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Information Flows, Stock Market Volatility and the Systemic Risk in Global Finance

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ABSTRACT

Information flows are a theoretical explanation for stock market volatility, but controversy remains regarding how to measure them. Based on cross-sectional and temporal properties of information flows, we decompose total trading volume into four types: cross-country shocks and country-specific shocks due to arrivals of private information, and trading volume shocks and stock volatility shocks due to public information. We then use a Structural Vector Autoregressive model to reconstruct historical trading volume resulted from the four types of information shocks. The evidence shows that the historical trading volumes due to private information flow can explain volatility clustering of stock markets. By analysing sources of information flow, we find private information flow reflects systemic risk in the global financial system. The result conforms to Mixture of Distribution Hypothesis and finds that quality of information content is what differentiates privately informed trading from public information trading. It further suggests the main drivers of stock market volatility are uncertainties about fundamental values of assets and about other investors' behaviours.

JEL Classification: C32, D82, G12, G15

1 | Introduction

Research on finance has produced a large quantity of papers exploring the relationship between stock market volatility and trading volume. A cornerstone of this area of research is mixture of distribution hypothesis (MDH), which posits a joint dependence of returns and volume on an underlying information flow variable. However, controversy remains as to how to empirically measure information flow variables since they are latent. In this paper, we decompose total trading volume into cross-country shocks and country-specific shocks due to arrivals of private information, as well as trading volume shocks and stock volatility shocks due to public information flows. We found that trading volumes due to private information flow can explain volatility clustering of stock markets, and the private information flow reflects systemic risk in the global financial system.

The notion that privately informed trading and returns are driven by the intensity of information arrivals, hence inducing a decaying autocorrelation function for the variance of stock returns, was developed in a modified version of MDH by Andersen (1996) that was further refined by Suominen (2001). According to the modified MDH, daily returns are conditionally normal but have variances that reflect the arrivals of private information. Trading volume conditional on information arrivals also has an informed component that reflects how strongly volume fluctuates in response to news, as well as an uninformed component. By contrast, the public information flows arrive randomly in stock markets, which induce fat tails and excess kurtosis in the distribution of returns but have little impacts on volatility. The implication is that stock markets are the destination of information flows and therefore, the arrivals of information flows should be classified by their effects on markets rather than by their origins. This perspective on information flows has received little attention in literature.

Given a large quantity of literature on co-movements of the indices of different national stock markets (e.g., Brooks and Negro 2006; Chen and Fraser 2010; Madaleno and Pinho 2012; Chen and Quan 2013; Chuluun 2017; Wang and Guo 2020; Anagnostopoulos et al. 2022), the classification of information flows by their effects necessarily results in two forms of private information shocks. One is 'country-specific shock' where private information flows only affect one country, and the other is 'cross-country shock' where private information flows affect several countries. For example, information flows to Japan's stock market can be originated from any national stock markets, credit markets or money markets; however, it will be classified as private information flow if its arrivals cause co-movements of volume and stock prices in Japan's stock market.

The modified MDH also suggests that part of public information flows would result in the movements of stock volatility alone. In addition, periodic news releases and events would induce a relatively heavy trading but would have little effect on stock volatility.[1] We therefore classify public information flow into two forms; one caused by unexpected nature of public information flow and the other caused by trading adjustments to periodic news and events. In the following discussion, we shall call the shocks due to public information flow 'stock volatility shocks' since they only affect stock volatility, and the shocks due to periodic economic activities 'trading volume shocks' since they only result in trading volume adjustments. Because of their 'public' nature, these two forms of public information shocks are not country-specific. The distinction of cross-country and country-specific information therefore contributes to the literature that considers the effects of 'heat waves' and 'meteor showers' (e.g., Engle et al. 1990; Yarovaya et al. 2016; Balcilar et al. 2023).

We also contribute to the literature by developing a two-variable three-country structural vector autoregressive (SVAR) model, whereby the endogenous variables are the trading volume and stock trading range of United States, United Kingdom and Japan. We choose the three mature stock indices because they are in every list of major international financial centres. Our study based on these markets helps to understanding the dynamic interaction of information flows across the globe. The results would be of interest to international and local investors, regulators as well as academics.

For tackling endogeneity issues of trading volume and stock prices, we impose both instantaneous and long-run restrictions in the SVAR. Given enough time, the realisations of private information flows, regardless of being country-specific or cross-country, would reveal information to markets, based on which other investors could infer judgements. To allow for identification, the two forms of private information shocks should be made with reference to timing and not just the effects. We therefore develop an identification scheme such that country-specific private information shocks have 'contemporaneous' effects only on one country's volume and volatility, while cross-country private information shocks have 'contemporaneous' effects on several countries' volume and volatility. Clearly, in short span of time, uninformed investors would not be able to distinguish public information trading from privately informed trading, and hence they would respond to the shocks by spontaneous trading. Given long enough time, however, public information flow would only induce higher stock volatility, while periodic economic activities would only result in adjustments of investors' positions. For identification, these two forms of public information shocks should therefore be made with reference to timing, such that their long-run effects on either trading volume or stock return volatility is neutral. In other words, although both forms of public information shocks are cross-country in nature, they only have 'temporary' effects on connections of volume and stock prices. In contrary, private information flows would have permanent effects on the connection of trading volume and stock prices.

Lastly, we contribute to the literature by seeking possible sources of information flows. We first assessed the importance of the different forms of information shocks by reconstructing historical trading volumes that responded to these information shocks. By inspecting an EGARCH model augmented with historical trading volume, the evidence showed that privately informed trading volumes can explain the volatility clustering of stock markets, but they cannot explain the fat tail phenomena in stock return distributions. An ensuing question was what information sources were driving trading volume and hence, stock market volatility. To seek possible answers, we analysed the relationship between the information shocks and the Financial Stress Index (OFR FSI) published by the Office of Financial Research. We found that private information flows reflect financial stress more than public information flows do, and the financial stress indicator of volatility is the most important source of surprising information. The study suggests trading volume contains information regarding to the quality of traders' information signals about systemic risk.

The rest of this study is structured as follows. Section 2 is a brief literature review. Section 3 explains how we use a SVAR model to identify information shocks, based on which we reconstruct historical trading volumes. We then describe how we use an EGARCH model to test explanatory powers of historical trading volumes in stock market volatility. Section 4 presents data and their basic statistics, and Section 5 presents and discusses relevant empirical results. Section 6 reports the tests of the possible sources of information shocks. Section 7 tests the robustness of our results to different measures of trading volume and trading prices. Finally, Section 8 offers the concluding remarks.

2 | Literature Review

A common feature of stock returns is volatility clustering; that is, periods of large change in returns are usually followed by further periods of large change and small change in returns tends to be followed by small change (e.g., Engle 1982; Bollerslev 1987; Galeano and Tsay 2010). While empirical studies found significant evidence in favour of volatility clustering in stock returns, there have been debates on the underlying economic explanations for this phenomenon.

To explain this phenomenon, some authors explore possible connections between stock market volatility and trading volume.[2] In particular, several theories have tried to connect trading volume and asset price movements with information precision. For example, Blume et al. (1994) argue that trading volume captures important information contained in the quality of traders' information signals. They postulate that current trading volume may be sufficient to reveal some information but not all, because the underlying uncertainty in economy is not resolved in one period. However, sequences of trading volume can provide information that is not impounded in a single market price. Schneider (2009) suggests investors infer judgements from trading volume about private information that other investors might possess. In other words, observing volume allows investors to decide how the aggregate information beyond their own private signals should be weighted relative to their private information. Empirically, Atiase et al. (2011) tested whether their proxies of heterogeneous prior beliefs, differential interpretation and the consensus effect of investors were related to trading volume reactions, and found that these factors were distinct and incremental to each other, contributing to trade-inducing effects in trading volumes. Their paper confirms that the process of information disclosures can stimulate trades. In short, these arguments suggest private information flows and hence, privately informed trading, are a key driver to asset price volatility.

A related explanation of volatility-volume relationship is the MDH initially developed by Clark (1973), Epps and Epps (1976) and Tauchen and Pitts (1983). Subsequently, Lamoureux and Lastrapes (1990) conducted an empirical test of the MDH on 20 actively traded individual stocks, and found that volatility persistence reduced substantially when total trading volume was included in the variance equation of the GARCH model. A large quantity of later studies also applied the GARCH models to investigate the role of trading volume as the determinant of return volatility. In general, many studies on individual securities (e.g., Gallo and Pacini 2000; Pyun et al. 2001; Bohl and Henke 2003; Qiao and Wong 2010; Carroll and Kearney 2012; Al-Ajmi 2017; Bajzik 2021) found that the effect of volatility clustering disappeared when trading volume was included in the variance equation. However, when trying to explain aggregate market returns, Sharma et al. (1996) found that the ARCH effect did not completely vanish with the inclusion of trading volume. Other authors, for example Chen et al. (2001), Bose and Rahman (2015) and Patra and Bhattacharyya (2021), also found that total trading volume could not satisfactorily explain volatility clustering in stock markets.

In the wake of evidence against MDH, Andersen (1996) modified the hypothesis by integrating a market microstructural setting at the daily frequency. Suominen (2001) further theoretically extends the MDH to show that the dynamic feature of private information flow induces a positive and geometrically decaying autocorrelation function for the variance of stock returns. Bollerslev and Jubinski (1999) and Luu and Martens (2003) also suggest stock prices and trading volume share a common dynamic structure. Covrig and Ng (2004) show that the clustering of trading upon new information arrivals in markets on average is generated more by institutions than by individual investors. Li and Wu (2006) show that the positive relationship between return volatility and volume is driven by informed trading, and the MDH model is robust for characterising temporal behaviours of return volatility and volume. Park (2010) also modifies the MDH to allow for separating general information from surprising information with a sign effect. Darolles et al. (2015, 2017) extend the MDH to specify how liquidity frictions, apart from information flows, can have impacts on intra-daily price variations and volumes. Many studies also found evidence for the MDH; for example, Carroll and Kearney (2015) found that the MDH held before and after the announcement of business takeover, Slim and Dahmene (2016) found evidence of a positive volume–volatility relationship driven by the informed component of trading volume that supports the MDH, while Ngene and Mungai (2022) found intertemporal evidence of contemporaneous causal relationship from trading volume to volatility, which they claimed supports the MDH. Some other studies, however, do not fully support the MDH. The study of Fleming et al. (2006), for example, suggests non-persistent component of volatility is closely related to contemporaneous non-persistent component of volume. Rossi and De Magistris (2013) found no evidence of the presence of a common long memory stochastic process in volume and volatility; however, their study based on the MDH indicated the existence of bi-directional Granger causality between these two market variables. Xu et al. (2020) found little evidence of correlation between privately informed trades and stock market volatility, but they also found that the disagreement due to different opinions of investor was a key determinant of volatility. Overall, the MDH provides a theoretical ground for understanding the volume–volatility relation, with a quantity of literature suggesting that the arrival of private information would result in co-movements of trading volume and stock prices.

In addition, some empirical papers measure the unexpected parts of trading volume, and test their effects on stock market volatility. For instance, Arago and Nieto (2005) used a forward-looking ARMA model to derive unexpected volume from total trading volume, and then analysed the effect of unexpected volume on the conditional volatility of nine developed stock markets. Wanger and Marsh (2005) used Hodrick & Prescott filtering method to derive unexpected volume, which they claim helps to explain volatility persistence and excess kurtosis. Wen and Yang (2009) used a GARCH model to filter out time trend, serial correlation and heteroskedasticity in total trading volume to derive 'persistence-free' trading volume, which they suggest has better explanatory power than unexpected volume for volatility clustering in stock returns. Rzayev and Ibikunle (2019) used a state-space model to decompose trading volume into liquidity-driven and information-driven components, and found that informed trading was associated with the reduction in stock volatility and illiquidity. Dey and Wang (2021) decomposed volume into expected and unanticipated components, and found the expected volume signified liquidity while unanticipated volume contained information content. They also found that the trading volumes asymmetrically affected both the variance and covariance of stocks. The evidence on whether unexpected volume could reduce volatility persistence in stock returns is inconclusive, but the overall results suggest parts of unexpected trading volume help explain stock market volatility.

The literature review indicates that trading volume is a response to information flows, but only private information flows would cause the co-movements of asset prices and trading volume, whereas public information flows would have little impacts on their co-movements.

3 | Empirical Methodology

3.1 | Information Shocks on Trading Volume and Stock Price Movements

Consider a model where stock markets are determined by the country-specific shock and the cross-country shock that are classified as private information shocks, as well as the trading volume shock and the stock volatility shock that are classified as public information shocks. According to the previous discussion, variables in stock markets, such as stock price movement and trading volume, are determined by these exogenous shocks.

$$y_{it} = b_{i1}\varepsilon_{it} + b_{i2}\varepsilon_{wt} + b_{i3}\varepsilon_{vt} + b_{i4}\varepsilon_{ht} \tag{1}$$

where y_{it} is the variable of interest for country i in time period t, ε_{it} is the country-specific shock for i in period t, ε_{wt} is the cross-country shock in period t, ε_{vt} is the trading volume shock in period t, ε_{ht} is the stock volatility shock in period t and b_{ij} are coefficients.

These four shocks can be empirically identified by their cross-sectional and temporal characteristics. Cross-country shocks are unrestricted such that they can affect all countries' volume and volatility contemporaneously and in the long run. Country-specific shocks are restricted such that they can affect other countries' volume and volatility only after the lag of one period. The stock volatility shock is restricted such that it has no long-run effect on all countries' volume, while the trading volume shock is restricted such that it has no long-run effect on all countries' volatility.

3.2 | Empirical Identification of Information Shocks

To empirically distinguish permanent and temporary effects of trading volume and stock volatility shocks, it is necessary to have two variables. To identify the three global shocks plus i local shocks, we include three stock markets for analysis. Therefore, we have a two-variable three-country model with the vector of dependent variables being,

$$y = \left[V_a \ V_b \ V_j \ H_a \ H_b \ H_j\right]^T \tag{2}$$

where V_i is the natural logarithm of properly detrended trading volume and H_i is the difference between the natural logarithm of highest stock price and of lowest stock price, for country $i = a$, b, j that represent United States, United Kingdom and Japan, respectively. We take natural logarithm of the variables because works of structural decomposition invokes normality. With such transformation, the underlying assumption is that trading volume and stock price share common lognormal stochastic volatility processes, as in Andersen (1996).

Consider the representation of the above system by a six-equation VAR.

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \tag{3}$$

where y_t is a (6×1) vector of the observed variables as defined in (2), the A_j's $(j = 1, \ldots, p)$ are the (6×6) reduced form coefficient matrices and c is a (6×1) vector of intercept terms allowing for nonzero mean of y_t. In addition, u_t is 6-dimensional regression residuals with $E(u_t) = 0$, $E(u_t u_t^T) = \Sigma_u$ and $E(u_t u_s^T) = 0$, $\forall s \neq t$. The lag length p of the VAR is selected by the Final Prediction Error, so that the u_t represents the unexpected components of trading volume and stock price movements.

In the VAR system, the regression residuals are composed of three country-specific shocks, one cross-country shock, one trading volume shock and one stock volatility shock. As previously discussed, country-specific shocks are local in nature such that they have instantaneous effects only on one market's variables, while the cross-country shock, trading volume shock and stock volatility shock are global in nature such that they have instantaneous effects on several markets' variables. These properties of information shocks will allow for identification through their short-run restrictions in $\boldsymbol{u_t} = \boldsymbol{B\varepsilon_t}$, that is,

$$\begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \\ u_{5t} \\ u_{6t} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & b_{14} & b_{15} & b_{16} \\ 0 & b_{22} & 0 & b_{24} & b_{25} & b_{26} \\ 0 & 0 & b_{33} & b_{34} & b_{35} & b_{36} \\ b_{41} & 0 & 0 & b_{44} & b_{45} & b_{46} \\ 0 & b_{52} & 0 & b_{54} & b_{55} & b_{56} \\ 0 & 0 & b_{63} & b_{64} & b_{65} & b_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_{at} \\ \varepsilon_{bt} \\ \varepsilon_{jt} \\ \varepsilon_{wt} \\ \varepsilon_{vt} \\ \varepsilon_{ht} \end{bmatrix} \tag{4}$$

where the six structural shocks follow a stochastic process with zero mean and a unit variance, that is, $\boldsymbol{\varepsilon_t} \sim (\boldsymbol{0}, \boldsymbol{I_t})$. For interpretations, notice that the first three columns catch the three country-specific shocks. For example, an US-specific shock ε_{at} has no contemporaneous effects on UK's trading volume and stock price movements so that $b_{21} = 0$ and $b_{51} = 0$. It also has no contemporaneous effects on Japan's volume and stock price movements, so that $b_{31} = 0$ and $b_{61} = 0$. Similarly, an UK-specific or Japan-specific shock has no contemporaneous effects on other countries' variables, so we have $b_{12} = b_{42} = b_{32} = b_{62} = 0$ and $b_{13} = b_{43} = b_{23} = b_{53} = 0$.

In addition, private information shocks will have permanent effects on the connection of volume and volatility, while public information shocks will only have temporary effects on either trading volume or stock volatility. These properties will allow for identification through their long-run restrictions. The long-run restrictions may be written as,

$$\left(I - A_1 - A_2 - \cdots - A_p\right)^{-1} u_t = \Psi u_t = F\varepsilon_t \tag{5}$$

where $\Psi = \left(I - A_1 - A_2 - \cdots - A_p\right)^{-1}$ is the long run multiplier and A_j's $(j = 1, \ldots, p)$ are the coefficient matrices from (3). The long-run F matrix is therefore related to the short-run B matrix in (4) through $F = \Psi B$. To distinguish trading volume shock ε_{vt} and stock volatility shock ε_{ht} from cross-country shock ε_{wt}, restrictions can be imposed on elements of F matrix with $F_{ij} = 0$ indicating that the accumulated response of the ith variable to the jth structural shock is zero in the long-run. Specifically, we impose the restrictions that $F_{45} = F_{55} = F_{65} = 0$ for identifying the trading volume shock since ε_{vt} has no long-run effects on the three countries' price movements, and the restrictions that $F_{16} = F_{26} = F_{36} = 0$ for identifying the stock volatility shock since ε_{ht} has no long-run effects on the three countries' trading volume. By contrast, ε_{wt} will catch the cross-country shock since it has permeant effects on both trading volumes and price movements.

Exact identification requires $\left(6^2 - 6\right)/2 = 15$ restrictions, but there are 18 restrictions in the system, so it is over-identified with three degrees of freedom. Since we model the system based on economic implications, there is no reason to imposing less restrictions. In our empirics, we report the result of the likelihood ratio test with three degrees of freedom.

3.3 | Trading Volumes and Conditional Volatility

The six-equation VAR as in (3) can be expressed as a vector moving average $\boldsymbol{y_t} = [\boldsymbol{I} - \boldsymbol{A}(L)\boldsymbol{L}]^{-1}\boldsymbol{u_t}$, where I is an identity matrix, $A(L)$ is a finite-number autoregressive lag polynomial, A is the coefficient matrix from the VAR process (3) and L is the lag operator. Since $\boldsymbol{u_t} = \boldsymbol{B}\boldsymbol{\varepsilon_t}$ in (4), the structural vector moving average is $\boldsymbol{y_t} = [\boldsymbol{I} - \boldsymbol{A}(\boldsymbol{L})\boldsymbol{L}]^{-1}\boldsymbol{B}\boldsymbol{\varepsilon_t}$. As such, each volume (i.e., V_a, V_b, V_j) can be expressed as a function of current and lagged values of the six structural shocks, $\varepsilon_{at}, \varepsilon_{bt}, \varepsilon_{jt}, \varepsilon_{wt}, \varepsilon_{vt}$ and ε_{ht}. We use historical decompositions to measure the cumulative contribution of each structural shock to evolutions of trading volume over time. In other words, we decompose each trading volume to six historical trading volumes.

$$V_i = v_{i\leftarrow a} + v_{i\leftarrow b} + v_{i\leftarrow j} + v_{i\leftarrow w} + v_{i\leftarrow v} + v_{i\leftarrow h}, \forall i = a, b, j \quad (6)$$

Historical trading volumes are reconstructions of trading volume as if they were subject to only one type of structural shocks. For example, $v_{a\leftarrow a}$ represents the part of US trading volume that responded only to US-specific shock, and $v_{a\leftarrow b}$ represents the US trading volume that responded only to UK-specific shock. Similarly, $v_{j\leftarrow v}$ represents the Japan trading volume that responded only to trading volume shock and $v_{j\leftarrow h}$ represents the Japan trading volume that responded only to stock volatility shock.

The decomposition of trading volume and stock price movements implies that they share common stochastic volatility processes. To test the importance of historical trading volumes on variance of stock returns, we employ an EGARCH model that is closely related to stochastic volatility processes. Specifically, we use the following ARMA(1,1)-EGARCH(1,1) model augmented with historical volumes to test their relative importance in determining variance of stock returns.

$$R_t = c + \phi R_{t-1} + \theta \mu_{t-1} + \mu_t$$

$$\mu_t = \zeta_t \sigma_t \ \ \zeta_t \sim GED\left(0, 1, \frac{1}{k}\right)$$

$$\ln\left(\sigma_t^2\right) = \omega + \alpha\left|\frac{\mu_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\mu_{t-1}}{\sigma_{t-1}} + \beta\ln\left(\sigma_{t-1}^2\right) + \boldsymbol{\delta^T v_t} \quad (7)$$

where R_t is the stock return, and σ_t^2 is the conditional variance of stock returns. The standardised error ζ_t follows a Generalised Error Distribution. When the parameter $k = 2$, the distribution is recognised as the probability distribution function for the univariate Standard Normal, that is, $GED\left(0, 1, \frac{1}{2}\right) = N(0, 1)$. When the parameter $k < 2$, the distribution is leptokurtic, and when $k > 2$, it is platykurtic. The parameter γ measures asymmetric effects of positive and negative returns on volatility. The impact is asymmetric if $\gamma \neq 0$. The parameter β measures the persistence of log variances. The closer the estimate of β is to the unity, the greater is the persistence of conditional variance. $\boldsymbol{v_t}$ is the vector of variables with its elements being the selected historical trading volumes in (6), and $\boldsymbol{\delta}$ is the relevant coefficient vector. The modified MDH predicts that the coefficient β would be substantially reduced if informed trading volumes were included in the variance equation.

4 | Data and Basic Statistics

The raw data sets were collected from Bloomberg that comprises daily price levels and total trading volume for three national stock markets, including S&P500 of the United States, FTSE100 of the United Kingdom, and TOPIX of Japan, for the period from the 1st of January 2007 to the 30th of June 2019. The sample in estimation excludes dates when the markets were not opened, and the trading volume were not available. We report the analysis from the full sample. Because there were dramatic changes in international financial environments during the full period, especially the Global Financial Crisis, we also report our analysis by splitting the full sample into two sub-periods, namely the crisis period from the 1st of January 2007 to the 31th of August 2012, and the post-crisis period from the 1th of September 2012 to the 30th of June 2019. The comparison of the sub-sample analyses with the full sample analysis allows for checking the stability of our model and the robustness of our evidence. The number of observations for the full period is 2910, while for the sub-periods they are 1322 and 1588 respectively.

There are many indicators of stock price movement, one of which is trading range being defined as the relative difference between the high and the low of stock prices. Since information flows would drive price movements of stock markets according to the modified MDH, the trading range in a given day would reflect intensity of intraday trading and therefore, is a good measure of the historical risk of stock prices. Specifically, the variable of interest H is the percentage difference of the logarithm of highest price against the logarithm of lowest price in a given day, that is, $H_t = 100\left(\ln P_{max} - \ln P_{min}\right)$. For total trading volume TV_t, the modified MDH suggests noise component is not proportional to information flows, so we remove the constant in the volume. We also remove linear and nonlinear time trends to account for different time-dependent paths of stock market developments. To these aims, we use the regression:

$$\ln TV_t = c_1 + c_2 t + c_3 t^2 + V_t \quad (8)$$

where the residuals V_t are the variable of interest. For properly accounting for time-dependent paths of stock markets, we only regress log total volume on the time trend where the coefficient is significant. Finally, the stock return R_t in the ARMA(1,1)-GARCH(1,1) model is calculated as 100 times the logarithmic first differences of daily closing prices of stock index.

Table 1 presents the basic statistics relating to daily stock trading range H_t and log total volume $\ln TV_t$ of the three markets for the full period and two sub-periods. Generally, the stock trading range and log total volumes are all positively skewed. In addition, the stock trading range is also highly leptokurtic. These features of stock trading range suggest the variable can properly reflect stock price risk that is observed in stock markets. The BG tests suggest the variables of stock trading range and log total volume are both highly autocorrelated, and the ARCH tests suggest stock trading ranges are highly heteroskedastic. These features further imply that stock price movements and total trading volume may be driven by some common factors. In our empirical tests, we apply an EGARCH model to analyse connections of trading volume to stock volatility.

We also performed unit-root tests on the variables of interest as the prerequisite for a stable VAR model. In short, we performed the following Dickey–Fuller tests.

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + e_t \tag{9}$$

where Δ is the difference operator, y_t is the variable of interest, and t is a time trend. Under the null hypothesis $\gamma = 0$, the equation is a random walk model with drift and a linear time trend. The parameter of interest is γ; if $\gamma = 0$, the $\{y_t\}$ sequence contains a unit root. The τ_t test statistic of the Dickey–Fuller has the null $\gamma = 0$, so rejections of the null mean the $\{y_t\}$ sequence is not stochastically non-stationary. The ϕ_3 test statistic of the Dickey–Fuller has the null $\gamma = a_2 = 0$, so rejections of the null mean the $\{y_t\}$ sequence is neither stochastically non-stationary nor deterministically non-stationary. The ϕ_2 test statistic further includes a drift term, so it has the null $a_0 = \gamma = a_2 = 0$, and rejections of the null would confirm that the $\{y_t\}$ sequence has no unit root.[3] In Table 2, the three test statistics of the Augmented Dickey-Fuller test with lag length selected by the Schwarz Information Criterion all suggest the two variables of interest, that is, stock trading range H_t and trading volume V_t, are stationary.

5 | Empirical Results

The estimated VAR includes a constant, and its lag length is selected by the Final Prediction Error. We model the structural shocks from the VAR residuals using the structural restrictions as specified in Section 3.2.

For analysing dynamic effects of structural shocks on the system, we report the impulse responses given the restricted ***B***

TABLE 1 | Basic statistics.

Stock price range		Mean	SD	Skewness	Kurtosis	BG(5)	ARCH(5)
Full	USA	1.2813	1.0786	3.3426	20.8304	878.1689***	412.2127***
	UK	1.4094	0.9825	3.0016	18.3874	649.2402***	252.8793***
	Japan	1.3057	1.0039	4.1664	32.7252	403.1539***	146.7118***
Crisis	USA	1.7160	1.3347	2.8590	14.8491	361.6584***	156.1456***
	UK	1.8162	1.1730	2.5651	13.5535	274.9081***	113.9596***
	Japan	1.4614	1.1621	4.2044	30.7161	244.8135***	81.7598***
Post-crisis	USA	0.9195	0.6010	2.1579	9.9533	224.9945***	124.6070***
	UK	1.0707	0.6094	3.2449	29.0814	130.0385***	13.4626***
	Japan	1.1762	0.8284	3.4772	24.8269	121.8039***	19.7057***
Log total volume		**Mean**	**SD**	**Skewness**	**Kurtosis**	**BG(5)**	
Full	USA	20.4196	0.4133	0.5320	2.5433	1513.668***	
	UK	20.6351	0.3899	0.4303	4.1902	1091.678***	
	Japan	20.9935	0.3377	0.0218	3.8641	1630.658***	
Crisis	USA	20.7330	0.3515	−0.2194	2.9801	527.729***	
	UK	20.8627	0.3967	−0.0610	3.6995	511.769***	
	Japan	21.0489	0.2243	0.2603	4.2276	230.454***	
Post-crisis	USA	20.1586	0.2455	1.3070	8.3514	76.5283***	
	UK	20.4456	0.2619	−0.1971	9.0269	124.556***	
	Japan	20.9475	0.4030	0.2223	3.1264	1287.642***	

Note: SD is standard deviation. For BG(5) and ARCH(5) tests, ** indicates significance at the 5% level, while *** indicates significance at the 1% level.

TABLE 2 | The Dickey–Fuller tests.

Stock price range		Test statistics τ_t	ϕ_3	ϕ_2
Full	USA	−6.9432***	24.1274***	16.0850***
	UK	−8.2063***	33.6890***	22.4595***
	Japan	−7.2362***	26.1867***	17.4587***
Crisis	USA	−4.1534***	8.6998**	5.8001**
	UK	−5.0671***	12.9009***	8.6007***
	Japan	−4.6609***	10.8648***	24.5157***
Post-crisis	USA	−9.9161***	49.1671***	32.7787***
	UK	−10.2213***	52.2392***	34.8276***
	Japan	−7.5249***	28.3252***	18.8836***
Log volume		**Test statistics** τ_t	ϕ_3	ϕ_2
Full	USA	−6.3737***	20.3572***	13.5925***
	UK	−7.5476***	28.5023***	19.0221***
	Japan	−4.6766***	11.0380***	7.4023***
Crisis	USA	−8.9051***	39.6794***	26.4912***
	UK	−9.8094***	48.1122***	32.1071***
	Japan	−7.8536***	30.8580***	20.5727***
Post-crisis	USA	−11.4245***	65.2608***	43.5095***
	UK	−11.3011***	63.8573***	42.5725***
	Japan	−7.5328***	28.4494***	18.9807***

Note: **Significance at the 5% level. ***Significance at the 1% level.

matrix and the VAR estimates. Table 3 reports the parameter estimates of $\boldsymbol{B}$ matrix. Almost all parameter estimates are significant for the full sample model and the two sub-period models, indicating that our model specification has realistically captured the characteristics of data. The reported $\chi^2(3)$ test statistics are a likelihood ratio test of the over-identified model with three degrees of freedom with respect to the exact identification. The tests indicate that some zero restrictions can be relaxed for the crisis model. However, there is no theoretical reason to relax restrictions since the model specification is based on economic implications. For comparisons of the estimated models in different sample periods, we proceed with the over-identified model.

5.1 | Responses of Stock Trading Ranges to Information Shocks

We report 50-step impulse response functions in Figure 1. The graphs in the three columns illustrate the responses of stock trading ranges to information shocks for full period, and two sub-periods respectively. The first column shows that the cross-country shock and the US-specific shock have long-lasting dynamic impacts on trading ranges of all stock markets. The second column further shows that in the crisis period, the US-specific shock and the cross-country shock also have long-lasting dynamic impacts on stock trading ranges. In addition, the stock volatility shocks also have long-lasting but negative impacts on stock trading ranges. In the post-crisis period, dynamic impacts of the cross-country shock on stock trading ranges are still noticeable, though the impacts died out more quickly. The UK-specific shock and JP-specific shock also have dynamic impacts on their own stock markets. This feature suggests that persistence of stock volatility is more likely the consequence of privately informed trading responding to global information shocks.

Interestingly, the first column shows that the US-specific shocks have negative impacts on trading ranges of each stock market. This is consistent with the parameter estimates of $b_{11} = 0.1063$ and $b_{41} = -0.2923$ in Table 3. The graphs and the parameter estimates together suggest the US-specific shocks have opposite effects on trading volumes and stock trading ranges. The second column also shows that the stock volatility shocks have positive impacts on trading volumes but negative impacts on stock trading ranges in the crisis period. The parameter estimates of the crisis period in Table 3 confirm that b_{16}, b_{26}, b_{36} are positive while b_{46}, b_{56}, b_{66} are negative. The feature that information shocks have opposite effects on trading volume and stock

TABLE 3 | The estimates of ***B*** matrix.

Full	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
u_{1t}	0.1063***			0.1045***	0.1388***	0.0095***
	(0.0064)			(0.0051)	(0.0043)	(0.0019)
u_{2t}		0.0891***		−0.0049	0.1974***	0.0172***
		(0.0050)		(0.0044)	(0.0029)	(0.001)
u_{3t}			0.1602***	0.0076**	0.0516***	0.0090***
			(0.0021)	(0.0032)	(0.0021)	(0.0002)
u_{4t}	−0.2923***			0.5697***	0.1804***	0.0780***
	(0.0263)			(0.0170)	(0.0026)	(0.0090)
u_{5t}		0.5276***		0.3327***	0.0191***	0.1414***
		(0.0083)		(0.0136)	(0.0026)	(0.0105)
u_{6t}			0.2409***	0.0595***	0.0815***	0.6784***
			(0.0130)	(0.0143)	(0.0076)	(0.0089)
$\chi^2(3) = 42.31^{***}$						
Crisis	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
u_{1t}	0.0406***			0.1751***	0.0192**	0.0606***
	(0.0094)			(0.0050)	(0.0092)	(0.0032)
u_{2t}		0.1611***		0.1371***	0.0449***	0.0151***
		(0.0037)		(0.0063)	(0.0079)	(0.0022)
u_{3t}			0.0688***	0.0059	0.1409***	0.0171***
			(0.0054)	(0.0073)	(0.0037)	(0.0014)
u_{4t}	0.7290***			0.3536***	0.0523***	−0.2507***
	(0.0154)			(0.0341)	(0.0068)	(0.0260)
u_{5t}		−0.0047		0.4920***	0.0971***	−0.5775***
		(0.0280)		(0.0247)	(0.0032)	(0.0176)
u_{6t}			0.7502***	0.1303***	−0.0704***	−0.1276***
			(0.0150)	(0.0215)	(0.0193)	(0.0240)
$\chi^2(3) = 8.80$						
Post-crisis	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
u_{1t}	0.1655***			0.0508***	0.1167***	0.0138**
	(0.0049)			(0.0143)	(0.0043)	(0.0065)
u_{2t}		0.0345***		0.0230***	0.2068***	0.0155***
		(0.0059)		(0.0058)	(0.0037)	(0.0037)
u_{3t}			0.1584***	0.0164***	0.0338***	0.0392***
			(0.0030)	(0.0045)	(0.0032)	(0.0008)
u_{4t}	0.0257			0.4486***	0.0625***	−0.0747***
	(0.0401)			(0.0102)	(0.0030)	(0.0202)

(Continues)

TABLE 3 | (Continued)

Post-crisis	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
u_{5t}		0.4298***		0.2200***	0.0677***	0.0613***
		(0.0078)		(0.0121)	(0.0043)	(0.0112)
u_{6t}			0.1260***	0.2461***	−0.0348***	0.6216***
			(0.0166)	(0.0361)	(0.0069)	(0.0176)
$\chi^2(3) = 47.65^{***}$						

Note: **Significance at the 5% level. ***Significance at the 1% level. Standard errors in parentheses.

trading ranges suggests more trading volume does not necessarily correspond with higher stock volatility.

5.2 | Historical Volumes and the Persistence of Stock Volatility

To test contributions of trading volumes to stock volatility, we reconstruct historical trading volumes based on the historical decomposition (6), and then add historical volumes into the variance equation of the ARMA(1,1)-EGARCH(1,1). We do this in the following steps. First, we measure the volatility persistence, volatility asymmetry and kurtosis of distribution by the ARMA(1,1)-EGARCH(1,1) model. Second, we test the importance of trading volume on stock volatility by augmenting the model with all six types of historical volume. These six types of trading volumes can be classified as: (1) trading volume based on private information, that is, the historical volumes from US-specific shock, UK-specific shock, JP-specific shock and cross-country shock respectively, and (2) trading volume based on public information, that is, the historical volumes from trading volume shock and stock volatility shock. Third, we build ARMA(1,1)-EGARCH(1,1) augmented with historical volumes that could substantially reduce volatility persistence, by following the rule of parsimony. We then discuss whether and to what degree the historical volumes can explain volatility clustering, volatility asymmetry and fat tail phenomena in stock prices.

The result of the first step is reported in Table 4. There are some noticeable characteristics in the data. First, there is high persistence in stock market volatility, as can be seen from the estimates of β coefficient, which are all close to 1. Second, there is negative volatility asymmetry, that is, negative stock returns cause higher volatility than positive stock returns do, as can be seen from the estimates of γ coefficient, which are all negative and significant at 1% level. Third, the stock returns distribution is fat tailed, as can be seen from the estimates of k coefficient, which are all lower than 2 at 1% significance level. The empirical results suggest the model is powerful in catching the stylised facts of stock prices.

To see connections of stock market volatility with historical volumes, we graph conditional variances estimated from the models in Table 4, and then add into graphs the six types of historical volume. These graphs are shown in Figure 2.[4] The first row shows that the historical volume from US-specific shock shares common structure with conditional variances of all three stock markets in the global financial crisis during 2008 and 2009. The second row shows that the historical volume from UK-specific shock shares common structure with the conditional variances of UK stock market. The third row shows that the historical volume from JP-specific shock shares common structure with the conditional variances of Japan's stock market after 2013. The fourth row, interestingly, shows that the historical volume from the cross-country shocks appears to share common structure with all three stock markets throughout the crisis period and post-crisis period. The fifth row instead shows that there is no common structure between conditional variances of stock returns and the historic volume from trading volume shock. Finally, the six row shows that the Japan historical volume from stock volatility shock and Japan stock market conditional variances follow similar patterns, especially in the post-crisis period. In short, the illustration suggests trading volumes based on private information tend to move together with stock market volatility.

To test contributions of trading volumes to stock market volatility, we augment the ARMA(1,1)-EGARCH(1,1) with all the six types of historical volumes, with the result reported in Table 5. There are some interesting changes with the inclusion of historical volumes. First, high persistence in stock volatility is substantially reduced or disappeared, as can be seen from the estimates of β coefficient, which have changed to be insignificantly different from zero or negative values. Second, negative volatility asymmetry is also substantially decreased or disappeared, as can be seen from the estimates of γ coefficient, which have mostly become insignificant. Although the estimates are still significant for the United Kingdom in full period, for the USA and Japan in the post-crisis period, the magnitude has decreased. Third, there is weak evidence that historical trading volumes contribute to fat tail phenomena in stock return distributions. For example, by comparing to Table 4, the k coefficient for the USA in the full period has been closer to 2, and for the UK and Japan in the post-crisis period has become insignificantly different from 2.

Interestingly, signs of the coefficients of historical volumes are negative in some cases. For example, the historical volume from US-specific shocks has a negative effect on US stock volatility in the full period, and it also has a negative effect on US stock volatility in the post-crisis period. In addition, the historical volume from stock volatility shock has a negative effect on US stock volatility in the crisis period, and the historical volume from trading volume shock also has a negative effect on UK stock volatility in the post-crisis period. This confirms that more trading volume does not necessarily correspond with higher stock volatility.

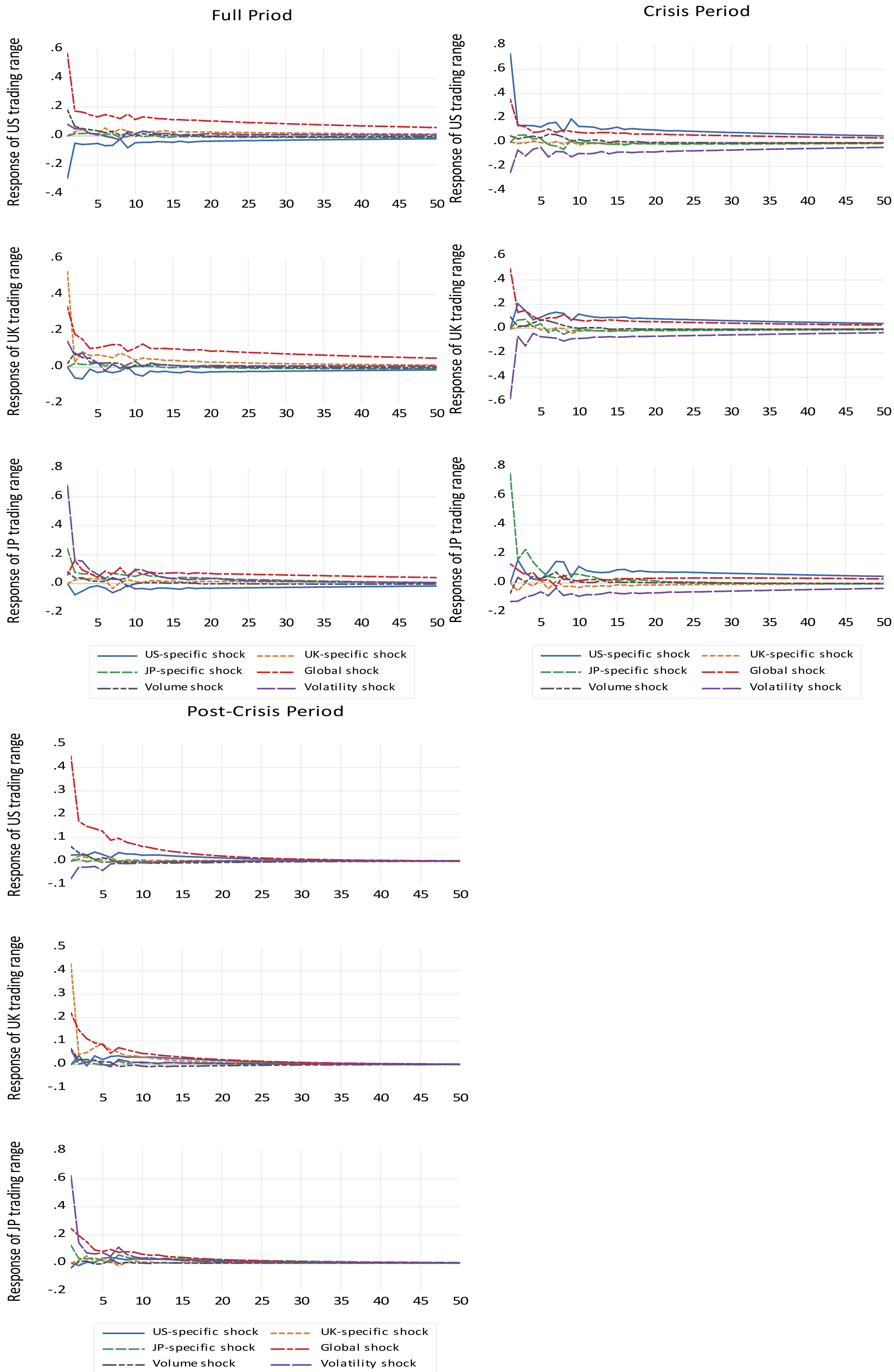

FIGURE 1 | Impulse responses of stock trading ranges to structural shocks. [Colour figure can be viewed at wileyonlinelibrary.com]

Intuitively speaking, traders can have divergent interpretations on the information content of news, resulting in large trading volume but small stock price movement.

The parsimonious models for the factors catching persistence of stock volatility are reported in Table 6. Interestingly, the historical volumes from trading volume shock and from stock

TABLE 4 | The variance equation of the ARMA(1,1)-EGARCH(1,1) models.

Full	ω	α	γ	β	k	Log likelihood
USA	−0.1394***	0.1740***	−0.1811***	0.9737***	1.2359***	−3737.574
	(0.0163)	(0.0216)	(0.0163)	(0.0041)	(0.0427)	
UK	−0.1115***	0.1409***	−0.1261***	0.9809***	1.4611***	−3887.202
	(0.0143)	(0.0184)	(0.0109)	(0.0036)	(0.0484)	
Japan	−0.1373***	0.2083***	−0.1224***	0.9593***	1.4050***	−4738.776
	(0.0170)	(0.0228)	(0.0120)	(0.0065)	(0.0441)	
Crisis	ω	α	γ	β	k	**Log likelihood**
USA	−0.1030***	0.1406***	−0.1412***	0.9753***	1.2981***	−2084.818
	(0.0236)	(0.0324)	(0.0228)	(0.0055)	(0.0748)	
UK	−0.0851***	0.1244***	−0.1460***	0.9747***	1.6444***	−2083.401
	(0.0240)	(0.0300)	(0.0181)	(0.0051)	(0.0889)	
Japan	−0.1215***	0.1852***	−0.1363***	0.9666***	1.7188***	−2284.213
	(0.0254)	(0.0315)	(0.0167)	(0.0072)	(0.0935)	
Post-crisis	ω	α	γ	β	k	**Log likelihood**
USA	−0.1860***	0.1807***	−0.2510***	0.9305***	1.2864***	−1613.671
	(0.0299)	(0.0354)	(0.0243)	(0.0106)	(0.0529)	
UK	−0.1846***	0.1887***	−0.1601***	0.9242***	1.4002***	−1762.665
	(0.0305)	(0.0365)	(0.0200)	(0.0120)	(0.0624)	
Japan	−0.1694***	0.2577***	−0.1326***	0.9374***	1.2528***	−2429.024
	(0.0259)	(0.0359)	(0.0220)	(0.0129)	(0.0536)	

Note: **Significance at the 5% level. ***Significance at the 1% level. Standard errors in parentheses. The parameter k has the null $k = 2$.

volatility shock are not required for catching persistence of stock market volatility. The result shows that the historical volume from cross-country shocks alone can explain persistence of stock volatility in 3 of 9 cases, namely the USA in the full period, and the USA and Japan in the post-crisis period. The historical volume from country-specific shocks alone can explain in 4 of 9 cases, namely the United Kingdom in the full period, the USA and Japan in the crisis period, and the United Kingdom in the post-crisis period. The remaining two cases are the Japan in the full period and the United Kingdom in the crisis period, where persistence of stock volatility can be captured by combinations of historical volumes from country-specific and cross-country shocks. The result suggests privately informed trading can explain volatility clustering of stock markets. The models also suggest privately informed trading can explain only some part of volatility asymmetry, and is unable to explain fat tail phenomena in stock return distributions. In short, since historical volumes are constructed from structural shocks that catch surprising information, our study displays the importance of surprising information, especially private information shocks, in explaining volatility clustering of financial markets.

Overall, the results are consistent with the study on MDH by Park (2010) in the following aspects. First, surprising information should be distinguished from general information when testing volume–volatility relationship. Second, surprising information can have opposite effects on trading volume and stock volatility, suggesting that sign effects of surprising information also influence volume–volatility relationship. More interestingly, the tests conform to the modified MDH in the following aspects. First, privately informed trading volumes can explain volatility clustering of stock markets. Second, privately informed trading volumes cannot explain fat tail phenomena in stock return distributions, and the phenomena are more likely due to public information trading volume.

6 | The Sources of Information Shocks

So far, the analysis confirms the importance of arrivals of information flows, especially private information shocks, in volume–volatility relationship. In particular, the volume-augmented EGARCH models show that the clustering of stock markets can be explained by privately informed trading. Since historical volumes are driven by information flows, it is natural to enquire what are the sources of surprising information that drive information flows and hence, stock market volatility. For such an enquiry, we test whether the information shocks as measured in (4) reflect financial systemic risk from different sources.

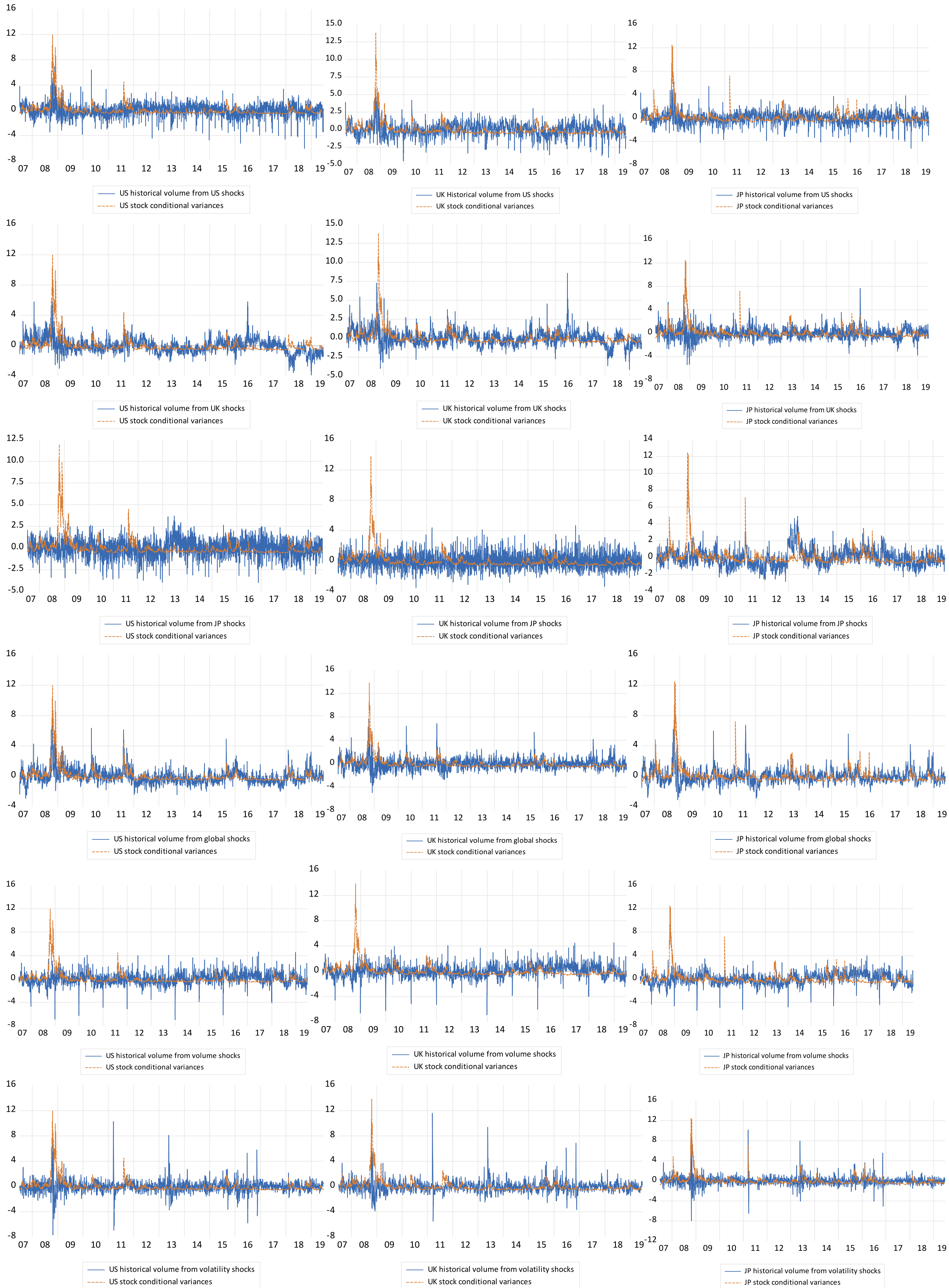

FIGURE 2 | Historical trading volumes and conditional variances of stock returns. [Colour figure can be viewed at wileyonlinelibrary.com]

We use daily data of the Financial Stress Index (OFR FSI) published by the Office of Financial Research that includes five categories of indicator: credit, funding, safe assets, equity valuation and volatility.[5] As explained in their website, the OFR FSI is constructed from 33 financial market variables, such as interest rates, valuation measures and yield spreads. The index is essentially a

TABLE 5 | The variance equation of the ARMA(1,1)-EGARCH(1,1) augmented with historical trading volumes.

Full	ω	α	γ	β	δ_a	δ_b	δ_j	δ_w	δ_v	δ_h	k	**Log likelihood**
USA	−0.6615***	0.2545***	−0.0241	−0.0362	−3.5807***	8.0112***	0.1989	8.5237***	1.1336***	0.1237	1.7001***	−3397.809
	(0.0445)	(0.0371)	(0.0217)	(0.0232)	(0.2273)	(1.4028)	(0.7024)	(0.2801)	(0.1974)	(1.1797)	(0.0496)	
UK	−0.2563***	0.3776***	−0.0546***	−0.1717***	0.1569	6.1145***	−1.1553	0.9812	0.4608***	4.3891***	1.2317***	−3901.896
	(0.0546)	(0.0342)	(0.0198)	(0.0345)	(0.7639)	(0.2730)	(0.9859)	(0.7680)	(0.0637)	(0.8057)	(0.0363)	
Japan	0.5841***	0.2384***	−0.0130	−0.1582***	5.2158***	1.7437	2.2729***	8.8308***	1.6019***	17.3628***	1.4374***	−4719.613
	(0.0633)	(0.0401)	(0.0220)	(0.0432)	(1.0934)	(1.6398)	(0.1640)	(0.8290)	(0.4381)	(1.1430)	(0.0523)	
Crisis	ω	α	γ	β	δ_a	δ_b	δ_j	δ_w	δ_v	δ_h	k	**Log likelihood**
USA	0.3335***	0.3267***	−0.0061	−0.2901***	12.6140***	1.2787	1.6324	3.0890***	1.1790	−5.9419***	1.2936***	−2042.811
	(0.0949)	(0.0496)	(0.0371)	(0.0437)	(0.7450)	(2.7513)	(1.1638)	(0.2733)	(0.8930)	(0.7332)	(0.0635)	
UK	0.2943***	0.2511***	−0.0056	−0.1084**	7.1633***	−0.3525	0.0497	4.0768***	1.8564***	−10.0653***	1.4764***	−2063.323
	(0.0931)	(0.0701)	(0.0342)	(0.0498)	(0.7083)	(0.2599)	(0.6963)	(0.2520)	(0.6917)	(1.1938)	(0.0823)	
Japan	0.7409***	0.2236***	−0.0123	−0.1827***	11.8719***	4.4221**	6.2923***	5.4117***	0.7221**	1.8722	1.7424**	−2269.187
	(0.0889)	(0.0606)	(0.0358)	(0.0528)	(1.2040)	(2.0970)	(0.4543)	(1.1191)	(0.2814)	(1.3632)	(0.1059)	
Post-crisis	ω	α	γ	β	δ_a	δ_b	δ_j	δ_w	δ_v	δ_h	k	**Log likelihood**
USA	−1.4671***	0.1805***	−0.1142***	−0.3469***	0.4106	1.1440	−0.6684	13.1483***	0.5485***	−3.3683	1.7731***	−1417.608
	(0.0901)	(0.0650)	(0.0338)	(0.0538)	(0.2699)	(1.6474)	(0.7618)	(0.7603)	(0.1888)	(2.5301)	(0.0744)	
UK	−1.2136***	0.1352**	−0.0297	−0.4763***	−7.0986***	13.9622***	−1.1889	13.2347***	−0.2842***	0.7206	1.8442	−1580.689
	(0.0755)	(0.0572)	(0.0373)	(0.0378)	(0.9343)	(0.9403)	(1.1952)	(1.2549)	(0.0995)	(1.6264)	(0.0855)	
Japan	−0.0949	0.0834	−0.1040***	−0.1468***	1.6639	0.6155	2.5564***	11.2455***	0.5382	12.9856***	1.8910	−2281.788
	(0.0631)	(0.0589)	(0.0371)	(0.0452)	(1.3234)	(2.4744)	(0.2257)	(1.0128)	(0.7163)	(0.9985)	(0.1023)	

Note: **Significance at the 5% level. ***Significance at the 1% level. Standard errors in parentheses. The parameter k has the null $k = 2$.

TABLE 6 | The parsimonious augmented ARMA(1,1)-EGARCH(1,1) for explaining volatility persistence.

Full	ω	α	γ	β	δ_a	δ_b	δ_j	δ_w	δ_v	δ_h	k	**Log likelihood**
USA	−0.5273***	0.2116***	−0.01672	−0.0686***				8.1188***			1.5522***	−3518.805
	(0.0479)	(0.0436)	(0.0273)	(0.0251)				(0.2624)			(0.0464)	
UK	−0.2732***	0.4175***	−0.0827***	−0.1120***		5.8513***					1.2190***	−4073.544
	(0.0496)	(0.0339)	(0.0202)	(0.0240)		(0.2429)					(0.0331)	
Japan	0.4630***	0.2582***	−0.0792**	0.0092			2.0625***	8.7139***			1.3279***	−4787.848
	(0.0613)	(0.0472)	(0.0308)	(0.0545)			(0.1599)	(0.7200)			(0.0467)	
Crisis	ω	α	γ	β	δ_a	δ_b	δ_j	δ_w	δ_v	δ_h	k	**Log likelihood**
USA	0.9859***	0.1113**	−0.0273	−0.5946***	13.2758***						1.0760***	−2142.313
	(0.1214)	(0.0453)	(0.0337)	(0.0409)	(0.9500)						(0.0559)	
UK	0.3694***	0.2397***	0.0038	−0.1228	5.9560***			3.7344***			1.4073***	−2096.188
	(0.0923)	(0.0675)	(0.0400)	(0.0632)	(0.6085)			(0.1703)			(0.0753)	
Japan	0.9742***	0.1749***	−0.0570	−0.2443***			6.2154***				1.4140***	−2336.313
	(0.0951)	(0.0624)	(0.0388)	(0.0616)			(0.4720)				(0.0751)	
Post-crisis	ω	α	γ	β	δ_a	δ_b	δ_j	δ_w	δ_v	δ_h	k	**Log likelihood**
USA	−1.4700***	0.1817***	−0.1206***	−0.3540***				13.3426***			1.7874***	−1423.357
	(0.0822)	(0.0618)	(0.0322)	(0.0456)				(0.7187)			(0.0693)	
UK	−1.0465***	0.2428***	−0.0464	−0.4753***		13.7906***					1.4607***	−1700.133
	(0.0696)	(0.0432)	(0.0258)	(0.0400)		(0.8864)					(0.0571)	
Japan	0.5228***	0.0450	0.0129	−0.6879***				16.5751***			1.3097***	−2429.601
	(0.0920)	(0.0394)	(0.0282)	(0.0927)				(1.4672)			(0.0695)	

Note: **Significance at the 5% level. ***Significance at the 1% level. Standard errors in parentheses. The parameter k has the null $k = 2$.

daily market-based snapshots of stress in global financial markets. Positive numbers in the index means stress levels are above leverage, while negative numbers mean they are below average.

All five financial stress indicators contain a unit root but are stationary in first differences. As such, we take differences of the five indicators, so a positive number in indicator variables means an increase of financial stress, while a negative number means a decrease of financial stress. Specifically, the five indicator variables, including ΔCR, ΔFU, ΔSA, ΔEQ and ΔVO, represent changes of financial stress in the categories: credit, funding, safe assets, equity valuation and volatility respectively. Since by construction historical volumes are trading activities responding to information flows, we conjecture that financial stress is an important source of surprising information that drives information flows. In other words, movements of these indicator variables should have impacts on information shocks that catch the arrivals of information flows. To verify this conjecture, we perform a Granger causality test between the indicator variables and information shocks. Empirically, changes of financial stress index should have more dynamic impacts on information shocks than the other way around.

The results of Granger causality tests from indicator variables to information shocks are reported in Table 7. As can be seen, most F-statistics are significant in the full period. Most of the F-statistics are also significant in the crisis period, although the UK-specific shock is not Granger-caused by financial stress. In the post-crisis period, most F-statistics are still significant for the Granger causality from indicator variables to private information shocks, but interestingly the F-statistics also suggest indicator variables do not Granger-cause public information flows. In short, there is strong evidence that financial stress Granger-causes private information flows, while the impacts of financial stress on public information flows may be unimportant or short-lived. The results of Granger causality tests from information shocks to indicator variables are reported in Table 8. Apparently, there is much weaker evidence that information shocks Granger-cause financial stress. The exception is that stock volatility shock Granger-causes indicator variables in the full period, mostly resulted from the significance in the post-crisis period. This characteristic in the empirical result suggests common volatility in stock markets could generate stress to the global financial system. In other words, there is a strong feedback effect between the global financial system and stock market volatility. Overall, the results imply that financial stress is an important source of surprising information that gives rise to trading activities in stock markets.

To test which category of financial stress indicators is the main source of surprising information, we measure instantaneous

TABLE 7 | The Granger causality tests of information shocks on the financial stress variables.

Full	**ΔCR**	**ΔFU**	**ΔSA**	**ΔEQ**	**ΔVO**
ε_{at}	11.3778***	1.1263	3.7856**	21.0513***	13.0676***
ε_{bt}	15.8331***	31.6447***	7.4917***	7.5091***	7.0642***
ε_{jt}	2.2235	1.7783	5.1427***	1.2012	0.7237
ε_{wt}	41.7811***	18.6699***	18.0574***	69.2992***	44.0792***
ε_{vt}	1.2141	7.0272***	0.9773	4.9435***	4.8948***
ε_{ht}	26.0292***	13.0065***	9.4919***	50.6300***	25.6314***
Crisis	**ΔCR**	**ΔFU**	**ΔSA**	**ΔEQ**	**ΔVO**
ε_{at}	9.3924***	7.2920***	11.2381***	26.8107***	19.9589***
ε_{bt}	0.9233	0.7366	0.0149	1.1205	1.4950
ε_{jt}	11.2510***	9.3741***	3.6626***	28.4419***	19.3381***
ε_{wt}	16.4194***	10.8511***	10.0872***	10.8300***	10.0761***
ε_{vt}	3.7188**	2.3995	1.5065	2.3216	0.5724
ε_{ht}	17.4658***	25.7971***	3.5387**	13.8180***	5.6897***
Post-crisis	**ΔCR**	**ΔFU**	**ΔSA**	**ΔEQ**	**ΔVO**
ε_{at}	4.1184**	5.9352***	0.5994	7.3790***	5.0795***
ε_{bt}	3.0448**	0.8207	0.6421	3.1052**	2.8238
ε_{jt}	0.4861	0.2291	9.4355***	4.0797**	1.5451
ε_{wt}	23.3834***	1.1375	5.0927***	54.0094***	30.2177***
ε_{vt}	1.9990	0.0323	1.5871	0.9898	0.8939
ε_{ht}	1.2436	1.7391	0.6682	0.8909	1.1091

Note: The variables in the first column are dependent variables, while the variables in the rows are independent variables. The coefficients are F-statistics based on the Granger causality tests with 2 lags. **Significance at the 5% level. ***Significance at the 1% level.

TABLE 8 | The Granger causality tests of financial stress variables on information shocks.

Full	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
ΔCR	5.2409***	8.3585***	1.3057	4.8985***	0.5283	10.4424***
ΔFU	0.0758	5.0738***	0.0776	0.9980	1.4812	7.0435***
ΔSA	0.3571	1.8087	0.2425	2.4736	0.5835	1.3681
ΔEQ	0.1822	0.6852	0.1187	1.1892	0.0912	4.4415**
ΔVO	2.2431	5.3212***	1.3208	8.2648***	0.8498	11.1317***
Crisis	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
ΔCR	9.8886***	0.25767	2.5700	3.7062**	3.9972**	3.1363**
ΔFU	2.31979	1.76623	2.2720	0.6446	2.1388	0.5601
ΔSA	1.48661	0.26548	1.4989	1.3894	1.2639	2.0306
ΔEQ	0.67874	1.11112	0.5802	0.1999	3.2531**	1.4543
ΔVO	7.59911***	1.22895	2.3519	0.9558	5.5468***	0.9280
Post-crisis	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
ΔCR	0.1825	1.7124	0.2605	1.3464	0.7493	3.3452**
ΔFU	0.7713	1.0628	2.4335	1.4907	2.0324	4.4596**
ΔSA	0.4964	1.1433	1.3930	0.2251	0.4274	4.7316***
ΔEQ	0.5979	1.4784	1.3504	4.0344**	3.0359**	7.4033***
ΔVO	1.5723	2.5430	0.1405	3.6311**	1.4000	8.1585***

Note: The variables in the first column are dependent variables, while the variables in the rows are independent variables. The coefficients are F-statistics based on the Granger causality tests with 2 lags. **Significance at the 5% level. ***Significance at the 1% level.

influences of indicator variables on the arrivals of information flows. For such a purpose, information shocks are regressed on the contemporaneous and lagged values of indicator variables to account for both instantaneous dynamic effects. The estimated models have the form:

$$\begin{aligned}\varepsilon_{k,t}=c+\sum_{q=1}^{Q}\vartheta_q\varepsilon_{k,t-q}+\sum_{q=0}^{Q1}\theta_{1q}\Delta CR_{t-q}+\sum_{q=0}^{Q2}\theta_{2q}\Delta FU_{t-q}\\+\sum_{q=0}^{Q3}\theta_{3q}\Delta SA_{t-q}+\sum_{q=0}^{Q4}\theta_{4q}\Delta EQ_{t-q}+\sum_{q=0}^{Q5}\theta_{5q}\Delta VO_{t-q}+\epsilon_t\end{aligned} \tag{10}$$

where the dependent variables are the information shocks $\varepsilon_{k,t}$ for $k=a,b,j,w,v,or\ h$ that represents the six information shocks, namely US-specific shock, UK-specific shock, Japan-specific shock, cross-country shock, trading volume shock and stock volatility shock. The independent variables are the five indicator variables, the ϑ_q and θ_{kq} are coefficients and ϵ_t is a white-noise error term. The lag lengths Q's of each model are determined by the AIC.

The point estimates of instantaneous influences are reported in Table 9. Regarding private information flows, the financial stress indicators of funding and volatility are significant for both US-specific shock and UK-specific shock, while the indicators of safe assets and volatility are significant for Japan-specific shock. In particular, the cross-country shock is instantaneously influenced by the financial stress of credit, funding and volatility. Regarding public information flows, the financial stress indicators of funding and volatility are significant for stock volatility shock, but trading volume shock is not instantaneously influenced by any financial stress indicators. Further inspections suggest during the crisis period, financial stress indicators tend to have more instantaneous influences on information shocks. For example, in the crisis the indicators of credit, funding and volatility have immediate impacts on US-specific shock, but in the post-crisis only the indicator of funding has impacts. In short, financial stress in the global finical system is an important source of surprising information to stock markets.

Overall, there are two interesting results. First, the indicator of volatility is the most important source of surprising information. The high significance of the indictor of volatility implies that uncertainty about fundamental values of assets is the main driver of stock market volatility. Economically, when investors are uncertain about the present value of future cash flows, market prices of the asset would exhibit greater volatility. If, in addition, investors also face uncertain economic conditions, they would even be less sure of the fundamental values of assets. A financial innovation could also render investors unable to properly assigning probabilities to different outcomes due to the lack of experience. Hautsch and Hess (2007) argue that investors would react more strongly to news when facing increased uncertainty about fundamental values of assets, leading to greater volatility in asset prices. The high significance of the indicator of volatility

TABLE 9 | The Autoregressive Distributed Lag Models of information shocks.

Full	ΔCR	ΔFU	ΔSA	ΔEQ	ΔVO
ε_{at}	−0.7898	−0.5020**	1.4292	0.0586	−0.4383**
	(0.5501)	(0.2427)	(0.7323)	(0.5106)	(0.1874)
ε_{bt}	0.1635	−1.1890***	0.2943	−0.9712	1.4141***
	(0.5237)	(0.2398)	(0.7148)	(0.5012)	(0.1841)
ε_{jt}	0.0642	0.0040	−1.4726**	−0.7974	0.5826***
	(0.5274)	(0.2417)	(0.7368)	(0.5143)	(0.1886)
ε_{wt}	1.2228**	−0.4663**	1.1791	−0.4394	2.1870***
	(0.4884)	(0.2194)	(0.6685)	(0.4663)	(0.1714)
ε_{vt}	0.2096	0.1612	−0.7757	0.7770	0.0670
	(0.5558)	(0.2454)	(0.7397)	(0.5159)	(0.1889)
ε_{ht}	−0.9329	−0.5604**	0.0238	−0.8604	1.6532***
	(0.5197)	(0.2343)	(0.7148)	(0.4972)	(0.1830)
Crisis	ΔCR	ΔFU	ΔSA	ΔEQ	ΔVO
ε_{at}	1.4256**	0.5570**	0.7368	−0.4227	0.8158***
	(0.5656)	(0.2398)	(0.8584)	(0.6090)	(0.2178)
ε_{bt}	−0.4900	0.2588	−1.8300**	0.8083	−0.3482
	(0.5662)	(0.2461)	(0.8812)	(0.6308)	(0.2265)
ε_{jt}	−0.5595	0.0045	−1.2624	−1.6973***	1.5045***
	(0.5607)	(0.2414)	(0.8743)	(0.6179)	(0.2204)
ε_{wt}	0.1971	−0.7023***	0.6687	−0.8768	1.6344***
	(0.5382)	(0.2334)	(0.8396)	(0.6015)	(0.2153)
ε_{vt}	0.9181	0.1223	−1.5403	−0.6250	0.0754
	(0.5603)	(0.2484)	(0.9047)	(0.6416)	(0.2284)
ε_{ht}	0.2823	−0.7548	0.1872	−1.3792**	1.7374***
	(0.5398)	(0.2340)	(0.8508)	(0.6030)	(0.2148)
Post-crisis	ΔCR	ΔFU	ΔSA	ΔEQ	ΔVO
ε_{at}	−0.4154	3.5610**	0.7085	0.8719	0.0298
	(1.6869)	(1.3961)	(1.3998)	(0.8621)	(0.3351)
ε_{bt}	2.1319	−0.2465	0.5641	−0.6710	1.4583***
	(1.6935)	(1.3827)	(1.3937)	(0.8614)	(0.3319)
ε_{jt}	−1.5246	2.1489	−1.2143	−0.2024	0.8529**
	(1.6830)	(1.3853)	(1.3987)	(0.8596)	(0.3335)
ε_{wt}	0.6496	−0.1181	1.4944	1.4929**	2.9830***
	(1.4831)	(1.2328)	(1.2419)	(0.7582)	(0.2958)
ε_{vt}	1.2825	−1.8138	−0.8826	0.7895	0.3761
	(1.6955)	(1.4028)	(1.4071)	(0.8667)	(0.3358)
ε_{ht}	−0.3322	0.9447	−0.9733	1.2323	0.0852
	(1.6513)	(1.4073)	(1.3915)	(0.8619)	(0.3357)

Note: The variables in the first column are dependent variables, while the variables in the rows are independent variables. **Significance at the 5% level. ***Significance at the 1% level. Standard errors in parentheses.

TABLE 10 | The estimates of $\boldsymbol{B}$ matrix with alternative measures of trading volume and stock price movement.

New trading volume	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
u_{1t}	0.0410***			0.1795***	0.0029	−0.0871***
	(0.0081)			(0.0042)	(0.0082)	(0.0024)
u_{2t}		0.1655***		0.1364***	−0.0128**	−0.0326***
		(0.0026)		(0.0045)	(0.0060)	(0.0009)
u_{3t}			0.1216***	0.0409***	−0.1023***	−0.0072***
			(0.0026)	(0.0044)	(0.0025)	(0.0003)
u_{4t}	0.5898***			0.2587***	−0.0549***	0.1998***
	(0.0079)			(0.0195)	(0.0056)	(0.0174)
u_{5t}		0.0248		0.4342***	0.0228***	0.4626***
		(0.0209)		(0.0140)	(0.0022)	(0.0100)
u_{6t}			0.6279***	0.1339***	0.3287***	0.1140***
			(0.0103)	(0.0169)	(0.0057)	(0.0213)
$\chi^2(3) = 105.75^{***}$						
New stock price movement	ε_{at}	ε_{bt}	ε_{jt}	ε_{wt}	ε_{vt}	ε_{ht}
u_{1t}	0.1525***			0.1176***	0.0505***	−0.0584***
	(0.0023)			(0.0037)	(0.0046)	(0.0010)
u_{2t}		0.0571***		0.2001***	0.0651***	−0.0222***
		(0.0054)		(0.0036)	(0.0063)	(0.0004)
u_{3t}			0.1089***	0.0073	0.1253***	−0.0026***
			(0.0028)	(0.0046)	(0.0018)	(0.0001)
u_{4t}	0.3729***			0.1618***	0.1672***	0.6131***
	(0.0139)			(0.0146)	(0.0031)	(0.0084)
u_{5t}		−0.5882***		0.3841***	0.0352***	0.1955***
		(0.0135)		(0.0198)	(0.0039)	(0.0141)
u_{6t}			0.6589***	0.2035***	−0.2826***	0.0552***
			(0.0108)	(0.0155)	(0.0083)	(0.0161)
$\chi^2(3) = 94.79^{***}$						

Note: **Significance at the 5% level. ***Significance at the 1% level. Standard errors in parentheses.

may also imply that uncertainty about behaviours of other investors is the driver of stock market volatility. If an investor needs to sell an asset, the expected return can depend on the actions of other investors rather than on the fundamental value. Like the beauty contest illustrated by Keynes, where the prize is rewarded for picking the face that most people picked, the investor in this situation would anticipate 'what average opinion expects average opinion to be'. The behaviour would be more prevalent when investors become more uncertain about the fundamental values of assets.[6]

Second, compared with private information flows, public information flows tend to reflect very few financial stresses. This is particularly obvious for trading volume shock that does not reflect any financial stress indicator. This is as expected because trading volume shock is the response to periodic economic events; however, the result implies the importance of distinguishing different information flows. In sum, our study points towards a feedback mechanism of information flows and trading activities that heightens the systemic risk between stock markets and the global financial system.

7 | Robustness Checks

As discussed in Section 4, the trading volumes used for analysis were detrended by regressing the total volume on a deterministic function of time. In addition, the indicator of stock price movements was the trading range between the high and the low of stock prices. In this section, we use different measures of

TABLE 11 | The parsimonious augmented ARMA(1,1)-EGARCH(1,1) with alternative measures of trading volume and stock price movement.

New trading volume	ω	α	γ	β	δ_a	δ_b	δ_j	δ_w	δ_v	δ_h	k	Log likelihood
USA	−0.4232***	0.3027***	−0.0103	−0.1358***	11.0589***	3.6734***	4.7270***	3.0709***			1.2936***	−3787.359
	(0.0485)	(0.0373)	(0.0261)	(0.0346)	(0.5193)	(1.2762)	(1.0059)	(0.1218)			(0.0395)	
UK	−0.3278***	0.3761***	−0.0334	0.1452***	4.6391***	−0.3718***		4.0635***			1.3447***	−3982.726
	(0.0484)	(0.0472)	(0.0298)	(0.0365)	(0.4229)	(0.0828)		(0.1492)			(0.0400)	
Japan	0.4464***	0.2097***	−0.0067	−0.2127	7.8399***	4.5463***	3.5021***	4.9060***			1.5379***	−4821.227
	(0.0521)	(0.0379)	(0.0281)	(0.0428)	(0.7150)	(1.0403)	(0.1819)	(0.4598)			(0.0590)	
New stock price movement	ω	α	γ	β	δ_a	δ_b	δ_j	δ_w	δ_v	δ_h	k	**Log likelihood**
USA	−0.3823***	0.3054***	−0.0341	0.0572*	4.1559***	11.6959***	3.1211***	3.0083***			1.2781***	−3794.630
	(0.0478)	(0.0413)	(0.0293)	(0.0324)	(0.1537)	(1.1451)	(1.1127)	(0.1602)			(0.0378)	
UK	−0.6448***	0.2716***	−0.1660***	−0.2668***	−6.2183***	−13.6340***		3.0197***			1.5105***	−3593.631
	(0.0488)	(0.0172)	(0.0084)	(0.0142)	(0.8519)	(0.3831)		(0.0857)			(0.0345)	
Japan	0.5640***	0.1432***	−0.0712***	−0.4024***		10.6338***	4.4290***	4.6901***			1.6072***	−4799.643
	(0.0544)	(0.0357)	(0.0204)	(0.0397)		(2.0373)	(0.1771)	(0.6749)			(0.0659)	

Note: **Significance at the 5% level. ***Significance at the 1% level. Standard errors in parentheses. The parameter k has the null $k = 2$.

trading volume and stock price movement in the empirical tests to check the robustness of our results.

We first use the method of Hodrick & Prescott filtering to measure the detrended trading volumes. The newly acquired detrended trading volume is then paired for analysis with the original stock trading range that is the difference between the high and low of stock prices. The upper part of Table 10 reports the parameter estimates of $\boldsymbol{B}$ matrix for the full sample model. Almost all parameter estimates are significant, and the reported $\chi^2(3)$ test statistics also point to the rejection of the exact identification model. In the second robustness check, we measure an alternative indicator of stock price movements by calculating the price range between closing price and opening price. The new indicator of price range is then paired with the original trading volume that was obtained from regressions. The lower part of Table 10 reports the parameter estimates of $\boldsymbol{B}$ matrix for the full sample model. Almost all parameter estimates are significant, and the reported $\chi^2(3)$ test statistics also indicate the rejection of the exact identification model. The result suggests our model specification is robust to different measures of market variables, and the model can empirically capture the characteristics of the data.

Following the process in Section 5.2, we use the newly acquired historical trading volumes, based on the different measures of trading volume and stock price movement, to test the contributions of trading volumes to stock volatility by the ARMA(1,1)-EGARCH(1,1). The parsimonious models of ARMA(1,1)-EGARCH(1,1) augmented with historical volumes are reported in Table 11. Both robustness checks suggest the historical volumes from trading volume shock and stock volatility shock are not required for catching persistence of stock market volatility. They also suggest privately informed trading can explain volatility clustering of stock markets, even though for the case of the United Kingdom with the alternative measure

TABLE 12 | The ADL models of information shocks with alternative measures of trading volume and stock price movement.

New trading volume	**Δ *CR***	**Δ *FU***	**Δ *SA***	**Δ *EQ***	**Δ *VO***
ε_{at}	1.4421***	0.4993**	−0.1576	0.1807	1.1838***
	(0.5283)	(0.2305)	(0.6950)	(0.4856)	(0.1783)
ε_{bt}	−0.5531	0.1391	−1.6832**	0.4373	−0.0654
	(0.5319)	(0.2460)	(0.7329)	(0.5138)	(0.1889)
ε_{jt}	0.0642	−0.0349	−1.4920**	−0.8281	1.1429***
	(0.5274)	(0.2401)	(0.7315)	(0.5100)	(0.1873)
ε_{wt}	0.6095	−1.0408***	0.9668	−0.3612	1.7404***
	(0.5050)	(0.2320)	(0.7072)	(0.4933)	(0.1805)
ε_{vt}	−0.8439	−0.3783	1.2244*	0.0513	0.6470***
	(0.5434)	(0.2418)	(0.7300)	(0.5088)	(0.1866)
ε_{ht}	0.3214	−0.8820***	0.2721	−1.3065***	1.9416***
	(0.5249)	(0.2336)	(0.7046)	(0.4913)	(0.1802)
New stock price movement	**Δ *CR***	**Δ *FU***	**Δ *SA***	**Δ *EQ***	**Δ *VO***
ε_{at}	−0.2736	0.2020	2.1279***	0.2688	0.7619***
	(0.5454)	(0.2421)	(0.7298)	(0.5094)	(0.1863)
ε_{bt}	−0.8498	1.5045***	−0.1265	2.0077***	−1.6475***
	(0.5417)	(0.2393)	(0.7177)	(0.5006)	(0.1834)
ε_{jt}	−1.3056**	−0.6710***	−0.6215	−1.6553***	1.8901***
	(0.5459)	(0.2408)	(0.7248)	(0.5056)	(0.1855)
ε_{wt}	−0.3895	−1.1142***	0.2007	−0.5095	1.6054***
	(0.5365)	(0.2316)	(0.7130)	(0.4965)	(0.1826)
ε_{vt}	0.8388	0.7144***	−1.6087**	0.7608	−0.6077***
	(0.5259)	(0.2412)	(0.7349)	(0.5122)	(0.1881)
ε_{ht}	−0.7955	0.6222***	0.8943	−0.7990	0.8896***
	(0.5492)	(0.2405)	(0.7241)	(0.5057)	(0.1856)

Note: The variables in the first column are dependent variables, while the variables in the rows are independent variables. **Significance at the 5% level. ***Significance at the 1% level. Standard errors in parentheses.

of trading volume, the volatility clustering of stock market has not totally vanished. The models also suggest privately informed trading can explain a good part of volatility asymmetry, especially for the cases with the alternative measure of trading volume. However, they are unable to explain fat tail phenomena in stock return distributions. The robustness checks confirm the connections of stock return volatility and privately informed trading, being consistent with the modified MDH.

Finally in Table 12, we report the tests of the main sources of surprising information by employing the ADL model as in (10). The point estimates of instantaneous influences, interestingly, suggest both private information flows and public information flows reflect global financial stress when the alternative measures of trading volume and price range are considered. Both robustness checks suggest the financial stress indicator of volatility is the most important source of surprising information, followed by the indicator of funding. Economically, the evidence implies that financial stress in stock markets is mainly caused by uncertainties about fundamental values of assets and about behaviours of other investors. Overall, the checks suggested our empirical results are robust to different measures of trading volume and stock price movement, despite whether the proxies can represent the intensity of information flows and the indicator of stock price movements is still empirically debatable.

8 | Concluding Remarks

How to explain stock market volatility? A popular theoretical explanation is MDH with the proxy of information arrivals being trading volume. However, inconclusive evidence regarding how trading volume can explain persistence of stock market volatility has led to a debate about relationships between information arrival processes and trading volumes.

Based on temporal and cross-sectional properties of the comovements of stock prices and trading volumes, we developed a two-variable three-country SVAR model to measure different forms of information arrival process, including country-specific shock, cross-country shock, trading volume shock and stock volatility shock, whereby the former two are resulted from private information surprises and the latter two resulted from public information surprises. We then reconstructed historical trading volumes based on these information arrival processes, and test whether these historical trading volumes could explain volatility clustering of stock markets. The empirical results indicated that the privately informed trading volumes could account for the volatility clustering in stock markets, but they were unable to explain the fat tail phenomena in stock return distributions. We also found that surprising information could have opposite effects on trading volume and stock volatility.

Since historical volumes are trading activities responding to information flows, we then tested what information sources were driving these information arrival processes and hence, the historical trading volumes. By analysing data from the Financial Stress Index (OFR FSI), we found that financial stress in the global finical system was an important source of surprising information to stock markets. In particular, the financial stress indicator of volatility was the most important source of surprising information. The test further suggested private information flows tend to reflect more systemic risk than public information flows do.

Overall, our paper has three interesting findings. First, our result is consistent with implications of the modified MDH, indicating the hypothesis is a good theoretical ground for understanding the volume–volatility relation, despite there are empirical arguments on how to measure information arrival processes. We also found that surprising information could have opposite effects on trading volume and stock volatility. Our work corroborates the study of Park (2010) that sign effects of surprising information also influence the volume–volatility relationship. Second, our evidence suggests trading volume contains information regarding to the quality of traders' information signals, the quality being the degree to which the information reveals possible systemic risk. Finally, the study implies that the main drivers of stock market volatility and trading activities are uncertainties about fundamental values of assets and about other investors' behaviours.

Author Contributions

The authors confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data is available upon request from corresponding author.

Endnotes

[1] One example for periodic news releases is periodic macroeconomic announcements. One example for periodic events is the dates when futures and options on stock indices expire simultaneously.

[2] For variables other than trading volume in explaining volatility clustering, see, for example, Gallo and Pacini (2000), Kalev et al. (2004), Rangel (2011), Shi et al. (2016), Chiu et al. (2018) and Megaritis et al. (2021).

[3] See Enders (2015) for the discussion of the Dickey–Fuller test statistics.

[4] We only display the full period graphs because those of the two subperiods have qualitatively similar patterns.

[5] Data source: Office of Financial Research. 'OFR Financial Stress Index'. OFR, updated daily. https://www.financialresearch.gov/financial-stress-index/ (accessed Wednesday 02 October 2024).

[6] See Hakkio and Keeton (2009) for the discussion of financial stress and its coincident manifestations.

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