International Stock Return Co-movements and Trading Activity

Abstract

This paper analyses return co-movements across eight major international stock markets while considering the nature of motives to trade for a given daily price change. Daily volume as an information signal is dissected into quintiles and its interaction with returns is examined. The results show that international return spillover effects are sensitive to different levels of trading activity and price changes driven by liquidity-based and information-based trades can both spill over across borders. We find trades originating in Asia are information-based, those originating in America are liquidity-based, and those originating in Europe are a mixture of these two types.

JEL classification: C32; G14; G15

Keywords: Return Spillovers; Trading Volume; Interaction Effects; Intraday Data; GARCH Models

1. Introduction

The role of trading volume has been largely overlooked in extant literature on the integration of financial markets. While a large number of studies investigate stock return co-movements, little research has been done on the informational role of trading activity in the dynamics of return spillovers across markets.[1] The few existing studies provide some evidence that return spillovers are sensitive to interactions with trading volume (see e.g., Gagnon and Karolyi, 2003; 2009, and more recently, Gębka and Serwa, 2015). It is not yet clear, however, what the signalling role of trading volume is in shaping stock return transmission mechanisms across international markets, and how levels of, and changes in, trading activity relate to variations in return spillovers. It is also not entirely obvious what the nature of the relation between the informational role of trading volume and price discovery mechanisms across international stock markets is.[2] These issues, which motivate the analysis in this study, have direct practical relevance to international investors and financial market regulators around the globe.

Gagnon and Karolyi (2003) provide a methodological framework for studying variations over time in return spillovers. Their approach, which accounts for interactions between trading volume and returns, is of particular relevance to our paper given the challenges that the earlier literature faced in finding the driving forces behind the spillovers.[3] They frame their analysis of the joint dynamics of stock return co-movements and trading volume in the context of the heterogeneous-agent trading model proposed by Campbell, Grossman and Wang (1993) (hereafter, the CGW model). In the CGW model, the aggregate trading volume of the market

[1] See Gagnon and Karolyi (2006) for a review of the spillover literature.
[2] Prediction of stock price movements based on volume patterns has been widely used for many decades by technical analysts and this group of techniques dates back to the beginning of the 20th century and the emergence of the, so called, Dow Theory. For example, one of the elements of the Dow Theory is the assumption that trading volume should confirm the development of trends in stock prices (see Karpoff, 1987, for a review of relevant literature).
[3] Some studies have also found that return spillovers vary over time and their time-varying nature can be explained by macroeconomic information variables, such as GDP, inflation rate and interest rate (e.g., Karolyi and Stulz, 1996; Connolly and Wang, 2003).

is used as an indicator that helps market participants to distinguish between price movements associated with public information from those associated with liquidity trading. Trading volume, therefore, is regarded as a signal of the information content of price changes. Price movements accompanied by heavy volume during a particular trading day are normally associated with shifts in demand created by liquidity traders. Since these shifts are not due to changes in fundamental factors that affect asset (re)valuation, the price movements are more likely to be reversed on the next trading day. Gagnon and Karolyi (2003) first extend the implications of the CGW model to an international setting by allowing trading volume to explain variations of cross-correlations between international stock markets. They distinguish between two types of price movement: liquidity-based movement associated with heavy volume, and (public) information-based movement normally accompanied by low or normal levels of volume. They further argue that the liquidity-based price movements are less likely to be transmitted across borders because they are not due to any fundamental revaluation of the underlying stocks. In this paper, we test this conjecture. It is important to emphasise, however, that the CGW model addresses only domestic market trading. It shows that liquidity trading is usually associated with high trading volume and tends to cause the often-observed negative first-order autocorrelation in stock returns. Gagnon and Karolyi's (2003) interpretation regarding the CGW model in an international context is arguable as fundamental value is not the only determinant of price, or price variations. Liquidity shocks too can carry information. It is, therefore, not immediately obvious why liquidity-based price movements should be less likely to transmit across borders. According to the contagion hypothesis, for example, non-information-based price movements can also spill over to other countries (Lin, Engle and Ito, 1994). It is also reasonable to assume that fads and herding behaviour may occur in an international context. This paper addresses this issue by analysing whether or not liquidity-based price movements transmit across borders and whether only a particular magnitude of such movements is transmitted, while others do not. Further, Gagnon and Karolyi (2003) focus on the US and Japanese markets only and, hence, our analysis is also motivated by whether or not Gagnon and Karolyi's (2003) hypothesis can be verified for a broader set of international stock markets.

This paper addresses these issues by investigating the transmission across borders of information-based and liquidity-based price movements using different levels of trading volume over eight major international markets from April 2004 to September 2015. The return transmission mechanism is examined by focusing on the interactions between international stock markets intraday returns and the associated levels of trading volume. The objective is to verify the informational role of trading volume in affecting the magnitude and significance of the spillover effects in open-to-close daily returns. The markets analysed are those of the US, UK, Canada, France, Germany, Japan, Hong Kong and China. A new empirical model is proposed that allows for the investigation of how international return spillover effects vary with different levels of trading volume. This approach provides rich insights into this relationship within the dynamics of international stock market return spillovers. To the best of our knowledge, this study is the first to analyse explicitly the behaviour of the international return spillovers with respect to different levels of trading volume.

The remainder of this paper is organised as follows: Section 2 describes the data and models, Section 3 presents the results, and Section 4 summarises and concludes.

2. Data and Methodology

Our data, obtained from Datastream, comprises daily opening and closing prices and trading volume from 26 April 2004 to 25 September 2015 for the FTSE100, DAX 30, CAC 40, TOPIX, SSE Composite, Hang Seng, S&P 500 and S&P/TSX indices. Open-to-close returns, denoted by R_t, are calculated as the difference between the natural logarithms of the closing and opening prices. The daily trading volume is measured by turnover by value.[4] Table 1 presents basic statistics of the open-to-close (daytime) returns of the eight market indices during the sample period.[5]

In order to capture the informational role of foreign market volume in affecting the magnitude and significance of return spillovers across markets, we propose a model in which daytime returns in each market follow an AR(p)-GARCH(1,1)-t process with the mean equation augmented with lagged foreign return and an interaction term with foreign trading volume.[6]

$$R_{H,t} = \mu + \sum_{i=1}^{i=p} \alpha_{i,H} R_{H,t-i} + \beta_{0,F} R_{F,t-1} + \beta_{1,F} V_{F,t-1} R_{F,t-1} + \epsilon_t, \quad (1)$$

$$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1}, \quad (2)$$

where $R_{H,t}$ is the open-to-close return in the domestic market at day t and $R_{F,t-1}$ and $V_{F,t-1}$ are the daytime return and trading volume in the foreign market at day t-1, respectively. The error ϵ_t is assumed to follow a Student's t-distribution with conditional variance h_t.[7] The coefficient

[4] We apply the de-trending procedure used by Lee and Rui (2002) and Gębka (2012) where trading volume is regressed on a constant, time and time squared to control for the impact of linear and nonlinear (quadratic) trends in volume data. Turnover by value data for the S&P 500 index is not directly available in Datastream and is calculated by constructing a portfolio that consists of constituents of the S&P 500 index. We also use turnover by volume data from Datastream as an alternative measure but the main findings and results are qualitatively identical and available on request from the authors.

[5] All return series show skewness and high kurtosis indicating fat-tailed distributions. The Ljung-Box Q-statistics (denoted by LB(8)) are used to examine serial correlations in daytime returns, and LB 2(8) are used for squared returns. The null hypothesis of no serial correlations up to eight lags is rejected at the 5% level for all series except for Germany, indicating significant serial dependence of stock returns in these markets. The results of serial correlations in squared returns are statistically significant at the 1% level for all markets, which suggests that strong volatility clustering is present and that a GARCH-type methodology is required.

[6] We also conduct a partial correlation analysis on stock returns while controlling for volume and its interaction with returns. These additional results suggest that the interaction can explain, at least in part, the observed return correlations, while trading volume itself has little direct influence on these correlations. Note that, based on correlations alone, it is not possible to determine what "causes" the relationships. By contrast, our models investigate causal relationships of stock returns and their interaction with trading volume on the dynamics of return spillovers between markets. These results are not reported here to conserve space, but are available from the authors upon request.

[7] Baillie and Bollerslev (1989) suggest that a GARCH model with conditionally t-distributed errors provides a good representation of the leptokurtosis and time-dependent conditional heteroscedasticity of financial time series. Sun and Zhou (2014) confirm that the GARCH(1,1) model with a Student's t distribution fits daily returns of the S&P500 index better than one that follows a Gaussian normal distribution. We find that the AR(1)-GARCH(1,1)-t model well captures the characteristics of stock returns in all markets, except for China for which an AR(4)-GARCH(1,1)-t specification is more appropriate.

$\beta_{1,F}$ captures the interaction effect of foreign market return and trading volume at day *t*-1 on domestic market return at day *t*. Negative estimates ($\beta_{1,F} < 0$) would imply that the magnitude of positive return spillovers from foreign to domestic markets tends to decline with yesterday's foreign trading volume. This effect is consistent with Gagnon and Karolyi's (2003) interpretations of the CGW model. The coefficient $\beta_{0,F}$ captures the marginal (partial) effect of $R_{F,t-1}$ on $R_{H,t}$, *ceteris paribus*.

To investigate return effects over different scale intervals of volume, we divide volume into quantiles and rewrite Equation (1) as:

$$R_{H,t} = \mu + \sum_{i=1}^{i=p} \alpha_{i,H} R_{H,t-i} + \bar{\theta}_{i,F} R_{F,t-1} + \beta_{1,F} R_{F,t-1}\left(V_{F,t-1} - \bar{V}_{i,F}\right) + \epsilon_t, \qquad (3)$$

where $\bar{\theta}_{i,F} = \left(\beta_{0,F} + \beta_{1,F}\bar{V}_{i,F}\right)$ and $\bar{V}_{i,F}$ represents the mean value of foreign market trading volume that belongs to the i^{th}-quantile. $\bar{\theta}_{i,F}$ measures the partial effect of $R_{F,t-1}$ on $R_{H,t}$ when $V_{F,t-1} = \bar{V}_{i,F}$ (see, e.g., Wooldridge, 2012, Chapter 6) and, hence, it captures the size and significance of international return spillover effects in different quantiles of volume.

From an international asset pricing perspective, Fama and French (1998) argue that there should exist a set of global risk factors that explain international stock returns. We follow this approach, and our regression model that accounts for the Fama-French common risk factors, as well as the Carhart momentum factor, is specified as:

$$R_{H,t} = \mu + \sum_{i=1}^{i=p} \alpha_{i,H} R_{H,t-i} + \bar{\theta}_{i,F} R_{F,t-1} + \beta_{1,F} R_{F,t-1}\left(V_{F,t-1} - \bar{V}_{i,F}\right) + \sum_{i=1}^{i=4} \gamma_i X_i + \epsilon_t, \qquad (4)$$

where X_i stands for a set of control variables: the global excess market returns, SMB (small-minus-big stocks), HML (high-minus-low book-to-value stocks) and WML (winners-minus-losers).[8]

[8] We also test for robustness by estimating models that control for the global and local Fama-French common risk and momentum factors, dividend yields, conditional variances of domestic market returns and January and Friday dummies. We find that adding those control variables does not change the overall results. The empirical findings from those models are qualitatively very similar and are available upon request. The Fama-French common risk

3. Empirical Results

We first present evidence about information-based and liquidity-based motives to trade in the context of market activity. This is then followed by an analysis and a discussion of detected geographical patterns in the returns spillover mechanism.

3.1 Information-based *vs.* Liquidity-based Motives to Trade and Market Activity

Table 2, panels A-H, report the estimation results of Equation (3). The country in the top-left cell of each panel is the signalling market (foreign market) and the countries listed in the first column are the signal-receiving markets (domestic markets). The foreign market trading volume over the sample period is sorted by ascending order and binned into quintiles. Accordingly, the parameter $\bar{\theta}_{1,F}$ captures the effect of volume from the lowest quintile and $\bar{\theta}_{5,F}$ captures the effect of volume from the highest quintile. For each quintile i = 1, …, 5, the estimated parameter $\bar{\theta}_{i,F}$ measures the return spillover from the foreign market to the domestic market when trading volume in the previously traded foreign market is at the mean level of the i^{th}-quintile. This provides information about the dynamics of the return spillovers in relation to different levels of trading activity.

The results in Table 2 provide evidence of how information-based and liquidity-based price movements transmit across borders. Estimates of $\bar{\theta}_{i,F}$ depict a general pattern that stock returns accompanied by low trading volume are more likely to spill over to other markets on the next trading day, which is consistent with the findings of Gagnon and Karolyi (2003; 2009). Estimates of $\beta_{1,F}$ are negative for thirty two out of the fifty relations investigated in this study, and six of these are statistically significant (Japan-US, Japan-Canada, Hong Kong-Canada,

and momentum factors are available from the database on Kenneth French website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Canada-China, Germany-France, and Germany-Japan). Overall, there are six cases in Table 2 of statistically significant and negative estimates of $\beta_{1,F}$, and only three cases of statistically significant and positive estimates of this parameter (US-UK, US-Japan, and Canada-UK).[9] The same pattern is observed for the statistically significant estimates of $\beta_{1,F}$ for all the relationships where additionally all estimates of $\bar{\theta}_{i,F}$ (for all i = 1, …, 5) are statistically significant, i.e., there are five cases of statistically significant and negative estimates of $\beta_{1,F}$ and only two cases of statistically significant and positive estimates of this parameter. We thus conclude that there is a general dominance of negative estimates of $\beta_{1,F}$, but the picture varies across geographical regions, i.e. this pattern is very clear and consistent in case of all the signalling markets located in Asia, while it is mixed for signalling American and European markets (in particular when only statistically significant estimates of $\beta_{1,F}$ are considered). We further explore those geographical differences in the next subsection.

3.2. Geographical Patterns in the Returns Spillover Mechanism

Inspecting variations of the statistically significant estimates of $\bar{\theta}_{i,F}$ across all i = 1, …, 5 reveals a more complex picture of interesting geographical patterns across all countries in our sample.

First, out of the eighteen relationships presented in Table 2, where estimates of $\bar{\theta}_{i,F}$ are statistically significant for all i = 1, …, 5, thirteen cases have estimates declining monotonically from $\bar{\theta}_{1,F}$ to $\bar{\theta}_{5,F}$, and five cases have estimates increasing monotonically. A closer inspection

[9] Using monthly frequency data, we find more evidence that the interaction between foreign market trading volume and returns contains valuable information in explaining domestic market returns. Estimates of $\beta_{1,F}$ parameter are statistically significant in 21 out of 50 cases. However, these results show that monthly returns are less likely to spill over across borders due to different information transmission mechanisms from daily returns. We also test if volatility creates a similar impact as trading volume by replacing foreign market trading volume with squared returns on the regression. We find the interaction of trading volume and returns contains some valuable information that is different from the one captured by the interaction between volatility and returns. To conserve space, these results are not reported here, but are available from the authors upon request.

of the patterns of the $\bar{\theta}_{i,F}$ estimates across all countries unveils a much clearer geographical variation, which depicts differences regarding the role of trading volume from the point of view of the type of trade (i.e., information based versus liquidity based). This relates to the information conveyed through the volume dynamics that originates in signalling markets.

Panels A to C of Table 2 report the results of the spillover relationships with Asian trading centres acting as the foreign signalling markets (Japan, Hong Kong and China). The dominance of the nine *vs.* one cases of a clear and monotonic decline from $\bar{\theta}_{1,F}$ to $\bar{\theta}_{5,F}$ of $\bar{\theta}_{i,F}$ estimates, implies that price movements associated with information trades are more likely to spill over from Asia and exert greater influence over stock returns in other markets that open next. This pattern in $\bar{\theta}_{i,F}$ estimates confirms the results of the earlier analysis of $\beta_{1,F}$, which also concluded a dominance in the return signal transmission mechanism of information-based trades originating from Asian markets.

Panels D and E of Table 2 report the results of the spillover relationships with American trading centres (US and Canada) acting as the foreign signalling markets. These results show quite a different picture. In American signalling centres there are two cases of a clear and monotonic increase from $\bar{\theta}_{1,F}$ to $\bar{\theta}_{5,F}$ in $\bar{\theta}_{i,F}$ estimates, and one case showing a monotonic decline. This implies that it is more likely for price movements associated with liquidity trades to spill over from American markets, and, as mentioned above, exert greater influence over stock returns in other markets that open next. In addition, the positive and statistically significant estimates of $\beta_{1,F}$ are observed only in American markets (reported above). Together, these results suggest a dominance of liquidity-based trades originating from American signalling markets.

Panels F, G and H of Table 2 report the results of the spillover relationships with European trading centres (UK, France and Germany) acting as the foreign signalling markets. Of the five cases in which all estimates of $\bar{\theta}_{1,F}$ to $\bar{\theta}_{5,F}$ are significant, two show a monotonic increase and three a monotonic decrease from $\bar{\theta}_{1,F}$ to $\bar{\theta}_{5,F}$. Thus, Euopean based signals are motivated by a balanced mixture of information and liquidity. Table 3 summarises the patterns discussed in this sub-section.[10]

In summary, it is clear that trading activity in Asian markets, which is linked to positive return spillovers to other markets, tends to be more information based, while the activity in American markets tends to be more liquidity based and the activity in European markets tends to be motivated equally by information and liquidity. A possible rationale for these results is that signalling may follow the chronological sequence of trading, where Asian markets open first in calendar time during the overnight period of the other two regions, followed by European markets and then American markets. Accordingly, overnight information is digested first in Asia. An alternative rationale is that the volume of demand is dominated by liquidity traders in American markets and by information traders in Asian markets, while it is equally motivated by information and liquidity in European markets (which is consistent with Europe being a central hub of global trading).

4. Conclusions

This paper investigates the interactions between stock index daytime returns and trading volume in eight major international markets. We investigate explicitly the joint dynamics between stock returns and trading volume using a new modelling approach.

We present new evidence that the foreign return spillover effect is sensitive to the volume of trade in foreign markets. Trading activity, therefore, provides valuable information that can help explain the time-varying nature of stock market co-movements. We find that

[10] The monotonic patterns are very clear in all cases presented in Table 2 and discussed in this section. For example, in Panel A the estimates of $\bar{\theta}_{i,F}$ for the relationship between Japan as the signalling market and US as the signal receiving market decrease consistently from 0.2701 through 0.2437, 0.2233 and 0.2040 to 0.1811, while in Panel D the estimates of $\bar{\theta}_{i,F}$ for the relationship between US as the signalling market and UK as the signal receiving market increase consistently from 0.3205 through 0.3491, 0.3642 and 0.3793 to 0.4121 (and they are all statistically significant at 1% level).

international return spillovers can be driven by both liquidity-based and information-based price changes. By considering quintiles of volume, we find that the size of international return spillovers tends to decline with foreign market trading volume and, thus, stock returns accompanied by low trading volume tend to have a significant positive impact on returns of the next trading day. This pattern strongly supports the hypothesis of Gagnon and Karolyi (2003) implying that information based price movements are more likely to transmit across countries and have a greater positive impact on stock returns of subsequently opened stock markets. However, we also find evidence that liquidity-based price changes, which are usually associated with heavy trading volume, can spill over across borders too. Our findings also show interesting geographical patterns in the returns transmission mechanism, unreported in prior literature, namely that trades originating in Asian markets tend to be more information-based, those originating in American markets tend to be liquidity based, and those originating in Europe are a mixture. These results are directly relevant to stock market investors in constructing better trading strategies that rely on the information content of trading volume. This should lead to more accurate predictions of stock market returns. Our results should also be useful to financial market regulators by better understanding the stock market mechanisms in relation to stock price movements induced by particular levels of trading activity.

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Table 1 Basic statistics of daytime returns

Stock Markets	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	LB(8)	$LB^2(8)$
UK	0.0097	1.1625	-0.1699	11.9685	50.5017***	1766.4357***
France	-0.0274	1.1385	-0.3566	7.4951	21.3439***	979.2797***
Germany	0.0034	1.1793	0.1761	11.3744	10.5858	739.6777***
US	0.0251	1.1644	-0.2640	15.6426	52.1084***	1821.2869***
Canada	-0.0247	0.9222	-0.8521	14.3693	18.4535**	2397.7807***
Japan	-0.0403	1.0338	-0.3924	16.4848	30.4131***	1972.6280***
Hong Kong	-0.0448	1.0585	0.2948	19.0942	63.0447***	1386.0733***
China	0.1014	1.5396	-0.2900	6.4574	20.1045***	518.0952***

Notes: The asterisks *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively

Table 2 The dynamics of return spillovers related to trading volume from foreign to domestic markets

Panel A: The dynamics of return spillovers from Japan to other markets

F=Japan	$\bar{\theta}_{1,F}$	$\bar{\theta}_{2,F}$	$\bar{\theta}_{3,F}$	$\bar{\theta}_{4,F}$	$\bar{\theta}_{5,F}$	$\beta_{1,F}$
Germany	0.1059	0.0991	0.0937	0.0887	0.0827*	-0.0208

France	0.1883**	0.1667**	0.1499**	0.1340**	0.1152**	-0.0656
UK	0.2400***	0.2364***	0.2335***	0.2309***	0.2277***	-0.0110
US	0.2701***	0.2437***	0.2233***	0.2040***	0.1811***	-0.0797*
Canada	0.1839**	0.1615***	0.1441***	0.1277***	0.1082***	-0.0678**
Hong Kong	-0.0226	-0.0283	-0.0327	-0.0369	-0.0418	-0.0172
China	-0.1864	-0.1662	-0.1505*	-0.1357*	-0.1182*	0.0611

Panel B: The dynamics of return spillovers from Hong Kong to other markets

F=Hong Kong	$\bar{\theta}_{1,F}$	$\bar{\theta}_{2,F}$	$\bar{\theta}_{3,F}$	$\bar{\theta}_{4,F}$	$\bar{\theta}_{5,F}$	$\beta_{1,F}$
Germany	0.1534***	0.1464***	0.1417***	0.1363***	0.1243***	-0.0239
France	0.1767***	0.1600***	0.1490***	0.1361***	0.1077***	-0.0567
UK	0.2641***	0.2662***	0.2676***	0.2693***	0.2728***	0.0072
US	0.1959***	0.1873***	0.1816***	0.1750***	0.1604***	-0.0291
Canada	0.1516***	0.1360***	0.1256***	0.1135***	0.0868***	-0.0531**
Japan	-0.0653	-0.0539	-0.0464	-0.0376	-0.0182	0.0386
China	0.0135	-0.0064	-0.0196	-0.0350	-0.0690***	-0.0677

Panel C: The dynamics of return spillovers from China to other markets

F=China	$\bar{\theta}_{1,F}$	$\bar{\theta}_{2,F}$	$\bar{\theta}_{3,F}$	$\bar{\theta}_{4,F}$	$\bar{\theta}_{5,F}$	$\beta_{1,F}$
Germany	-0.0412	-0.0326	-0.0254	-0.0163	-0.0016	0.0187
France	-0.0296	-0.0241	-0.0194	-0.0136	-0.0042	0.0120
UK	0.0362	0.0400	0.0432*	0.0473**	0.0538***	0.0083
US	0.0203	0.0214	0.0224	0.0237	0.0257**	0.0026
Canada	0.0668**	0.0599***	0.0542***	0.0469***	0.0352***	-0.0149
Hong Kong	0.0181	0.0103	0.0039	-0.0043	-0.0175	-0.0168
Japan	-0.0072	-0.0088	-0.0101	-0.0118	-0.0145	-0.0034

Panel D: The dynamics of return spillovers from the US to other markets

F=US	$\bar{\theta}_{1,F}$	$\bar{\theta}_{2,F}$	$\bar{\theta}_{3,F}$	$\bar{\theta}_{4,F}$	$\bar{\theta}_{5,F}$	$\beta_{1,F}$
Germany	0.0997	0.1070	0.1108*	0.1147**	0.1231***	0.0372
France	0.1079	0.0925	0.0844	0.0763	0.0587	-0.0781
UK	0.3205***	0.3491***	0.3642***	0.3793***	0.4121***	0.1455**
Canada	0.0127	0.0050	0.0009	-0.0032	-0.0120	-0.0392
Japan	-0.2655***	-0.2348***	-0.2186***	-0.2024***	-0.1672***	0.1562***
Hong Kong	-0.0243	-0.0325	-0.0369	-0.0412	-0.0506	-0.0417
China	0.1010	0.0856	0.0774	0.0693	0.0516	-0.0785

Panel E: The dynamics of return spillovers from Canada to other markets

F=Canada	$\bar{\theta}_{1,F}$	$\bar{\theta}_{2,F}$	$\bar{\theta}_{3,F}$	$\bar{\theta}_{4,F}$	$\bar{\theta}_{5,F}$	$\beta_{1,F}$
Germany	0.0152	0.0209	0.0236	0.0266	0.0315	0.0187
France	0.0968	0.0737	0.0630	0.0508	0.0313	-0.0749
UK	0.0529	0.0958	0.1156**	0.1383***	0.1745***	0.1392**
US	0.0215	0.0100	0.0047	-0.0014	-0.0110	-0.0372
Japan	-0.0226	-0.0108	-0.0054	0.0008	0.0107	0.0381
Hong Kong	0.0210	0.0245	0.0261	0.0279	0.0308	0.0112
China	0.2077*	0.1605*	0.1386**	0.1136**	0.0737*	-0.1535*

Panel F: The dynamics of return spillovers from the UK to other markets

F=UK	$\bar{\theta}_{1,F}$	$\bar{\theta}_{2,F}$	$\bar{\theta}_{3,F}$	$\bar{\theta}_{4,F}$	$\bar{\theta}_{5,F}$	$\beta_{1,F}$
France	0.0633	0.0473	0.0393	0.0284	0.0104	-0.0538
Germany	-0.0241	-0.0365	-0.0428	-0.0514	-0.0653**	-0.0419
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.0746***	0.0814***	0.0847***	0.0893***	0.0968***	0.0226
Hong Kong	0.0076	0.0074	0.0073	0.0071	0.0069	-0.0008
China	-0.0046	0.0035	0.0075	0.0130	0.0220	0.0271

Panel G: The dynamics of return spillovers from France to other markets

F=France	$\bar{\theta}_{1,F}$	$\bar{\theta}_{2,F}$	$\bar{\theta}_{3,F}$	$\bar{\theta}_{4,F}$	$\bar{\theta}_{5,F}$	$\beta_{1,F}$
Germany	-0.0986**	-0.1071**	-0.1110***	-0.1160***	-0.1246***	-0.0238
UK	-0.0525	-0.0676**	-0.0746***	-0.0834***	-0.0989***	-0.0424
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.0879***	0.0969***	0.1010***	0.1062***	0.1154***	0.0251
Hong Kong	0.0124	0.0118	0.0115	0.0112	0.0106	-0.0017
China	0.0856*	0.0729*	0.0671*	0.0598*	0.0469	-0.0354

Panel H: The dynamics of return spillovers from Germany to other markets

F=Germany	$\bar{\theta}_{1,F}$	$\bar{\theta}_{2,F}$	$\bar{\theta}_{3,F}$	$\bar{\theta}_{4,F}$	$\bar{\theta}_{5,F}$	$\beta_{1,F}$
France	0.1200**	0.1002**	0.0877**	0.0743**	0.0492	-0.0544*
UK	-0.0637*	-0.0744***	-0.0812***	-0.0885***	-0.1022***	-0.0296
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1232***	0.1103***	0.1021***	0.0933***	0.0769***	-0.0356*
Hong Kong	-0.0109	-0.0041	0.0002	0.0048	0.0134	0.0187
China	0.0423	0.0421	0.0420	0.0418	0.0416	-0.0006

Notes: Due to the overlap in trading hours between European and US markets, the open-to-close return spillovers cannot be explicitly investigated for these sequences at daily intervals, and "N/A" is reported where relevant in the table.

Table 3 Patterns of estimates of $\boldsymbol{\beta_{1,F}}$ and of $\boldsymbol{\bar{\theta}_{i,F}}$ across all *i* = 1, …, 5

	Signal from markets in:			
	Asia	America	Europe	Sum:
All estimates of $\beta_{1,F}$				
# Negative	14	7	11	32
# Positive	7	7	4	18
Significant estimates of $\beta_{1,F}$				
# Negative	3	1	2	6
# Positive	0	3	0	3
Significant estimates of $\beta_{1,F}$ when all estimates of $\bar{\theta}_{1,F}$ to $\bar{\theta}_{5,F}$ are also significant				
# Negative of $\beta_{1,F}$	3	1	1	5
# Positive of $\beta_{1,F}$	0	2	0	2
Direction of change from $\bar{\theta}_{1,F}$ to $\bar{\theta}_{5,F}$ of significant estimates of $\bar{\theta}_{i,F}$				
# Cases showing monotonic decrease	9	1	3	13
# Cases showing monotonic increase	1	2	2	5

Notes: The count in Table 3 is based on the parameter estimates reported in Panels A-H in Table 2.