Overconfident Trading of Asian Investors

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Abstract

This study investigates whether Asian investors trade overconfidently and what factors affect their overconfident trading based on the theoretical predictions of Gervais and Odean (2001) that market gains make investors trade overconfidently in subsequent periods. We find that Asian investors trade more aggressively subsequent to both domestic and U.S. market gains and their overconfident trading corresponds to underestimate exchange rate risks. Moreover, we find that Asian investors' overconfident trading is affected both by the market states and by biased self-attribution. Although the results regarding Asian investors' overconfident trading conditional on the market states are mixed, the results regarding the impact of biased self-attribution on Asian investors' overconfident trading, in general, are consistent with the theoretical predictions.

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I. Introduction

It has long been argued that trading volume in speculative markets is too large to be justified on rational grounds (e.g., Dow and Gordon (1997)).[1] Excess trading volume is therefore one puzzle representing a great challenge to the field of finance. De Bondt and Thaler (1995, p.393) state, "…the key behavioral factor needed to understand the trading puzzle is overconfidence." Along this line of thinking, a growing number of researchers have made an effort recently to develop theoretical models rooted in investor overconfidence to account for the observed excess trading volume in securities markets.

For example, Gervais and Odean (2001) (henceforth, GO) propose a self-learning model predicting that overconfident investors, who hold long positions in the equity market, mistakenly attribute market gains to their ability to pick winning stocks and process their private information and consequently trade more aggressively in subsequent periods, which implies a positive causality running from stock returns to trading volume. A similar argument that overconfidence leads to greater trading is also made in De Long, Shleifer, Summers, and Waldmann (1991), Kyle and Wang (1997), Benos (1998), Odean (1998), Wang (1998, 2001), Daniel, Hirshleifer, and Subrahmanyam (2001), Hirshleifer and Luo (2001), Caballé and Sákovics (2003), and Scheinkman and Xiong (2003).

Several empirical studies confirm the conjecture that overconfidence plays a pivotal role in explaining investors' propensity to trade too much and too speculatively. For example, Odean (1999) and Barber and Odean (2000, 2001, and 2002), using a specific sample of discount brokerage accounts, focus on the investigation of the irrational trading behavior of U.S. individuals and find that individual investors appear overconfident about their perceived information and ability to trade in that they trade too much and too speculatively and their active trading detracts their performance.[2]

Odean (1998), Daniel et al. (2001), and GO (2001) argue that aggregate investor overconfidence should be detectable from the market level if most investors succumb to an overconfidence bias. Many researchers also argue that overconfident investors can survive

[1] From a theoretical viewpoint, trading volume can be generated due to risk-sharing, hedging, speculation, and liquidity. Moreover, factors such as asymmetric information, transaction costs, idiosyncratic risks, and other forms of market imperfections are also likely to be relevant for determining the level and variability of trading activity. However, trading volume motivated from theoretical arguments and market imperfections seems to fail to support a substantial trade observed in the real world.
[2] The notion that overconfidence leads individual investors to trade too much and too speculatively is also empirically supported by several experimental studies (e.g., Biais et al. (2004), Deaves, Lüders, and Luo (2004) and Glaser and Weber (2004)).

and dominate the markets in the long run (e.g., Kyle and Wang (1997), Benos (1998), Daniel et al. (1998), GO (2001), Hirshleifer and Luo (2001), and Wang (2001)), which implies the detectability of aggregate investor overconfidence.

Motivated by these arguments, Statman, Thorley, and Vorkink (2005) first study whether overconfidence is a *systematic* cognitive bias from which most U.S. investors suffer to trade too much and too speculatively. They find that high market-wide returns are followed by high market-wide trading volume, a positive causal relation between lagged stock returns and current trading volume, which, in essence, is consistent with the theoretical prediction of the GO (2001) model that market gains make investors overconfident and consequently trade too much and too speculatively in subsequent periods. In a related paper, Chuang and Lee (2005) evaluate the broad empirical implications of the overconfidence hypothesis from the perspective of the aggregate market. With regard to the causal relation between stock returns and trading volume, they confirm the Statman et al. results and further show that this causal relation is more pronounced in bull markets than in bear markets. Moreover, they present evidence that investors become more overconfident and trade more aggressively following market gains as they make right forecasts of future stock returns than as they make wrong forecasts.[3]

Previous empirical research on the causal relation between overconfidence and trading volume focuses primarily on U.S. investors. However, overconfidence is not a patent for U.S. investors. Psychologists have demonstrated that Asians also exhibit overconfidence in general knowledge (e.g., Yates, Lee, and Shinotsuka (1996) and Yates, Lee, and Bush (1997)), which implies, among other things, that Asian investors may suffer from an overconfidence bias and trade overconfidently. In this article, we examine empirically whether Asian investors exhibit overconfidence-based trading behavior, and if so, what factors affect their overconfidence-based trading behavior.[4] Our study is related to Statman, Thorley, and Vorkink (2005) and Chuang and Lee (2005) in that we explore this issue by also

[3] In Chuang and Lee's (2005) paper, they also test the other three overconfidence hypotheses: First, if investors are overconfident, they overreact to private information and underreact to public information. Second, excess trading volume of overconfident investors in securities markets contributes to the observed excess volatility. Third, overconfident investors underestimate risk and trade more in riskier securities. Overall, they find empirical evidence in support for these three hypotheses of the overconfidence hypothesis.

[4] Seven Asian stock markets under examination are Japan, Korea, Hong Kong, Philippines, Indonesia, Singapore, and Thailand. We also examine Taiwan and Malaysia stock markets in our preliminary analysis of the Granger causality tests. However, we exclude them from our succeeding analysis because we can not rule out the possibility that a positive feedback relation between stock returns and trading volume in these two stock markets may fit the story of other theories. For details, see our discussion in Sections III.A and IV.A.

focusing on aggregate investor trading behavior.[5] We believe that our study provides an out-of-sample test to address any lingering concern that the causal relation between overconfidence and trading volume documented in previous studies is simply an outcome of data snooping.

Moreover, we extend previous studies by positing that Asian investors' overconfidence and their overconfident trading can be induced by U.S. market gains for two reasons. First, to satisfy the need of international diversification, Asian investors have a desire to invest in various U.S.-based equity-type instruments (e.g., French and Poterba (1991) and Bekaert and Urias (1996)). In this circumstance, Asian investors directly benefit from U.S. market gains and, if becoming overconfident, are encouraged to trade more in subsequent periods. Second, because of the close trade and economic relationships between Asian countries and the U.S., any news about economic fundamentals in the U.S. stock markets has important implications for their domestic stock markets.[6] If Asian investors recognize this, they infer the future price movements in their domestic stock markets from the current price movements in the U.S. stock markets. Consequently, Asian investors' overconfidence can be fostered by U.S. market gains and, as such, trade more aggressively in subsequent periods even though they do not invest in U.S.-based equity-type instruments. If, on the other hand, Asian investors fail to recognize the fact that U.S. stock prices contains useful information on the future price movements of their domestic stock markets, their overconfident trading will not be affected by U.S. market gains in the absence of direct investments in U.S.-based equity-type instruments.

The main finding of our study is that Asian investors are subject to an overconfidence bias in that they trade more aggressively subsequent to domestic as well as U.S. market gains, as predicted by the GO (2001) model. Although we find that the price movements in each Asian stock market always follow the price movements in the U.S. stock markets and that the overconfident trading of investors in some Asian countries can be induced by U.S. market gains, the pattern of their overconfident trading is not affected if we use Asian currency-

[5] The monthly and weekly market level data are used in Statman, Thorley, and Vorkink (2005) and Chuang and Lee (2005), respectively. Motivated by a trend that short-term trading such as day trading and online trading is becoming popular in the U.S. and Asian stock markets (see, for example, Barber and Odean (2002) and Barber, Lee, Liu, and Odean (2004)) and by a conclusion drawn from Barber and Odean's (2002) study that online traders exhibit significant overconfidence-based trading behavior, we use the daily market level data to conduct our analysis in the hope of capturing the overconfident trading of short-term traders in Asian stock markets.

[6] Numerous studies present the evidence of the information spillover effect from the U.S. stock markets to Asian stock markets. Among them are Eun and Shim (1989), Hamao, Masulis, and Ng (1990), Lin, Engle, and Ito (1994), Koutmos and Booth (1995), Liu and Pan (1997), Copeland and Copeland (1998), Miyakoshi (2003), and Lee, Oliver, and Steven (2004).

adjusted returns in our analysis. This finding is accordance with the notion of overconfidence that overconfident investors tend to underestimate the risk and underreact to relevant information.

Moreover, consistent with the arguments presented in Odean (1998) and GO (2001) that investors' overconfident trading is likely to significantly rise right after a bull market and thus more detectable in a bull market, our results show that some Asian investors trade more aggressively following market gains in bull markets than in non-bull markets. Inconsistent the argument of Odean and GO, however, some Asian investors trade more aggressively following market gains in non-bull markets than in bull markets or their overconfident trading exhibits no significant differences across the state of the market.

Daniel et al. (1998) and GO (2001) incorporate a self-attribution bias into their models predicting that investors' overconfident trading increases more as they make right forecasts for future stock returns than as they make wrong forecasts. To understand how biased self-attribution affects Asian investors' overconfident trading, we classify Asian investors' forecasts of future stock returns into three categories: (i) the wrong forecast, (ii) the right but less precise forecast, and (iii) the right and more precise forecast. If biased self-attribution causes Asian investors to make overconfident trading, they should trade relatively most aggressively subsequent to market gains as they make a right and more precise forecast for future stock returns and relatively least aggressively as they a wrong forecast. In general, our results show that Asian investors' overconfident trading is attributable to biased self-attribution in that their overconfidence-based trading behavior is consistent with the theoretical predictions.

Overall, our empirical findings demonstrate that overconfidence is not a patent for U.S. investors and Asian investors are also subject to an overconfidence bias. Like U.S. investors, Asian investors engage in overconfident trading in that market gains make them irrationally trade too much and too speculatively in subsequent periods. The remainder of the paper is organized as follows. Section II introduces the data, describes the method we employ to detrend the trading volume series to achieve its stationarity, and reports some descriptive statistics of the data. Section III discusses our empirical methodologies. Section IV presents and discusses the empirical results. Finally, Section V offers some concluding remarks.

II. Data Description and Detrending Trading Volume Series

A. Data Description

The data set comprises daily market price index and trading volume for nine Asian stock markets: Japan, Korea, Taiwan, Hong Kong, Philippines, Indonesia, Malaysia, Singapore, and Thailand and two daily market price indices for the U.S. The stock indices for the nine Asian stock markets are the Tokyo Stock Exchange Price Index (TOPIX) for Japan, the Korea Stock Exchange Composite Index (KOSPI) for Korea, the Taiwan Weighted Index (TWI) for Taiwan, the Hang Seng Index (HSI) for Hong Kong, the Philippines Stock Exchange Composite Index (PSECI) for Philippines, the Jakarta Composite Index (JKSE) for Indonesia, the Kuala Lumpur Composite Index (KLSE) for Malaysia, the Straits Times Index (STI) for Singapore and Thailand Index (SET) for Thailand. The stock indices for the U.S. stock markets are the S&P 500 and NASDAQ indices.[7] The data are extracted from *Datastream International*. The daily close-to-close returns of each market index are measured as the log-difference of the index prices and are expressed in percent. The log of the total number of shares traded in a trading day is defined as a measure of *raw* (or undetrended) trading volume.

The data cover the period from January 5, 1998 to December 30, 2004, and consist of 1,280 observations for each variable.[8] The beginning date of the sample period is chosen for two reasons. First, we employ the multivariate econometric models in our analysis, which requires all the series of stock returns and trading volume are matched. Unfortunately, trading volume is not available prior to 1998 for Singapore's STI. Second, to avoid the problem that the structural change before and after the Asia financial crisis in the second half of 1997 makes the empirical estimates biased, we choose the sample period to start from 1998.

To identify the potential effects of the exchange rate changes on the test results, daily U.S. index prices in terms of both U.S. dollars and Asian currencies are used. The rationale for the conversion of U.S. stock returns to Asian currency-adjusted returns rather than that of Asian stock returns to U.S. dollar-adjusted stock returns is that it makes no sense to converse the trading volume of Asian stock markets to U.S. dollar-adjusted trading volume for the

[7] During the sample period, the contemporaneous correlation between the returns of the S&P 500 and NASDAQ indices is 0.858. Our empirical results using NASDAQ returns in place of S&P 500 returns are similar to what we report in the paper using S&P 500 returns. To conserve space, we do not report the results using NASDAQ returns in the paper but are available upon request from the authors.

[8] The sample does not include the dates when the trading volume of any stock market is not available.

purpose of our study. Exchange rates between the U.S. dollar and each Asian currency are also obtained from *Datastream International*.

B. Detrending Trading Volume Series

Previous work finds significant evidence of both linear and nonlinear time trend in the trading volume series (e.g., Gallant, Rossi, and Tauchen (1992)). As a result, many empirical studies of trading volume use some form of detrending to achieve stationarity. In the spirit of Gallant, Rossi, and Tauchen (1992), we detrend the raw trading volume series, RV_t^A, for each Asian stock market *A* by also taking into account the calendar effect on trading volume as follows (see also Lo and Wang (2000)):

$$\begin{aligned} V_t^A = RV_t^A - (&\hat{\alpha}_1 + \alpha_2 t + \hat{\alpha}_3 t^2 + \alpha_4 MON_t + \hat{\alpha}_5 TUE_t + \alpha_6 WED_t + \hat{\alpha}_7 FRI_t \\ &+ \hat{\beta}_1 JAN_t + \beta_2 FEB_t + \hat{\beta}_3 MAR_t + \beta_4 APR_t + \hat{\beta}_5 MAY_t + \beta_6 JUL_t \\ &+ \ldots + \hat{\beta}_{10} NOV_t + \beta_{11} DEC_t + \sum_{p=1}^{P^A} \hat{\gamma}_p RV_{t-p}^A), \end{aligned} \quad (1)$$

where the regressors $MON_t,\ldots, FRI_t$ denote daily indicator variables for the days of Monday through Friday, and $JAN_t,\ldots, DEC_t$ denote monthly indicator variables for the months of January through December. Specifically, Thursday and June are omitted to avoid perfect collinearity. The regressors of the autoregressive terms of RV_t^A whose number is denoted by L^A are added to filter out autocorrelation of trading volume series until the Ljung-Box *Q*-statistic shows that there is no autocorrelation of the residual terms for the detrended trading volume series. This procedure helps prevent the model from misspecification as trading volume is used as a dependent variable. The resulting V_t^A is used as the measure of trading volume for Asian stock market *A*.[9]

C. Summary Statistics

Table 1 presents descriptive statistics on the daily return and trading volume series for nine Asian market indices and the daily return series for two U.S. market indices for the sample period from January 5, 1998 to December 30, 2004. Specifically, the table reports the mean,

[9] We hereafter refer to the detrended trading volume as trading volume.

standard deviations, skewness, kurtosis, the *D*-statistic of the Kolmogorov-Smirnov test statistic for normality, the chi-squared statistic for the ARCH Lagrange Multiplier test (Engle, 1982), and the test statistic (*t*-statistic) of the augmented Dickey-Fuller test (Dicky and Fuller, 1979).

Over the entire sample period, Indonesia has the highest mean return of 0.070%, while Taiwan has the lowest one of -0.022%. Korea is the most volatile market with the standard deviation of 2.804%, whereas the S&P 500 is the most stable index with the standard deviation of 1.470%. On the other hand, the detrended trading volume for all Asian stock markets exhibits the mean equal to zero. Trading volume appears to be more stable relative to stock returns for all Asian stock markets. Except for Japan, Taiwan, Singapore, and the U.S., most of stock market returns exhibit significant skewness; all of stock market returns have excess kurtosis. All of stock market trading volume display significant skewness and excess kurtosis. Taken together, these findings indicate that the distribution for stock market returns and trading volume seems to deviate from normalality. This can be demonstrated formally by the Kolmogorov-Smirnov *D*-statistic, which leads to the rejection of normality for all of stock market returns and trading volume. The application of the ARCH Lagrange Multiplier test suggests that each series strongly depends on their past values and follows an ARCH-type process. Lastly, the results of the ADF test show that the null hypothesis of a unit root can be rejected for each variable, indicating that the series of stock market returns and detrended trading volume are stationary.

III. Empirical Framework

GO (2001) develop a self-learning model describing a dynamic by which investors' overconfidence may wax and wane conditional on the successes or failures of their past trading. Their model predicts that if investors, who hold long positions in the equity markets, are overconfident, they mistakenly attribute market gains to their ability to pick winning stocks and overestimate the quality of information signals they gather and consequently trade too much and too speculatively in subsequent periods. Since investors in aggregate hold long positions in the equity market, the overconfidence hypothesis predicts a positive causality running from market-wide returns to market-wide volume, but not vice versa.[10]

[10] The causality from trading volume to stock returns is consistent with an old Wall Street adage that "It takes volume to make prices move." This adage was later confirmed empirically by Smirlock and Starks (1985),

As discussed in the previous section, we hypothesize that both domestic and U.S. market gains make Asian investors overconfident and, as a result, trade more aggressively in subsequent periods. From an empirical perspective, our hypothesis predicts, in each Asian stock market, a positive causality running from domestic stock returns to domestic trading volume as well as a positive causality running from U.S. stock returns to domestic trading volume. The GO (2001) model does not explicitly specify an exact time frame for the causal relation between stock returns and trading volume. The formal causality tests discussed in the following subsection help identify this time frame.

A. Causal Relation between Stock Returns and Trading Volume

To identify whether Asian investors engage in overconfident trading as predicted by GO (2001), our empirical procedure tests whether a positive relation exists between stock returns and trading volume by employing Granger (1969, 1988) causality tests. Formally, if the prediction of Y using past values of X is more accurate than the prediction without using X in the mean square error sense [i.e., $\sigma^2(Y_t|\Omega_{t-1}) < \sigma^2(Y_t|\Omega_{t-1} - X_t)$, where Ω_{t-1} is the information set at time $t - 1$], then X Granger-causes Y.

It should be noted that some extant theories on trading volume share some, though not all, of the implications of the overconfidence hypothesis regarding the relation between stock returns and trading volume. For example, the sequential information arrival model of Copeland (1976) and Jennings, Starks, and Fellingham (1981) suggests a positive causal relation between stock returns and trading volume in either direction (i.e., a feedback relation).[11] To reconcile the difference between the short- and long-run autocorrelation properties of aggregate stock returns, De Long, Shleifer, Summers, and Waldmann (1990) develop a positive-feedback trading model, implying a positive bi-directional causal relation between trading volume and stock returns.[12] Our empirical framework helps us distinguish

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Harris (1986, 1987), Gallant, Rossi, and Tauchen (1992), Cooper (1999), Lee and Swaminathan (2000), Gervais, Kaniel, and Mingelgrin (2001), and Llorente, Michaely, Saar, and Wang (2002), among others.

[11] The sequential information arrival model assumes that new information flows into the market and is disseminated to investors one at a time. Due to the sequential information flow, lagged trading volume could have predictive power for current stock returns, and lagged stock returns could have predictive power for current trading volume.

[12] A positive causal relation from trading volume to stock returns is consistent with the assumption made in the model that the trading strategies pursued by noise traders cause stock prices to move. A positive causal relation from stock returns to trading volume is consistent with the positive-feedback trading strategies of noise traders, for which the decision to trade is conditional on past stock price movements.

between the overconfidence hypothesis and alternative hypotheses of trading volume in explaining Asian investors' trading behavior.

We employ Zellner's (1962) Seemingly Unrelated Regression (SUR) model to perform the trivariate Granger causality tests for each Asian stock market A:[13]

$$\begin{aligned} V_t^A = \alpha_{11}^A + \sum_{b=0}^{B^A} \alpha_{12b}^A \,|\, R_{t-b}^A \,| + \sum_{c=1}^{C^A} \alpha_{13c}^A \,|\, R_{t-c}^{\mathrm{US}} \,| \\ + \sum_{d=1}^{D^A} \beta_{11d}^A V_{t-d}^A + \sum_{d=1}^{D^A} \beta_{12d}^A R_{t-d}^A + \sum_{d=1}^{D^A} \beta_{13d}^A R_{t-d}^{\mathrm{US}} + \varepsilon_{1,t}^A, \end{aligned} \tag{2.1}$$

$$R_t^A = \alpha_{21}^A + \sum_{d=1}^{D^A} \beta_{21d}^A V_{t-d}^A + \sum_{d=1}^{D^A} \beta_{22d}^A R_{t-d}^A + \sum_{d=1}^{D^A} \beta_{23d}^A R_{t-d}^{\mathrm{US}} + \varepsilon_{2,t}^A, \tag{2.2}$$

$$R_t^{US} = \alpha_{31}^A + \sum_{d=1}^{D^A} \beta_{31d}^A V_{t-d}^A + \sum_{d=1}^{D^A} \beta_{32d}^A R_{t-d}^A + \sum_{d=1}^{D^A} \beta_{33d}^A R_{t-d}^{\mathrm{US}} + \varepsilon_{3,t}^A, \tag{2.3}$$

where V_t^A is the Asian stock market A trading volume at time t, R_t^A is the Asian stock market A return at time t, R_t^{US} is the U.S. stock market return at time t, $|R_t^A|$ is the absolute value of R_t^A at time t, and $|R_t^{\mathrm{US}}|$ is the absolute value of R_t^{US} at time t. The number of lags in each equation is selected by considering both the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). Specifically, the causality in the SUR model is tested using a likelihood-ratio test of the theoretically implied parameter restrictions.[14]

Ross (1989) shows that in a frictionless market characterized by an absence of arbitrage opportunities, the rate of information flow is revealed by the degree of the volatility of asset returns. Based on this intuition, previous studies employ the absolute value of stock returns as a proxy for information flow to the stock markets (e.g. Bessembinder, Chan, and Seguin (1996), Covrig and Ng (2004), and Chuang and Lee (2005)). Following previous studies, we use $|R_t^A|$ and $|R_t^{\mathrm{US}}|$ to proxy for information flow emanated from Asian stock

[13] Engle and Granger (1987) point out that when a set of variables is cointegrated, a vector autoregression (VAR) model in first difference will be misspecified because first differencing of all the nonstationary variables imposes too many unit roots and any potentially important long-term relationship between the variables will be obscured (see also Granger (1988) and Sims, Stock, and Watson (1990)). An effective remedy they provide for this misspecification problem is the incorporation of the error correction terms into the VAR model. An error correction representation of the cointegrated variables is devised to capture a long-term relationship shared by those variables. To take into account the possibility that three endogenous variables in the SUR system are cointegrated, we perform the multivariate cointegration test developed by Johansen (1988, 1991) and find no evidence of cointegration among domestic raw trading volume, domestic stock prices, and U.S. stock prices. Consequently, we do not incorporate the error correction terms into the SUR system.

[14] See Anthony (1988) for detailed derivations of the multivariate causality tests using the SUR model.

market A and from the U.S. stock market, respectively, to account for informational trades. These two control variables play an important role in our attempt to identify Asian investors' overconfident trading because the GO (2001) model suggests that overconfident investors trade for noninformational motivates (i.e., cognitive biases).

In the trivariate Granger causality tests, the rejection of the null hypothesis that domestic stock returns do not Granger-cause domestic trading volume (i.e., $\beta_{12d}^{A} = 0$, for all d), together with the observation that the sum of the lagged β_{12d}^{A} coefficients is significantly positive, indicates that domestic market gains make country A investors overconfident and consequently trade more actively in subsequent periods, while the rejection of the null hypothesis that U.S. stock returns do not Granger-cause domestic trading volume (i.e., $\beta_{13d}^{A} = 0$, for all d), together with the observation that the sum of the lagged β_{13d}^{A} coefficients is significantly positive, indicates that U.S. market gains make country A investors overconfident and consequently trade more actively in subsequent periods. In addition, the rejection of the null hypothesis that U.S. stock returns do not Granger-cause domestic stock returns (i.e., $\beta_{23d}^{A} = 0$, for all d), together with the observation that the sum of the lagged β_{23d}^{A} coefficients is significantly positive, indicates that U.S. market gains are followed by the market gains of Asian stock market A.

As pointed out earlier, there two reasons to argue that U.S. market gains contribute to Asian investors' overconfident trading. One is that their investments in U.S.-based equity-type instruments benefit directly from U.S. market gains. The other is that they realize the fact that U.S. stock prices precede their domestic stock prices. In the framework of our causality tests, for the former to be the case, R_t^{US} should positively Granger-cause V_t^A in the absence of a positive causality from R_t^{US} to R_t^A. For the latter to be the case, R_t^{US} should positively Granger-cause V_t^A in the presence of a positive causality from R_t^{US} to R_t^A. However, the second case may subsume the first case based on our empirical framework here. In other words, we can not rule out the possibility that a positive causality from R_t^{US} to V_t^A is in the presence of a positive causality from R_t^{US} to R_t^A is due partly to Asian investors' investments in U.S.-based equity-type instruments which benefit directly from U.S. market gains.[15]

More importantly, if we find a positive feedback relation between stock returns and trading volume, it provides evidence in favor of the sequential information arrival or positive-feedback trading hypotheses. In this case, we exclude any Asian stock market with a positive feedback relation between stock returns and trading volume from our succeeding analysis in that the observed positive causality running from stock returns to trading volume may be part of the story of the alternative hypotheses on trading volume.

B. Aggregate Overconfident Trading across Asian Stock Markets

After performing the trivariate causality tests for each Asian stock market, we turn our attention to simultaneously examine the causal relations among domestic trading volume, domestic stock returns, and U.S. stock returns across seven Asian stock markets by estimating the following SUR model:

$$V_t^A = \alpha_1^A + \sum_{d=0}^{D^A} \alpha_{2d}^A \mid R_{t-d}^A \mid + \sum_{d=1}^{D^A} \alpha_{3d}^A \mid R_{t-d}^{\text{US}} \mid + \sum_{d=1}^{D^A} \beta_d^A R_{t-d}^A + \sum_{d=1}^{D^A} \gamma_d^A R_{t-d}^{\text{US}} + \varepsilon_t^A, \quad (3)$$

where the variables are defined as above, the superscript A represents the cross-sectional units of seven Asian stock markets, and the subscript t represents the daily time unit. Specifically, the superscript A = JA (Japan), KO (Korea), HK (Hong Kong), PH (Philippines), IN (Indonesia), SI (Singapore), and TH (Thailand). One advantage of employing the SUR approach is that it accounts for the cross-market correlations of the contemporaneous residuals in drawing inferences concerning the regression parameters. In equation (3), the lagged β_d^A coefficients measure country A investors' overconfident trading due to past domestic market gains, while the lagged γ_d^A coefficients measure country A investors' overconfident trading due to past U.S. market gains.

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[15] One way to disentangle these two cases is to decompose R_t^{US} into two components. One Granger-causes R_t^A and the other does not Granger-cause R_t^A. Then we can investigate the causal relations between V_t^A and these two components of R_t^{US} in order to more precisely measure the contribution of R_t^{US} to Asian investors' overconfident trading. Since disentangling these two cases is not the main of this paper, we do not explore this issue.

To avoid the potential problem of overparameterization and obtain a parsimonious model, we use a two-step procedure to estimate the SUR model of equation (3). In the first step, the SUR model is estimated with a lag length of $D^A = 5$ on each independent variable of Asian stock market *A*. In the second step, the SUR model estimated from the first-step procedure is reestimated by dropping all insignificant independent variables at the 5% level.[16] The SUR model estimated using this two-step procedure contains the independent variables that are significant at least at the 5% level.[17]

In addition to taking into account the cross-market correlations, another advantage of employing the SUR model is that we can, for example, further investigate whether the extent to which the overconfident trading of investors in each Asian country varies by testing the cross-equation restrictions imposed on the model. Since the estimated SUR model is parsimonious with the independent variables that are statistically significant at least at the 5% level, such a cross-equation test will yield more reliable results without the disturbances of the insignificant independent variables.

C. The Effect of Exchange Rates on Asian Investors' Overconfident Trading

In this article, we first address the issue whether Asian investors' overconfidence and their corresponding overconfident trading can be induced by U.S. market gains if they invest in various financial instruments underlying U.S. stocks and/or the index of the U.S. stock market or if they recognize the fact that their domestic stock prices tend to follow U.S. stock prices. It goes without saying that exchange rate movements are particularly important for international investments. As a consequence, Asian investors' overconfident trading due to

[16] The potential problem for our two-step procedure may occur if there is significant multicollinearity among the independent variables. To detect whether there exists multicollinearity among independent variables, we examine the pairwise correlations between R^{A}_{t-d} and R^{US}_{t-d} and find that their range is between -0.070 (R^{JA}_{t-1} and R^{JA}_{t-4}) and 0.304 (R^{HO}_{t-3} and R^{US}_{t-4}). The results thus suggest that multicollinearity is not a serious problem for our empirical procedure. Hereafter, we always use the same two-step procedure to estimate the empirical models introduced in the following subsections to conduct our analysis.

[17] It is noted that the sign of few of the significant independent variables associated with Asian and U.S. stock returns in equation (2) turn out to be negative rather than positive. Although we still keep the significant independent variables with negative signs in the estimated SUR model, we are unaware that any extant theory can fully explain a negative relation between lagged stock returns and current trading volume. One possible theory to explain this relation is tax-loss selling by investors in common stocks near the end of calendar years (e.g., Lakonishok and Smidt (1989) and Badrinath and Lewellen (1991)). However, the tax-loss selling hypothesis can only explain this relation near the end of calendar years, which is obviously not the case for our observations.

U.S. market gains may depend on the interrelationship between exchange rate movements and U.S. stock price movements.

If Asian investors, though overconfident, fully understand the impact of exchange rate fluctuations on their U.S.-based equity-type investments, the degree of their overconfident trading that is triggered by U.S. market gains in terms of local currency should be greater than that in terms of U.S. dollars. Consider, for example, an overconfident Japanese investor who invests in a U.S.-based index mutual fund. The value of her investments depends on the interrelationship between the movements of the yen-dollar exchange rates and the equity index price. She will trade aggressively in subsequent periods if U.S. equity index returns are positive in terms of Japanese yen irrespective of whether the U.S. equity index returns are originally positive or negative in terms of U.S. dollars.[18] As such, using the Asian local currency-denominated returns of the U.S. stock market can more precisely measure how Asian investors' overconfident trading is induced by U.S. market gains if they recognize the impact of exchange rate fluctuations on their investments in U.S.-based equity-type instruments.

On the other hand, it is also likely that overconfident Asian investors may ignore the impact of exchange rate risks on their investments in U.S.-based equity-type instruments since overconfident investors tend to underestimate risk (e.g., De Long et al. (1991), Kyle and Wang (1997), Benos (1998), Odean (1998), Wang (1998, 2001), Gervais and Odean (2001), Daniel et al. (1998, 2001), Hirshleifer and Luo (2001), and Scheinkman and Xiong (2003)) and underweight relevant, important information (e.g., Daniel et al. (1998), Odean (1998), and Hirshleifer (2001)). In this case, Asian investors only pay attention to the movements of U.S. stock prices denominated in dollars and their overconfident trading is elicited only by U.S. stock returns denominated in dollars, even though the local currency-denominated returns of the U.S. stock market are negative. As a result, their overconfident trading due to U.S. market gains or the measure of the correlation between lagged U.S. stock returns and current domestic trading volume is not affected by whether U.S. stock returns are expressed in terms of Asian local currencies or U.S. dollars.

To analyze the potential effect of exchange rate movements on Asian investors' overconfident trading, we employ a multivariate SUR system of fourteen equations in which

[18] Obviously, the Japanese investors profit (lose) more if U.S. dollars tend to appreciate (depreciate) following a rise (fall) in the U.S. stock market when they liquidate their investments in the U.S.-based index mutual fund and converts back to Japanese yen.

first seven equations are the same as equation (3) and the other seven equations using U.S. stock returns denominated in Asian local currencies:

$$V_t^A = \alpha_1^A + \sum_{d=0}^{D^A} \alpha_{2d}^A \,|\, R_{t-d}^A \,| + \sum_{d=1}^{D^A} \alpha_{3d}^A \,|\, R_{t-d}^{\mathrm{US}} \,| + \sum_{d=1}^{D^A} \beta_d^A R_{t-d}^A + \sum_{d=1}^{D^A} \gamma_d^A R_{t-d}^{\mathrm{US}} + \varepsilon_t^A, \qquad (4.1)$$

$$V_t^A = \alpha_{21}^A + \sum_{d=0}^{D^A} \alpha_{22d}^A \,|\, R_{t-d}^A \,| + \sum_{d=1}^{D^A} \alpha_{23d}^A \,|\, R_{t-d}^{\text{A-US}} \,| + \sum_{d=1}^{D^A} \beta_{2d}^A R_{t-d}^A + \sum_{d=1}^{D^A} \gamma_{2d}^A R_{t-d}^{\text{A-US}} + \varepsilon_{2t}^A, \qquad (4.2)$$

where the variables are defined as above and $R_t^{\text{A-US}}$ is the U.S. stock return denominated in country *A* currency at time *t*.

Equations (4.1) and (4.2) provide a straightforward way to identify the effect of exchange rate movements on Asian investors' overconfident trading by testing the null hypothesis that the sum of the lagged γ_{1d}^A coefficients is equal to that of the lagged γ_{2d}^A coefficients. However, since we adopt the above-mentioned two-step procedure to estimate the SUR system of equations (4.1) and (4.2), one potential problem which may occur is that two equations associated with the same Asian stock market are identical after the second-step estimations. If this, unfortunately, happens, we only estimate the SUR system of equation (4.2) and compare the estimated results of equation (4.2) with those of equation (3) to infer whether Asian investors' overconfident trading is affected by exchange rate movements.

D. Asian Investors' Overconfident Trading Conditional on the Market States

An old Wall Street adage that "Don't confuse brains with a bull market" warns investors of the danger of becoming overconfident during a market rally. Odean (1998) and GO (2001) argue that investors' overconfident trading is likely to significantly rise right after a bull market.[19] This implies that overconfidence is likely to be stronger and, thus, more detectable in bull markets than in non-bull markets. Along this line of thinking, Asian investors will make more overconfident trading following market gains during bull markets than during non-bull markets, which implies that the positive relation between lagged stock returns and current trading volume should be stronger right after a bull market than in the other time

[19] It should be noticed that the GO argument means that investors engage in overconfident trading both in bull and in non-bull markets, but they engage more in overconfident trading in bull markets than in non-bull markets. Accordingly, investors still engage in overconfident trading in non-bull markets.

periods of the market. We therefore conduct our analysis of Asian investors' overconfident trading conditional on the state of the market.

The investigation of Asian investors' overconfident trading conditional on the state of the market requires a consistent definition of a bull market for each Asian stock market. The determination of a bull market is, however, somewhat subjective. Following Hardouvelis and Theodossiou (2002), we define a bull market as a period during which there are at least *m* consecutive monthly positive market returns. The monthly market returns are calculated by averaging daily market returns. The horizon *m* of our analysis takes three possible values, *m* = 2, 3, and 4.[20] The advantage of using this definition of a bull market is that it applies for each Asian stock market. To investigate the asymmetries in Asian investors' trading behavior responses to past domestic and U.S. market gains as the domestic and U.S. stock markets are in bull and non-bull markets, we adopt the above-mentioned two-step procedure to estimate the following seemingly unrelated multivariate regression system over the full sample period:

$$\begin{aligned} V_t^A = \alpha_1^A &+ \sum_{d=0}^{D^A} \alpha_{2d}^A \,| R_{t-d}^A \times D_{mw,t-d}^A | + \sum_{d=0}^{D^A} \alpha_{3d}^A \,| R_{t-d}^A \times (1 - D_{mw,t-d}^A) | \\ &+ \sum_{d=1}^{D^A} \alpha_{4d}^A \,| R_{t-d}^{\text{US}} \times D_{mw,t-d}^{\text{US}} | + \sum_{d=1}^{D^A} \alpha_{5d}^A \,| R_{t-d}^{\text{US}} \times (1 - D_{mw,t-d}^{\text{US}}) | \\ &+ \sum_{d=1}^{D^A} \beta_{1d}^A (R_{t-d}^A \times D_{mw,t-d}^A) + \sum_{d=1}^{D^A} \beta_{2d}^A (R_{t-d}^A \times (1 - D_{mw,t-d}^A)) \\ &+ \sum_{d=1}^{D^A} \gamma_{1d}^A (R_{t-d}^{\text{US}} \times D_{mw,t-d}^{\text{US}}) + \sum_{d=1}^{D^A} \gamma_{2d}^A (R_{t-d}^{\text{US}} \times (1 - D_{mw,t-d}^{\text{US}})) + \varepsilon_t^A, \end{aligned} \tag{5}$$

where the variables are defined as above. Specifically, the dummy variable $D_{mw,t}^A$ ($D_{mw,t}^{\text{US}}$) takes a value of one if day *t* is included in the period from *w* weeks after the beginning of a bull market whose definition is based on *m* consecutive monthly positive market returns for Asian stock market *A* (the U.S. stock market), and zero otherwise. Since the GO (2001) model provides no guidance with respect to the value of *w*, we consider three possible values for *w*, namely *w* = 1, 2, and 3. Such a definition of a bull market takes into proper account the GO argument that overconfident investors trade much more aggressively *right after* a bull market.

[20] We stop to try the value of *m* greater than 4 because not every Asian stock market confirms to this definition.

In equation (5), the lagged β_{1d}^{A} and β_{2d}^{A} coefficients measure the relation between lagged domestic stock returns and current domestic trading volume as Asian stock market *A* is in bull and non-bull markets, respectively, while the lagged γ_{1d}^{A} and γ_{2d}^{A} coefficients measure the relation between lagged U.S. stock returns and current domestic trading volume as the U.S. stock market is in bull and non-bull markets, respectively. If the GO argument empirically valid, for each Asian stock market *A* we expect to observe that the sum of the lagged β_{1d}^{A} coefficients is greater than that of the lagged β_{2d}^{A} coefficients and that the sum of the lagged γ_{1d}^{A} coefficients is greater than that of the lagged γ_{2d}^{A} coefficients.

E. The Effect of Biased Self-Attribution on Asian Investors' Overconfident Trading

Psychologists have documented the presence of self-attribution bias, wherein people tend to attribute good outcomes to their own qualities and bad outcomes to bad luck or other factors (e.g., Miller and Ross (1975), Nisbett and Ross (1980), and Fiske and Taylor (1991)). Some theoretical work of behavioral finance has incorporated a self-attribution bias into the model to describe its impact on investor overconfidence over time. For example, Daniel et al. (1998) propose a dynamic model of outcome-dependent confidence built on an important assumption that when an investor receives confirming information, his overconfidence rises, but disconfirming information causes overconfidence to fall only modestly, if at all. GO (2001) present a self-learning model in which a trader who successfully forecasts dividends weights this success too heavily when applying Bayes' rule to assess his own ability and, consequently, trade overconfidently in subsequent periods.

An important empirical implication from these theoretical works is that if self-attribution bias causes investors to learn to be overconfident, they will trade more aggressively following market gains as their forecasts of future stock returns turn out right than their forecasts turn out wrong (see also Chuang and Lee (2005)). For instance, if investors make a right forecast in that they predict positive stock returns at time $t-1$ and realized stock returns are positive at time *t*, then their overconfident trading rises significantly in subsequent periods. If, on the other hand, investors make a wrong forecast in that they predict negative stock returns at time $t-1$ and realized stock returns are positive at time *t*, then their overconfident trading may fall only modestly because they still benefit from market gains. Put together, investors always trade overconfidently subsequent to market gains regardless of whether they make right or wrong forecasts for future stock returns, and they trade more overconfidently as they make right forecasts than as they make wrong forecasts.

The above discussion illustrates the effect of whether investors make right or wrong forecasts for future stock returns on their overconfident trading. However, the situations in the real world may be more complicated than we have discussed above. For instance, given that investors make a right forecast of future stock returns, investors should trade particularly overconfidently as their forecasts are more precise than as less precise. To more comprehensively capture the effect of self-attribution bias on Asian investors' overconfident trading, we classify their forecasts of future stock returns into three categories: (i) the wrong forecast, (ii) the right but less precise forecast, and (iii) the right and more precise forecast.

To investigate how a self-attribution bias affects Asian investors' overconfident trading, we utilize a trivariate GJR-GARCH-M model, which is originally proposed by Glosten, Jagannathan, and Runkle (1993). The model appropriately accounts for an asymmetric effect in which a negative return shock increases volatility more than does a positive return shock (i.e., the so-called leverage effect by Black (1976)) and for the return and volatility spillover effects from the U.S. stock market to Asian stock market *A* as well documented in previous studies. The specification of the trivariate GJR-GARCH-M model is described as below.

Conditional mean equations:[21]

$$\begin{aligned} V_t^A = {} & \alpha_1^A + \sum_{e=0}^{E^A} \alpha_{11e}^A \,|R_{t-e}^A| + \sum_{e=1}^{E^A} \alpha_{12e}^A \,|R_{t-e}^{\mathrm{US}}| \\ & + \sum_{e=1}^{E^A} \beta_{11e}^A R_{t-e}^A + \sum_{e=1}^{E^A} \beta_{12e}^A Z_{t-e}^{A+} R_{t-e}^A + \sum_{e=1}^{E^A} \beta_{13e}^A Z_{t-e}^{A+} Z_{t-e}^{A+<} R_{t-e}^A \\ & + \sum_{e=1}^{E^A} \gamma_{11e}^A R_{t-e}^{\mathrm{US}} + \sum_{e=1}^{E^A} \gamma_{12e}^A Z_{t-e}^{\mathrm{US}+} R_{t-e}^{\mathrm{US}} + \sum_{e=1}^{E^A} \beta_{13e}^A Z_{t-e}^{\mathrm{US}+} Z_{t-e}^{\mathrm{US}+<} R_{t-e}^{\mathrm{US}} + \varepsilon_{1,t}^A, \end{aligned} \tag{6}$$

$$R_t^A = \alpha_2^A + \sum_{f=1}^{F^A} \mu_{2f}^A R_{t-f}^A + \sum_{g=1}^{G^A} \delta_{2g}^A \varepsilon_{2,t-g}^A + \sum_{i=1}^{I^A} \phi_i^A R_{t-i}^{\mathrm{US}} + \pi_2^A h_{2,t}^A + \varepsilon_{2,t}^A \equiv E_{t-1} R_t^A + \varepsilon_{2,t}^A, \tag{7}$$

$$R_t^{\mathrm{US}} = \alpha_3^A + \sum_{f=1}^{F^A} \mu_{3f}^A R_{t-f}^{\mathrm{US}} + \sum_{g=1}^{G^A} \delta_{3g}^A \varepsilon_{2,t-g}^{\mathrm{US}} + \pi_3^A h_{3,t}^{\mathrm{US}} + \varepsilon_{3,t}^{\mathrm{US}} \equiv E_{t-1} R_t^{\mathrm{US}} + \varepsilon_{3,t}^{\mathrm{US}}, \tag{8}$$

[21] We do not model the conditional mean of domestic trading volume as an ARMA process since its serial correlation has been adjusted when we detrend it as described in equation (1).

where V_t^A, R_t^A, and R_t^{US} are defined as above, $h_{1,t}^A$, $h_{2,t}^A$, and $h_{3,t}^{\text{US}}$ are the conditional variances of V_t^A, R_t^A, and R_t^{US}, respectively, and will be defined immediately below, and E_{t-1} denotes an expectation formed at the end of period $t-1$. The dummy variable Z_t^{A+} $(Z_t^{\text{US}+})$ takes a value of one if $E_{t-1}R_t^A \times R_t^A > 0$ ($E_{t-1}R_t^{\text{US}} \times R_t^{\text{US}} > 0$) and zero otherwise, while the dummy variable $Z_t^{A+<}$ $(Z_t^{\text{US}+<})$ takes a value of one if $|R_t^A - E_{t-1}R_t^A| = |\varepsilon_{2,t}^A| < std(\varepsilon_{2,t}^A)$ ($|R_t^{\text{US}} - E_{t-1}R_t^{\text{US}}| = |\varepsilon_{3,t}^{\text{US}}| < std(\varepsilon_{3,t}^{\text{US}})$) and zero otherwise where $std(\varepsilon_{2,t}^A)$ $(std(\varepsilon_{3,t}^{\text{US}}))$ is the standard deviation of $\varepsilon_{2,t}^A$ $(\varepsilon_{3,t}^{\text{US}})$. In other words, the dummy variable Z_t^{A+} $(Z_t^{\text{US}+})$ is defined based on whether Asian investors make right forecasts of future domestic (U.S.) stock returns and the dummy variable $Z_t^{A+<}$ $(Z_t^{\text{US}+<})$ is defined based on whether Asian investors' forecast errors of future domestic (U.S.) stock returns are within one standard deviation of the mean forecast errors.

In equation (6), the lagged β_{11e}^A (γ_{11e}^A) coefficients measure country *A* investors' overconfident trading due to domestic (U.S.) market gains as they make a wrong forecast for future domestic (U.S.) stock returns. As country *A* investors make a right but less precise forecast for future domestic (U.S.) stock returns, their subsequent overconfident trading is measured by the sum of the lagged β_{11e}^A and β_{12e}^A (γ_{11e}^A and γ_{12e}^A) coefficients. As country *A* investors make a right and more precise forecast for future domestic (U.S.) stock returns, their subsequent overconfident trading is measured by the sum of the lagged β_{11e}^A, β_{12e}^A, and β_{13e}^A (γ_{11e}^A, γ_{12e}^A, and γ_{13e}^A) coefficients. If biased self-attribution contributes to country *A* investors' overconfident trading, all estimated lagged beta and gamma coefficients should be positive. Specifically, the significantly positive lagged β_{11e}^A (γ_{11e}^A) coefficients demonstrate that country *A* investors, though making a wrong forecast of future domestic (U.S.) stock returns, trade overconfidently in subsequent periods as long as $R_{t-e}^A > 0$ $(R_{t-e}^{\text{US}} > 0)$. The significantly positive lagged β_{12e}^A (γ_{12e}^A) coefficients demonstrate that country *A* investors' overconfident trading increases more as they make a right but less precise forecast of future domestic (U.S.) stock returns than as they make a wrong forecast, while the significantly positive lagged β_{13e}^A (γ_{13e}^A) coefficients demonstrate that country *A* investors' overconfident trading increases more as they make a right and more precise forecast of future domestic (U.S.) stock returns than as they make a right but less precise forecast.

In equation (7), the lagged ϕ_i^A coefficient captures the return spillover effect from the U.S. stock market to Asian stock market *A*, and such a spillover effect exists if the lagged ϕ_i^A coefficient is significantly different from zero. In equations (7) and (8), the π_2^A and π_3^A coefficients are the measure of the risk premium. Engle, Lilien, and Robins (1987), for example, contend that the risk premium is an increasing function of the conditional variance of asset returns in that risk-averse investors should be compensated for holding a risky asset. For this contention to be empirically held, the π_2^A and π_3^A coefficients should be significantly positive.

Conditional variance equations:

$$h_{1,t}^A = \omega_1^A + \sum_{j=1}^{J^A} \theta_{1j}^A h_{1,t-j}^A + \sum_{k=1}^{K^A} \lambda_{1k}^A (\varepsilon_{1,t-k}^A)^2 + \varphi_1^A S_{1,t-1}^{A+} (\varepsilon_{1,t-1}^A)^2, \tag{9}$$

$$h_{2,t}^A = \omega_2^A + \sum_{j=1}^{J^A} \theta_{2j}^A h_{2,t-j}^A + \sum_{k=1}^{K^A} \lambda_{2k}^A (\varepsilon_{2,t-k}^A)^2 + \varphi_2^A S_{2,t-1}^{A-} (\varepsilon_{2,t-1}^A)^2 + \delta_2^A (\varepsilon_{3,t-1}^A)^2, \tag{10}$$

$$h_{3,t}^{\mathrm{US}} = \omega_3^A + \sum_{j=1}^{J^A} \theta_{3j}^A h_{3,t-j}^{\mathrm{US}} + \sum_{k=1}^{K^A} \lambda_{3k}^A (\varepsilon_{3,t-k}^{\mathrm{US}})^2 + \varphi_3^A S_{3,t-1}^{\mathrm{US}-} (\varepsilon_{3,t-1}^{\mathrm{US}})^2, \tag{11}$$

where the dummy variable $S_{1,t-1}^{A+}$ takes a value of one if $\varepsilon_{1,t-1}^A > 0$ and zero otherwise and the dummy variable $S_{2,t-1}^{A-}$ ($S_{3,t-1}^{\mathrm{US}-}$) takes a value of one if $\varepsilon_{2,t-1}^A < 0$ ($\varepsilon_{3,t-1}^{\mathrm{US}} < 0$) and zero otherwise. The asymmetry effect in equations (10) and (11) is captured by the volatility parameters φ_2^A and φ_3^A, respectively. When the estimated φ_2^A and φ_3^A volatility parameters are significantly positive, a negative shock has a larger impact on the conditional volatility than does a positive shock. In equation (10), the δ_2^A parameter measures the volatility spillover effect from the U.S. stock market to Asian stock market *A*, and the statistical significance of the estimated δ_2^A parameter illustrates such a volatility spillover effect.

Following the suggestion by Bollerslev (1987) and Baillie and Bollerslev (1989), the innovations in equations (6), (7), and (8) are assumed to follow a multivariate Student-*t* distribution with v^A degrees of freedom to deal with the possible excess kurtosis of the innovations:

$$\varepsilon_t \mid \Omega_{t-1}^A \equiv [\varepsilon_{1,t}^A,\ \varepsilon_{2,t}^A,\ \varepsilon_{3,t}^{\text{US}}]' \mid \Omega_{t-1}^A \sim \text{Student-}t\ (0,\ H_t^A,\ v^A), \tag{12}$$

$$H_t^A = \begin{vmatrix} h_{1,t}^A & h_{12,t}^A & h_{13,t}^A \\ h_{21,t}^A & h_{2,t}^A & h_{23,t}^A \\ h_{31,t}^A & h_{32,t}^A & h_{3,t}^A \end{vmatrix}, \tag{13}$$

$$h_{xy,t}^A = \rho_{xy}^A (h_{x,t}^A \times h_{y,t}^A)^{0.5},\ \text{for } x,\ y = 1,2,3 \text{ and } x \neq y;\ -1 \leq \rho_{xy}^A \leq 1, \tag{14}$$

where Ω_{t-1}^A is the information set at time $t-1$ and H_t^A is the 3×3 conditional variance-covariance matrix at time *t*.

Finally, to achieve efficiency, parameters for the conditional mean and variance equations are simultaneously estimated using a full information maximum likelihood estimation (FIML) approach. The trivariate Student-*t* GJR-GARCH-M model is estimated by maximizing the log-likelihood function as follows:

$$\begin{aligned} L(\Theta) &= \ln\Gamma\left(\frac{v^A+n}{2}\right) - \ln\Gamma\left(\frac{v^A}{2}\right) - \frac{n}{2}\ln[(v^A-2)\pi] \\ &\quad - \frac{1}{2}\sum_{t=1}^{T}[\ln|H_t^A| + (v^A+n)\ln(1+\frac{\varepsilon_t' H_t^A \varepsilon_t}{v^A-2})], \quad \text{for } v^A > 2 \end{aligned} \tag{15}$$

where Θ is a parameter vector to be estimated, *n* is the number of variables (i.e., 3), and $\Gamma(\cdot)$ is the gamma function. We use the Constrained Maximum Likelihood (CML) module with the Berndt, Hall, Hall, and Hausman (1974) algorithm—BHHH algorithm in GAUSS to obtain the parameter estimates. Baillie and Bollerslev (1995) point out that using the Student-*t* distribution to accomplish the estimation of the model is appropriate, provided that the estimated degree-of-freedom parameter *v* is significantly greater than 4.

As before, we employ a two-step procedure to estimate the trivariate GJR-GARCH model. In the first step, the model is estimated with a lag length of 5 on each independent variable with a summation sign. In the second step, the model estimated from the first step is reestimated by dropping all insignificant independent variables at the 5% level and simultaneously considering the diagnostic checks of the standardized residuals and squared standardized residuals to make sure that the model is well specified. Thence, some of insignificant coefficients are still kept in the model.

IV. Empirical Results

A. Causality Tests

Table 2 reports the results of the trivariate Granger-causality tests for nine Asian stock markets. The $\chi^2(D^A)$ statistic with D^A degrees of freedom obtained from the likelihood-ratio test based on the causality restrictions and the $\chi^2(1)$ statistic with one degree of freedom obtained from the Wald test based on the null hypothesis that the sum of the lagged coefficients is equal to zero are also shown in the table. In particular, the $\chi^2(1)$ statistic is used to identify the sign of the causal relation. Our empirical procedure for the trivariate Granger-causality tests is to first examine whether a causal relation between the variables exists and then further identify the sign of the causal relation only if there exists a causal relation between the variables.

We only present the results associated with equations (2.1) and (2.2) to save space.[22] The following observations, among other things, are noted.[23] First, at the 5% significance level, domestic trading volume, V_t^A, is Granger-caused by domestic stock returns, R_t^A, in all Asian stock markets under consideration. Moreover, the sum of the lagged β_{12d}^A coefficients is positive and significantly different from zero at the 1% level in all Asian stock markets except for the Singapore stock market whose sum of the lagged $\beta_{12d}^{\mathrm{SI}}$ coefficients is statistically significantly negative. These observations suggest a positive causal relation between lagged domestic stock returns and current domestic trading volume in all Asian stock markets except for Singapore.

Second, the statistical significance of the $\chi^2(D^A)$ statistic indicates that there exists casual relation between lagged U.S. stock returns, R_t^{US}, and current domestic trading volume, V_t^A, in the Taiwan, Singapore, and Thailand stock markets. The sum of the lagged β_{13d}^A

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[22] As for the results associated with equation (2.3), we find that neither of domestic stock returns, R_t^A, and trading volume, V_t^A, Granger-cause U.S. stock returns R_t^{US}, in each Asian stock market.

[23] Sims (1980) and Lee (1992) point out that the results between bivariate and multivariate (e.g., three-variable) causality tests may potentially be different. As a result of this possibility, we check the robustness of our results by using three bivariate models (i.e., domestic trading volume and domestic stock returns, domestic trading volume and U.S. stock returns, and domestic stock returns and U.S. stock returns) and find that the results are still similar to what we report in Table 2. To save space, the results of the bivariate causality tests are not report in the paper.

coefficients and the corresponding $\chi^2(1)$ statistic indicate that this casual relation is significantly positive at the 1% and 10% levels for the Singapore and Thailand markets, respectively. For the Taiwan stock market, the sum of the lagged $\beta_{13d}^{\mathrm{TA}}$ coefficients is positive but the corresponding $\chi^2(1)$ statistic is not significant at conventional levels.

Third, the null hypothesis that domestic stock returns, R_t^A, are not Granger-caused by domestic trading volume, V_t^A, is rejected at the 10% and 1% levels, as indicated by the $\chi^2(D^A)$ statistic, for the Taiwan and Malaysia stock markets, respectively. Moreover, the sum of the lagged $\beta_{21d}^{\mathrm{TA}}$ coefficients and that of the lagged $\beta_{21d}^{\mathrm{MA}}$ coefficients are positive and their corresponding $\chi^2(1)$ statistics are significant at the 5% and 1% levels, respectively, which indicates that there is a significantly positive causal relation between lagged domestic trading volume and current domestic stock returns in the Taiwan and Malaysia stock markets. Combined with the above observations, there is a positive feedback relation between domestic stock returns and domestic trading volume in the Taiwan and Malaysia stock markets.

Fourth, the null hypothesis that domestic stock returns, R_t^A, are not Granger-caused by U.S. stock returns, R_t^{US}, can be rejected at the 1% level for all Asian stock markets, which implies that U.S. stock prices help predict domestic stock prices during the sample period. Moreover, the observation that the sum of the lagged β_{23d}^{A} coefficients is positive and statistically significant at the 1% level for all Asian stock markets implies that U.S. market gains (losses) are followed by domestic market gains (losses) in these stock markets. Combined with the above observations, there exists a positive causality running from U.S. stock returns to domestic stock returns as well as a positive causality running from domestic stock returns to domestic trading volume in all Asian stock markets except for the Singapore stock market.

In sum, based on the results of the causality tests, all Asian investors are encouraged by their domestic market gains to trade more aggressively in subsequent periods except for investors in Singapore, while investors Singapore and Thailand investors are encouraged by U.S. market gains to trade more actively in subsequent periods. Indeed, Thailand investors are encouraged both by their domestic market gains and by U.S. market gains to trade more frequently in subsequent periods. These observations are consistent with the theoretical prediction of the GO (2001) model that overconfident investors mistakenly attribute market gains to their stock selection skills and ability to process information and, as a result, unconsciously trade too much and too speculatively in subsequent periods.

However, care must be taken in drawing a conclusion for the trading behavior of Taiwan and Malaysia investors. Because there exists a positive feedback relation between domestic stock returns and domestic trading volume in the Taiwan and Malaysia stock markets, there is the possibility that the observed causal relation between lagged domestic stock returns and current domestic trading volume in these two stock markets may be part of the story of either the sequential information arrival model or the positive feedback trading hypothesis. Deliberately taking account of this possibility, we decide to exclude the Taiwan and Malaysia stock markets from our succeeding analysis in the following sections.[24]

B. Aggregate Overconfident Trading across Asian Stock Markets

Table 3 reports the estimates of the SUR model of equation (3). The β_d^A coefficients measure the effect of the lagged domestic stock returns on current domestic trading volume. The results show that the statistical significance of the lagged positive β_d^A coefficients illustrates a causal linkage between lagged domestic stock returns and current domestic trading volume for All Asian stock markets with one exception of the Singapore stock market, which is consistent with what we observe from Table 2. Moreover, a coincidence among these six Asian stock markets is the statistical significance of the lagged β_1^A coefficients, which implies that these Asian investors' overconfidence can be quickly fostered by the increases in yesterday's domestic stock returns and they therefore are irrationally encouraged to trade more actively today.

The γ_d^A coefficients measure the effect of the lagged U.S. stock returns on current domestic trading volume. Consistent with the results of Table 2, the results of Table 3 show that the lagged positive γ_d^A coefficients are significant at conventional levels for the Singapore and Thailand stock markets. Combined with the statistical insignificance of the lagged β_d^{SI} and the statistical significance of the lagged β_d^{TH} coefficients, the results imply

[24] Although the causal relation between lagged domestic trading, V_t^{TA}, and current domestic stock returns, R_t^{TA}, is significant only at the 10% level for the Taiwan stock market, the lagged β_{21d}^{TA} coefficients are all positive and β_{211}^{TA} are significant at the 5% level, for the sake of conservatism, we still decide to exclude the Taiwan stock market from our succeeding analysis.

that Singapore investors' overconfident trading is directly attributable to U.S. market gains, while Thailand investors' overconfident trading may be attributable partly to U.S. market gains and partly to they recognize the fact that U.S. market gains tend to be followed by domestic market gains.

In addition, we are also interested in comparing the degree of Asian investors' overconfident trading with each other. However, we fail to obtain the consistent pairwise comparisons and a complete order from the highest degree of investor' overconfident trading to the lowest one. As a consequence, we concentrate our attention on examining whether the degree of Asian investor' overconfident trading differs across seven sample stock markets. The Wald statistic with six degrees of freedom, $\chi^2(6)$, which is reported in the last row of Table 3, is the test result of such an examination. The statistic has a value of 17.789, with a corresponding *p*-value of 0.007 under the $\chi^2(6)$ distribution. This provides evidence that the degree of Asian investors' overconfident trading varies across seven sample stock markets.

As for the diagnostic checks of the model, the Ljung-Box *Q*-statistics for 16 lags show, in general, no evidence of time-varying dependencies in the residuals, indicating the appropriateness of the estimated SUR model. Further, except for the Ljung-Box test on the squared residuals of V_t^{IN} and V_t^{TH}, all the others show significant evidence of time-varying dependencies, suggesting the possibility of the presence of autoregressive conditional heteroskedasticity.[25]

C. The Effect of Exchange Rate Movements on Asian Investors' Overconfident Trading

To investigate the effect of exchange rate movements on Asian investors' overconfident trading, we use our two-step procedure to estimate the SUR model of equations (4.1) and (4.2). Unfortunately, some of two volume equations associated with the same stock market are identical based on our two-step procedure. As a consequence, we only estimate the SUR model of equation (4.2) and the results are reported in Table 4.

A few notable observations emerge from Tables 3 and 4. Compared the estimates of equation (4.2) that use U.S. stock returns denominated in Asian currencies with those of equation (3) that use U.S. stock returns denominated in U.S. dollars, there only exist slight differences in the estimates of the control variables. Most importantly, the results of Table 4

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[25] The $Q^2(8)$ statistic for V_t^{IN} and V_t^{TH} is 20.980 with a *p*-value of 0.007 and 16.736 with a *p*-value of 0.033, respectively.

show that the estimated β_{2d}^{A} and γ_{2d}^{A} coefficients in equation (4.2) which are statistically significant at least at the 5% are identical to the corresponding estimated β_{d}^{A} and γ_{d}^{A} coefficients in equation (3) with one exception of the lagged $\gamma_{22}^{\mathrm{IN}}$ coefficient which now is statistically significant at the 1% level. Moreover, the magnitudes and significance levels of the estimated β_{2d}^{A} and γ_{2d}^{A} coefficients in equation (4.2) are very similar to those of the corresponding estimated β_{d}^{A} and γ_{d}^{A} coefficients in equation (3).

Overall, the results of the causal relations among domestic trading volume, domestic stock returns, and U.S. stock returns remain virtually unchanged regardless of whether U.S. stock returns are denominated in U.S. dollars or Asian currencies. This provides evidence that Asian investors' overconfident trading is not affected by exchange rate movements, which implies that they underestimate exchange rate risks and underweight relevant, important information. Indeed, these are two well-known symptoms of overconfident investors.

D. Asian Investors' Overconfident Trading Conditional on the Market States

Table 5 reports a summary of the estimates of equation (5). We present only the results with the bull dummies of $D_{mw,t}^{A}$ and $D_{mw,t}^{\mathrm{US}}$ with m = 3 and w = 2 to conserve space in that those with the bull dummies defined using the other possible values of m and w yield the similar results.[26] The following observations, among other things, are noted. First, Table 5 shows that the Japanese, Hong Kong, Philippines, Indonesia, and Thailand stock markets have a stronger positive relation between lagged domestic stock returns and current domestic trading volume in bull markets than in non-bull markets, which implies that Asian investors in these five stock markets trade more actively subsequent to their domestic market gains as their domestic market is in bull markets than in non-bull markets. With respect to investors in Korea, their overconfident trading exhibits no significant differences across the state of their domestic market.

Second, of five Asian stock markets with a positive relation between current domestic trading volume and lagged U.S. stock returns, the Korea and Hong Kong stock markets have

[26] We also consider a joint bull dummy of $D_{mw,t}^{A-\mathrm{US}}$ which is defined as the intersection of two bull dummies of $D_{mw,t}^{A}$ and $D_{mw,t}^{\mathrm{US}}$ and substitute $D_{mw,t}^{A-\mathrm{US}}$ into $D_{mw,t}^{A}$ to estimate equation (5) in order to see whether Asian investors trade particularly aggressively after the increases in their domestic or U.S. stock returns as both of the domestic and U.S. markets are in bull markets. We find that the results yielded from this alternative bull dummy are similar to what we report in Table 5.

such a relation stronger in bull markets than in non-bull markets and the Japanese, Singapore, and Thailand stock markets have such a relation stronger in non-bull markets than in bull markets. These observations imply that investors in Korea and Hong Kong, as expected, trade more aggressively following U.S. market gains as the U.S. stock market in bull markets than in non-bull markets and that investors in Japan, Singapore, and Thailand, as unexpected, trade more aggressively following U.S. market gains as the U.S. stock market in non-bull markets than in bull markets.

Finally, compared to the identified overconfident trading of Asian investors in Tables 3 and 4, the results of Table 5 show that Asian investors' overconfident trading is more easily identified when it is conditional on the market states. For example, in Tables 3 and 4, we do not observe that investors in Japan, Korea, and Hong Kong trade actively in response to past U.S. market gains. Now, we observe from Table 5 that investors in Japan trade actively in response to past U.S. market gains as the U.S. stock market is in non-bull markets and that investors in Korea and Hong Kong trade actively in response to past U.S. market gains as the U.S. stock market is in bull markets.

E. The Effect of Biased Self-Attribution on Asian Investors' Overconfident Trading

Table 6 presents the estimates of the trivariate GJR-GARCH-M model. We start from discussing the results associated with the lagged domestic stock returns and then those associated with the lagged U.S. stock returns, and these results are reported in Panel A of Table 6. If biased self-attribution causes Asian investors to make overconfident trading, all estimated beta coefficients should be significantly positive. Specifically, the estimated β_{11e}^{A} coefficients, as expected, are significantly positive at conventional levels for the Japanese, Korean, Philippines, Indonesia, and Singapore stock markets, which implies that investors in these stock markets, though making a wrong forecast for future domestic stock returns, engage in overconfident trading as long as past domestic stock returns are positive. For the Korean stock market, the estimated positive $\beta_{125}^{\mathrm{KO}}$ coefficient, coupled with the estimated positive $\beta_{111}^{\mathrm{KO}}$ coefficient, implies that Korean investors trade more actively subsequent to domestic market gains as they make a right but less precise forecast for future domestic stock returns than as they make a wrong forecast. For the Thailand stock market, its estimated positive $\beta_{131}^{\mathrm{TH}}$ coefficient implies that Thailand investors trade more actively subsequent to domestic market gains only as they make a right and more precise forecast for future domestic stock returns.

The results associated with U.S. stock returns are somewhat different from those associated with domestic stock returns. Specifically, Asian investors are not devoted to overconfident trading if they make a wrong forecast for future U.S. stock returns. The statistical significance of the estimated positive $\gamma_{122}^{\mathrm{KO}}$ and $\gamma_{124}^{\mathrm{TH}}$ coefficients implies that Korea and Thailand investors are devoted to overconfident trading following U.S. market gains as they make a right but less precise forecast for future U.S. stock returns than as they make a wrong forecast. Moreover, the statistical significance of the estimated positive γ_{13e}^{A} coefficients implies that Japanese, Korean, and Singapore investors make more overconfident trading following U.S. market gains only as they make a right and more precise forecast for future U.S. stock returns and that Hong Kong investors make more overconfident trading following U.S. market gains as they make a right and more precise forecast for future U.S. stock returns than as they make a right but less precise forecast and as they make a wrong forecast.

In sum, Korean investors' overconfident trading triggered by domestic market gains increases more as they make a right but less precise forecast for future domestic stock returns than as they make a wrong forecast. Thailand investors trade overconfidently in response to past domestic market gains only as they make a right and more precise forecast for future domestic stock returns. Japanese, Korean, and Singapore investors make overconfident trading in response to past U.S. market gains only as they make a right and more precise for future U.S. stock returns, while Thailand investors make more overconfident trading in response to past U.S. market gains only as they make a right but less precise forecast for future U.S. stock returns. Hong Kong investors tend to trade more aggressively following U.S. market gains as they a right and more precise forecast for future U.S. stock returns than as they make a wrong forecast. These findings, in essence, are consistent with biased self-attribution.

Previous studies have demonstrated the presence of the leverage effect that a negative shock has a larger impact on volatility than does a positive shock. Inspection of Panel B of Table 6, we find that the volatility parameter φ_2^{A} is statistically significantly positive for the Japanese, Hong Kong, and Philippines stock markets and that the volatility parameter φ_3^{A} is statistically significantly positive for the U.S. stock market, suggesting the leverage effect exists in these stock markets. But we no evidence of the leverage effect in the Korea, Indonesia, Singapore, and Thailand stock markets.

With respect to the spillover effect, we find evidence from Panel A of Table 6 that the statistical significance of the estimated ϕ_i^A coefficients for all Asian stock markets illustrate the return spillover effect from the U.S. stock market to these stock markets. Moreover, the results of Panel B of Table 6 show that the statistical significance of the estimated δ_2^{JA}, δ_2^{SI}, and δ_2^{TH} coefficients illustrate the volatility effect from the U.S. stock market to the Japanese, Singapore, and Thailand stock markets.

Lastly, as noted from the results of previous tables, the fact that domestic trading volume, domestic stock returns, and U.S. stock returns display significant linear and nonlinear dependencies suggests that it is appropriate to employ the GARCH specification to model their dynamic processes. The Ljung-Box *Q*-statistics for 8 and 16 lags, which are reported in Panel D of Table 6, show no evidence of any type of linear and nonlinear dependencies in the standardized residuals and squared standardized residuals, which demonstrates that the estimated trivariate GJR-GARCH-M model appropriately capture linear and nonlinear dependencies in domestic trading volume, domestic stock returns, and U.S. stock returns.

V. Concluding Remarks

Evidence on U.S. investors' involvement in overconfident trading is well documented in previous studies. Yet, to date there is little empirical evidence that investors in other areas dedicate themselves to overconfident trading. This article takes a step toward filling this void in the literature by showing that Asian investors also engage in overconfident trading. More importantly, we extend previous studies by taking into account the effect of U.S. market gains on Asian investors' overconfident trading. Our empirical results are summarized as follows.

First, we find that U.S. market gains are always followed by the domestic market gains of all Asian stock markets under examination. Investors in Thailand trade more aggressively following domestic as well as U.S. market gains, investors in Singapore trade more actively following U.S. market gains, and investors in Japan, Korea, Hong Kong, Philippines, and Indonesia trade more frequently following domestic market gains. These findings are consistent with the theoretical predictions of the GO (2001) model that market gains make investors overconfident and consequently trade excessively in subsequent periods and provide evidence that Asian investors, like U.S. investors, trade overconfidently.

Second, we find that Asian investors appear to underestimate exchange rate risks in that the pattern of their overconfident trading is not affected if we use local currency-adjusted returns in our analysis. This finding is accordance with the notion of overconfidence that overconfident investors tend to underestimate the risk and underweight relevant, important information.

Third, we find that Japanese, Hong Kong, Philippines, Indonesia, and Thailand investors trade more aggressively following domestic market gains as their domestic stock markets are in bull markets than in non-bull markets and that Korean and Hong Kong investors trade more actively following U.S. market gains as the U.S. stock markets are in bull markets than in non-bull markets, which is consistent with the argument by Odean (1998) and GO (2001) that investors' overconfident trading is likely to significantly rise right after a bull market. Inconsistent with their argument, however, we find that Korean investors' overconfident trading induced by domestic market gains exhibits no significant differences across the state of their domestic stock market and that Japanese, Singapore, and Thailand investors' overconfident trading induced by U.S. market gains is more conspicuous as the U.S. stock market is in non-bull market than in bull markets. As such, our empirical examination yields mixed results regarding Asian investors' overconfident trading conditional on the market states.

Finally, we find that Asian investors' overconfident trading behavior is, in essence, consistent with the theoretical predictions of the Daniel et al. (1998) and GO (2001) models in which biased self-attribution makes investors learn to be overconfident. Specifically, we find that Korean investors make more overconfident trading after the increases in their domestic stock returns as they make right but less precise forecasts for future domestic stock returns than as they make wrong forecasts and that Thailand investors make overconfident trading after the increases in their domestic stock returns only as they make right and more precise forecasts for future domestic stock returns. In addition, Japanese, Korean, and Singapore investors trade overconfidently following U.S. market gains only as they make right and more precise forecasts for future U.S. stock returns, while Thailand investors trade overconfidently following U.S. market gains only as they make right but less precise forecasts for future U.S. stock returns. Hong Kong investors' overconfident trading increases more in response to past U.S. market gains as they make right and more precise forecasts for future U.S. stock returns than as they make right but less precise forecasts.

Overall, our study provides extensive evidence that Asian investors engage in overconfident trading. Their overconfident trading corresponds to underestimate risk and underreact to relevant, important information, and is affected both by the market states and by a self-attribution bias. In addition to providing the existing literature with out-of-sample evidence on investors' overconfident trading, our study sheds additional light on understanding the causes and complexities of investors' overconfident trading. There are, of course, several aspects of investors' overconfident trading extant studies have left unaddressed. For example, according to the overconfidence hypothesis, overconfident investors tend to overestimate the precision of their private information. Although Chuang and Lee (2005) present evidence that overconfident U.S. investors overreact to private information and underreact to public information, they do not attempt to investigate the relation between investors' overconfident trading and the types of information. We conjecture that investors' overconfident trading should respond more to private information than public information. For the present, we leave this as a topic for future research.

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TABLE 1
Descriptive Statistics of Daily Sample

Market	Japan (JA)		Korea (KO)		Taiwan (TA)		Hong Kong (HK)		Philippines (PH)	
Index	TOPIX		KOSPI		TWI		HSI		PSECI	
Variable	Return	Volume	Return	Volume	Return	Volume	Return	Volume	Return	Volume
Mean	-0.002	0.000	0.063	0.000	-0.022	0.000	0.025	0.000	-0.002	0.000
Std. dev.	1.536	0.273	2.804	0.193	2.076	0.223	2.063	0.322	1.954	0.617
Skewness	0.024	-3.459***	-0.237***	0.407***	-0.103	0.043	0.291***	0.430***	1.653***	0.613***
Excess Kurtosis	2.470***	36.400***	3.327***	0.901***	3.782***	1.015***	7.134***	6.655***	16.675***	1.849***
D-stat.	0.042***	0.124***	0.063***	0.048***	0.060***	0.018	0.071***	0.043***	0.102***	0.034***
ARCH(8)	20.451***	37.139***	31.006***	78.549***	27.831***	66.279***	71.271***	19.142**	22.833***	50.120***
ADF	-22.237***	-35.115***	-22.030***	-35.391***	-15.820***	-35.046***	-20.748***	-35.735***	-12.538***	-35.875***
Lags (*L*)	(2)	(0)	(2)	(0)	(4)	(0)	(2)	(0)	(5)	(0)
Market	Indonesia (IN)		Malaysia (MA)		Singapore (SI)		Thailand (TH)		U.S.	
Index	JKSE		KLSE		STI		SET		S&P 500	NASDAQ
Variable	Return	Volume	Return	Volume	Return	Volume	Return	Volume	Return	Return
Mean	0.070	0.000	0.0340	0.000	0.025	0.000	0.047	0.000	0.026	0.024
Std. dev.	2.316	0.483	1.942	0.376	1.862	0.487	2.328	0.350	1.470	2.387
Skewness	0.403***	-0.885***	1.106***	-1.358***	-0.028	-0.218***	1.476***	0.474***	0.111	0.000
Excess Kurtosis	10.796***	13.521***	16.662***	28.692***	7.600***	7.309***	20.632***	0.820***	2.082***	3.058***
D-stat.	0.094***	0.059***	0.123***	0.052***	0.082***	0.093***	0.076***	0.059***	0.050***	*0.048****
ARCH(8)	135.561***	17.065**	113.158***	58.722***	58.545***	81.201***	25.886***	15.892**	120.630***	96.430***
ADF	-10.873***	-35.928***	-9.830***	-35.536***	-17.796***	-35.836***	-22.684***	-24.299***	-10.565***	-33.423***
Lags (*L*)	(8)	(0)	(10)	(0)	(3)	(0)	(2)	(1)	(7)	(0)

This table reports descriptive statistics on the time series of the daily index returns and detrended trading volume for the sample period from January 5, 1998 to December 30, 2004. The null hypotheses for the skewness and excess kurtosis are that they are equal to zero. The *D*-statistic denotes the Kolmogorov-Smirnov test for normality. ARCH(8) denotes the chi-squared statistic of the Lagrange Multiplier test for autoregressive conditional heteroskedasticity effect with 8 lags. ADF denotes the *t*-statistic of the augmented Dickey-Fuller test (1979) for a unit root. The lag length in the ADF test is chosen by considering Akaike Information Criterion (AIC).

Note:

1. Critical values for the Kolmogorov-Smirnov *D*-statistic with observations are: 0.023, 10%, 0.025, 5%, and 0.029, 1%.
2. Critical values for the ADF unit root statistic with observations are: -2.57, 10%, -2.86, 5%, and -3.43, 1% (Fuller, 1976, Table 8.5.2, p. 373).
3. ***, **, * denote significant level at the 1%, 5%, and 10%, respectively.

TABLE 2
Causality Tests

The following Seemingly Unrelated Regression (SUR) model is estimated to investigate the causal relations among domestic trading volume, domestic stock returns, and U.S. stock returns for each Asian stock market *A* over the sample period from January 1998 to December 2004:

$$V_t^A = \alpha_{11}^A + \sum_{b=0}^{B^A} \alpha_{12b}^A \,| R_{t-b}^A | + \sum_{c=1}^{C^A} \alpha_{13c}^A \,| R_{t-c}^{\mathrm{US}} | + \sum_{d=1}^{D^A} \beta_{11d}^A V_{t-d}^A + \sum_{d=1}^{D^A} \beta_{12d}^A R_{t-d}^A + \sum_{d=1}^{D^A} \beta_{13d}^A R_{t-d}^{\mathrm{US}} + \varepsilon_{1,t}^A, \tag{2.1}$$

$$R_t^A = \alpha_{21}^A + \sum_{d=1}^{D^A} \beta_{21d}^A V_{t-d}^A + \sum_{d=1}^{D^A} \beta_{22d}^A R_{t-d}^A + \sum_{d=1}^{D^A} \beta_{23d}^A R_{t-d}^{\mathrm{US}} + \varepsilon_{2,t}^A, \tag{2.2}$$

$$R_t^{\mathrm{US}} = \alpha_{31}^A + \sum_{d=1}^{D^A} \beta_{31d}^A V_{t-d}^A + \sum_{d=1}^{D^A} \beta_{32d}^A R_{t-d}^A + \sum_{d=1}^{D^A} \beta_{33d}^A R_{t-d}^{\mathrm{US}} + \varepsilon_{3,t}^A, \tag{2.3}$$

where V_t^A is the domestic trading volume at time *t*, R_t^A is the domestic return at time *t*, $| R_t^A |$ is the absolute value of R_t^A at time *t*, R_t^{US} is the U.S. stock return at time *t*, $| R_t^{\mathrm{US}} |$ is the absolute value of R_t^{US} at time *t*, and the superscript *A* represents Asian stock markets *A*. The number of lags in each equation is selected by considering both the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC).

Asian Stock Market *A*	JA (Japan)			
Dependent Variable	V_t^{JA}		R_t^{JA}	
Independent Variable (D^A = 2)	R_{t-d}^{JA}	R_{t-d}^{US}	V_{t-d}^{JA}	R_{t-d}^{US}
Lagged Coefficient	$\beta_{12d}^{\mathrm{JA}}$	$\beta_{13d}^{\mathrm{JA}}$	$\beta_{21d}^{\mathrm{JA}}$	$\beta_{23d}^{\mathrm{JA}}$
$\chi^2(D^A)$ (*p*-value)	11.526 (0.003)	1.861 (0.394)	0.306 (0.858)	116.415 (0.000)
Sum of Lagged Coefficients	0.023			0.318
$\chi^2(1)$ (*p*-value)	9.024 (0.003)			53.999 (0.000)
Asian Stock Market *A*	**KO (Korea)**			
Dependent Variable	V_t^{KO}		R_t^{KO}	
Independent Variable (D^A = 3)	R_{t-d}^{KO}	R_{t-d}^{US}	V_{t-d}^{KO}	R_{t-d}^{US}
Lagged Coefficient	$\beta_{12d}^{\mathrm{KO}}$	$\beta_{13d}^{\mathrm{KO}}$	$\beta_{21d}^{\mathrm{KO}}$	$\beta_{23d}^{\mathrm{KO}}$
$\chi^2(D^A)$ (*p*-value)	34.995 (0.000)	1.658 (0.646)	1.510 (0.680)	92.627 (0.000)
Sum of Lagged Coefficients	0.018			0.741
$\chi^2(1)$ (*p*-value)	22.820 (0.000)			60.225 (0.000)
Asian Stock Market *A*	**TA (Taiwan)**			
Dependent Variable	V_t^{TA}		R_t^{TA}	
Independent Variable (D^A = 3)	R_{t-d}^{TA}	R_{t-d}^{US}	V_{t-d}^{TA}	R_{t-d}^{US}
Lagged Coefficient	$\beta_{12d}^{\mathrm{TA}}$	$\beta_{13d}^{\mathrm{TA}}$	$\beta_{21d}^{\mathrm{TA}}$	$\beta_{23d}^{\mathrm{TA}}$
$\chi^2(D^A)$ (*p*-value)	40.240 (0.000)	37.7291 (0.000)	7.191 (0.066)	60.070 (0.000)
Sum of Lagged Coefficients	0.022	0.006	1.197	0.476
$\chi^2(1)$ (*p*-value)	13.865 (0.000)	0.727 (0.394)	5.652 (0.022)	44.644 (0.000)
Asian Stock Market *A*	**HK (Hong Kong)**			
Dependent Variable	V_t^{HK}		R_t^{HK}	
Independent Variable (D^A = 2)	R_{t-d}^{HK}	R_{t-d}^{US}	V_{t-d}^{HK}	R_{t-d}^{US}
Lagged Coefficient	$\beta_{12d}^{\mathrm{HK}}$	$\beta_{13d}^{\mathrm{HK}}$	$\beta_{21d}^{\mathrm{HK}}$	$\beta_{23d}^{\mathrm{HK}}$
$\chi^2(D^A)$ (*p*-value)	30.406 (0.000)	3.763 (0.152)	2.192 (0.334)	132.136 (0.000)

Sum of Lagged Coefficients	0.037			0.534
$\chi^2(1)$ (p-value)	29.761 (0.000)			83.534 (0.000)
Asian Stock Market A	PH (Philippines)			
Dependent Variable	V_t^{PH}		R_t^{PH}	
Independent Variable (D^A = 2)	R_{t-d}^{PH}	R_{t-d}^{US}	V_{t-d}^{PH}	R_{t-d}^{US}
Lagged Coefficient	β_{12d}^{PH}	β_{13d}^{PH}	β_{21d}^{PH}	β_{23d}^{PH}
$\chi^2(D^A)$ (p-value)	11.641 (0.003)	0.354 (0.838)	1.804 (0.406)	44.658 (0.000)
Sum of Lagged Coefficients	0.038			0.262
$\chi^2(1)$ (p-value)	8.796 (0.003)			24.711 (0.000)
Asian Stock Market A	IN (Indonesia)			
Dependent Variable	V_t^{IN}		R_t^{IN}	
Independent Variable (D^A = 3)	R_{t-d}^{IN}	R_{t-d}^{US}	V_{t-d}^{IN}	R_{t-d}^{US}
Lagged Coefficient	β_{12d}^{IN}	β_{13d}^{IN}	β_{21d}^{IN}	β_{23d}^{IN}
$\chi^2(D^A)$ (p-value)	19.529 (0.000)	2.656 (0.448)	2.473 (0.480)	19.403 (0.000)
Sum of Lagged Coefficients	0.043			0.290
$\chi^2(1)$ (p-value)	18.294 (0.000)			16.021 (0.000)
Asian Stock Market A	MA (Malaysia)			
Dependent Variable	V_t^{MA}		R_t^{MA}	
Independent Variable (D^A = 5)	R_{t-d}^{MA}	R_{t-d}^{US}	V_{t-d}^{MA}	R_{t-d}^{US}
Lagged Coefficient	β_{12k}^{MA}	β_{13k}^{MA}	β_{21k}^{MA}	β_{23k}^{MA}
$\chi^2(D^A)$ (p-value)	33.746 (0.000)	6.107 (0.296)	24.706 (0.000)	50.215 (0.000)
Sum of Lagged Coefficients	0.051		1.114	0.279
$\chi^2(1)$ (p-value)	18.804 (0.000)		11.379 (0.001)	11.820 (0.001)
Asian Stock Market A	SI (Singapore)			
Dependent Variable	V_t^{SI}		R_t^{SI}	
Independent Variable (D^A = 3)	R_{t-d}^{SI}	R_{t-d}^{US}	V_{t-d}^{SI}	R_{t-d}^{US}
Lagged Coefficient	β_{12d}^{SI}	β_{13d}^{SI}	β_{21d}^{SI}	β_{23d}^{SI}
$\chi^2(D^A)$ (p-value)	10.784 (0.013)	15.319 (0.002)	5.480 (0.140)	83.723 (0.000)
Sum of Lagged Coefficients	-0.027	0.064		0.449
$\chi^2(1)$ (p-value)	3.841 (0.050)	12.639 (0.000)		51.772 (0.000)
Asian Stock Market A	TH (Thailand)			
Dependent Variable	V_t^{TH}		R_t^{TH}	
Independent Variable (D^A = 3)	R_{t-d}^{TH}	R_{t-d}^{US}	V_{t-d}^{TH}	R_{t-d}^{US}
Lagged Coefficient	β_{12d}^{TH}	β_{13d}^{TH}	β_{21d}^{TH}	β_{23d}^{TH}
$\chi^2(D^A)$ (p-value)	27.374 (0.000)	10.757 (0.013)	3.677 (0.299)	31.686 (0.000)
Sum of Lagged Coefficients	0.025	0.019		0.418
$\chi^2(1)$ (p-value)	10.017 (0.002)	2.820 (0.093)		27.834 (0.000)

The $\chi^2(D^A)$ statistic is the Chi-square statistic with D^A degrees of freedom obtained from a joint test of the null hypothesis based on the causality restrictions and the corresponding p-value is the probability of the $\chi^2(D^A)$ statistic under the null hypothesis for Asian stock market A. The $\chi^2(1)$ statistic is the Chi-square statistic with one degree of freedom under the null hypothesis that the sum of lagged coefficients is equal to zero and the corresponding p-value is the probability of the $\chi^2(1)$ statistic under the null hypothesis. Sims' (1980, p.17) multiplier correction is employed to improve the small sample properties of the test.

TABLE 3
Aggregate Causal Relations among Current Domestic Trading Volume, Lagged Domestic Stock Returns, and Lagged U.S. Stock Returns across Asian Stock Markets

The following Seemingly Unrelated Regression (SUR) model is estimated using a two-step procedure to investigate the causal relations among domestic trading volume, domestic stock returns, and U.S. stock returns across seven Asian stock markets over the sample from January 1998 to December 2004. In the first step, the SUR model is estimated with a lag length of $D^A = 5$ on each independent variable of Asian stock market A. In the second step, the SUR model estimated from the first-stage procedure is reestimated by dropping all insignificant independent variables at the 5% level:

$$V_t^A = \alpha_1^A + \sum_{d=0}^{D^A} \alpha_{2d}^A \,|\, R_{t-d}^A \,| + \sum_{d=1}^{D^A} \alpha_{3d}^A \,|\, R_{t-d}^{\mathrm{US}} \,| + \sum_{d=1}^{D^A} \beta_d^A R_{t-d}^A + \sum_{d=1}^{D^A} \gamma_d^A R_{t-d}^{\mathrm{US}} + \varepsilon_t^A, \qquad (3)$$

where V_t^A is the domestic trading volume at time t, R_t^A is the domestic return at time t, $|\, R_t^A \,|$ is the absolute value of R_t^A at time t, R_t^{US} is the U.S. stock market return at time t, $|\, R_t^{\mathrm{US}} \,|$ is the absolute value of R_t^{US} at time t, the superscript A represents the cross-sectional units of seven Asian stock markets, and the subscript t represents the daily time unit.

Asian Stock Market A	JA (Japan)	KO (Korea)	HK (Hong Kong)	PH (Philippines)	IN (Indonesia)	SI (Singapore)	TH (Thailand)
Dependent Variable	V_t^{JA}	V_t^{KO}	V_t^{HK}	V_t^{PH}	V_t^{IN}	V_t^{SI}	V_t^{TH}
α_1^A	-0.022 (-1.612)	-0.041*** (-4.406)	-0.072*** (-5.243)	-0.056** (-2.447)	-0.087*** (-4.894)	-0.061** (-2.532)	-0.052** (-2.520)
α_{20}^A	0.038*** (5.149)	0.012*** (4.505)	0.076*** (12.582)	0.046*** (3.632)	0.058*** (7.161)	0.042*** (3.972)	0.074*** (12.336)
α_{21}^A							-0.011 (-2.041)**
α_{22}^A	-0.018** (-2.478)		-0.024*** (-4.219)				
α_{23}^A						-0.027** (-2.458)	
α_{24}^A							-0.019*** (-3.568)
α_{25}^A							-0.012** (-2.185)
α_{32}^A		0.015*** (2.856)					-0.027*** (-2.909)
α_{33}^A						0.039***	

						(2.740)	
α_{34}^{A}							0.029***
							(3.100)
β_{1}^{A}	0.019***	0.011***	0.018***	0.030***	0.017***		0.018***
	(3.835)	(5.819)	(4.422)	(3.417)	(2.984)		(4.535)
β_{2}^{A}			0.010**		0.014**		
			(2.434)		(2.419)		
β_{3}^{A}		0.006***				-0.024***	
		(2.934)				(-3.013)	
β_{4}^{A}	0.012**						
	(2.512)						
β_{5}^{A}	0.011**						
	(2.191)						
γ_{1}^{A}						0.018**	
						(1.972)	
γ_{3}^{A}						0.028***	0.014**
						(2.931)	(2.325)
$\overline{R}^2$	0.007	0.014	0.095	-0.013	0.015	-0.002	0.101
$Q(16)$	7.147	18.164	20.686	12.844	15.816	21.435	17.778
(p-value)	(0.970)	(0.315)	(0.191)	(0.684)	(0.466)	(0.162)	(0.337)
$Q^2(16)$	135.638	204.829	46.071	67.453	22.590	156.183	21.697
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.125)	(0.000)	(0.153)
Sum of the Lagged β_{d}^{A} and γ_{d}^{A} Coefficients	0.042	0.017	0.028	0.030	0.032	0.046	0.032
$\chi^2(6)$				17.789			
(p-value)				(0.007)			

$\overline{R}^2$ is the adjusted coefficient of determination. $Q(16)$ and $Q^2(16)$ are the Ljung-Box Q-statistics used to test the joint significance of the autocorrelations up to 16 lags for the residuals and squared residuals, respective. The $\chi^2(6)$ statistic is the Chi-square statistic with six degrees of freedom under the null hypothesis that the sum of the lagged positive β_{d}^{A} and γ_{d}^{A} coefficients is equal for all A. t-statistics are shown in parentheses below the estimated coefficients.
*** and ** denote significance at the 1% and 5% levels, respectively.

TABLE 4

Aggregate Causal Relations among Current Domestic Trading Volume, Lagged Domestic Stock Returns, and Lagged U.S. Stock Returns Using Asian Currency-Based Data across Asian Stock Markets

The following Seemingly Unrelated Regression (SUR) model is estimated using a two-step procedure to investigate the causal relations among domestic trading volume, domestic stock returns, and U.S. stock returns using Asian currency-based data across seven Asian stock markets over the sample from January 1998 to December 2004. In the first step, the SUR model is estimated with a lag length of $D^A = 5$ on each independent variable of Asian stock market A. In the second step, the SUR model estimated from the first step procedure is reestimated by dropping all insignificant independent variables at the 5% level:

$$V_t^A = \alpha_{21}^A + \sum_{d=0}^{D^A} \alpha_{22d}^A \mid R_{t-d}^A \mid + \sum_{d=1}^{D^A} \alpha_{23d}^A \mid R_{t-d}^{A-\text{US}} \mid + \sum_{d=1}^{D^A} \beta_{2d}^A R_{t-d}^A + \sum_{d=1}^{D^A} \gamma_{2d}^A R_{t-d}^{A-\text{US}} + \varepsilon_{2t}^A, \quad (4.2)$$

where V_t^A is the domestic trading volume at time t, R_t^A is the domestic stock return at time t, $\mid R_t^A \mid$ is the absolute value of R_t^A at time t, $R_t^{A-\text{US}}$ is the U.S. stock return denominated in country A currency at time t, $\mid R_t^{A-\text{US}} \mid$ is the absolute value of $R_t^{A-\text{US}}$ at time t, the superscript A represents the cross-sectional units of seven Asian stock markets, and the subscript t represents the daily time unit.

Asian Stock Market *A*	JA (Japan)	KO (Korea)	HK (Hong Kong)	PH (Philippines)	IN (Indonesia)	SI (Singapore)	TH (Thailand)
Dependent Variable	V_t^{JA}	V_t^{KO}	V_t^{HK}	V_t^{PH}	V_t^{IN}	V_t^{SI}	V_t^{TH}
α_{21}^A	-0.041*** (-2.681)	-0.025*** (-3.346)	-0.071*** (-5.155)	-0.012 (-0.491)	-0.061*** (-3.104)	-0.024 (-0.875)	-0.051*** (-2.618)
α_{220}^A	0.038*** (5.256)	0.012*** (4.561)	0.076*** (12.566)	0.046*** (3.706)	0.060*** (7.431)	0.043*** (4.015)	0.071*** (11.968)
α_{222}^A	-0.019** (-2.258)						
α_{223}^A						-0.023** (-2.087)	
α_{224}^A							-0.019*** (-3.487)
α_{225}^A							-0.013** (-2.357)
α_{232}^A			-0.025*** (-4.355)	-0.036** (-2.310)	-0.017*** (-2.948)	-0.030** (-2.307)	-0.029*** (-3.491)
α_{233}^A						0.029** (2.165)**	
α_{234}^A							0.021** (2.523)

α_{235}^{A}	0.001***						
	(1.795)						
β_{21}^{A}	0.018***	0.011***	0.018***	0.030***	0.020***		0.017***
	(3.768)	(5.814)	(4.359)	(3.327)	(3.433)		(4.332)
β_{22}^{A}			0.010**		0.012**		
			(2.421)		(2.098)		
β_{23}^{A}		0.005***				-0.022***	
		(2.668)				(-2.786)	
β_{24}^{A}	0.012**						
	(2.392)						
β_{25}^{A}	0.011**						
	(2.312)						
γ_{21}^{A}						0.019**	
						(2.219)	
γ_{22}^{A}					-0.012***		
					(-2.646)		
γ_{23}^{A}						0.021**	0.012**
						(2.362)	(2.062)
$\overline{R}^{2}$	0.010	0.001	0.093	-0.012	0.025	-0.006	0.094
$Q(16)$	6.980	18.353	20.531	13.491	17.290	22.615	16.809
(p-value)	(0.974)	(0.304)	(0.197)	(0.637)	(0.367)	(0.124)	(0.398)
$Q^{2}(16)$	136.066	225.975	46.232	67.498	39.346	166.494	21.971
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.144)
Sum of the Lagged β_{2k}^{A} and γ_{2k}^{A} Coefficients	0.041	0.016	0.028	0.030	0.032	0.040	0.029
$\chi^{2}(6)$				16.367			
(p-value)				(0.012)			

$\overline{R}^{2}$ is the adjusted coefficient of determination. $Q(16)$ and $Q^{2}(16)$ are the Ljung-Box Q-statistics used to test the joint significance of the autocorrelations up to 16 lags for the residuals and squared residuals, respective. The $\chi^{2}(6)$ statistic is the Chi-square statistic with six degrees of freedom under the null hypothesis that the sum of the lagged positive β_{2d}^{A} and γ_{2d}^{A} coefficients is equal for all A. t-statistics are shown in parentheses below the estimated coefficients.
*** and ** denote significance at the 1% and 5% levels, respectively.

TABLE 5

Aggregate Causal Relations among Current Domestic Trading Volume, Lagged Domestic Stock Returns, and Lagged U.S. Stock Returns Conditional on the Market States across Asian Stock Markets

The following Seemingly Unrelated Regression (SUR) model is estimated using a two-step procedure to investigate the causal relations among domestic trading volume, domestic stock returns, and U.S. stock returns conditional on the market states across seven Asian stock markets over the sample from January 1998 to December 2004. In the first step, the SUR model is estimated with a lag length of $D^A = 5$ on each independent variable of Asian stock market *A*. In the second step, the SUR model estimated from the first-stage procedure is reestimated by dropping all insignificant independent variables at the 5% level:

$$V_t^A = \alpha_{10}^A + \sum_{d=0}^{D^A} \alpha_{2d}^A \,|\, R_{t-d}^A \times D_{mw,t-d}^A \,| + \sum_{d=0}^{D^A} \alpha_{3d}^A \,|\, R_{t-d}^A \times (1 - D_{mw,t-d}^A) \,| + \sum_{d=1}^{D^A} \alpha_{4d}^A \,|\, R_{t-d}^{US} \times D_{mw,t-d}^{US} \,| + \sum_{d=1}^{D^A} \alpha_{5d}^A \,|\, R_{t-d}^{US} \times (1 - D_{mw,t-d}^{US}) \,|$$
$$+ \sum_{d=1}^{D^A} \beta_{1d}^A (R_{t-d}^A \times D_{mw,t-d}^A) + \sum_{d=1}^{D^A} \beta_{2d}^A (R_{t-d}^A \times (1 - D_{mw,t-d}^A)) + \sum_{d=1}^{D^A} \gamma_{1d}^A (R_{t-d}^{US} \times D_{mw,t-d}^{US}) + \sum_{d=1}^{D^A} \gamma_{2d}^A (R_{t-d}^{US} \times (1 - D_{mw,t-d}^{US})) + \varepsilon_t^A, \quad (5)$$

where V_t^A is the domestic trading volume at time *t*, R_t^A is the domestic return at time *t*, $|R_t^A|$ is the absolute value of R_t^A at time *t*, R_t^{US} is the U.S. stock market return at time *t*, $|R_t^{US}|$ is the absolute value of R_t^{US} at time *t*, the superscript *A* represents the cross-sectional units of seven Asian stock markets, and the subscript *t* represents the daily time unit. The dummy variable $D_{mw,t}^A$ ($D_{mw,t}^{US}$) takes a value of one if day *t* is included in the period from *w* weeks after the beginning of a bull market whose definition is based on *m* consecutive monthly positive market returns for Asian stock market *A* (the U.S. stock market), and zero otherwise. The estimates reported below use $m = 3$ and $w = 2$ for the dummy variables $D_{mw,t}^A$ and $D_{mw,t}^{US}$ (i.e., $D_{32,t}^A$ and $D_{32,t}^{US}$).

Asian Stock Market *A*	JA (Japan)	KO (Korea)	HK (Hong Kong)	PH (Philippines)	IN (Indonesia)	SI (Singapore)	TH (Thailand)
Dependent Variable	V_t^{JA}	V_t^{KO}	V_t^{HK}	V_t^{PH}	V_t^{IN}	V_t^{SI}	V_t^{TH}
Sum of the Lagged β_{1d}^A Coefficients	0.102	0.018	0.058	0.059	0.061	0.000	0.032
Sum of the Lagged β_{2d}^A Coefficients	0.012	0.015	0.014	0.000	0.000	0.000	0.010
$\chi_\beta^2(1)$ (*p*-value)	18.016 (0.000)	0.344 (0.558)	8.862 (0.003)	12.350 (0.000)	20.582 (0.000)	NA	5.387 (0.020)
Stronger Overconfident Trading in Bull Markets of the Domestic Stock Market	Yes	No	Yes	Yes	Yes	NA	Yes
Sum of the Lagged γ_{1d}^A Coefficients	0.000	0.031	0.040	0.000	0.000	0.000	0.000

Sum of the Lagged γ_{2d}^{A} Coefficients	0.015	0.000	0.000	0.000	0.000	0.050	0.016
$\chi_{\gamma}^{2}(1)$	7.427	9.793	5.330	NA	NA	12.235	6.016
(p-value)	(0.006)	(0.002)	(0.021)			(0.000)	(0.014)
Stronger Overconfident Trading in Bull Markets of the U.S. Stock Market	No	Yes	Yes	NA	NA	No	No
$\overline{R}^{2}$	0.006	0.007	0.086	-0.030	0.012	-0.021	0.086
Q(16)	8.140	18.621	22.221	11.929	18.677	23.423	18.005
(p-value)	(0.945)	(0.289)	(0.136)	(0.749)	(0.286)	(0.103)	(0.324)
$Q^{2}(16)$	132.122	195.275	47.949	68.350	19.605	169.158	21.989
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.239)	(0.000)	(0.144)

$\overline{R}^{2}$ is the adjusted coefficient of determination. Q(16) and $Q^{2}(16)$ are the Ljung-Box Q-statistics used to test the joint significance of the autocorrelations up to 16 lags for the residuals and squared residuals, respectively. The $\chi_{\beta}^{2}(1)$ statistic is the Chi-square statistic with one degree of freedom under the null hypothesis that the sum of the lagged β_{1d}^{A} coefficients is equal to the sum of the lagged β_{2d}^{A} coefficients. The $\chi_{\gamma}^{2}(1)$ statistic is the Chi-square statistic with one degree of freedom under the null hypothesis that the sum of the lagged γ_{1d}^{A} coefficients is equal to the sum of the lagged γ_{2d}^{A} coefficients.

TABLE 6

The Causal Relations among Domestic Trading Volume, Domestic Stock Returns, and U.S. Stock Returns Conditional on Investors' Forecasts of Future Stock Returns

The following trivarate GJR-GARCH-M model is estimated using a two-step procedure to investigate the causal relations among domestic trading volume, domestic stock returns, and U.S. stock returns conditional on Investors' forecasts of future stock returns for each Asian stock market *A* over the sample period from January 1998 to December 2004. In the first step, the trivarate GJR-GARCH-M model is estimated with a lag length of 5 on each independent variable with a summation sign. In the second step, the trivarate GJR-GARCH-M model estimated from the first-stage procedure is reestimated by dropping all insignificant independent variables at the 5% level and simultaneously considering the diagnostic checks of the standardized residuals and squared standardized residuals:

$$V_t^A = \alpha_1^A + \sum_{e=0}^{E^A} \alpha_{11e}^A \,|R_{t-e}^A| + \sum_{e=1}^{E^A} \alpha_{12e}^A \,|R_{t-e}^{\mathrm{US}}| + \sum_{e=1}^{E^A} \beta_{11e}^A R_{t-e}^A + \sum_{e=1}^{E^A} \beta_{12e}^A Z_{t-e}^{A+} R_{t-e}^A + \sum_{e=1}^{E^A} \beta_{13e}^A Z_{t-e}^{A+} Z_{t-e}^{A+<} R_{t-e}^A$$
$$+ \sum_{e=1}^{E^A} \gamma_{11e}^A R_{t-e}^{\mathrm{US}} + \sum_{e=1}^{E^A} \gamma_{12e}^A Z_{t-e}^{\mathrm{US}+} R_{t-e}^{\mathrm{US}} + \sum_{e=1}^{E^A} \beta_{13e}^A Z_{t-e}^{\mathrm{US}+} Z_{t-e}^{\mathrm{US}+<} R_{t-e}^{\mathrm{US}} + \varepsilon_{1,t}^A, \quad (6)$$

$$R_t^A = \alpha_2^A + \sum_{f=1}^{F^A} \mu_{2f}^A R_{t-f}^A + \sum_{g=1}^{G^A} \delta_{2g}^A \varepsilon_{2,t-g}^A + \sum_{i=1}^{I^A} \phi_i^A R_{t-i}^{\mathrm{US}} + \pi_2^A h_{2,t}^A + \varepsilon_{2,t}^A \equiv E_{t-1} R_t^A + \varepsilon_{2,t}^A, \quad (7)$$

$$R_t^{\mathrm{US}} = \alpha_3^A + \sum_{f=1}^{F^A} \mu_{3f}^A R_{t-f}^{\mathrm{US}} + \sum_{g=1}^{G^A} \delta_{3g}^A \varepsilon_{2,t-g}^{\mathrm{US}} + \pi_3^A h_{3,t}^{\mathrm{US}} + \varepsilon_{3,t}^{\mathrm{US}} \equiv E_{t-1} R_t^{\mathrm{US}} + \varepsilon_{3,t}^{\mathrm{US}}, \quad (8)$$

$$h_{1,t}^A = \omega_1^A + \sum_{j=1}^{J^A} \theta_{1j}^A h_{1,t-j}^A + \sum_{k=1}^{K^A} \lambda_{1k}^A (\varepsilon_{1,t-k}^A)^2 + \varphi_1^A S_{1,t-1}^{A+} (\varepsilon_{1,t-1}^A)^2, \quad (9)$$

$$h_{2,t}^A = \omega_2^A + \sum_{j=1}^{J^A} \theta_{2j}^A h_{2,t-j}^A + \sum_{k=1}^{K^A} \lambda_{2k}^A (\varepsilon_{2,t-k}^A)^2 + \varphi_2^A S_{2,t-1}^{A-} (\varepsilon_{2,t-1}^A)^2 + \delta_2^A (\varepsilon_{3,t-1}^A)^2, \quad (10)$$

$$h_{3,t}^{\mathrm{US}} = \omega_3^A + \sum_{j=1}^{J^A} \theta_{3j}^A h_{3,t-j}^{\mathrm{US}} + \sum_{k=1}^{K^A} \lambda_{3k}^A (\varepsilon_{3,t-k}^{\mathrm{US}})^2 + \varphi_3^A S_{3,t-1}^{\mathrm{US}-} (\varepsilon_{3,t-1}^{\mathrm{US}})^2, \quad (11)$$

where V_t^A is the domestic trading volume at time *t*, R_t^A is the domestic return at time *t*, $|R_t^A|$ is the absolute value of R_t^A at time *t*, R_t^{US} is the U.S. stock market return at time *t*, $|R_t^{\mathrm{US}}|$ is the absolute value of R_t^{US} at time *t*, and E_{t-1} denotes an expectation formed at the end of period $t-1$. The dummy variable Z_t^{A+} ($Z_t^{\mathrm{US}+}$) takes a value of one if $E_{t-1}R_t^A \times R_t^A > 0$ ($E_{t-1}R_t^{\mathrm{US}} \times R_t^{\mathrm{US}} > 0$) and zero otherwise, and the dummy variable $Z_t^{A+<}$ ($Z_t^{\mathrm{US}+<}$) takes a value of one if $|R_t^A - E_{t-1}R_t^A| = |\varepsilon_{2,t}^A| < std(\varepsilon_{2,t}^A)$ ($|R_t^{\mathrm{US}} - E_{t-1}R_t^{\mathrm{US}}| = |\varepsilon_{3,t}^{\mathrm{US}}| < std(\varepsilon_{3,t}^{\mathrm{US}})$) and zero otherwise where $std(\varepsilon_{2,t}^A)$ ($std(\varepsilon_{3,t}^{\mathrm{US}})$) is the standard deviation of $\varepsilon_{2,t}^A$ ($\varepsilon_{3,t}^{\mathrm{US}}$).

Panel A: Conditional Mean Equations							
Asian Stock Market *A*	JA (Japan)	KO (Korea)	HK (Hong Kong)	PH (Philippines)	IN (Indonesia)	SI (Singapore)	TH (Thailand)
Domestic Trading Volume Equation							
α_{1}^{A}	-0.034**	-0.036**	-0.097***	-0.094	-0.104	-0.032	-0.110
	(-2.061)	(-2.154)	(-2.593)	(-1.343)	(-0.608)	(-1.143)	(-1.358)
α_{110}^{A}	0.028***	0.011***	0.090***	0.047***	0.078***	0.077***	0.069***
	(5.339)	(3.931)	(12.328)	(2.765)	(8.667)	(7.000)	(9.267)
α_{112}^{A}	-0.009**		-0.019***			-0.017**	
	(-1.995)		(-3.600)			(-2.125)	
α_{113}^{A}			-0.012**			-0.020**	
			(-2.167)			(-2.417)	
α_{114}^{A}			0.020***				-0.018***
			(3.030)				(-3.051)
β_{111}^{A}		0.012***			0.023**		
		(3.575)			(2.091)		
β_{112}^{A}				0.025**			
				(2.478)			
β_{113}^{A}	0.015**					0.023**	
	(2.412)					(2.091)	
β_{123}^{A}						-0.039***	
						(-2.651)	
β_{125}^{A}		0.004**					
		(2.052)					
β_{131}^{A}							0.043***
							(3.455)
γ_{112}^{A}			-0.020**				
			(-1.998)				
γ_{114}^{A}							-0.022**
							(-1.974)
γ_{122}^{A}			0.038**				
			(1.981)				
γ_{124}^{A}							0.042**
							(2.089)
γ_{131}^{A}	0.028***	0.035***					
	(2.545)	(3.034)					
γ_{132}^{A}						0.039**	
						(2.167)	
γ_{133}^{A}			0.029**				

			(2.054)				
γ_{134}^{A}						0.044**	
						(2.095)	
Domestic Stock Return Equation							
α_{2}^{A}	-0.057	0.146	0.028	-0.040	0.141	0.049	0.103
	(-0.550)	(1.473)	(0.372)	(-0.506)	(1.549)	(0.803)	(0.959)
μ_{21}^{A}			-0.049**				
			(-1.979)				
μ_{22}^{A}		-0.029			0.078***		0.034***
		(-1.111)			(2.689)		(5.622)
μ_{23}^{A}	-0.046*	-0.088**					
	(-1.805)	(-3.424)					
ϕ_{1}^{A}	0.315***	0.457***	0.392***	0.189***	0.148***	0.269***	0.167***
	(11.334)	(11.070)	(14.404)	(6.967)	(4.484)	(9.607)	(5.626)
ϕ_{2}^{A}						0.041	
						(1.519)	
ϕ_{3}^{A}		0.150***			0.104***	0.084***	0.082***
		(3.086)			(3.152)	(3.108)	(2.776)
ϕ_{5}^{A}				0.049***			
				(1.801)			
π_{2}^{A}	0.013	-0.009	0.002	0.001	-0.024	-0.021	-0.029
	(0.267)	(-0.524)	(0.067)	(0.030)	(-0.923)	(-0.808)	(-1.031)
U.S. Stock Return Equation							
α_{3}^{A}	0.075	0.122*	0.106	0.089	0.081	0.124*	0.096
	(1.090)	(1.829)	(1.581)	(1.290)	(1.227)	(1.851)	(1.421)
μ_{33}^{A}	-0.051**	-0.033	-0.050***	-0.041*	-0.033	-0.033	-0.041**
	(-2.044)	(-1.225)	(-2.701)	(-1.708)	(-1.322)	(-1.222)	(-2.478)
μ_{35}^{A}	-0.054**	-0.043**	-0.049***	-0.060**	-0.051**	-0.054**	-0.048**
	(-2.081)	(-2.316)	(-2.988)	(-2.498)	(-2.556)	(-2.348)	(-2.528)
π_{3}^{A}	-0.017	-0.042	-0.036	-0.026	-0.021	-0.044	-0.032
	(-0.442)	(-1.014)	(-0.949)	(-1.443)	(-0.538)	(-0.037)	(-0.767)

Panel B: Conditional Variance Equations

Asian Stock Market *A*	JA (Japan)	KO (Korea)	HK (Hong Kong)	PH (Philippines)	IN (Indonesia)	SI (Singapore)	TH (Thailand)
Conditional Variance Equation of Domestic Trading Volume							
ω_{1}^{A}	0.028***	0.002*	0.016**	0.239***	0.086***	0.027***	0.105**
	(16.353)	(1.656)	(1.982)	(4.780)	(3.877)	(3.375)	(2.471)
θ_{11}^{A}	0.723***	0.923***	0.756***	0.795***	0.442***	0.642***	0.892***
	(16.66)	(87.942)	(6.377)	(5.638)	(3.397)	(8.447)	(4.890)

λ_{11}^{A}	0.210***	0.047**	0.013	0.110*	0.114***	0.186***	0.081***
	(2.750)	(2.300)	(0.515)	(1.833)	(2.973)	(4.325)	(3.135)
φ_{1}^{A}	0.018*	0.006	0.049*	0.026	0.001	0.002	0.003
	(0.120)	(0.237)	(1.718)	(2.878)	(0.488)	(0.498)	(0.053)
Conditional Variance Equation of Domestic Stock Returns							
ω_{2}^{A}	0.138***	0.071***	0.031***	0.184***	0.264***	0.133**	0.290***
	(2.876)	(2.384)	(2.872)	(4.035)	(2.404)	(1.985)	(3.663)
θ_{21}^{A}	0.861***	0.923***	0.958***	0.808***	0.795***	0.798***	0.841***
	(24.659)	(65.957)	(72.647)	(26.06)	(12.23)	(12.276)	(28.110)
λ_{21}^{A}	0.002	0.060***	0.017***	0.075***	0.090***	0.083***	0.079***
	(0.634)	(3.532)	(2.634)	(3.947)	(2.571)	(2.862)	(4.202)
φ_{2}^{A}	0.106***	0.003	0.025***	0.067**	0.054	0.068	0.011
	(3.576)	(0.176)	(3.662)	(2.310)	(1.317)	(1.581)	(0.473)
δ_{2}^{A}	0.032**	0.001	-0.003	0.009	0.018	0.039**	-0.017**
	(2.013)	(0.035)	(-1.083)	(0.883)	(0.818)	(2.294)	(-1.982)
Conditional Variance Equation of U.S. Stock Returns							
ω_{3}^{A}	0.122***	0.084***	0.091***	0.099***	0.088***	0.099***	0.097***
	(3.612)	(3.521)	(3.799)	(3.807)	(3.034)	(3.300)	(3.412)
θ_{31}^{A}	0.853***	0.879***	0.878***	0.872***	0.876***	0.875***	0.868***
	(30.562)	(40.488)	(39.376)	(29.06)	(35.04)	(33.65)	(33.388)
λ_{31}^{A}	0.016	0.002	0.001	0.003	0.018	0.017	0.001
	(0.863)	(0.111)	(0.058)	(0.167)	(1.059)	(0.944)	(0.088)
φ_{3}^{A}	0.131***	0.119***	0.120***	0.124***	0.105***	0.108***	0.129***
	(4.142)	(4.517)	(4.498)	(4.593)	(3.621)	(3.600)	(4.263)
Panel C: Conditional Correlation Coefficients and Shape Parameters							
Asian Stock Market *A*	JA (Japan)	KO (Korea)	HK (Hong Kong)	PH (Philippines)	IN (Indonesia)	SI (Singapore)	TH (Thailand)
ρ_{12}^{A}	0.174***	0.313***	0.108***	0.101***	0.234***	0.146***	0.346***
	(3.789)	(11.378)	(3.211)	(2.886)	(8.069)	(4.709)	(11.972)
ρ_{13}^{A}	0.029	0.059**	-0.017	0.012	0.013	0.046	0.061**
	(0.500)	(1.979)	(-0.518)	(0.363)	(0.433)	(1.533)	(1.967)
ρ_{23}^{A}	0.224***	0.222***	0.267***	0.137***	0.094***	0.241***	0.149***
	(7.492)	(7.830)	(9.391)	(4.419)	(3.133)	(8.310)	(5.016)
v^{A}	5.695***	8.736***	7.801***	7.131***	6.436***	5.067***	7.708***
	(3.483)	(9.497)	(11.756)	(12.06)	(11.12)	(13.99)	(12.463)
Panel D: Diagnostic Tests of the Model							
Asian Stock Market *A*	JA (Japan)	KO (Korea)	HK (Hong Kong)	PH (Philippines)	IN (Indonesia)	SI (Singapore)	TH (Thailand)
Domestic Trading Volume Equation							

$Q(8)$	12.589	7.704	7.036	10.700	5.050	6.112	8.137
(p-value)	(0.127)	(0.463)	(0.533)	(0.219)	(0.752)	(0.635)	(0.420)
$Q(16)$	17.580	14.233	22.971	13.229	16.135	14.611	11.281
(p-value)	(0.349)	(0.581)	(0.115)	(0.656)	(0.444)	(0.553)	(0.792)
$Q^2(8)$	5.353	5.505	2.484	8.216	1.876	2.351	12.555
(p-value)	(0.719)	(0.702)	(0.962)	(0.413)	(0.985)	(0.968)	(0.128)
$Q^2(16)$	26.592	17.365	4.898	21.221	2.688	17.543	17.785
(p-value)	(0.046)	(0.362)	(0.996)	(0.170)	(1.000)	(0.351)	(0.337)
Domestic Stock Return Equation							
$Q(8)$	2.019	5.214	2.647	15.970	12.031	5.150	10.128
(p-value)	(0.980)	(0.734)	(0.955)	(0.143)	(0.150)	(0.741)	(0.281)
$Q(16)$	10.377	17.065	6.641	24.596	22.310	11.202	30.169
(p-value)	(0.846)	(0.381)	(0.576)	(0.107)	(0.133)	(0.797)	(0.197)
$Q^2(8)$	1.499	8.919	15.292	1.901	9.0427	1.214	2.064
(p-value)	(0.993)	(0.349)	(0.503)	(0.984)	(0.207)	(0.997)	(0.979)
$Q^2(16)$	7.942	16.733	9.061	4.097	16.043	3.628	2.537
(p-value)	(0.951)	(0.403)	(0.911)	(0.999)	(0.198)	(0.999)	(1.000)
U.S. Stock Return Equation							
$Q(8)$	12.589	7.704	7.036	10.700	5.050	6.112	8.137
(p-value)	(0.127)	(0.463)	(0.533)	(0.219)	(0.752)	(0.635)	(0.420)
$Q(16)$	17.426	19.843	17.263	17.810	16.724	17.067	17.171
(p-value)	(0.359)	(0.227)	(0.369)	(0.335)	(0.404)	(0.381)	(0.375)
$Q^2(8)$	5.353	5.505	2.484	8.216	1.876	2.351	12.555
(p-value)	(0.719)	(0.702)	(0.962)	(0.413)	(0.985)	(0.968)	(0.128)
$Q^2(16)$	7.941	6.521	17.340	17.559	14.939	16.131	17.521
(p-value)	(0.951)	(0.981)	(0.364)	(0.350)	(0.529)	(0.444)	(0.353)

$Q(L)$ and $Q^2(L)$ are the Ljung-Box Q-statistic used to test the joint significance of the autocorrelations up to L lags for the standardized residuals and squared standardized residuals, respective. t-statistics are shown in parentheses below the estimated coefficients.
*** and ** denote significance at the 1% and 5% levels, respectively.