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Financial market spillovers around the globe

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Working Papers on Global Financial Markets

No. 20

Financial market spillovers around the globe

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Financial market spillovers around the globe¹

Financial market spillovers around the globe This paper investigates the transmission of return and volatility spillovers around the globe. It draws on index futures of three representative indices, namely the Dow Jones Euro Stoxx 50, the S&P 500 and the Nikkei 225. Devolatised returns and realised volatilities are modeled separately using a structural vector autoregressive model, thereby accounting for the particular sequential time structure of the trading venues. Within this framework, we test hypotheses in the spirit of Granger causality tests, investigate the short-run dynamics in the three markets using impulse response functions, and identify leadership effects through variance decomposition. Our key results are as follows. We find weak and short-lived return spillovers, in particular from the USA to Japan. Volatility spillovers are more pronounced and persistent. The information from the home market is most important for both returns and volatilities; the contribution from foreign markets is less pronounced in the case of returns than in the case of volatility. Possible gains in terms of forecasting precision when applying our modelling strategy are illustrated by a forecast evaluation.

JEL classification: C32, G15

Keywords: Spillovers; Index Futures; Realized Volatility; Structural VAR model

I. Introduction

This paper investigates the correlation dynamics of stock index returns and volatility in the three major financial centres around the globe: Asia, Europe and the United States. It continues a strand of the literature in empirical finance that goes back to the seminal papers of Hamao, Masulis, and Ng (1990), Lin, Engle, and Ito (1994) and Susmel and Engle (1994), if not further, and builds upon the quite

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distinctive definition of spillovers developed therein. Unfortunately, there is no generally agreed upon definition of spillovers in the financial literature and therefore, the closely related concepts ‘spillover’, ‘contagion’, ‘interdependence’ and ‘co-movement’ are often used interchangeably. Gallo and Otranto (2008) provide a clarificatory discussion of these terms and attempt to establish some practical definitions. Following, first and foremost, Hamao, Masulis, and Ng (1990), return and volatility spillovers are defined in the present study to be effects from foreign stock markets on the conditional means and variances of daytime returns of subsequently trading markets. As has already been pointed out by Hamao, Masulis, and Ng (1990), this particular concept of spillovers requires the use of intraday data to divide daily (close-to-close) returns into daytime (open-to-close) and overnight (close-to-open) returns. Subsequent work such as that of Baur and Jung (2006) and Soriano and Climent (2006) stresses the importance of this partitioning.

Classic financial theory, like the (strong-form) efficient market hypothesis, predicts that return spillovers do not occur, as the information from previously trading markets should be fully reflected in the overnight returns. However, there is ample empirical evidence that stock markets do not instantly incorporate all overnight information into the opening prices, see e.g. Hamao, Masulis, and Ng (1990), Lin, Engle, and Ito (1994), Baur and Jung (2006) and Savva, Osborn, and Gill (2009). Explanations for this empirical phenomenon can be found in the literature on asset valuation models, such as Kyle (1985) and Admati and Pfleiderer (1988), and in the behavioural finance literature. According to the former body of literature, traders may not yet perceive the entire information content of previous trading in foreign markets, and, thus, be unwilling to fully trade their demand schedule and thereby reveal their share of private information. Therefore, the full incorporation of newly arriving information might take time and, thus, might cause spillovers into the daytime returns of the domestic market. In this context, spillovers are an expression of valuation insecurity, but not market inefficiency and are caused by the rational actions of agents. The behavioural finance literature has developed several psychological explanations for the existence of mean spillovers (see Fung, Lam, and Lam, 2010, and the literature cited therein).

In contrast to mean spillovers, the existence or nonexistence of volatility spillovers is an issue with regard to which classic financial theory has remained rather silent. An extensive empirical literature has provided ample evidence of (short-lived) volatility spillovers from foreign stock markets into domestic ones. The paper by Soriano and Climent (2006) provides a useful survey, while Melvin and Melvin (2003) dis-

cuss different sources of volatility spillovers in the context of the closely related exchange rate markets. Diebold and Yilmaz (2009) and Harrison and Moore (2009) are recent contributions which investigate international volatility dynamics and spillovers. While their approaches are quite distinct from ours, their general results, namely the detection of foreign volatility influences on home market volatility, are in line with the results of this paper.

On a more general level, the financial economics literature has developed a number of theoretical foundations with regard to the interdependence of international stock markets. See, for example, Gębka and Serwa (2007) for an overview and Pritsker (2001) for an extensive discussion of transmission channels from one market to the other.

In the present paper we propose separate structural vector autoregressive (SVAR) models for stock index future returns and a suitable volatility measure which enable us to test various hypotheses in the spirit of Granger causality testing. Within this framework we are able to use impulse response functions to analyse short-run dynamics in the system of global financial markets. Finally, we are able to adopt variance decomposition to identify leadership effects in both the mean and volatility systems. The three major financial centres around the globe are represented by the Nikkei 225 index future for Asia, the Dow Jones Euro Stoxx 50 future for Europe and the S&P500 future for the United States. The structure in our model follows naturally from the timing of the trading in these three markets and requires us to model returns and volatility separately, as is done by, for example, Diebold and Yilmaz (2009). As a volatility measure we employ the realised volatilities as suggested by Andersen, Bollerslev, Diebold, and Labys (2003). To overcome the widely documented stale quote problem, we base the empirical analysis on index future data instead of the underlying indices, as is done, for example, by Ryoo and Smith (2004).

We proceed as follows. Section Two discusses the methodology employed in our empirical analysis, and Section Three describes the data. Section Four presents the empirical results, while Section Five provides the results of an illustrative out-of-sample forecast and, finally, Section Six concludes.

II. Methodology

The first part of this section describes the generic multivariate modelling framework proposed here for the analysis of return and volatility spillovers, the structure of which results directly from the opening and closing of the markets considered in this study. In the second part, details of the specific return and volatility measurement employed are presented.

II.1. Trading Times and the Econometric Model

An analysis of the information transmission between the three financial centres under scrutiny here is affected by the trading times in the different representative markets. Figure 1 provides a detailed account of the various opening and closing times of the markets from which the index futures data have been acquired. Let a particular trading day t start at 23:00 GMT. In this setting, the first market to trade on day t is Japan, followed by Europe and then the USA. Trading times between Japan and any of the two other markets are non-overlapping, while there is up to three hours overlap between the trading times of the European and US markets. This setting has important consequences for the analysis of spillovers between the various markets: European and US trading on day t can influence trading in Asia only on the following trading day $t + 1$. Europe on day $t + 1$ may be influenced by same-day $t + 1$ trading in Asia, and US trading that took place on the previous day t . Similarly, the US market on day $t + 1$ may be influenced by same-day $t + 1$ European and Japanese trading.

We therefore suggest a multivariate model with a structure that reflects the chronological ordering of the financial markets and allows us to analyse the short run dynamic interactions between the three markets in consideration, numbered 1, 2, and 3 according to the sequence of opening. The resulting structural vector autoregressive model of order p for returns or volatilities, using the generic notation $x_{i,t}$, $i = 1, 2, 3$, is of the following form:

Figure 1: Trading Times

GMT	23:55	6:25	8:00	12:00	14:30	21:00	23:55
CST					CME 8:30 - 15:15		
SGT		SGX 7:55 - 10:15					SGX
CET		11:15 - 14:25		EUREX 9:00 - 22:00			

The figure presents the trading times at the different exchanges in Singapore (SGX), Frankfurt (Eurex) and Chicago (CME). GMT is Greenwich Mean Time, CST is Central Standard Time, SGT is Singapore Time and CET is Central European Time. Trading hours are presented as of 1 January 2006.

$$\begin{pmatrix} x_{1,t} \\ x_{2,t} \\ x_{3,t} \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 \\ b_{21,0} & 0 & 0 \\ b_{31,0} & b_{32,0} & 0 \end{pmatrix} \begin{pmatrix} x_{1,t} \\ x_{2,t} \\ x_{3,t} \end{pmatrix} + \\ + \sum_{l=1}^p \begin{pmatrix} b_{11,l} & b_{12,l} & b_{13,l} \\ b_{21,l} & b_{22,l} & b_{23,l} \\ b_{31,l} & b_{32,l} & b_{33,l} \end{pmatrix} \begin{pmatrix} x_{1,t-l} \\ x_{2,t-l} \\ x_{3,t-l} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix}. \quad (I)$$

The equivalent matrix notation is given by

$$x_t = a + B_0 x_t + \sum_{l=1}^p B_l x_{t-l} + \varepsilon_t, \quad (2)$$

where $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t})'$ are assumed to be independent white noise processes. Note that coefficients of the contemporaneous effects are collected in the matrix B_0 whose lower diagonal form with zeros on the main diagonal is a direct consequence of the sequence of trading in the three markets. The zero elements reflect the fact that no mean or volatility spillovers can occur on that day between these markets.

Due to the specific form of the matrix B_0 , we can simply use OLS separately on each equation to estimate the parameters of the system consistently. As a unified way to estimate standard errors we use a parametric bootstrap with 1000 bootstrap replications. In order to trace the dynamic linkages between the three markets, we perform impulse response analysis and variance decomposition. Impulse response

analysis provides an easy-to-interpret tool for measuring both the magnitude and the speed of adjustment of the three markets to a shock in one of these markets. Variance decomposition (in the sense of Hasbrouck, 1991) allows us to measure the magnitude of the spillover effect.

A direct consequence of the timing of the opening and closing of the markets coupled with our definition of spillovers inhibits joint modelling of returns and volatilities. Separate modelling is required, in contrast to often employed multivariate GARCH models where covariance terms would allow counter-clockwise feedback effects, which are impossible in our framework.

II.2. Return and Volatility Measurement

The daytime returns $r_{i,t}$ relevant for our analysis are computed as the log-difference of suitable opening and closing transaction prices. Specific details concerning the different markets are given in Section III. To account for the presence of conditional heteroskedasticity in the return time series we rely upon so-called ‘devolatised returns’, computed as daytime returns $r_{i,t}$ standardised by the corresponding realised volatility $\sigma_{i,t}$ (as defined below), following the recent proposal of Pesaran and Pesaran (2010). Formally, they are computed as

$$\tilde{r}_{i,t} = \frac{r_{i,t}}{\sigma_{i,t}}. \quad (3)$$

As shown by Pesaran and Pesaran (2010), devolatised return series are approximately Gaussian and homoscedastic.

We consider two different approaches that may be followed in constructing the volatility time series: the realised volatility measure as proposed by Andersen, Bollerslev, Diebold, and Labys (2003), and the daily volatility estimate developed by Bollen and Inder (2002) (subsequently labelled ABDL and BI, respectively). Both methods seek to overcome the well-documented market microstructure effects present in high-frequency financial data when estimating the unobservable volatility process.

Andersen, Bollerslev, and Diebold (2010) propose that the true underlying volatility process be estimated by summing squared intraday returns computed over suitably large time intervals Δ . Specifically, they define the daily realised variance on

day t as

$$\sigma_{i,t}^2 = \sum_{j=1}^{1/\Delta} r_{i,t,\Delta_j}^2 \quad (4)$$

where r_{i,t,Δ_j} is the return computed over the intraday time interval Δ_j and $\frac{1}{\Delta}$ defines the number of intervals used for calculating the volatility measures. Andersen, Bollerslev, and Diebold (2010) argue that due to market microstructure frictions it is undesirable to sample returns infinitely often (i.e. $\Delta \rightarrow 0$), as would be required to approach the true underlying volatility. When summing the squared returns, one would at the same time accumulate the noise present in the market, which would lead to non-trivial measurement errors. To overcome this issue, Andersen, Bollerslev, Diebold, and Labys (2003)'s realised volatility is calculated using returns computed over sufficiently large time intervals Δ . For the subsequent application we have chosen to use 5-minute returns for the calculation of the realised variance in Eq. (4), as done, for example, by Andersen, Bollerslev, Christoffersen, and Diebold (2006). The realised volatility is then given by the square-root of $\sigma_{i,t}^2$.

A drawback of using returns computed over 5-minute intervals is the possible loss of information contained in the observations within the interval. Bollen and Inder (2002) therefore propose a VARHAC estimator in order to explicitly account for the different autocorrelation structures in intraday returns induced by market microstructure effects. Specifically, they estimate for each trading day t an autoregressive model of order q_t ,

$$r_{i,t,\Delta_j} = \sum_{l=1}^{q_t} \alpha_{l,t} r_{i,t,\Delta_{j-l}} + v_{t,\Delta_j},$$

where $\alpha_{l,t}$ denotes the autocorrelation parameter(s) and v_{t,Δ_j} are iid errors. The optimal lag length per day q_t is chosen by an information criterion. The purpose of this procedure is to purge the returns of microstructure noise. The estimate of the daily volatility is then computed as

$$\sigma_{i,t}^2 = \frac{RSS_{i,t}}{\left[1 - \sum_{l=1}^{q_t} \hat{\alpha}_{l,t}\right]^2}, \quad (5)$$

$$RSS_{i,t} = \sum_{j=q_t+1}^{n_t} \left(r_{i,t,\Delta_j} - \sum_{l=1}^{q_t} \hat{\alpha}_{l,t} r_{i,t,\Delta_{j-l}} \right)^2$$

and n_t is the number of observations per day t . The estimator in Eq. (5) is efficient in the sense that it utilises the data at the highest available frequency (one minute for the data set at hand).

To model the volatility transmission between the three major financial centres around the globe, we follow Andersen, Bollerslev, Christoffersen, and Diebold (2006), who suggest that the derived volatility time series be treated as if it were directly observed. This allows the straightforward application of standard estimation techniques.

III. Data Description

The data set on which our analysis is based consists of intraday transaction prices of the Dow Jones Euro Stoxx 50 future (traded at Eurex), the S&P 500 future (traded at the Chicago Mercantile Exchange, CME) and the Nikkei 225 future (traded at the Singapore Exchange, SGX²). The datasets were obtained from Olsen Financial Technologies and are sampled in minutes. Subsequently, we employ the following acronyms for the future data from these three markets: FESX for the Eurex data, FSP for the CME data and FNI for the SGX data. The data cover futures contracts from 1st July 2002 to 31st May 2006, and all futures are denominated in local currencies. The model is estimated using data up to and including 18th May 2006; the remaining days are used to evaluate the out-of-sample forecast.

Previous studies dedicated to spillover analysis, such as Lin, Engle, and Ito (1994) and Baur and Jung (2006), have used indices instead of futures. The use of stock market indices, however, could entail the so-called stale quote problem (cf. Ryoo and Smith, 2004). To overcome this problem, it has been proposed that a suitable proxy be used for the opening quote of the stock index, varying from opening plus 5 minutes into the trading day up to opening plus 30 minutes. This strategy, however, might dilute the results in the same way as the stale quote problem: prices of some underlying stocks might already have changed substantially within these 5 to 30 minutes. The approximate opening quote would then again not reflect the true opening index value. Using index future data helps to overcome the stale quote problem without loss of information from the market opening. Index futures are self-contained securities and, thus, the first transaction in the morning of a new

²We use the Nikkei 225 future as traded at the SGX, as during the time period at hand the SGX was the market with the highest trading volume of Nikkei 225 futures.

trading day is driven only by information available to the market at this point in time. A slight drawback of using futures is that a continuous dataset is not available for a time horizon greater than nine months. So in order to obtain a continuous sample, we construct the return and volatility time series for each future contract and roll to the contract closest to maturity. The last trading day is excluded in order to avoid the possibility of the settlement having an influence.

Essential for our analysis of spillover effects is the calculation of returns and volatilities based on non-overlapping trading hours. Trading at the SGX starts at 7:55 and ends at 14:25 Singapore Time (SGT) and did not change throughout the four years under study. As there is no overlap in trading times between the SGX and the CME or between the SGX and Eurex (see Figure 1), we compute the log-returns for the FNI as open-to-close returns and the volatility measures for the full trading day.

The FESX was traded at Eurex from 9:00 to 20:00 Central European Time (CET) until 20 November 2005. From 21 November 2005 on, Eurex extended trading hours for OTC-trade from 9:00 to 22:00 CET. The FSP is traded in Chicago from 8:30 to 15:15 Central Standard Time (CST) throughout our sampling period. Thus, there is an overlap of up to 6.5 hours of trading between the two exchanges.

In order to obtain a clear-cut time structure, we apply the ideas of Menkveld, Koopman, and Lucas (2007) and Susmel and Engle (1994), who suggest that the intraday observation period be restricted according to economically relevant points in time. We choose to truncate the FESX at 13:30 CET, well in advance of potential macroeconomic news announcements made in the USA ahead of trading.³ The reason for this choice is the assumption that European morning trade should convey information which is of interest for the traders in the United States and accounted for as soon as trading opens. We therefore compute the return and the volatility measures of the FESX from the market opening to 13:30 CET. The respective measures for the FSP are computed from the opening to the close of the CME.

The data are sampled such that days where at least one market was closed for trading are excluded from the dataset. We thus obtain a dataset containing 912 observations. The upper part of Table 1 provides descriptive statistics for the standardised return series of the FNI, FESX and FSP based upon the estimation period only, which comprises 905 observations. The return series are computed as set out in Eq. (3). As can be seen, the standardisation leaves the time series slightly mesokurtic. The Jarque-Bera test indicates that for two of the three series (FNI and FSP)

³We also investigated different cutting times which did not lead to qualitatively different results.

Table 1: Descriptive Statistics of Devolatised Returns

	FNI	FESX	FSP
Mean	0.0126	-0.0091	0.0428
Median	0.0441	0.0000	0.1207
Maximum	3.0464	2.1968	2.7201
Minimum	-3.4388	-2.3782	-2.7335
Variance	1.0659	0.7966	0.8781
Skewness	-0.0901	-0.0398	-0.0908
Kurtosis	2.7892	2.4402	2.7276
Jarque-Bera	2.8267 (0.2433)	11.9467 (0.0025)	3.9531 (0.1385)
QS(10)	5.7550 (0.8354)	7.0732 (0.7185)	17.2162 (0.0697)
Sample Correlations			
FNI_t	1.0000		
$FESX_t$	0.1098	1.0000	
FSP_t	0.0295	0.0433	1.0000
FNI_{t-1}	-0.0309	0.0018	0.0614
$FESX_{t-1}$	0.0241	-0.0539	-0.0236
FSP_{t-1}	-0.1329	-0.0706	-0.0130

The table provides descriptive statistics for the devolatised returns of the Dow Jones Euro Stoxx 50 future (FESX), the S&P500 future (FSP) and the Nikkei 225 future (FNI). The Jarque-Bera test for normality and the McLeod Li Q-test (QS) for heteroscedasticity using the squared devolatised returns are presented together with p-values, which are given in parentheses.

the normality assumption can be rejected only at the 1% level. Overall, the standardisation of the returns leads to time series which are approximately Gaussian. For illustrative purposes we have also employed McLeod and Li's (1983) Q-test, which uses the squared devolatised returns to check for conditional heteroskedasticity. The p-values displayed in Table 1 indicate no rejection of the null hypothesis of conditional homoskedasticity for all three series. The bottom part of Table 1 presents sample autocorrelations and (lagged) cross-correlations between the FNI, FESX and FSP returns. It should be noted that FNI_t and FSP_{t-1} as well as $FESX_t$ and FSP_{t-1} are negatively correlated.

In order to analyse the volatility transmission, we take the logarithm of the volatility measures which were computed according to Eqs. (4) and (5), respectively. We build on a result obtained by Andersen, Bollerslev, Diebold, and Labys (2003), who demonstrate in an empirical study that using $\ln(\sigma)$ should entail approximate

Table 2: Descriptive Statistics of log-Volatilities (ABDL)

	FNI	FESX	FSP
Mean	-0.0700	-0.2152	-0.1006
Median	-0.0538	-0.2875	-0.1378
Maximum	0.4223	0.5811	0.6049
Minimum	-0.5033	-0.7183	-0.5465
Variance	0.0253	0.0616	0.0287
Skewness	-0.2100	0.6667	1.0131
Kurtosis	2.6119	2.5742	4.2168
Jarque-Bera	12.2654 (0.0022)	74.2011 (< 0.0001)	213.0982 (< 0.0001)
Sample Correlations			
FNI_t	1.0000		
$FESX_t$	0.6144	1.0000	
FSP_t	0.5506	0.7982	1.0000
FNI_{t-1}	0.7711	0.6030	0.5410
$FESX_{t-1}$	0.6123	0.8947	0.7800
FSP_{t-1}	0.5403	0.8007	0.8031

The table provides descriptive statistics for the daily volatility measure as proposed by Andersen, Bollerslev, Diebold, and Labys (2003) in logarithms of the Dow Jones Euro Stoxx 50 future, the S&P500 future and the Nikkei 225 future. The Jarque-Bera test for normality is presented together with p-values, which are given in parentheses.

normality, which allows standard estimation techniques to be applied in a straightforward manner and guarantees that forecasts of the realised volatility are positive.

Tables 2 and 3 provide descriptive statistics for the two log-volatility time series of the FNI, FESX and FSP. We find that there is no qualitative difference between the ABDL and BI volatility measures. It should be noted that negative values of the mean, median and minimum are direct results of the logarithmic transformation employed. Skewness and kurtosis measures and the associated Jarque-Bera test, in particular for the FESX and FSP, show a significant deviation from the normality assumption. However, for the raw, non-transformed volatility series the associated measures (not reported) indicated an even stronger deviation from normality.

The bottom part of Tables 2 and 3 presents sample autocorrelations and (lagged) cross-correlations between the FNI, FESX and FSP log-volatilities. For the volatility measures they are substantially higher than in the case of the return series (cf. Table 1), suggesting that the interdependence of the volatilities might be more pronounced than dependence among the returns.

Table 3: Descriptive Statistics of log-Volatilities (BI)

	FNI	FESX	FSP
Mean	-0.0706	-0.2205	-0.1133
Median	-0.0544	-0.2862	-0.1482
Maximum	0.4793	0.7597	0.6004
Minimum	-0.6945	-0.8541	-0.6237
Variance	0.0263	0.0692	0.0337
Skewness	-0.3143	0.6465	0.7846
Kurtosis	3.0510	2.8733	3.6524
Jarque-Bera	15.1287 (0.0005)	64.0098 (< 0.0001)	110.0881 (< 0.0001)
Sample Correlations			
FNI_t	1.0000		
$FESX_t$	0.5988	1.0000	
FSP_t	0.5348	0.7860	1.0000
FNI_{t-1}	0.7136	0.5897	0.5183
$FESX_{t-1}$	0.5857	0.8544	0.7598
FSP_{t-1}	0.5376	0.7852	0.7975

The table provides descriptive statistics of the daily volatility measure as proposed by Bollen and Inder (2002) in logarithms of the Dow Jones Euro Stoxx 50 future, the S&P500 future and the Nikkei 225 future. The Jarque-Bera test for normality is presented together with p-values, which are given in parentheses.

IV. Empirical Results

In order to estimate the SVAR model in Eq. (1) for the standardised returns and the volatilities, it is necessary to specify a priori the order in which the three markets enter our equations. We will set the Asian market as the first market of a specific trading day t , followed by the European market and the US market, such that in our generic notation $x_t = (x_{FNI,t} \ x_{FESX,t} \ x_{FSP,t})'$. Alternative orderings are possible by setting either Eurex or the CME as the first market on trading day t . The estimation results obtained from these different models are qualitatively similar. Subsequently, we therefore report only the results obtained with the specification where the SGX is ordered first. As a check for robustness of the empirical results presented below, we additionally split the sample but found no qualitatively different results.

IV.1. Modelling daily returns

The first model we consider is the SVAR model for the devolatised returns \tilde{r} using the three time series in the ordering described above. Raw returns are standardised using the realised volatility measure proposed by Andersen, Bollerslev, Diebold, and Labys (2003). Standardisation with the daily volatility measure devised by Bollen and Inder (2002) does not alter the conclusions. The lag length is set to $p = 1$ as suggested by an information criterion. The estimation results are presented in panel 1 of Table 4.

We find a strong and statistically significant negative return spillover from the previous day's trading in the United States to the daytime returns of the Nikkei 225 (see the second column in Table 4). This finding implies that, on average, if CME closes with a high (positive) return, subsequent trading at SGX realises a substantially negative return. This result is consistent, however, with the sample correlations presented in Table 1 and with results reported in other studies, such as Fung, Lam, and Lam (2010), who attribute the negative correlation to an overreaction of the Asian markets to US information. In a similar way, the daytime returns from trading day t in Asia exert a significant positive influence on the returns in the morning trading in Europe on the same trading day, as can be seen from the third column in Table 4. To the best of our knowledge, such a result has not been reported elsewhere in the literature before. Less surprising and frequently documented is the result that the only market which does not exhibit significant mean spillovers is the

Table 4: Model for daily returns

Panel 1: SVAR coefficient estimates			
	FNI	FESX	FSP
const	0.0204 (0.5438)	-0.0107 (0.7483)	0.0440 (0.1920)
FNI_t	0.0000 (-)	0.0899 (0.0073)	0.0245 (0.4495)
$FESX_t$	0.0000 (-)	0.0000 (-)	0.0401 (0.2322)
FSP_t	0.0000 (-)	0.0000 (-)	0.0000 (-)
FNI_{t-1}	-0.0302 (0.3480)	0.0110 (0.7455)	0.0595 (0.0667)
$FESX_{t-1}$	0.0377 (0.2509)	-0.0555 (0.0936)	-0.0304 (0.3600)
FSP_{t-1}	-0.1469 (< 0.0001)	-0.0523 (0.1039)	-0.0077 (0.8177)
Panel 2: Long-run variance decomposition			
	FNI	FESX	FSP
FNI	0.9817	0.0007	0.0176
FESX	0.0107	0.9846	0.0047
FSP	0.0049	0.0024	0.9930

In panel 1, the table provides the structural VAR estimates for the return model given in Equation (2), where the variables are ordered as FNI - FESX - FSP. P-values are given in parentheses. Panel 2 presents the long-run variance decomposition according to Hasbrouck (1991). It is to be read as the proportion of the forecast error variance of the market in row i that is due to the variance of the market in column j .

US market.

We also find support in our results for the often documented negative autocorrelation of (index) return series. All coefficient estimates that make up the the main diagonal of the lag one coefficient matrix B_1 are negative, but only one of them is statistically significant at a conventional level.

Turning to the impulse response analysis, we find that foreign market shocks are generally weak and die out quickly. Panels 1-3 in Figure 2 present impulse responses to one-standard-deviation shocks together with bootstrapped two-standard-errors confidence bounds. The first panel contains the response of FNI (left), FESX (centre) and FSP (right) to a shock to the FNI. While such a shock will affect the home market only on the same day and the US market not at all, it does have a significant impact on the European market's return variance. On the other hand, innovation shocks in Europe (second panel) do not have a significant impact on either of the other two markets. The last panel presents the reaction to a shock in the USA. Its impact is significantly perceivable in the SGX market, which trades subsequently, but no longer in the European market.

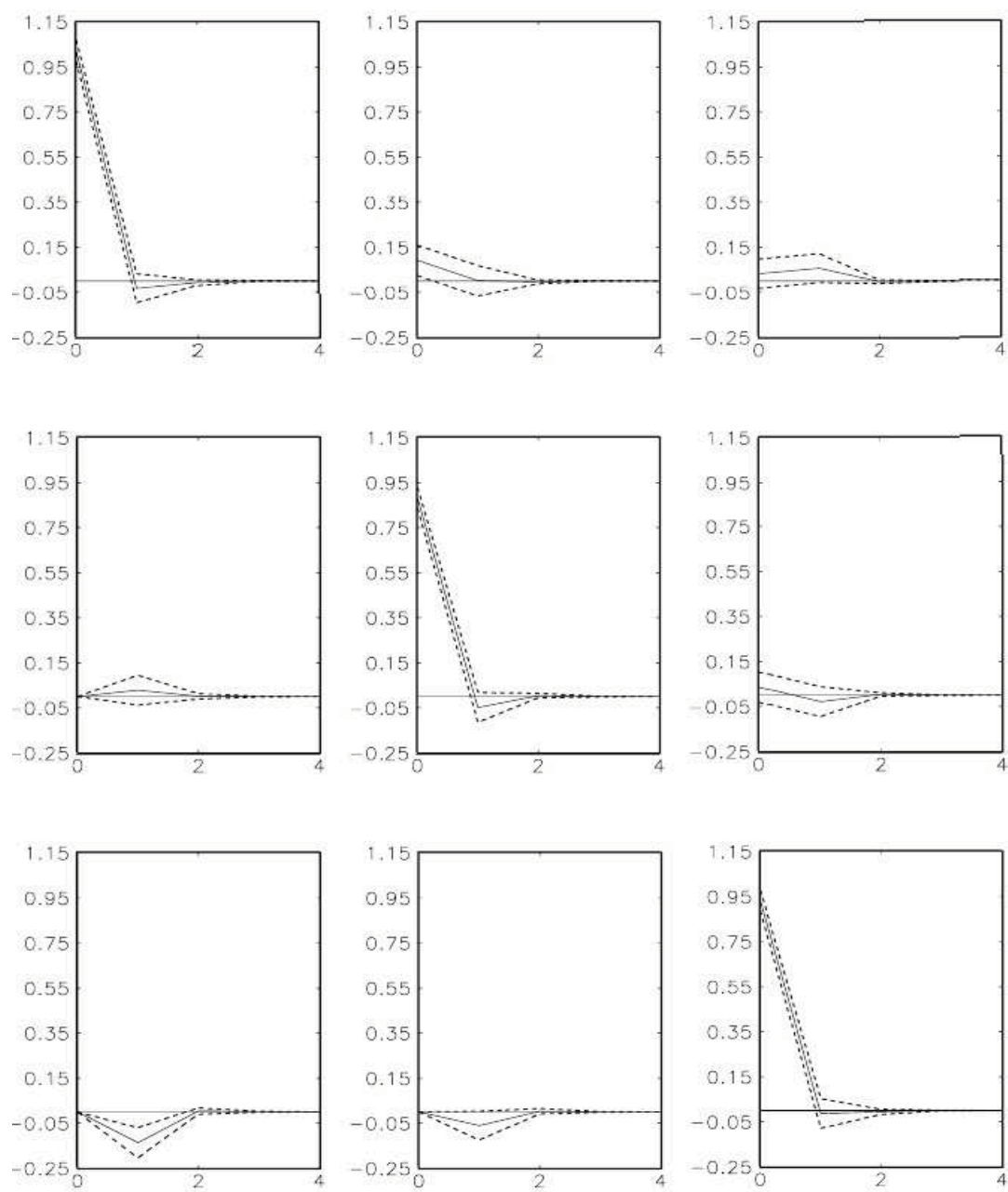
The fact that the effect of an innovation shock in one market on day t dies out quickly would also be supported by the cumulative impulse response functions (which are not provided to save space). The reason is that from $t + 1$ to $t + 2$, the difference is already almost no longer perceptible.

Our analysis allows us to conclude the following. We find small, diminishing and short lived mean spillover effects from the USA to Japan and from Japan to Europe, following the chronological ordering as expected. Moreover, the US market turns out to be robust against return spillovers. A possible explanation may be the differing speed of information processing in the USA compared to Japan and Europe, which is compatible with the theoretical models discussed in the introduction.

IV.2. Volatility modelling

The second model we examine is the SVAR model for the two different volatility measures σ (see Eqs. (4) and (5)), once again using the ordering as set out above. In order to capture the possible long memory property of the log realised volatility time series, Andersen, Bollerslev, and Diebold (2007) suggest to resort to the HAR-RV class of volatility models suggested by Corsi (2009). We find that the long persistence in our data is described best by a model which includes daily, weekly

Figure 2: Return Model: Impulse Response



The graphs depict the response of the FNI (left column), FESX (middle column), and FSP returns (right column) to a one standard deviation shock in Singapore (first row), Europe (second row), and the USA (third row), respectively. The dashed lines are two standard error bounds.

and half-yearly lags. We therefore specify a VAR which includes lags $p = (1, 5, 120)$. The results presented in the following are not altered if the half-yearly lag is, for example, specified as lag 125 or 130. It also turns out that the estimation results based on the ABDL and the BI volatility measures are not qualitatively different. We conclude from this finding that both measures efficiently account for possible microstructure effects and that our results are robust with respect to the way in which the volatility series is computed. We therefore limit the presentation and discussion of the results to those based on the realised volatilities in Eq. (4).

We find significant and substantial volatility spillover effects from the foreign markets to the home market, which stresses that the dependence of the markets' volatilities is more pronounced than the interdependence of their returns. This finding has already been reported in the literature (see, for example, Harrison and Moore, 2009). In general, foreign volatility tends to increase volatility in the home market (note that the negative parameter estimates are never significant with the only exception being the intercept of the FESX). Further, the impact is felt immediately, i.e. both the size of the coefficient estimates and the significance of foreign market influence are generally weak for lags higher than 1. We also document relatively strong volatility persistence, which is reflected in the positive and significant parameter estimates on the main diagonal of the coefficient matrices B_l . In short, our results indicate that volatility spillovers from one market to the next exist which affect the volatility of the upstream market immediately. When looking back more than 24 hours, the volatility of the home market dominates the effect on the respective volatility, which supports the notion of volatility persistence.

Considering the relative sizes of the coefficient estimates, in particular those collected in the matrices B_0 and B_1 , we find that volatility in Europe is more sensitive to influences from foreign market volatility than the other two markets considered. This may be due to the fact that we only model the volatility in morning trading in Europe. In particular, volatility from the previous trading day in the US market seems to exert a strong positive effect on the European market. Also, the European volatility has a positive and significant impact on the same day volatility in the US and the next day's volatility in the Japanese market.

Impulse response (IR) functions for the volatility model based on ABDL realised volatility are presented in Figure 3 together with bootstrapped two-standard-errors confidence bands. It is evident from the IR functions depicted that volatility shocks persist for an extended period of time, as the shocks' impact in general declines

Table 5: Model for daily volatilities (ABDL)

Panel 1: SVAR coefficient estimates			
	FNI	FESX	FSP
const	0.0090 (0.5381)	-0.0360 (0.0147)	-0.0239 (0.1086)
FNI _t	0.0000 (-)	0.0836 (0.0194)	0.0501 (0.1574)
FESX _t	0.0000 (-)	0.0000 (-)	0.1703 (< 0.0001)
FSP _t	0.0000 (-)	0.0000 (-)	0.0000 (-)
FNI _{t-1}	0.5441 (< 0.0001)	-0.0165 (0.6405)	0.0243 (0.4884)
FESX _{t-1}	0.1091 (0.0004)	0.4725 (< 0.0001)	0.0566 (0.1066)
FSP _{t-1}	-0.0354 (0.3079)	0.2519 (< 0.0001)	0.2207 (< 0.0001)
FNI _{t-5}	0.1713 (< 0.0001)	0.0221 (0.4676)	-0.0440 (0.1437)
FESX _{t-5}	-0.0303 (0.3078)	0.1640 (< 0.0001)	0.0107 (0.7266)
FSP _{t-5}	0.0947 (0.0095)	0.0266 (0.4703)	0.1095 (0.0015)
FNI _{t-120}	-0.0335 (0.2241)	-0.0062 (0.8283)	0.0145 (0.6119)
FESX _{t-120}	0.0577 (0.0400)	0.0425 (0.1340)	-0.0199 (0.4978)
FSP _{t-120}	-0.0337 (0.3247)	0.0968 (0.0055)	0.0948 (0.0081)
Panel 2: Long-run Variance Decomposition			
	FNI	FESX	FSP
FNI	0.9048	0.0711	0.0254
FESX	0.0427	0.8599	0.0991
FSP	0.0309	0.1579	0.8154

In panel 1, the table provides the structural VAR estimates for the volatility model given in Equation (2), where the volatilities are calculated as proposed by Andersen, Bollerslev, Diebold, and Labys (2003) and are ordered as FNI - FESX - FSP. P-values are given in parentheses. Panel 2 presents the long-run variance decomposition according to Hasbrouck (1991). It is to be read as the proportion of the forecast error variance of the market in row i that is due to the variance of the market in column j .

slowly. The longest lasting effect is documented for the home market where it takes up to 15 trading days until a shock is not significantly felt any longer. Otherwise, the IR analysis underpins the findings discussed above. In particular, it clearly depicts the significant impact of the European markets morning trading on the US volatility.

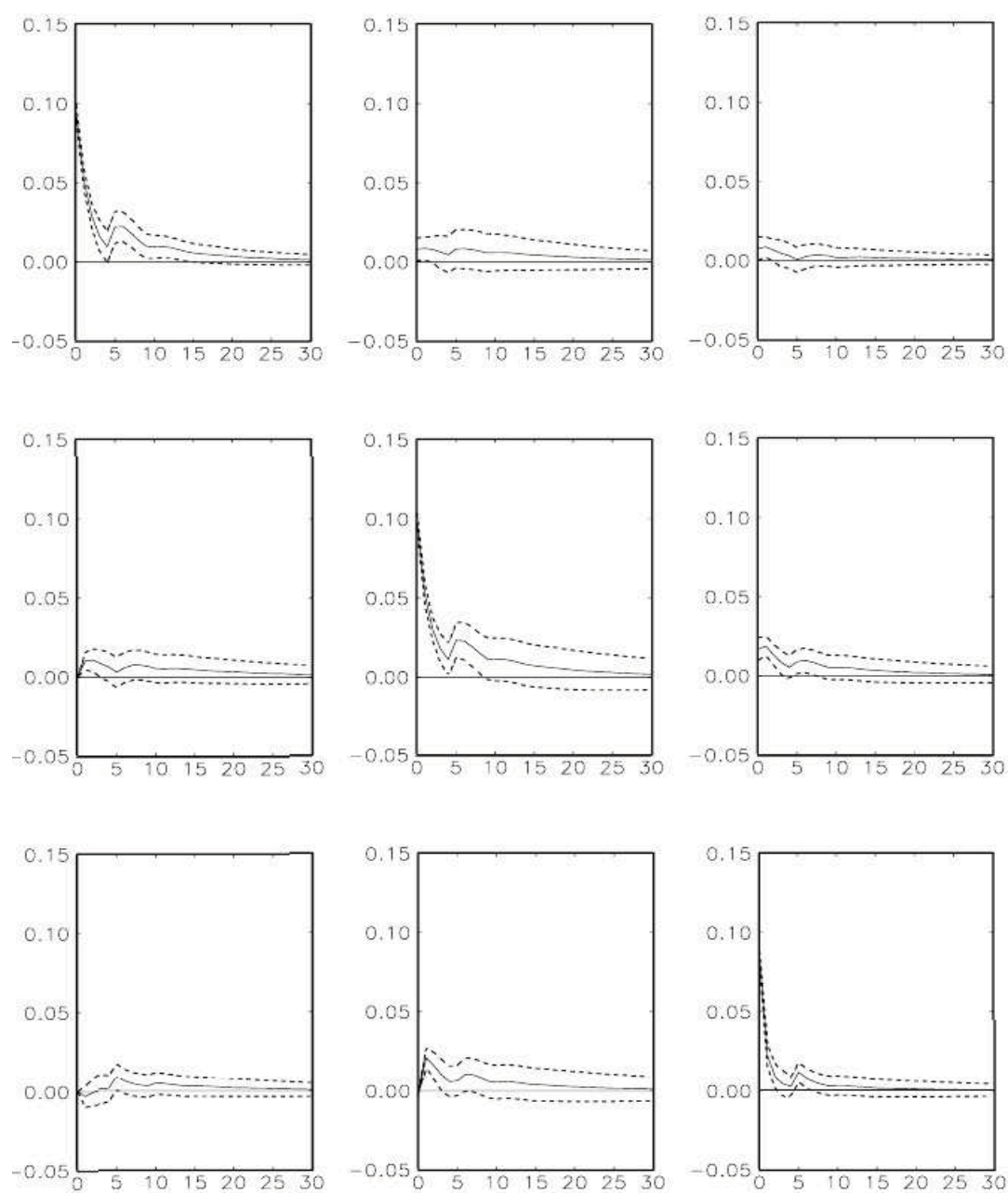
IV.3. Market leadership

Comparing the results of the mean model and the volatility model enables us to conclude that spillovers are more pronounced in the realised variance of the index futures than in their returns. This is supported by the decomposition of the long-run variance based on the approach taken by Hasbrouck (1991). Consider panel 2 in Tables 4 and 5: it emerges that in the long run, 99% of the return variance of a market is determined by information events in the home market. The contribution of foreign markets is negligible. This is surprisingly also the case for events taking place in the United States. As far as the ABDL realised volatilities are concerned, the contribution of foreign markets to the volatility's variance in the home market can be as high as 15.79%, as it is in the case of the FESX's contribution to the FSP variance. The Japanese market's volatility seems to be the least susceptible to foreign influences with its own contribution being as high as 90.48%. Results based on BI volatilities suggest the same conclusions.

V. Model Evaluation

An important aspect when deciding to model returns and volatilities separately instead of using, for example, a GARCH model, was Andersen, Bollerslev, Diebold, and Labys's (2003) finding that forecasts based on realised volatility were more accurate than those based on other forecast methods. In order to check the forecasting ability of our model, we, too, perform a simple forecast evaluation. We evaluate whether an out-of-sample return forecast based on the estimated SVAR models can compete with a univariate modelling approach forecasting the devolatised return and the realised volatility separately, and compare these two forecasts to a univariate GARCH(1,1)-model-based forecast, as well as a forecast based on a univariate AR(1) model. Note that the evaluation is intended to compare a forecast of the log-returns, not the devolatised returns. We therefore undo the devolatisation when using the multivariate and univariate models, i.e. we forecast the volatility and the

Figure 3: ABDL Volatility Model: Impulse Response



The graphs depict the response of the FNI (left column), FESX (middle column), and FSP volatilities (right column) to a unit shock in Singapore (first row), Europe (second row), or the USA (third row), respectively. The dashed lines are two standard error bounds.

standardised returns separately and combine the results according to Eq. (3). In order to account for distributional aspects of the log-returns, both the GARCH model and the univariate AR(1) model are estimated by maximum likelihood assuming t-distributed errors.

To evaluate the accuracy of the forecast we use the Mean Absolute Error (MAE), the Mean Absolute Percent Error (MAPE) and the Mean Percent Error (MPE) measures (e.g. Makridakis, Wheelwright, and Hyndman, 1998) which are defined as

$$MAE = \frac{1}{s} \sum_{t=1}^s |r_t - r_t^*| \cdot 100$$

$$MAPE = \frac{1}{s} \sum_{t=1}^s \left| \frac{r_t - r_t^*}{r_t} \right| \cdot 100$$

$$MPE = \frac{1}{s} \sum_{t=1}^s \frac{r_t - r_t^*}{r_t} \cdot 100$$

where s is the forecast horizon and r_t^* is the forecast of r_t .

The evaluation measures are reported in Table 6. Detailed estimation results of the different models are not reported, but are available from the authors upon request. We find that the multivariate model always performs better than any of the univariate models, with the only exception of the FSP two-step-ahead forecast. To justify the using of our estimation procedure in preference to the GARCH or AR approaches, consider the differences between these models in the MAPE of the one-step-ahead forecast. When modelling mean and volatility separately, the forecast of the FNI based on this approach is better by almost 5 percentage points than the forecast based on the GARCH model, and still slightly better than the forecast based on the AR(1)-model. In the case of the FESX forecast, the model is only slightly worse (by 0.5 percentage points) than the GARCH model and performs slightly better than the AR(1)-model. In the case of the FSP, the univariate model performs worse than the GARCH or AR model. However, in the two-step-ahead forecast this is reversed, and it performs decisively better. Forecasts errors of the FNI and FESX remain approximately stable in the two-step-ahead forecast.

To summarise the findings of the forecast evaluation, we can state that there are clearly two advantages in our modelling approach. First, the forecast based on the

Table 6: Out-of-sample Forecast Evaluation

Panel 1: one-step-ahead forecast					
		Multivariate Model	Univariate Model	Univariate GARCH(1,1)	Univariate AR(1)
MAE	FNI	0.6297	0.7927	0.8280	0.7922
	FESX	0.5238	0.5950	0.5921	0.5953
	FSP	0.2122	0.3255	0.2803	0.2574
MAPE	FNI	80.8106	101.7364	106.2602	101.6713
	FESX	89.5863	101.7648	101.2663	101.8158
	FSP	67.3212	103.2738	88.9394	81.6681
MPE	FNI	80.8106	101.7364	106.2602	101.6713
	FESX	89.5863	101.7648	101.2663	101.8158
	FSP	67.3212	103.2738	88.9394	81.6681
Panel 2: two-steps-ahead forecast					
		Multivariate Model	Univariate Model	Univariate GARCH	Univariate AR(1)
MAE	FNI	1.5971	1.6845	1.7073	1.6840
	FESX	0.3510	0.3900	0.3895	0.3898
	FSP	0.1688	0.1971	0.1911	0.1905
MAPE	FNI	90.4573	101.1500	103.6133	101.1090
	FESX	90.4135	98.2095	98.4466	98.0652
	FSP	112.8702	95.0450	108.7223	118.7869
MPE	FNI	90.4573	101.1500	103.6133	101.1090
	FESX	90.4135	98.2095	98.4466	98.0652
	FSP	112.8702	95.0450	108.7223	118.7869

The table provides a comparison of the out-of-sample forecast evaluation for the separate VAR models for mean and volatility (Multivariate Model), their univariate counterpart (Univariate Model), a univariate GARCH(1,1) model with t-distributed errors (Univariate GARCH(1,1)) and a univariate AR(1) model with t-distributed errors (Univariate AR(1)). Panel 1 contains the evaluation of the one-step-ahead forecast, while panel 2 contains the two-steps-ahead forecast. MAE is the mean absolute error, MAPE is the mean absolute percent error and MPE is the mean percent error as defined in section V.

strategy of modelling returns and variances separately pays off in terms of forecast accuracy, in particular when it comes to longer horizon forecasts. Second, by taking this approach we avoid the delicate issues that arise when using a multivariate GARCH model within the context of a structural VAR approach, especially the issues concerning the identification of a structural GARCH process.

VI. Concluding remarks

Our paper contributes to the fast-growing body of literature in empirical financial economics dedicated to the investigation of international financial market linkages. We propose a new modelling strategy designed to capture the short-run daytime spillover dynamics of the main financial centres around the globe. Specifically, we employ structural vector autoregressive models for the mean and the volatilities of the daytime returns, which draw their structure from the natural chronological ordering of the trading in the three markets used in our study (Europe, USA and Japan). This allows us to provide impulse response and variance decomposition analysis, as well as Granger-type causality testing, within this well-established framework.

For the mean system, we find only short-lived significant spillovers from the USA to Japan and from Japan to Europe, albeit in a small order of magnitude. It emerges that the Japanese market's returns are the most susceptible to foreign information, originating essentially from the United States. The European market, on the other hand, reacts only to information spilling over from the Japanese market. This indicates that, while the US and European markets are closed, the markets in Asia efficiently process information which then spill over to Europe, the market which opens first after Asian markets close. The US market, however, seems to have a particular position in that we do not find spillovers either from Europe or from Japan to the USA.

As regards volatility spillovers, we find that all markets react more intensely to the volatility of the previous market than in the case of the return spillovers. The effect originating in foreign markets dies out within 2-3 trading days; the influence of the home market is persistent, however, for approximately 10 days. In contrast to the findings for the mean model, the timing seems to be less important for volatility spillovers as it is not always the market which was open directly before that exerts the greatest influence. Our findings are robust with respect to the way the volatility

series is computed.

The dynamical systems estimated here can ultimately be employed to trace and forecast the impact of a shock in one of the world's leading markets on the other markets, as well as to generate a forecast of the returns in the markets. We find that the contribution of the separate modelling approach in the multivariate context is threefold. First, the multivariate structure allows for a more accurate forecast of the return series than a univariate approach. Second, the (univariate) separation of returns and volatilities and their detached forecast turns out to perform, on average, better than a univariate forecast based on a GARCH model or an AR model. And finally, the application of structural VARs is econometrically easier to manage than using multivariate GARCH models within this structural context. All in all, the model seems able to trace the linkages between international stock markets, and highlights once again the interdependence of global financial markets.

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