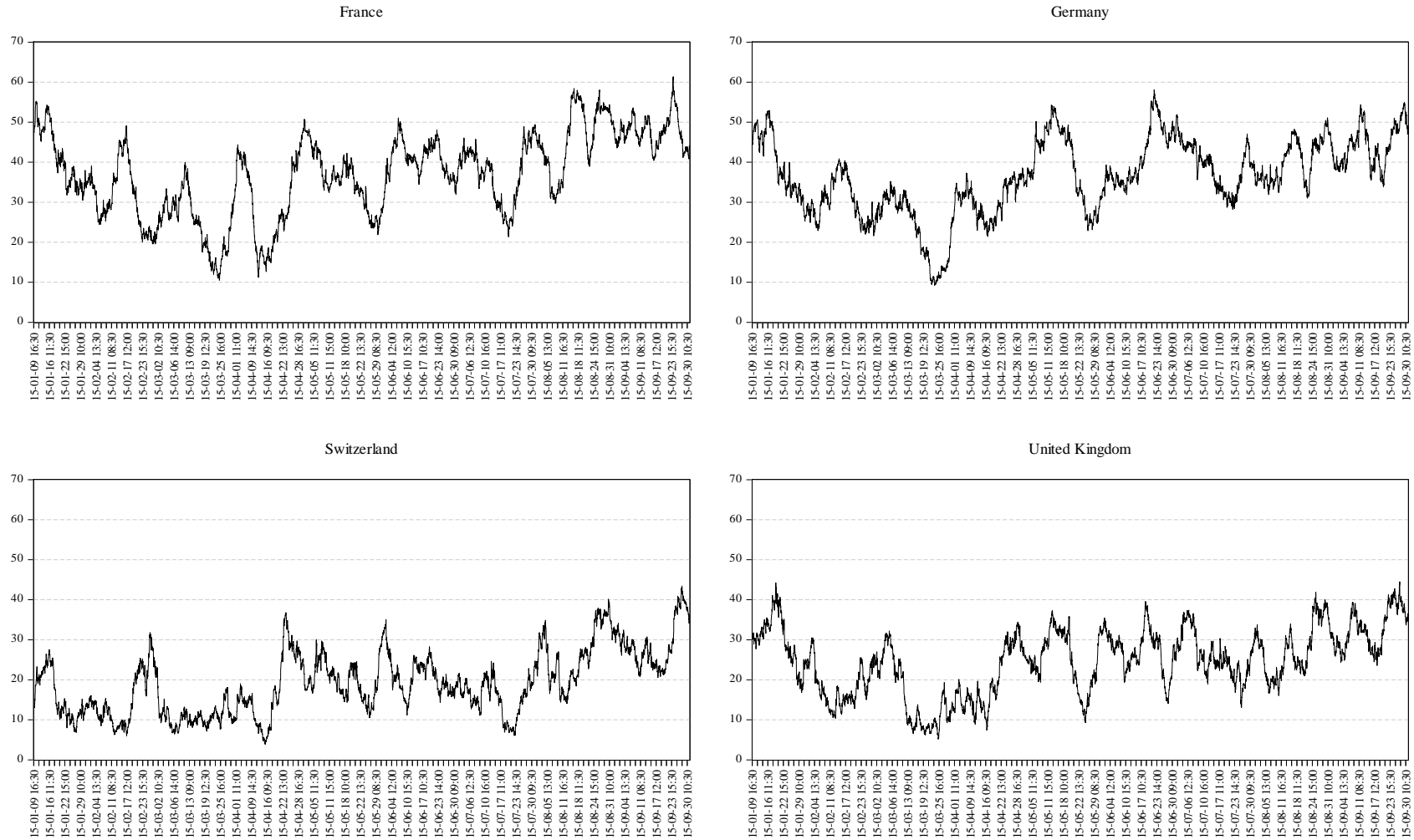
The figure plots the intraday total (non-directional) volatility spillovers (in %) for four stock markets using 200-observation rolling sample window. See also notes to Tables 1 and 2 and Figure 2.

Figure A4
Directional volatility spillovers received: January 2, 2015 to September 30, 2015



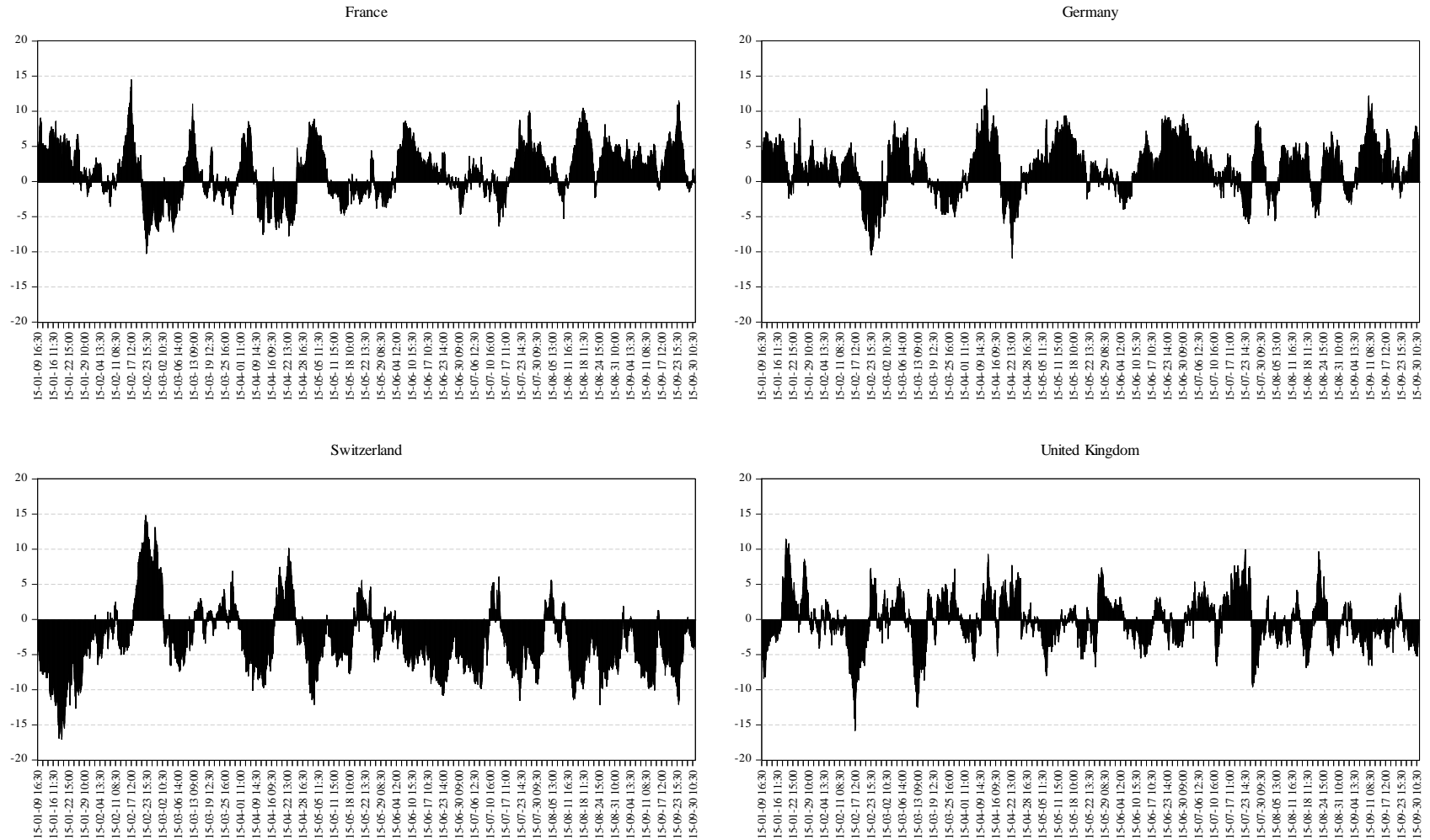
The figure plots the intraday directional volatility spillovers (in %) received by stock market i from all other stock markets j . See also notes to Tables 1 and 2 and Figure 2.

Figure A5
Directional volatility spillovers transmitted: January 2, 2015 to September 30, 2015



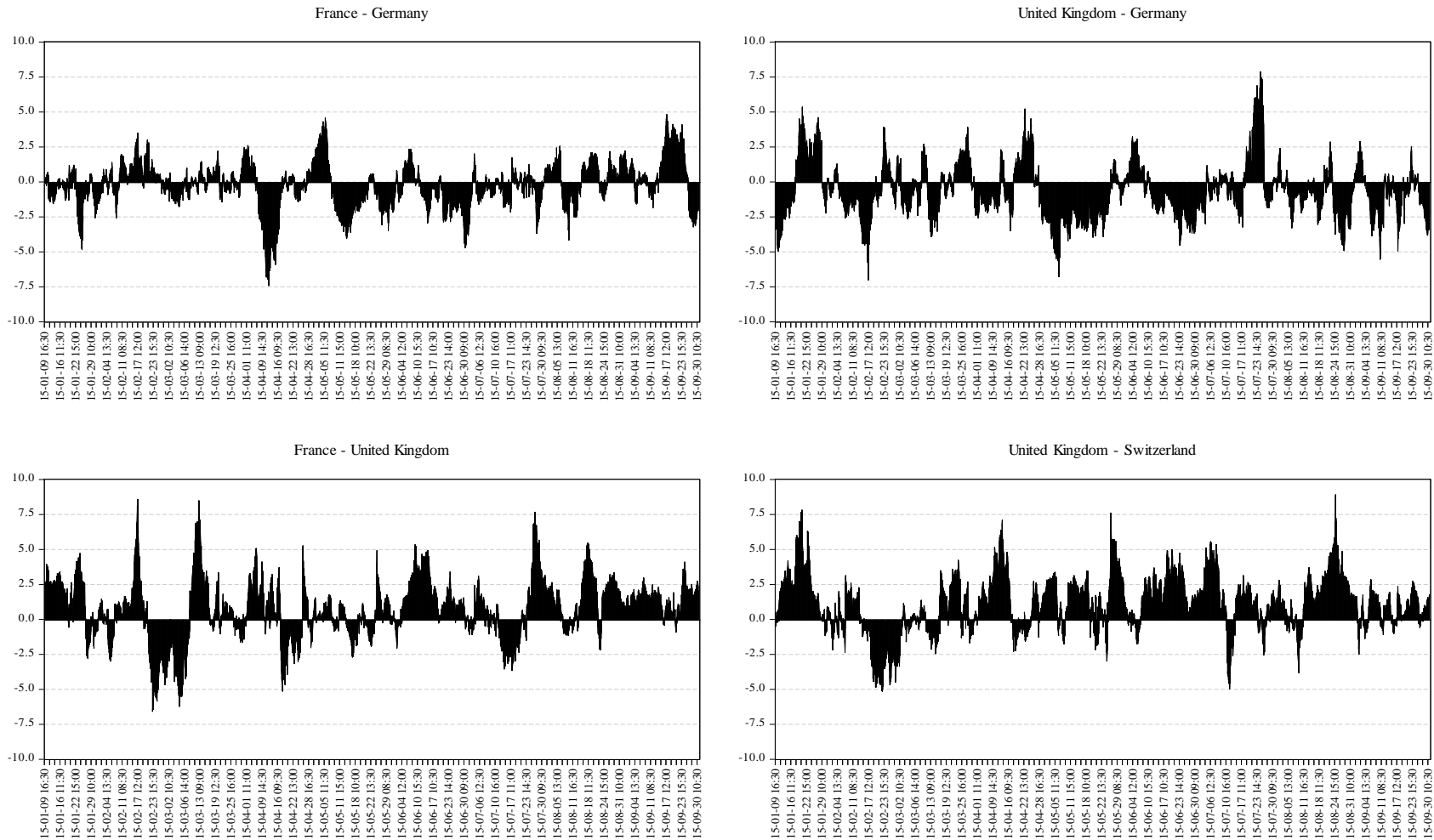
The figure plots the intraday directional volatility spillovers (in %) transmitted by stock market i to all other stock markets j . See also notes to Tables 1 and 2 and Figure 2.

Figure A6
Net directional volatility spillovers: January 2, 2015 to September 30, 2015



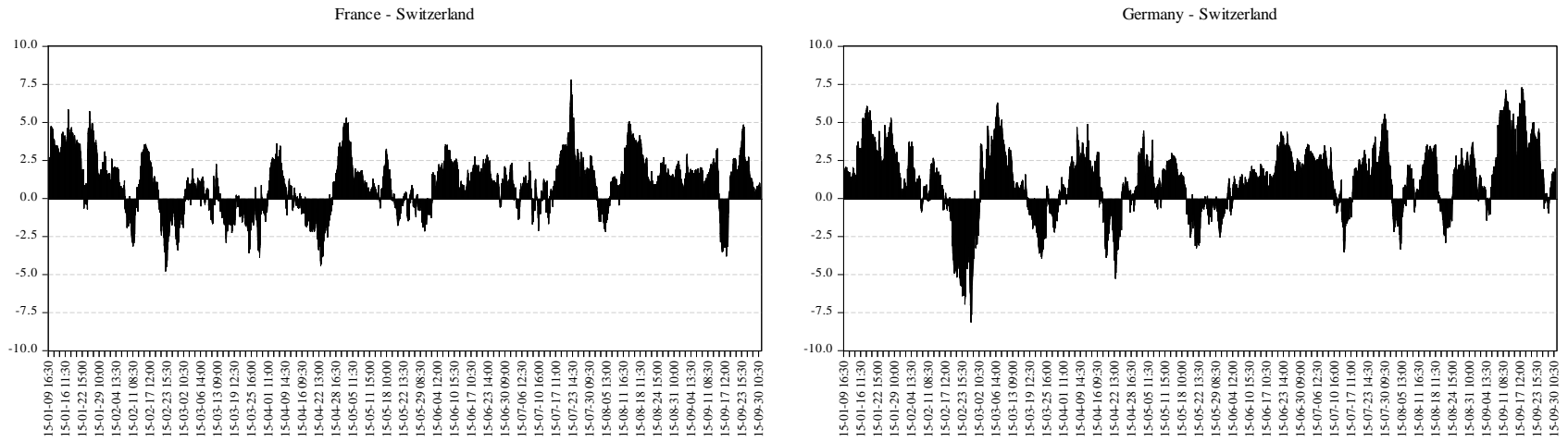
The figure plots the intraday net directional volatility spillovers (in %) from stock market i to all other stock markets j . See also notes to Tables 1 and 2 and Figure 2.

Figure A7
Net pairwise volatility spillovers: January 2, 2015 to September 30, 2015



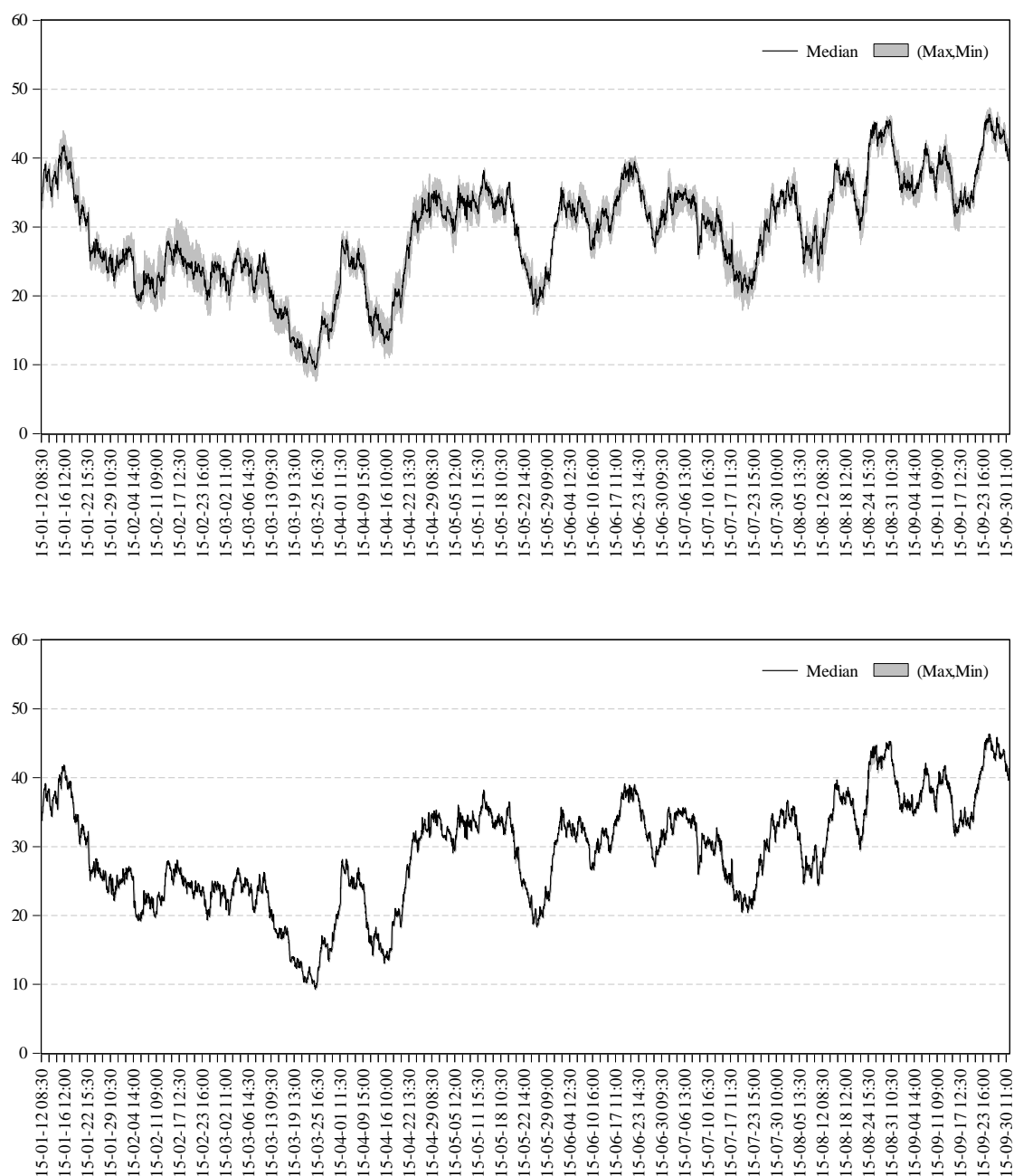
(Continued)

Figure A7 – *Continued*



The figure plots the intraday net pairwise volatility spillovers (in %) between markets i and j . See also notes to Tables 1 and 2 and Figure 2.

Figure A8
Sensitivities of the total volatility spillover index:
January 2, 2015 to September 30, 2015



The figure shows sensitivities of the intraday total (non-directional) volatility spillover index (in %) to the lag structure of the generalized vector autoregression system and to the forecast horizon. See also notes to Tables 2 and 3 and Figure A1.