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Leaders and Laggards: International Evidence on Spillovers in Returns, Variance, and Trading Volume*

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Abstract
This paper investigates the dynamic relationship between index returns, return volatility, and trading volume for eight Asian markets and the US. We find cross-border spillovers in returns to be nonexisting, spillovers in absolute returns between Asia and the US to be strong in both directions, and spillovers in variance to run from Asia to the US. Trading volume, especially on the Asian markets, depends on shocks in domestic and foreign returns as well as on variance, especially those shocks originating in the US. However, only weak evidence is found for trading volume influencing other variables.

JEL Classification: G15, F36

Keywords: Financial spillovers, trading volume, Asian crisis

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1 Introduction

The integration of national capital markets has been a distinctive phenomenon of the last few decades. As new transportation and information technologies were implemented worldwide and borders were disappearing due to liberalization of external economic relations, even markets distant from each other became interrelated. As a result of real economic and financial linkages, information emerging in one country is important for the asset valuation in other countries. This phenomenon of information spillovers manifests itself in the reactions of domestic financial variables such as returns, volatility, and trading volume to news that originated abroad. The interdependence between capital markets plays a significant role for asset pricing, cost of capital calculation, and risk assessment. Moreover, the nature and degree of cross-border interdependencies is important for the assessment of opportunities to, and benefits of, international portfolio diversification.

Traditionally, empirical studies on the cross-market linkages focused on the causal relationship between returns, i.e. on return spillovers. For instance, Eun and Shim (1989), Karolyi (1995), and Chen, Chiang, and So (2003) investigate interdependencies between mature markets, whereas Hu, Chen, Fok, and Huang (1997), Masih and Masih (2001), and Climent and Meneu (2003) study the linkages between mature and emerging markets. In addition to returns, other channels of cross-border information transmission, mainly return volatility, were considered (King and Wadhwani (1990), Bae and Karolyi (1994), Kanas (1998), Ng (2000), among others). These studies generally find statistically significant evidence for spillovers in both returns and volatility, with the US market being the most important source of information worldwide.

Yet another branch of the finance literature is concerned with the relationship between trading volume on the one hand, and asset returns and volatility on the other. Several theoretical approaches such as the sequential information arrival hypothesis (Copeland (1976)), the mixture of distributions hypothesis (Clark (1973)), and market models of asymmetry in information endowment (Kyle (1985), He and Wang (1995), Llorente, Michaely, Saar, and Wang (2002)) or interpretation (Harris and Raviv (1993), Kan-
del and Pearson (1995)) have been proposed, and testable hypotheses about the causal return-volume and volatility-volume relationship have been derived from them (a detailed discussion on the economic arguments explaining these phenomena is given in Section 2). However, the worldwide trend of capital market integration notwithstanding, these theoretical predictions have been empirically tested almost exclusively for the domestic relationships. Notable exceptions are Lee and Rui (2002) for the US, UK, and Japanese stock markets, who find trading volume in the US to influence returns and volatility abroad, Gagnon and Karolyi (2003) who report evidence for cross-border informativeness of volume for the New York and Tokyo stock exchanges, and Kim (2005) who observes for several developed Asian and the US markets significant contemporaneous return and volatility linkages as well as information spillovers from the US to Asia.

The interest in the behavior and predictability of stock returns and variance has traditionally been explained by the investment profitability and volatility risk being proxied by these two variables, respectively. However, trading volume also contains valuable information about the asset characteristics. First, as a proxy of market liquidity, volume can be interpreted as a measure of liquidity risk (e.g., a sudden decrease in trading volume makes it impossible for an investor to sell assets at a reasonable price). Second, through the price impact of trades or the size of bid-ask spreads, the level of trading activity is an important determinant of transaction costs. Hence, liquidity is an asset feature also relevant for investors.

In this paper, we aim to close the gap between the internationally-oriented literature about spillovers in returns and volatility and the domestically-oriented research on the interactions between trading volume, stock returns, and returns volatility. We contribute to the knowledge about the linkages between financial markets and, hence, asset characteristics, by investigating the dynamic relationships between stock returns, volatility, and trading volume, both domestically and internationally. Specifically, we test whether there are spillovers between trading volume and returns or volatility for eight market pairs, each consisting of the US and an Asian stock exchange. We focus on Asia because this region attracted much attention of policy-makers and investors alike. This is due to its high growth and increasing share in the global economy, but first of all to the common
view that Asia was the source of the 1997 financial crisis. In this study, we cover large, well established and regulated markets such as Japan and Hong Kong as well as emerging markets such as Indonesia and Thailand. These countries partially share common business conditions and are economically strongly linked with the US. These links are direct or indirect, be it via trade and direct investment, be it via banks and financial markets.

In this paper, we extend the available empirical evidence in many respects. First, evidence on stock exchanges outside the US is presented. Second, we go from the contemporaneous to lagged cross-variable relationship. Third, the focus is on cross-border, cross-variable causality. Finally, we study joined dynamics in returns, volatility, and volume. By doing so, more can be learned about the behavior of financial variables, and the forecasting power of econometric models can be improved. Specifically, a better understanding of the determinants of trading volume makes possible a superior liquidity risk hedging, transaction costs reduction, and sheds light on the information dissemination process on financial markets.

The results are obtained from a system of equations estimated by using the GMM method. We find trading volume to be more dependent on returns than vice versa. This finding is most pronounced for the reaction of Asian markets’ volume to US returns and for absolute returns. Further, return volatility influences trading volume, and these spillovers are more pronounced for the Asia-US causality than for the opposite direction. Moreover, US trading volume causes Asian trading volume, this relationship being mostly unidirectional. In contrast to previous findings, spillovers in returns are nonexisting, but we find significant bidirectional spillovers in absolute returns between the Asian and US markets, and volatility spillovers from Asia to the US. Also, after the 1997 crisis, the intensity and strength of cross-border spillovers seems to have increased. This last finding is in line with the existing empirical evidence (Climent and Meneu (2003), Chelley-Steeley (2004)) as well as our experience from the previous financial crisis of 1987 (e.g. Eun and Shim (1989)).

In the next section, we discuss theoretical arguments for the existence of causal linkages between stock returns, volatility, and trading volume, and present the relevant empirical findings. In Section 3, data and methodology are described, and in Section 4
results are presented and discussed. Section 5 concludes.

2 Literature Review

2.1 Determinants of Stock Returns

Several theoretical arguments support the hypothesis that stock returns are influenced by the trading volume. First, according to the sequential information arrival (SIA) hypothesis, as brought forward by Copeland (1976) and Jennings, Starks, and Fellingham (1981), new information becomes available and disseminates only sequentially on the market, giving rise to a graduate movement in both stock returns and trading volume. This dependence on a common latent factor induces a common behavior of (absolute) returns and volume and can manifest itself in a positive intertemporal causal relationship between these variables, in both directions. Second, according to the mixture of distributions (MD) approach (Clark (1973), Epps and Epps (1976)), trading volume acts as a measure of the disagreement among traders concerning the relevance of new information for the stock price. This model suggests a positive contemporaneous relationship between trading volume and (absolute) stock returns.

Furthermore, as noted by Hiemstra and Jones (1994) and others, the non-linearities in the volume-return causality should also be taken into account. The literature proposes models with agents who differ in information endowment or in interpretation of common information. Along these lines, Brock (1993) presents a heterogenous-agent model in which volume movements across investors are related mostly to the rapid movements in stock returns. Kyle (1985) interprets the trading volume as an indicator of increased probability of informed trading and shows that under this assumption, there is a positive causality from volume to asset prices and, hence, returns. Also He and Wang (1995) distinguish between private and public information and consider the behavior of heterogenous agents. Their model shows that multi-period trading on information induces autocorrelation in volume. However, while new, be it public or private, information generates both high price changes and high volume, existing private information might induce high trading volume without the corresponding price reaction. Hence, the volume-return causality
depends on the information type and is driven by timing by informed trades. In contrast, in the model of Harris and Raviv (1993), investors differ only in their opinions about the relevance of news and not in the information endowment. Under these conditions, the contemporaneous relation between price changes and trading volume is positive. Moreover, trading taking place due to the news arrivals is followed by the serially correlated returns, resulting in a lead-lag relationship between volume and returns. Kandel and Pearson (1995) also assume an equal access to information among agents and show that, given the differences in interpretation of news, volume changes can be observed even in the absence of price changes.

A further aspect discussed in the literature is the volume-return relationship in the presence of interaction between these variables. Theoretical models by Campbell, Grossman, and Wang (1993), Wang (1994), and Llorente, Michaely, Saar, and Wang (2002) show that returns accompanied by high trading volume tend to reverse (continue) if uninformed (informed) trades dominate, implying negative (positive) causality running from volume to returns. Blume, Easley, and O’Hara (1994) show that trading volume might provide data about the quality of price signals and, thus, its information content goes beyond that of present and past returns.

Empirical evidence on the volume-return causality is mixed. Early evidence on the positive correlation between (absolute) returns and trading volume is presented in Karpoff (1987). Hiemstra and Jones (1994) investigate the dynamic relation between Dow Jones returns and trading volume and find non-linear causality running from volume to returns. Chordia and Swaminathan (2000) show that movements of returns on portfolios containing high-volume stocks cause movements of returns on low-volume portfolios, and interpret this result as evidence of the high information content of the trading volume. However, for American, British, and Japanese stock exchanges, Lee and Rui (2002) report the lack of domestic Granger- causality between volume and returns for each of these markets, but find US volume to cause UK and Japanese returns. In Kim (2005), there is only weak evidence for the US volume causing the returns in Singapore and Hong Kong. No domestic causal relation is found by Chen, Firth, and Rui (2001) for Hong Kong, Japan, and other developed markets, either. Marsh and Wagner (2003) show for several national
markets that volume-return causality exists primarily for large positive values.

2.2 Determinants of Trading Volume

The literature offers various theoretical explanations for the return-volume causality. For instance, the SIA hypothesis (Copeland (1976)), as described above, can explain the virtual dependence of volume on past and present stock returns. Further, Epps and Epps (1976) show in their MD model that volume can be interpreted as a measure of disagreement among traders. The consequence of their model assumptions is a positive relationship between trading volume and stock returns. Further support for returns as a volume determinant stems from the noise trading theory. It is argued that the noise traders, pursuing a common strategy simultaneously, cause marketwide patterns in returns and volume (DeLong, Shleifer, Summers, and Waldmann (1990)). For instance, positive feedback traders buy (sell) following an observed increase (decrease) in stock prices. This behavior causes trading volume to be driven by returns. In the international context, Brennan and Cao (1997) develop a model of equity portfolio fund flows based on differences in information endowment between domestic and foreign traders. They show that when the former possess superior information than the latter concerning the domestic market, international investors will invest (divest) after an increase (decrease) in foreign stock prices. As a result, a positive causality relationship between returns and foreigners-induced volume can be observed.

Stock return volatility has been shown to be other potential determinant of trading volume. Early theoretical arguments and empirical findings for the contemporaneous volume-volatility relationship are summarized by Karpoff (1987), with the general finding of positive correlation. More recently, Harris and Raviv (1993) show that trading volume depends positively on contemporaneous and lagged return volatility if agents differ in their interpretation of the news. Additionally, He and Wang (1995) argue that this positive volume-volatility relationship can be observed only in case of trades driven by exogenous, but not existing, information. In the approach of Brock and LeBaron (1996), persistence of trading patterns generates autocorrelation in both volume and volatility, resulting in a contemporaneous, albeit not lagged, correlation between these variables.
The empirical findings are in line with these theoretical predictions. Gallant, Rossi, and Tauchen (1992) show for the NYSE daily data that a positive volume-volatility correlation prevails. In their study of nine markets, Chen, Firth, and Rui (2001) find domestic causality running from returns to volume, albeit mostly for absolute returns. Lee and Rui (2002) find positive contemporaneous and some lagged relationships between volume and returns in the US, UK, and Japan. For the NYSE/AMEX stocks, Statman, Thorley, and Vorkink (2004) report lagged returns to have a positive impact on current trading volume and attribute this to investor overconfidence. They also find return volatility to have a positive contemporaneous and a negative lagged effect on volume.

2.3 Determinants of Return Volatility

To complete the review of arguments for cross-variable causality, we shortly describe the possible determinants of return volatility. First, it is argued in the literature that a positive volume-volatility causality arises from the MD and SIA hypotheses as discussed above. Moreover, Andersen (1996) offers a modification of the MD hypothesis in form of a microstructure model in which news arrivals induce trades due to the information asymmetries and liquidity needs. This approach confirms the prediction of a positive volume-volatility relationship. More recently, Suominen (2001) presents a model in which information asymmetry prevails and past trading volume is used by market participants to learn about the level of private information, and to adjust trading strategies accordingly. Hence, spillovers from volume to volatility emerge. Empirical evidence is in favor of positive volatility-volume relationship, e.g. in Epps and Epps (1976) for the test of the MD hypothesis. Gallant, Rossi, and Tauchen (1992) show contemporaneous trading volume to be a good proxy for information arrivals for individual stocks and, hence, to explain conditional return volatility. In an international context, Lee and Rui (2002) and Kim (2005) find US volume to cause volatility on domestic and foreign markets, and Chen, Firth, and Rui (2001) report for nine developed capital markets that conditional volatility of index returns can be explained partly by market-wide trading volume.
3 Data and Methodology

3.1 Data

The data set comprises daily values of national stock market indices from the US and eight Asian markets: Hong Kong, Indonesia, Japan, Korea, Malaysia, Singapore, Taiwan, and Thailand.\(^1\) Data are obtained from Datastream and cover a recent period of more than 13 years from January 1990 to November 2003, resulting in 3606 observations in total. To analyze the changes in causality patterns due to the 1997 crisis, we also divide our period in three subperiods: precrisis (January 1990 - July 1997), crisis and postcrisis (August 1997 - October 2003) and postcrisis (March 1998 - October 2003) period.\(^2\) For our investigation, we use index returns, calculated as a difference in log prices, and trading volume, measured as a number of shares traded, are presented (we use logarithmic trading volume, detrended as described below).

The turnover ratio, defined as number of stocks trades to number of stocks outstanding, is another possible measures of trading activity. Lo and Wang (2000) argue that there are sound theoretical arguments for using turnover of individual stocks in the cross-sectional studies. However, they show that for portfolios (e.g. stock market indices as used in this study), as opposed to individual stocks, turnover is questionable as a measure of trading activity. Also, stock turnover is argued to be superior in the cross-sectional context, but we conduct a time-series investigation. For these reasons, we use detrended volume instead of turnover. Moreover, Gallant et al. (1993) report that the use of turnover might actually impose additional trends on a measure of trading activity. Also Bekaert, Harvey, and Lundblad (2005) criticize the turnover ratio as a poor measure of liquidity. Many studies use aggregated share volume, e.g. Epps and Epps (1976), Gallant et al. (1993), Hiemstra and Jones (1994). Campbell, Grossman, and Wang (1993) use aggregated turnover ratio only because they believe it reduces noise, a result achieved

\(^1\)These indices are: NYSE Composite, Hong Kong Datastream Market Index, JSX Composite, Japan Datastream Market Index, KOSPI, KLCI, ALL-SINGEQUITIES, TSE Weighted, and SET, respectively.

\(^2\)Our definition of the crisis window is in accordance with those widely employed in the literature, e.g. Forbes and Rigobon (2002), Billio and Pelizzon (2003), and Rigobon (2003). Since the crisis period is relatively short, its separate investigation would suffer from the low power of statistical tests, as shown by e.g. Dungey and Zhumabekova (2001).
here by detrending (as discussed below). Last, even if comparing trading volume between two stocks might be less informative than a comparison of their turnover ratios, this is a concern rather for a cross-sectional study than for an analysis of time series comovements. This is because in the multivariate regressions we analyze the impact of the change in one variable (e.g. trading volume in country A) on the behavior of another variable (e.g. change in trading volume in country B). Hence, we compare dynamic (changes in volume) rather than static (levels of volume) values.

In Table 1, Panel A, descriptive statistics for index returns and trading volume are presented. The mean return is positive for four countries and negative for the other four. A more detailed analysis of the time series reveals that the negative returns in these countries can be roughly associated with three events: the burst of the Japanese bubble (late 1989 - late 1992), the Asian crisis (late 1996 - late 1998), and the burst of the internet bubble (mid 2000 - early 2003). In accordance with common belief and results from earlier studies, the US market is less volatile than its Asian counterparts, as shown by the standard deviation of index returns. Further, the skewness statistics are negative for four markets (and positive for the other four), indicating heavy tails for large (small) values and hence higher probability of returns being lower (higher) than the mean return. The kurtosis is higher than 3 for all eight markets, meaning a leptokurtic return distribution and heavy tails, i.e. a higher probability of obtaining extreme values than under the standard normal distribution.

[Table 1 around here]

Previous studies have found evidence for linear and non-linear deterministic trends in volume data (Gallant, Rossi, and Tauchen (1992), Chen, Firth, and Rui (2001)). We test the existence of time trends by estimating the following equation for each market:

$$V_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \varepsilon_t,$$

where $V_t$ represents trading volume and $t$ the time trend. Results from these tests, presented in Table 1, Panel B, show that for all but one country the linear and quadratic time trends exist, as indicated by the significance of parameters $\alpha_1$ and $\alpha_2$, respectively.
(for Hong Kong, only a linear trend but no quadratic trend is found). Therefore, we adjust the trading volume series for the further analysis by subtracting the significant trend variables. Descriptive statistics of detrended log volume series are reported in Table 1., Panel A.

Detrending of variables is not unproblematic, since it has been shown to change the time-series properties of turnover (Lo and Wang (2000)). However, it is also acknowledged that for a time-series analysis and formal hypothesis testing stationarity of variables has to be ensured, which encourages volume detrending. From all methods analyzed by Lo and Wang (2000), log-linear detrending, as used in this paper, is shown to remove the trend while retaining the volatility of variables. Also, noise is argued to be reduced by detrending. Gallant, Rossi, and Tauchen (1992) also show that detrending removes long-term trends and quadratic detrending additionally removes outliers, while at the same time retaining the short-term variable movements. On the other hand, the use of more comprehensive detrending methods has been recommended in the literature (Gallant, Rossi, and Tauchen (1992), Andersen (1996)). Hence, our detrending method constitutes a compromise between using raw but instationary data on the one hand and intrusive detrending methods possibly changing the characteristics of the underlying variables on the other hand. This way, our results can be compared directly with those reported in previous studies: Campbell, Grossman, and Wang (1993), Gagnon and Karolyi (2003) and Kim (2005) subtract deterministic trends, and Bekaert, Harvey, and Lundblad (2005) notice that volume data, especially for emerging markets, are plagued by trends and outliers. Other variables used in this study, as shown below, are stationary and so no detrending is needed.

A further step is to test for the presence of stochastic trends in the time series employed here, i.e. for the stationarity of returns and (detrended logarithmic) volume. We use the augmented Dickey and Fuller (1979) test (ADF), the Philips and Perron (1988) test (PP), and the augmented weighted symmetric test (WS) (Pantula, Gonzales-Farias, and Fuller (1994)) to check for the presence of a unit root in the data. Results are presented in Table 1, Panel C. The test statistics and the corresponding p-values strongly indicate that the hypothesis of unit root in return and in detrended volume time series
can be rejected at very high significance levels for all countries under investigation. This confirms that index returns and detrended trading volume series are stationary. These variables are used in our further analysis.

The indices used in this study can be considered endogenously interrelated because of cross-listing of Asian companies in the US. However, in our opinion they cannot be seen as ”automatically” linked, i.e. an increase in the value of an Asian company from the point of view of US investors, causing them to buy ADRs in New York, will not automatically result in a stock price increase on the company’s home market. It will require additional investment to move prices on the domestic market to the new equilibrium level, either by domestic Asian investors of by international arbitrageurs. Hence, ADRs are simply one of the channels of cross-border information flows, as international investment is, and similarly contribute to the stock market integration (Chelley-Steeley (2004), Stulz (2005)). Without ADRs, stocks in country A would react to movements to stocks in country B as well, as far as the motives underlying this price change (news or liquidity needs) were relevant to their valuation, this being driven e.g. by actions of international arbitrageurs. Both the reasons for price changes and the actions of investors cause comovements of asset prices. The existence of cross-listing provides an additional transmission channel and might increase the degree of integration but is by itself no trigger of comovements. If cross-listing implied ”automatic” spillovers, we should observe strong interrelations between markets. However, rather the opposite is the case, since in contrast to previous studies we report in Section 4 the spillovers in returns to be almost non-existing and in other variables to be rather weak. Also, empirical evidence shows that liquidity measures are not sensitive to inclusion of ADRs (Bekaert, Harvey, and Lundblad (2005)). Barklay, Litzenberger, and Warner (1990) demonstrate that cross-listing constitutes only a small fraction of total trading of a stock, and other studies indicate that informed trading and, hence, price determination takes place on the domestic market rather than abroad (Grammig, Melvin, and Schlag (2005)). Also, the issuance of the

\[\text{We thank the referee for pointing this out.}\]

\[\text{To take an extreme example: if the price of an ADR would increase for reasons that have no impact on the issuing company and hence its domestic stock price, and in absence of international arbitrageurs, there would be no price movement on domestic market. Hence, the mere existence of cross-listing does not imply information spillovers.}\]
ADRs has been shown to have only negligible impact on stock return volatility (Kanas (1998)).

3.2 Methodology

The causal relationship between trading volume on the one hand, and returns, absolute returns, and return volatility on the other hand is estimated by using the following model:

\[ X_{US}^t = \alpha_0 + \sum_{i=1}^{5} \alpha_{1i} X_{US}^{t-i} + \sum_{i=0}^{5} \alpha_{2i} X_{AS}^{t-i} + \sum_{i=1}^{5} \alpha_{3i} V_{US}^{t-i} + \sum_{i=0}^{5} \alpha_{4i} V_{AS}^{t-i} + \varepsilon_1 \]  

\[ X_{AS}^t = \beta_0 + \sum_{i=1}^{5} \beta_{1i} X_{US}^{t-i} + \sum_{i=1}^{5} \beta_{2i} X_{AS}^{t-i} + \sum_{i=1}^{5} \beta_{3i} V_{US}^{t-i} + \sum_{i=1}^{5} \beta_{4i} V_{AS}^{t-i} + \varepsilon_2 \]  

\[ V_{US}^t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} X_{US}^{t-i} + \sum_{i=0}^{5} \gamma_{2i} X_{AS}^{t-i} + \sum_{i=1}^{5} \gamma_{3i} V_{US}^{t-i} + \sum_{i=0}^{5} \gamma_{4i} V_{AS}^{t-i} + \varepsilon_3 \]  

\[ V_{AS}^t = \delta_0 + \sum_{i=1}^{5} \delta_{1i} X_{US}^{t-i} + \sum_{i=1}^{5} \delta_{2i} X_{AS}^{t-i} + \sum_{i=1}^{5} \delta_{3i} V_{US}^{t-i} + \sum_{i=1}^{5} \delta_{4i} V_{AS}^{t-i} + \varepsilon_4, \]  

where \( V_{US}^t \) (\( V_{AS}^t \)) is trading volume on the US (Asian) market at time \( t \), \( \alpha \), \( \beta \), \( \gamma \), and \( \delta \) are parameters to be estimated, and \( \varepsilon \) represents the error term. The variable \( X \) can represent the returns, absolute returns, or return volatility on the US or an Asian market, i.e. \( X_{US}^t \in \{ R_t^{US}, |R_t^{US}|, Var_t^{US} \} \) and \( X_{AS}^t \in \{ R_t^{AS}, |R_t^{AS}|, Var_t^{AS} \} \). Equations (2)-(5) are estimated simultaneously to avoid the problem of simultaneity bias. The GMM method is used. With this method, standard errors can be calculated that are robust against heteroscedasticity and autocorrelation. The simultaneous estimation (full information estimation) is conducted due to efficiency gains as compared with single equation estimation (limited information estimation) which neglects information contained in other

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\(^5\)Tests of Engle and Granger (1987) and Johansen (1991) show no evidence of bi-variate cointegration between the variables used. Therefore, no error correction term appears in the model (2)-(5).

\(^6\)The Box-Pierce Q-Test on residuals and squared residuals reveals for the majority of cases the existence of autocorrelation and heteroscedasticity in error terms up to 20 lags for all country pairs (result not reported but available on request). Therefore, a robust variance-covariance matrix is estimated. The orthogonality conditions state that residuals are uncorrelated with instrumental variables, and the right-hand variables from all four equations are used as instruments. The latter implies that the system is overidentified and not all orthogonality conditions can hold exactly. The GMM method chooses parameter values by weighting the errors associated with the orthogonality conditions by their variances. By using all variables to estimate each equation, the method utilizes maximum information available and we consider it superior to the estimation of an exactly-identified system (Hansen (1982))
equations. Among possible full information estimates such as 3SLS, FIML, and GMM, the latter method can be shown to be asymptotically superior and to bring additional efficiency gains, especially in the presence of heteroscedasticity and autocorrelation in residuals. In fact, GMM estimates nest results from other methods (Greene (2000)). Due to its generality and asymptotic efficiency, and given a large number of observations in our sample which makes potential problems with finite sample properties of estimates negligible, we prefer GMM to other methods. To account for sluggish adjustment of financial variables to news, especially on the emerging markets, and for the day-of-the-week effect, we use five lags in all equations (in the context of cross-border spillovers, five lags are used by, e.g., Chen, Firth, and Rui (2001) and Lee and Rui (2002)). However, due to the differences in trading hours between the Asian and US markets, we also include contemporaneous values of Asian variables to explain the US ones, e.g. contemporaneous value of Asian volume ($V_{t}^{AS}$) as a regressor in Eq. (4), but no contemporaneous value of US volume ($V_{t}^{US}$) in Eq. (5).

One variable is said here to cause another variable if the sum of corresponding parameters is different from zero. For instance, to conclude that US trading volume causes return volatility on a selected Asian market, the model (2)-(5) is estimated for $X_{t}^{US} = Var_{t}^{US}$ and $X_{t}^{AS} = Var_{t}^{US}$, and following null hypothesis has to be rejected: $(\sum_{i=1}^{5} \beta_{i}) = 0$. In contrast to a classic Granger-causality test where the null hypothesis states that the parameters are jointly zero, the modified version of this test is used. Under the null, the sum of coefficients is assumed to equal zero. This approach is argued to test for both significance and sign of causality and, therefore, to be more stringent than the classic test (Chordia and Swaminathan (2000)). In the context of causality it is important to note that, due to non-synchronicity of opening hours between Asian and the US market, the result of significant cross-border causality can be, partially or completely, driven by contemporaneous rather than lagged correlation.\footnote{Several studies argued that correlations of daily close-to-close returns in presence of non-synchronous trading hours are biased (Kahya (1997), Burns, Engle, and Mezrich (1998)). However, adjustment methods proposed so far failed to deliver correct values, since they add noise to the data and are sensitive to model specification. Using weekly data might reduce the biases but, first, it causes a decrease in sample size and, hence, in efficiency of estimates. Second, low frequency data cannot capture daily spillover dynamics. Also studies using open-to-close and close-to-open returns (Hamao, Masulis, and Ng (1990),}
since it is not our aim to differentiate between contemporaneous and lagged relationship between financial variables. Finally, we use the Wald test since Geweke, Meese, and Dent (1983) have shown in their Monte Carlo simulations that this approach is superior to alternative tests of Granger causality in many respects.8

Last, since the asset-pricing models are mainly motivated by risk-return tradeoff, the lack of a risk measure in equations (2)-(3) could bias our results (we thank the referee for pointing this out). However, the inclusion of variance into the relevant equations does not improve the performance of the model (results not reported). First, in the majority of cases, the coefficients measuring the risk-return relationship are insignificant. Second, including risk has negative impact on the efficiency of estimates, resulting in the considerable increase of their variances and a loss of significance of single parameters and Wald-statistics alike. Third, based on the values of adjusted $R^2$, there is no convincing statistical evidence in our dataset that models with the risk measure included describe the behavior of variables more accurately. Also, empirical evidence on the risk-return relationship reported in the literature is inconclusive, with some studies showing the impact of risk to be positive but insignificant (Theodossiou and Lee (1995)) and other even revealing a negative relationship between these two variables (Bekaert and Wu (2000), Brandt and Kang (2004)). Hence, the model (2)-(5) for returns and absolute returns without variance as dependent variable is estimated, as we consider it superior.

Koutmos and Booth (1995)) cannot distinguish between contemporaneous and lagged interdependencies, and the results are reported to be similar to those obtained from close-to-close returns. See Martens and Poon (2001) for the discussion on this issue. Given these arguments, we follow the main branch of spillovers literature and use unadjusted close-to-close returns.

As the literature indicates (Arago and Nieto (2005)) and the Box-Pierce Q-Test on squared residuals reveals, there exist GARCH-effects in error terms. However, this fact has no impact on the parameter values in the mean equation, i.e. the parameters are unbiased even if conditional heteroscedasticity is not accounted for. Since in measuring spillovers we rely on these parameter values, our measure of spillovers is not biased, either. Moreover, we take the problem of heteroscedasticity into account and test for the existence of spillovers by calculating the Wald statistics that are robust against a general form of heteroscedasticity. We consider this procedure superior to testing for any specific form of heteroscedasticity, such as GARCH-effects.
4 Empirical Results

4.1 Returns and Trading Volume

To empirically assess the return-volume relationship, we estimate the model (2)-(5) with variable $X$ being the index return ($X_{US}^t = R_{US}^t$ and $X_{AS}^t = R_{AS}^t$). The results presented in Table 2 show that the relationship between returns and trading volume is rather weak for the countries under investigation. For the full period, we find trading volume in each country to be more dependent on other financial variables than returns are, first of all on domestic and foreign returns. This effect is more pronounced for volume on emerging Asian markets than on the US market. For the latter, only returns on Hong Kong, Singapore, and Taiwanese stocks are relevant. The subperiod analysis reveals that the dependence of Asian volume on US returns intensified after the 1997 crisis (results not reported).

[Table 2 around here]

The finding of return-volume causality is in line with the SIA hypothesis stating that both variables are driven by information disseminating only sequentially among traders, hence giving rise to a dynamic relationship. For the domestic return-volume causality this relationship is rather positive, while for cross-country causality it is mostly negative. A possible explanation for this is that the domestic causal effects are driven by positive information, whereas cross-border effects are driven by negative information. Hence, we observe e.g. increasing volume following increasing domestic returns in the former case and decreasing foreign returns in the latter. The return-volume causality can also be explained by common actions of feedback traders, as in DeLong, Shleifer, Summers, and Waldmann (1990). However, while investors on the domestic markets seem to follow a positive feedback approach, those investing internationally pursue a negative feedback strategy (sell abroad after domestic return has risen and vice versa). As a result, a positive domestic and negative cross-country return-volume dependence can emerge. The positive domestic causality can also be explained by an increase in trades by foreign investors after positive returns, as in Brennan and Cao (1997). Last, as Statman, Thorley, and Vorkink (2004) argue, the finding that volume follows returns is in line with the overconfidence of
financial investors.

As can also be seen from Table 2, almost no causality running from trading volume to returns can be found. In the light of the theories discussed before, these results indicate that returns are generally not driven by informed trades taking place domestically or abroad. For instance, in Kyle (1985), trading volume indicates the probability of informed trading and causes returns, and in Llorente et al. (2002) and related papers, the lack of causality is observed if neither informed nor uninformed trades dominate. Further, the independence of returns from volume suggests that investors with different access to information trade on existing, not new information (He and Wang (1995)), or that transactions are closed due to the differences in interpretation of news among market participants (Kandel and Pearson (1995)).

4.2 Absolute Returns and Trading Volume

As discussed in Section 2, both theoretical arguments and empirical findings stress the existence of a non-linear relationship between returns and volume. To capture the possible nonlinearities, we estimate the model (2)-(5) with X representing absolute instead of normal returns ($X_t^{US} = |R_t^{US}|$ and $X_t^{AS} = |R_t^{AS}|$) and report the results in Table 3.

The first conclusion that can be drawn from these results is that significant causal relationships are more pronounced for absolute than for normal returns. This indicates the existence of nonlinearities in the domestic and international return-volume relationship. Also, for absolute returns we find price changes to be more informative for other financial variables than for trading volume. This can be seen from the fact that trading volume is frequently caused by returns, being itself a source of spillovers in fewer cases. Additionally, we observe dependence of trading volume in Asian countries, primarily on the US volume, to have increased after the crisis of 1997 (results not reported). Moreover, for most countries under investigation, a strong bidirectional negative causality in absolute returns can be observed, i.e. returns in Asia are caused by the US market returns and are themselves a significant driving force behind the US returns.
4.3 Return Volatility and Trading Volume

Several studies report a lack in return causality and at the same time statistically significant causality in variance between markets (e.g. Booth, Martikainen, and Tse (1997), Xu and Fung (2002)). We also investigate the volume-variance relationship in order to identify variance as a possible channel of cross-border information dissemination. Hence, we re-estimate the model (2)-(5), with variable X being the variance of returns on each market ($X_t^{US} = Var_t^{US}$ and $X_t^{AS} = Var_t^{AS}$) and report our results in Table 4.

|Table 4 around here|

As for returns, we observe variance to be more informative for trading volume than vice versa, as indicated by significant causality. More specifically, trading volume on the Asian capital markets is the most sensitive variable, being driven particularly by the US volume (negatively) and the domestic variance (positively). Also, the US volume is mostly positively influenced by the volatility of Asian market returns, while the US volatility reacts negatively to the Asian market volatility, and to a lesser extent negatively on US volume. In general, emerging markets volatility exerts a stronger influence on other financial variables than the US volatility does, both domestically and internationally. In turn, trading volume on the US market is found to influence not only the US volatility, but also volume on the Asian markets. Furthermore, the 1997 Asian crisis apparently resulted in a larger number of significant spillovers from return volatility to trading volume, this effect being most pronounced for Asian volatility (results not reported).

The finding of a mostly positive lead-lag relationship between volatility and trading volume is in line with several theoretical predictions discussed above. First, conclusions from the SIA and MD approaches seem to be confirmed by the data: information arrives sequentially and traders disagree about its impact on asset valuation. Further, variance has been hypothesized to exert positive impact on volume in case of trades driven by new (public or private) rather than existing information (He and Wang (1995)), given differences in interpretation of news among traders (Harris and Raviv (1993)), or in presence of persistent trading patterns (Brock and LeBaron (1996)). On the other hand, we observe a pronounced volume-volatility causality only for the US variables. According to Suominen

17
(2001), this result suggests that US trading volume, but not the Asian one, is used by market participants to estimate the availability of private information about the stocks traded in the US, but not in the Asian markets.

Recent findings in Kim (2005) deserve additional attention since some results reported there appear to contradict the outcomes of our study. Kim (2005) conducts a study of spillovers from the US and Japan to Hong Kong and Singapore and finds evidence of cross-variable and cross-border causality. This effect is reported to have become stronger after the 1997 crisis and to be most pronounced for shocks originating in the US. However, his other findings are at odds with ours, e.g. the existence of 1) strong contemporaneous linkages, 2) spillovers in returns, and 3) causality from volume to other foreign variables. These differences can be attributed to a different model design that possibly biases the results in Kim (2005). For instance, while conducting the Granger-causality analysis in the OLS context, this author estimates single equation models where no spillovers from Asian markets to the US are accounted for, and does not control for the Asian country’s domestic factors such as autocorrelation in the dependent variable (returns or volatility) or volume. Additionally, in the GARCH framework only one lag for explanatory variables is used. Given these differences to our study, spillovers in returns and causal power of volume reported in Kim (2005) might be a statistical artifact and simply due to autocorrelation in returns and in volume of the “shock-receiving” country. Therefore, we consider our results more reliable. Also, the joint significance of parameters is considered for the causality tests in Kim (2005), whereas we focus on the sum of parameters, as discussed above. That is, causality in our study is reported if the cumulated impact is significant whereas Kim reports causality for any evidence of short-lived spillovers. We consider our measure superior since Kim’s measure tends to report existence of causality when e.g. the spillovers at lag one and two are of equal magnitude but different sign and, hence, cancel out. This is clearly not a case of sustainable impact of one market on another, and taking a sum of parameters, as we do, would result in a value of zero and a conclusion of no cumulated influence. In summary, the results in Kim (2005) constitute an important contribution to the spillovers literature but, due to the problems discussed above, should be interpreted with caution and do not imply incorrectness of our
findings.

4.4 Weekly Data

It has often been suggested in the spillovers literature that using weekly instead of daily data might help to avoid problems resulting from the non-overlapping trading hours of stock exchanges. Hence, we calculate weekly Wednesday-close-to-Wednesday-close values of index returns, returns volatility, and trading volume, and repeat our investigation. Specifically, for each country pair we analyze spillovers between trading volume and the variable $X_t$ representing returns, absolute returns, or returns volatility by regressing each on a constant and a contemporaneous (same week) value of other domestic and foreign variables, in analogy to the model (2)-(5). For instance, for the country pair US - Hong Kong and $X_t = R_t$, we employ trading volume and returns from both markets and estimate a system of four equations with US returns, Hong Kong returns, US volume, and Hong Kong volume as dependent variables and the remaining variables as explanatory ones. The estimated parameters are interpreted as a measure of spillovers (results not reported). The orthogonality conditions state that residuals are uncorrelated with instrumental variables, and the right-hand variables as well as their lagged values from all four equations are used as instruments.

The general observation is that we find fewer cases of significant spillovers. This is in line with our assertion that information transmission and incorporation is a short-lived phenomenon and low frequency data cannot capture and reveal the complex structure of cross-border and cross-variable interdependencies. Using aggregated weekly observations only obscures the picture.

The main findings for the weekly data correspond to those for daily observations. For the return-volume causality, hardly any significant cases of spillovers can be found. When absolute returns are analyzed instead, the number of revealed relationships increases, again showing that the degree of price changes is more informative than their sign. Also, trading volume is more sensitive to changes in absolute returns than vice versa, there is strong cross-border causality in absolute returns and some in trading volume. However, for the relationship between volatility and volume only weak cross-border causality can
be reported, in contrast to the daily data for which strong spillovers have been found. Apparently, economic phenomena captured by these variables such as disagreement among traders concerning the interpretation of news are of short-term character and cannot be captured by weekly data.

5 Conclusions

In this paper, we examined the relationship between trading volume on the one hand, and index returns, absolute returns, and return volatility on the other hand. We pursued our analysis for domestic cross-variable linkages, but the focus was most importantly on the cross-border causality between the variables under investigation. The results show that, for the US and eight Asian markets, after accounting for trading volume as an explanatory variable, no causality in returns and only infrequent causality in variance (especially from Asia to the US, but also in the opposite direction after the 1997 crisis) can be found. This contradicts previous evidence of strong causality in returns between markets. However, strong causality in absolute returns is found, indicating that it is not the sign but the magnitude of return changes that is transmitted abroad. Also, trading volume has virtually no predictive power for stock returns, and evidence is only found for US domestic volume-variance causality. However, trading volume, especially on the Asian markets, is sensitive to shocks in returns and in volatility, especially to those originating in the US, as well as to the US volume. These cross-border, cross-variable spillovers can also be observed for the US, as Asian volatility partially drives the volume and the volatility of the American market.

These findings indicate that news reach market participants only sequentially. From the return-volume causality, we learn that investors are overconfident and pursue feedback strategies, most trades are not driven by private information, and market participants make their investment decisions based on existing, rather than new, information. From the variance-volume relationship, we conclude that trading volume can be used as a measure of disagreement among traders, and their trade decisions are determined by new information arriving on the market. Apparently, the incorporation of new information
into securities prices causes return volatility to increase, whereas the adjustment of asset prices to existing information manifests itself in a change in the level of returns rather than of return volatility. Hence, an analysis of the interactions between financial variables such as returns, return volatility, and trading volume reveals a broader spectrum of cross-border information transmission mechanisms.

Concerning the impact of the 1997 financial crisis on the causal relationship between Asia and the US, an increase in cross-border spillovers can be observed. First, the dependence of trading volume, especially in the Asian countries, on the US returns became more pronounced after the crisis. Second, the spillovers from US volume to Asian volume also intensified. Hence, transmission of information originating abroad can be argued to have increased after 1997. On the basis of these facts, an argument in favor of increasing integration between financial markets can be made. Also, these results indicate an increase in the noise in stock returns following the 1997 crisis, forcing investors to extract relevant information from trading volume, as argued by Blume, Easley, and O’Hara (1994). The increased dependence of volume on returns can be explained by an increased application of feedback strategies among investors. Furthermore, a stronger impact of volatility on trading volume in the postcrisis period can also be observed. In the light of the theoretical approaches discussed in Section 2 (Harris and Raviv (1993), He and Wang (1995)), this finding indicates that differences among investors concerning the interpretation of news increased following the 1997 crisis. Apparently, although capital markets became more strongly interrelated due to progressing liberalization and openness of countries in real and financial sectors, the crisis experience made investors more sensitive and cautious to news, especially to those originating abroad. The increased noise in stock returns might have made investors actively search for additional information contained in trading volume and in investment decisions made by others, i.e. to employ feedback strategies in a herd-like manner. The latter can also be seen as a substitute for an information-based strategy, helping money managers to avoid inferior relative performance, as compared to their rivals.

As for the relative strength of spillovers originating in Asia and America, we find the US market to exert stronger influence on its Asian counterparts than vice versa only
in the models where return-volume relationship is investigated. This is due to the strong causality running from US returns to volume on the Asian markets. However, when absolute returns are analyzed, Asian stock markets are as informative for the US market as vice versa. In case of the dynamic volatility-volume relationship, it is even Asia that becomes a (slightly) dominating source of spillovers, mostly due to the strong impact of Asian volatility on the US variables. Given these results and the theoretical considerations on the cross-variable relationships, information spilling over from the US to Asia seems to be new and there is a consensus among market participants concerning its interpretation. However, the US market’s reactions to the behavior of the Asian markets suggests that markets in Asia are driven by trades on existing US information, with a high degree of disagreement among investors concerning its importance for asset valuation.

The results presented here indicate that stock returns and volatility contain valuable information about domestic and foreign trading volume, with the opposite effect being less pronounced. Hence, even if spillovers in returns are reported to be nonexisting and those in variance to run only from Asia to the US, information flows across borders via other, mostly cross-variable channels. This finding offers a potentially valuable extension of econometric models aimed at assessment of equity risk, defined either in terms of return volatility, or as liquidity risk resulting from a plunge in trading volume. Specifically, by including trading volume in the analysis, superior estimates of volatility- and liquidity-risk can be produced. In general, based on our results, we claim that more can be learned about the stock market behavior by studying the joint dynamics of returns, volatility, and trading volume, both domestically and internationally.
References


Table 1: Index Returns and Trading Volume: Descriptive Statistics and Trend Tests Results

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<td><strong>Panel A: Descriptive statistics of returns and trading volume</strong></td>
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<td>12.5870</td>
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<td>Mean</td>
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Note: In Panel A, StdDev denotes standard deviation. In Panel B, $\alpha_1$ and $\alpha_2$ are parameters from model (1) and measure the strength of the deterministic linear and quadratic trends in logarithmic trading volume, respectively. $R^2$ measures the goodness of fit of model (1). In Panel C, ADF denotes the test statistic from the adjusted Dickey-Fuller test, PP is the test statistic from the Philips-Perron test, and WS stands for the test statistic from the weighted symmetric test, all for the stationarity of time series. The optimal number of lags is selected by the Akaike-information-plus-two criterion (Pantula, Gonzales-Farias, and Fuller (1994)). P-values are in parentheses.
<table>
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<td>0.00023</td>
<td>0.00086</td>
<td>0.00078</td>
</tr>
<tr>
<td>$X_{US} \rightarrow V_{US}$</td>
<td>113.669*</td>
<td>-163.742</td>
<td>-198.905</td>
<td>-422.47</td>
<td>54.0941</td>
<td>64.5688**</td>
<td>35.3954**</td>
<td>461.477</td>
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<tr>
<td>$X_{AS} \rightarrow V_{US}$</td>
<td>-170.267*</td>
<td>332.884</td>
<td>420.249</td>
<td>8086.01</td>
<td>-114.117</td>
<td>-131.707**</td>
<td>-63.8631**</td>
<td>-745.863</td>
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<tr>
<td>$V_{AS} \rightarrow V_{US}$</td>
<td>-0.02142</td>
<td>-0.08274</td>
<td>-0.23110</td>
<td>-20.8223</td>
<td>0.17279*</td>
<td>0.19674**</td>
<td>0.14979*</td>
<td>1.91845</td>
</tr>
<tr>
<td>$X_{US} \rightarrow V_{AS}$</td>
<td>-76.6491**</td>
<td>-96.7838***</td>
<td>-145.140*</td>
<td>-10.9593***</td>
<td>-15.7133***</td>
<td>-26.9570***</td>
<td>-12.4050***</td>
<td>-20.1424***</td>
</tr>
<tr>
<td>$X_{AS} \rightarrow V_{AS}$</td>
<td>115.747**</td>
<td>186.781***</td>
<td>289.684*</td>
<td>16.5117***</td>
<td>30.3169***</td>
<td>41.7761***</td>
<td>13.2426***</td>
<td>23.2176***</td>
</tr>
<tr>
<td>$V_{US} \rightarrow V_{AS}$</td>
<td>-0.37820*</td>
<td>-0.08719</td>
<td>-0.84046</td>
<td>0.06051</td>
<td>-0.10691</td>
<td>-0.18522*</td>
<td>0.14847</td>
<td>-0.14233</td>
</tr>
</tbody>
</table>

Note: In the table, the estimated sums of parameters, i.e. $\sum_{i=1}^{5} \delta_{1i}$, are presented. Specifically, the model (2)-(5) is estimated with variable X representing index returns for eight pairs of countries, each pair consisting of the US and an Asian stock market. The null hypothesis for each variable is that its lagged (and in some cases also contemporaneous) values cause another variable. The exact information on which variables are investigated is reported in column 1. For instance, to test whether trading volume on the Hong Kong market causes US returns, model (2)-(5) is estimated with $X_{US} = R_{US}$ and $X_{AS} = R_{AS}$, and the null hypothesis is no causality: $(\sum_{i=1}^{5} \delta_{1i}) = 0$. The Wald test is employed, and the estimated sum of parameters is reported in line $V_{AS} \rightarrow X_{US}$ and in column AS = Hong Kong. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.
<table>
<thead>
<tr>
<th>AS:</th>
<th>Hong Kong</th>
<th>Indonesia</th>
<th>Japan</th>
<th>Korea</th>
<th>Malaysia</th>
<th>Singapore</th>
<th>Taiwan</th>
<th>Thailand</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_{US}^{AS} \rightarrow X_{US}^{AS}$</td>
<td>-0.27087***</td>
<td>-0.14821***</td>
<td>-0.29593***</td>
<td>-0.15769***</td>
<td>-0.08378</td>
<td>-0.20528**</td>
<td>-0.16455***</td>
<td>-0.14310***</td>
</tr>
<tr>
<td>$V_{US}^{US} \rightarrow X_{US}^{US}$</td>
<td>0.00094</td>
<td>0.00090</td>
<td>0.00084</td>
<td>0.00050</td>
<td>0.00048</td>
<td>0.00029</td>
<td>0.00147</td>
<td>-0.00041</td>
</tr>
<tr>
<td>$V_{AS}^{US} \rightarrow X_{US}^{US}$</td>
<td>0.00028</td>
<td>0.00060</td>
<td>-0.00043</td>
<td>-0.00060</td>
<td>-0.00030</td>
<td>0.00009</td>
<td>0.00017</td>
<td>-0.00046</td>
</tr>
<tr>
<td>$X_{US}^{US} \rightarrow X_{AS}^{US}$</td>
<td>-0.87249***</td>
<td>-0.79003***</td>
<td>-0.37008***</td>
<td>-0.71029***</td>
<td>-0.99329***</td>
<td>-0.46313***</td>
<td>-0.77481***</td>
<td>-0.72651***</td>
</tr>
<tr>
<td>$V_{US}^{US} \rightarrow X_{AS}^{US}$</td>
<td>0.00668</td>
<td>0.00009</td>
<td>0.00217</td>
<td>0.00454</td>
<td>0.00130</td>
<td>0.00693</td>
<td>0.00030</td>
<td>0.00103</td>
</tr>
<tr>
<td>$V_{AS}^{US} \rightarrow X_{AS}^{US}$</td>
<td>0.00097</td>
<td>0.00086</td>
<td>-0.00034</td>
<td>0.00045</td>
<td>-0.00001</td>
<td>0.00087</td>
<td>-0.00232</td>
<td>-0.00117</td>
</tr>
<tr>
<td>$X_{US}^{US} \rightarrow V_{US}^{US}$</td>
<td>-28.5261***</td>
<td>-61.2384**</td>
<td>-42.5866***</td>
<td>96.8163</td>
<td>-62.2416</td>
<td>-59.7936**</td>
<td>17.6185</td>
<td>-29.6546*</td>
</tr>
<tr>
<td>$X_{AS}^{US} \rightarrow V_{US}^{US}$</td>
<td>63.2578***</td>
<td>112.478**</td>
<td>90.4269***</td>
<td>-187.761</td>
<td>153.006</td>
<td>138.617**</td>
<td>-56.0101*</td>
<td>102.630**</td>
</tr>
<tr>
<td>$V_{AS}^{US} \rightarrow V_{US}^{US}$</td>
<td>-0.17151**</td>
<td>-0.39974**</td>
<td>0.02802</td>
<td>0.21877</td>
<td>-0.00952</td>
<td>-0.11058</td>
<td>0.29677**</td>
<td>-0.12021</td>
</tr>
<tr>
<td>$X_{US}^{AS} \rightarrow V_{AS}^{AS}$</td>
<td>-6.63773</td>
<td>-33.5653**</td>
<td>-31.5716</td>
<td>-50.0114**</td>
<td>2.01344</td>
<td>-14.9876*</td>
<td>2.25189</td>
<td>0.60163</td>
</tr>
<tr>
<td>$X_{AS}^{AS} \rightarrow V_{AS}^{AS}$</td>
<td>25.0945</td>
<td>92.7371***</td>
<td>107.854**</td>
<td>78.6041***</td>
<td>28.9353***</td>
<td>53.4344**</td>
<td>5.31735</td>
<td>21.3198***</td>
</tr>
<tr>
<td>$V_{US}^{AS} \rightarrow V_{AS}^{AS}$</td>
<td>-0.30680</td>
<td>-0.79527***</td>
<td>0.07499</td>
<td>-0.43026</td>
<td>-0.46942***</td>
<td>-0.30495**</td>
<td>0.21059</td>
<td>-0.21377*</td>
</tr>
</tbody>
</table>

Note: In the table, the estimated sums of parameters, i.e. $\sum_{i=1}^{5} \delta_{i}$, are presented. Specifically, the model (2)-(5) is estimated with variable $X$ representing absolute returns for eight pairs of countries, each pair consisting of the US and an Asian stock market. The null hypothesis for each variable is that its lagged (and in some cases also contemporaneous) values cause another variable. The exact information on which variables are investigated is reported in column 1. For instance, to test whether trading volume on the Hong Kong market causes US absolute returns, model (2)-(5) is estimated with $X_{US}^{AS} = |R_{US}^{AS}|$ and $X_{AS}^{US} = |R_{AS}^{US}|$, and the null hypothesis is no causality: $\left(\sum_{i=1}^{5} \delta_{i}\right) = 0$. The Wald test is employed, and the estimated sum of parameters is reported in line $V_{AS}^{US} \rightarrow X_{US}^{US}$ and in column AS = Hong Kong. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.
Table 4: Cross-border Spillovers in Return Volatility and Trading Volume \((X = \text{Var})\)

<table>
<thead>
<tr>
<th>AU</th>
<th>Hong Kong</th>
<th>Indonesia</th>
<th>Japan</th>
<th>Korea</th>
<th>Malaysia</th>
<th>Singapore</th>
<th>Taiwan</th>
<th>Thailand</th>
</tr>
</thead>
<tbody>
<tr>
<td>(X_{US} \rightarrow X_{US})</td>
<td>0.02795**</td>
<td>-0.00006*</td>
<td>-0.0004</td>
<td>-0.00008**</td>
<td>-0.00006*</td>
<td>-0.00004</td>
<td>-0.0007**</td>
<td></td>
</tr>
<tr>
<td>(V_{US} \rightarrow X_{US})</td>
<td>-0.00007*</td>
<td>-0.00006*</td>
<td>-0.00001</td>
<td>-0.00008**</td>
<td>-0.00006*</td>
<td>-0.00004</td>
<td>-0.00007**</td>
<td></td>
</tr>
<tr>
<td>(V_{AS} \rightarrow X_{US})</td>
<td>0.0001</td>
<td>4.89x10^{-7}</td>
<td>0.02165</td>
<td>0.036655</td>
<td>0.05451</td>
<td>-0.15282</td>
<td>-0.09446</td>
<td></td>
</tr>
<tr>
<td>(X_{US} \rightarrow X_{AS})</td>
<td>-0.01984</td>
<td>-0.13447</td>
<td>-0.00009</td>
<td>-0.00002</td>
<td>-0.00001</td>
<td>0.00004</td>
<td>-0.00021</td>
<td></td>
</tr>
<tr>
<td>(V_{US} \rightarrow X_{AS})</td>
<td>-0.00026**</td>
<td>-0.00009</td>
<td>-0.00006</td>
<td>-0.00005</td>
<td>-0.00001</td>
<td>0.00004</td>
<td>-0.00021</td>
<td></td>
</tr>
<tr>
<td>(V_{AS} \rightarrow X_{AS})</td>
<td>0.00004</td>
<td>0.00006</td>
<td>-0.00001</td>
<td>0.000004</td>
<td>5.77x10^{-6}</td>
<td>0.00003*</td>
<td>0.00003</td>
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</tr>
<tr>
<td>(X_{US} \rightarrow V_{US})</td>
<td>-1359.88**</td>
<td>-2424.66</td>
<td>-563.364</td>
<td>-260.173</td>
<td>-137.54</td>
<td>72.4585</td>
<td>64.9766</td>
<td></td>
</tr>
<tr>
<td>(X_{AS} \rightarrow V_{US})</td>
<td>1465.08*</td>
<td>4496.29</td>
<td>3961.45***</td>
<td>-37.7263</td>
<td>1936.21</td>
<td>5512.67**</td>
<td>-1565.10*</td>
<td>3304.98*</td>
</tr>
<tr>
<td>(V_{AS} \rightarrow V_{US})</td>
<td>-0.23258**</td>
<td>-0.79708</td>
<td>0.0930</td>
<td>-0.03356</td>
<td>-0.08635</td>
<td>0.46566**</td>
<td>-0.24357</td>
<td></td>
</tr>
<tr>
<td>(X_{US} \rightarrow V_{AS})</td>
<td>-283.144</td>
<td>-1585.73*</td>
<td>-746.69</td>
<td>-822.751</td>
<td>259.130</td>
<td>-442.946</td>
<td>7.09988</td>
<td>468.559**</td>
</tr>
<tr>
<td>(X_{AS} \rightarrow V_{AS})</td>
<td>265.860</td>
<td>3039.72***</td>
<td>6355.40***</td>
<td>2669.79</td>
<td>615.174**</td>
<td>2885.75***</td>
<td>468.062***</td>
<td>916.147***</td>
</tr>
<tr>
<td>(V_{US} \rightarrow V_{AS})</td>
<td>-0.07638</td>
<td>-1.23757**</td>
<td>0.21373</td>
<td>-1.53530</td>
<td>-0.96219***</td>
<td>-0.88372***</td>
<td>0.29137*</td>
<td>-0.58027***</td>
</tr>
</tbody>
</table>

Note: In the table, the estimated sums of parameters, i.e. \(\sum_{i=1}^{5} \delta_{1,i}\), are presented. Specifically, the model (2)-(5) is estimated with variable \(X\) representing return volatility for eight pairs of countries, each pair consisting of the US and an Asian stock market. The null hypothesis for each variable is that its lagged (and in some cases also contemporaneous) values cause another variable. The exact information on which variables are investigated is reported in column 1. For instance, to test whether trading volume on the Hong Kong market causes US return volatility, model (2)-(5) is estimated with \(X_{US} = \text{Var}_{US}\) and \(X_{AS} = \text{Var}_{AS}\), and the null hypothesis is no causality: \(\sum_{i=1}^{5} \delta_{1,i} = 0\). The Wald test is employed, and the estimated sum of parameters is reported in line \(V_{AS} \rightarrow X_{US}\) and in column \(AS = \text{Hong Kong}\). ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.
2001


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2002


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2003

- A Sequential Method for the Evaluation of the VaR Model Based on the Run between Exceedances, Laurentiu Mihailescu, Allgemeines Statistisches Archiv.
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2004


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2005

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