Cross-market herding: do ‘herds’ herd with each other?

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Cross-market herding: do "herds" herd with each other?

Although herding constitutes one of the most widely researched behavioral trading patterns internationally, the possibility of cross-market herding has remained largely underexplored in the literature. Our study provides a detailed empirical investigation of this issue in the context of ten Asia-Pacific markets for the February 1995 – March 2022 window. We find that all ten markets' "herds" project significant relationships with each other, with causality being identified within a minority of those relationships. These results are robust when controlling for financial crises (Asian; global financial; global pandemic) and US market returns.

JEL classification: G4; G11; G15

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1. Introduction

Herd behavior constitutes one of the oldest documented (Vega, 1688) and most widely researched facets of investors' behavior to date, with evidence denoting its presence and variations across different time periods, market conditions and investor-types in a rather large cross-section of markets internationally. Although much is known about herding and its determinants within individual markets, the same cannot be argued about cross-market herding[1]; the latter pertains to the case whereby different markets' herds interact with each other, something of key import in view of both the growing integration in the global financial architecture and the extant evidence (Masih and Masih, 1999; Gebka, 2012; Gebka and Serwa, 2015) on the spillovers/contagion among financial markets. To the extent that markets are becoming increasingly interlinked, one would expect these interlinkages to be observed not only in their return-dynamics (as the spillover/contagion literature has so amply confirmed) but

[1] For a detailed discussion on the empirical identification of cross-market herding in the extant literature and how our study contributes to the debate on the issue, please see the appendix.

also in the behavior of their market participants. In addition, extant attempts (Chiang and Zheng, 2010; Economou et al., 2011; Mobarek et al., 2014; Economou et al., 2015a; Andrikopoulos et al., 2017; Guney et al., 2017; Andrikopoulos et al., 2021) at calibrating cross-market herding empirically have largely relied on its identification by assessing how herding in a market is impacted by other markets' return-dynamics, without capturing cross-market herding *per se* (as they involve no direct examination of the relationships among different markets' herds). This suggests that the empirical identification of cross-market herding still constitutes a largely unresolved issue, despite the fact that it represents a key behavioral aspect of our globalized financial environment. Our study fills this gap in the literature by examining cross-market herding across a sample of ten Asia-Pacific equity markets during the February 1995 – March 2022 period. Drawing on Hwang and Salmon (2004)'s empirical design, we generate dynamic (i.e., time-varying) market-wide herding for each market, assess whether the herds of these markets are significantly related to each other, and investigate the extent to which each market's herding is causally related to herding in the rest of the sample's markets.

From a theoretical viewpoint, herding refers to the situation whereby investors copy the trades of their peers following interactive observation of each other's trades (or outcomes of those trades – see Hirshleifer and Teoh, 2003), without recourse to fundamentals or their own private information. Such choice can be intentional, motivated by the anticipation of positive externalities - "payoffs" - accruing from mimicking others. These payoffs can be *informational*, if investors choose to ignore their private signals and mimic others who may be better informed or possess better information-processing skills (Devenow and Welch, 1996); such behavior can render the public pool of information less informative and foment the evolution of informational cascades (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992). *Professional* payoffs can also underlie herding intent; in view of their relative (versus their peers) performance assessment, low ability fund managers, for example, can be tempted to track their "good" (better able) peers' trades in order to improve on their image and career prospects (Scharfstein and Stein, 1990; Jiang and Verardo, 2018). On the other hand, investors can also herd spuriously, as a result of their similar responses to factors they are commonly exposed to. Investment professionals, for instance, tend to exhibit commonalities in their trading patterns due to their *relative homogeneity* (De Bondt and Teh, 1997), the latter being reflected through similarities in their educational background, professional qualifications, and indicators they monitor (and the way they interpret them), as well as the common regulatory framework reigning their professional practice (Wermers, 1999; Voronkova and Bohl, 2005; Blake, Sarno, and Zinna, 2017). *Style investing* (i.e., choosing stocks based on specific stock-characteristics), a practice particularly popular among institutional investors (Bennett, Sias, and Starks, 2003; Jame and Tong, 2014), can also foment spurious herding; if many fund managers follow a certain style (e.g., momentum or value investing) in their trades, it is likely that the latter will exhibit enhanced correlation, without imitation mediating this process. In addition, investors may exhibit correlation in their trades, if their information sets are correlated, a possibility more formally known as "investigative herding" (Froot, Scharfstein, and Stein, 1992; Hirshleifer, Subrahmanyam, and Titman, 1994). What is more, spurious herding may also be the result of fads (investors chasing a popular sector; see Choi and Sias, 2009) and behavioral biases (particularly among retail investors; see Barber and Odean, 2013).

Empirically, herding has been reported internationally in a very wide cross-section of markets, both developed and emerging/frontier ones, with its presence being stronger in the latter (for evidence at the market-wide level see Chiang and Zheng, 2010; and Demirer et al., 2010, among others), something that has been attributed to the relatively lower quality of informational transparency (Chang et al., 2000; Gelos and Wei, 2005; Economou et al., 2015b; Guney et al., 2017) and governance (Fawwaz et al., 2017). Herding has also been found to vary with stock-size (it often appears stronger among small capitalization stocks, due to their elevated information risk rendering monitoring others' trades informative; see Lakonishok et al., 1992; Wermers, 1999; Sias, 2004; Hung et al., 2010; Benkraiem et al., 2021), as well as across industries (Choi and Sias, 2009; Zhou and Lai, 2009; Gavriilidis et al., 2013; Gebka and Wohar, 2013; Celiker et al., 2015). Furthermore, herding has been found to manifest itself asymmetrically contingent upon different states of a market's returns (Chang et al. 2000; Goodfellow et al., 2009; Chiang and Zheng, 2010; Chiang et al., 2010; Economou et al., 2011; Holmes et al., 2013; Elshqirat, 2020), volatility (Economou et al., 2011; Holmes et al., 2013; Balcilar et al., 2013; Guney et al. 2017), volume (Tan et al., 2008; Economou et al., 2011; 2015a; 2015b; Andrikopoulos et al., 2021) and sentiment (Liao et al., 2011; Blasco et al., 2012), without however, these asymmetries exhibiting any consistent pattern internationally. Evidence (Voronkova and Bohl, 2005; Holmes et al., 2013; Blake et al., 2017; Krokida et al., 2020; Andrikopoulos et al., 2021) also suggests that herding is sensitive to regulatory policies and their changes over time.

The bulk of the herding literature has focused on herding and its possible determinants within single markets, yet very little is known as to whether "herds" interact across markets. The study of cross-market herding is of key importance primarily for two reasons. On the one hand, cross-market herding is a particularly relevant issue in the contemporary financial environment, mainly due to the ongoing globalization process, whose acceleration since the 1990s has bolstered economic interdependence and foreign portfolio investment, increasing correlations among markets in the process (Chen, 2018). This has often given rise to cross-market spillovers and contagion (see e.g., Masih and Masih, 1999; Gebka, 2012 and Gebka and Serwa, 2015), which have been blamed (Kim and Wei, 2002) on overseas funds motivating herding within and across markets. To the extent that the ongoing global financial integration renders equity markets' returns increasingly correlated, it is possible that this correlation extends to the behavior of their investors; in a globalized environment, and with herding constituting one of the most frequently cited behavioral trading patterns internationally, one cannot preclude the possibility that the "herds" of different markets interact with each other. On the other hand, several studies (Chiang and Zheng, 2010; Economou et al., 2011; Mobarek et al., 2014; Economou et al., 2015a; Andrikopoulos et al., 2017; Guney et al., 2017; Andrikopoulos et al., 2021) have investigated cross-market herding by assessing how herding in a market is impacted by other markets' return-dynamics. Although their empirical designs capture an important exogenous determinant (other markets' return-dynamics)[2] of a market's herding, they cannot capture cross-market herding *per se*, as they involve no direct examination of the relationships among different markets' herds; it is this clearly major shortcoming in the relevant literature (which we elaborate on in good detail in appendix 1) that motivates the present study.

Our study addresses this issue in the context of a set of ten Asia-Pacific stock markets (Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Taiwan, Thailand, and the markets of Shanghai and Hong Kong in China) for the February 1995 – March 2022 period. Most of these markets (all of them, except Taiwan - which nevertheless belongs to the so-called "Four Asian Tigers", together with the other high-growth economies of Hong Kong, Singapore and South Korea) belong to the ASEAN Plus Three initiative. This means that these countries have made several agreements to increase their economic integration, including the link between the stock markets of member countries (Arsyad, 2015). Moreover, in September 2012, Indonesia, Malaysia, Philippines, Singapore, Thailand and Vietnam formed the ASEAN Exchanges and launched the ASEAN Trading Link, a gateway to offer easier access to the connected exchanges (Llovet Montanes and Schmukler, 2018). Therefore, we consider these

[2] To the best of our knowledge, the only study that has explicitly attempted to assess the relationships (yet not causality) between different markets' "herds" is Chiang et al. (2013); for more on their approach (and its innate shortcomings), see the discussion in the appendix.

countries an appropriate environment for the study, since the increasing interconnection could also lead to collective phenomena crossing borders.

Drawing on Hwang and Salmon (2004)'s empirical design that allows us to generate dynamic (i.e., time-varying) market-wide herding for each market[3], we report evidence of significant market-wide herding for all ten markets, in line with earlier literature (Choe et al., 1999; Kim and Wei, 2002; Chiang and Zheng, 2010; Chen, 2013; Chiang et al., 2013; Bui et al., 2015; Lam and Qiao, 2015; Chong et al., 2017)[4] on widespread herding in the region. Our sample markets' "herds" exhibit inter-temporal dependence both *per se* and with each other; results suggest that each market's "herd" is significantly related to the lagged values of itself and those of other "herds", with this relationship being bidirectional across herding-pairs (i.e., "herds" may be positively or negatively related to each other). We also present evidence suggestive of causality in a minority (about 15%) of these relationships, with herding in each market tending to motivate herding in one to two other markets from our sample, on average. Our estimates hold when controlling for the effect of the Asian crisis, global financial crisis, global pandemic and US market returns; in unreported results, we also show that our initial herding estimates' significance is not affected when controlling for the thin trading bias.

Our study contributes significantly to the behavioral finance literature, as it provides the first detailed examination of cross-market herding and reveals that correlations in the globalized financial environment do not only pertain to market returns, but also extend to the behavior of investors. To that end, it complements the literature on spillovers/contagion by showcasing that

[3] For more on why other measures and approaches proposed in the herding literature present issues in cross-market herding estimations (and, thus motivate the employment of the Hwang and Salmon, 2004 measure here), see the discussion in appendix 1.

[4] The overwhelming number of research papers relevant to our analysis of herding behavior published in the last years is presented in summary in a table in appendix 2. The papers have been classified according to the scope of our research in: (1) those focused on the Asian continent, (2) the ones that study the role of different crises, (3) papers that consider different markets and their possible relationships and, finally, (4) those papers that are relevant but do not fit into any of the three previous categories (and are classified as "Others").

behavioural correlations are possible across international markets and should be taken into account in future research in this literature. Perhaps more importantly, it proposes an empirical setting for the investigation of cross-market herding that is free from the shortcomings of previously proposed ones in the relevant herding literature. By establishing that cross-market herding exists irrespective of a market's size/stage of development (since all market-pairs are shown to reflect cross-market herding) or extreme events (several of which we account for in our tests), our study illustrates that the transmission of herding across markets is relatively systematic and not a function of factors considered to be traditional herding determinants. The results reported here bear important implications from a research perspective, as they raise the possibility of the presence of (causal or not) correlations in other widely documented behavioral trading patterns internationally. In addition, to the extent that herding in the literature has been shown to be subject to the effect of various determinants across markets, investor-types and time, the fact that our approach allows for an empirical examination of cross-market herding free from the shortcomings of earlier approaches (see appendix 1) suggests the possibility that cross-market herding may also have its own determinants that future research can investigate. Our findings are also of particular relevance to regulators and policy makers; given cross-market herding's capability of increasing the risk of contagion across markets (Bekaert et al., 2014), its monitoring for potential early warning signals is of obvious importance to regulatory authorities, in order to pre-empt, where possible, destabilizing outcomes. From the perspective of the investment community, the above results raise the possibility of cross-market herding being used as input to inform the strategies of investors, in particular those with an international outlook. Investors can, for example, devise trading rules taking into account the causal relationship between two markets' herds; indeed, if market A's herding is found to cause herding in market B and an increase in market A's herding is observed, then investors can use this information to trade in market B based on the anticipated increase in the latter's herding.

The rest of the paper is structured as follows: section 2 presents the data employed and the empirical design utilized, alongside descriptive statistics. Section 3 discusses the results and section 4 concludes.

2. Data and Methodology

2.1 Data

Our data involves daily observations of the closing prices of the universe of ordinary domestic stocks listed in the primary equity markets of Indonesia (Jakarta Stock Exchange), Japan (Tokyo Stock Exchange), Malaysia (Bursa Malaysia), Philippines (Philippine Stock Exchange), Singapore (Singapore Exchange Limited), South Korea (Korea Exchange), Taiwan (Taiwan Stock Exchange), Thailand (Stock Exchange of Thailand) and China's two largest equity markets (Shanghai Stock Exchange; Hong Kong Stock Exchange)[5] covering the period between February 1st, 1995 and March 31st, 2022.[6] The choice of our sample is motivated by the fact that the Asia-Pacific region is the one region with the most frequently cited evidence of market-wide herding in a variety of studies (much more consistently so, compared, for example, to markets in Europe and North America), thus rendering the study of cross-market herding in its context meaningful.[7] In addition, the sample contains a mix of markets of

[5] The two markets tend to bear differences in their institutional structures, hence choosing both of them, instead of only focusing on one to proxy for the Chinese market.
[6] The choice of the starting date was motivated by the limited availability of data for some of our sample markets (the Shanghai market had very few listed stocks pre-1995; some risk-free rate data was also unavailable pre-1995).
[7] East and South East Asian markets tend to generate market-wide herding much more often compared to their European and North American counterparts. This has often been ascribed to Asian markets' larger average retail participation increasing the potential for noise trading patterns. See, for example, Chang et al. (2000), Chiang and Zheng (2010), Chen (2013), Chiang et al. (2013), Lam and Qiao (2015) and Chong et al. (2017). Investigating

different sizes[8] and at different stages of development. Four of them (Hong Kong; Japan; Singapore; South Korea) are formally classified as developed and the rest as emerging and this further allows us to gauge whether cross-market herding exhibits any variations in its manifestation contingent on the level of markets' development (more so considering that developed markets tend to maintain fewer/no restrictions vis-à-vis foreign investors compared to their emerging counterparts).[9] East/South East Asian markets tend to exhibit enhanced levels of integration (Yang, et al. 2003; Prasetya and Sudrajad, 2022), reflected through their highly correlated market returns and volatility, particularly in the aftermath of financial crises (Tiwari et al., 2013; Guimarães-Filho and Hong, 2016; Wu, 2020) and it would be interesting to explore whether these correlations can be witnessed in their investors' herding as well. Table 1 shows some of the characteristics of the markets under study. Japan used to be the biggest equity market, but in the last years of the sample, China (Shanghai) has taken its place. However, Japan is still the first one with regard to the number of listed companies. Looking at the percentage of domestic companies, most of the markets in the sample show a weight of more than 98% of domestic over total companies listed, with only Hong Kong (92.8%), Taiwan (90.8%) and Singapore (65.7%) below that figure.

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cross-market herding in markets with lower probability of herding would be counterintuitive, as we would potentially end up with some markets exhibiting no herding at all.

[8] At least half of our sample's markets (Shanghai; Japan; Hong Kong; South Korea; Taiwan) feature among the top 20 markets in the world in terms of capitalization (according to the World Federation of Exchanges); our sample, therefore, allows us the opportunity to assess whether cross market herding varies in terms of its origins/effects contingent on a market's size.

[9] More restrictions in terms of foreign investors would be expected to culminate in an enhanced retail investors' base, something evident in many Asian (emerging, mainly) markets – see Chang et al. (2000), Chiang and Zheng (2010), Chen (2013), Chiang et al. (2013), Lam and Qiao (2015) and Chong et al. (2017). If so, and given retail traders' noise trading tendencies, this may imply greater potential for herding (particularly so in emerging markets – see the discussion in the previous section). In addition, many of our sample markets tend to accommodate concentrated corporate structures in the form e.g., of interfirm networks (keiretsu) in Japan (Kim and Nofsinger, 2001) or conglomerates (chaebol) in South Korea (Fitzgerald and Kang, 2022) and this may prompt greater response to foreign markets' signals, if news related to those corporate formations' sectors arrives from overseas markets (and potentially foments cross-market herding in their stock markets).

Daily data is also collected for that period for the main index of each of those ten stock exchanges[10] as well as each country's risk-free rate.[11] To mitigate the possibility of survivorship bias, our study includes data on all ordinary stocks, both active, as well as delisted and suspended ones, during the aforementioned period for each market. Our final sample includes 2142 stocks for Shanghai, 2565 stocks for Hong Kong, 899 stocks for Indonesia, 4281 stocks for Japan, 1195 stocks for Malaysia, 341 stocks for the Philippines, 838 stocks for Singapore, 1394 stocks for South Korea, 1175 stocks for Taiwan, and 1131 stocks for Thailand, with all data obtained from the Refinitiv database.

[Table 1 near here]

2.2. Methodology

2.2.1 Single market herding

To assess cross-market herding in our study, we first estimate herding for each of our sample markets based on the methodology proposed by Hwang and Salmon (2004), the sole approach to date capable of allowing for the direct extraction of herding as a time series.[12] This approach is based on the precept that behavioral biases introduce distortions in investors' perception of the relationship between risk and return among securities. Although Hwang and Salmon (2004) do not focus on any specific biases in that respect, they identify herding as a possible outcome of behaviorally biased trading and argue that, if investors herd towards the market consensus, individual securities' returns will begin tracking the return of the market, leading their betas to depart from their equilibrium values.

[10] The indices used are the following: Shanghai Stock Exchange Composite (Shanghai); Hang Seng (Hong Kong); IDX Composite (Indonesia); Nikkei 225 (Japan); FTSE Bursa Malaysia KLCI (Malaysia); PSEi (Philippines); FTSE ST All Share (Singapore); KOSPI (South Korea); TAIEX (Taiwan); SET (Thailand).
[11] In the vast majority of cases (China-Shanghai/Hong Kong; Indonesia; Japan; Malaysia; Singapore; Taiwan; Thailand), the risk-free rate used is the 3-month deposit rate of each market; exceptions include the Philippines (91-day Treasury Bill rate) and South Korea (91-day certificate of deposit rate).
[12] See also the discussion in appendix 1.

As a result, changes in herding will cause variations in individual securities' betas; in the presence of herding, securities' betas will cluster closely towards the value of the market's beta (i.e., one), thus leading the cross-sectional deviation of all listed stocks' betas to grow smaller. To empirically calibrate the effect of herding over a security's beta, Hwang and Salmon (2004) assume two versions of the beta, its equilibrium (β_{imt}) and its behaviorally biased one (β_{imt}^{b}), whose relationship is the following:

$$\left(E_t^b(r_{it})/E_t(r_{mt})\right) = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \tag{1}$$

In Equation (1) $E_t^b(r_{it})$ is the behaviorally biased version of the conditional expectation of excess returns of asset *i* at time *t*, $E_t(r_{mt})$ is the unbiased conditional expectation of excess returns of the market at time *t* and $h_{mt} \leq 1$ is a time-variant parameter designed to capture herding. To estimate herding at the market-wide level, Hwang and Salmon (2004) first calculate the cross-sectional deviation of both sides of Equation (1) as follows:

$$Std_c(\beta_{imt}^b) = Std_c(\beta_{imt})(1 - h_{mt}) \tag{2}$$

Taking logarithms on both sides of Equation (2), we have:

$$\log\,[Std_c(\beta_{imt}^b)] = \log\,[Std_c(\beta_{imt})] + \log\,(1 - h_{mt}) \tag{3}$$

To directly estimate herding, Equation (3) is expressed as:

$$\log\,[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt} \tag{4}$$

$$\text{where: } \log\,[Std_c(\beta_{imt})] = \mu_m + \upsilon_{mt} \tag{5}$$

$$\text{with } \mu_m = E\,[\log\,[Std_c(\beta_{imt})]],\ \upsilon_{mt} \sim iid(0, \sigma_{m,\upsilon}^2) \text{ and } H_{mt} = \log\,(1 - h_{mt}) \tag{6}$$

A key issue in Equation (6) is that H_{mt} is an unobserved variable, whose estimation necessitates some assumptions regarding herding structure; Hwang and Salmon (2004) assume that H_{mt} exhibits temporal dependence based on an autoregressive process of order one:

$$\log\,[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt} \tag{7}$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt} \tag{8}$$

$$\text{where } \eta_{mt} \sim \text{iid}(0, \sim \text{iid } (0, \sigma^2_{m,\eta}).$$

In the above system of Equations (7) - (8) the log $[Std_c(\beta^b_{imt})]$ varies with the level of herding (h_{mt}), the change in which is captured by H_{mt}, which, in turn is extracted via Kalman filter. Significant values of $\sigma^2_{m,\eta}$ suggest the presence of herding, while significant estimates for the autoregressive parameter (ϕ_m) denote that herding exhibits persistence.

The calculation of log $[Std_c(\beta^b_{imt})]$ for market m relies on all of its listed securities' betas estimated via ordinary least squares using daily excess return data within monthly intervals based on the standard market model:

$$r_{itd} = \alpha^b_{it} + \beta^b_{imt} r_{mtd} + \varepsilon_{itd} \tag{9}$$

where the subscript *td* refers to daily data *d* used within month *t*. Excess returns (r_{itd}; r_{mtd}) are calculated by first generating the percentage log-differenced returns from the closing prices of market *m*'s index and all listed stocks at any point in time in market *m*, and then adjusting them using that market's risk-free rate. Estimating Equation (9) yields each stock's beta per month, following which, we calculate the cross-sectional standard deviation of all listed stocks' betas for that month for each market. The concurrent monthly[13] time series of the cross-sectional standard deviation of securities' betas is then used, in its logarithmic form (log $[Std_c(\beta^b_{imt})]$) as input in the estimation of the system of Equations (7) and (8).

2.2.2 Cross-market herding

In order to test for cross-market herding we employ the Granger causality approach (Granger, 1969), which allows for the empirical testing of bidirectional causality between herding in different markets. This approach, as a first step, requires the series of variables included in its

[13] Hwang and Salmon (2004) rationalized the choice of the monthly frequency as a trade-off between reducing biases in beta-estimation and obtaining a number of h_{mt}-observations large enough to allow for the detection of herding.

estimation to be stationary, in order to provide robust estimates (Brooks, 2002). Herding here is reflected through h_{mt}, which is extracted as $h_{mt} = 1 - \exp(H_{mt})$ by converting Equation (6) ($H_{mt} = \log(1 - h_{mt})$) from logarithmic into exponential form. Having established[14] that all h_{mt} series are stationary, we assume their series-level in Granger causality estimations. Previous research reveals that causality tests are sensitive to differential lag lengths (Thornton and Batten, 1985); to tackle this issue, the VAR models' optimal lag length is assessed by using the following diagnostic tests: i) the sequential modified LR test statistic (LR); ii) the final prediction error (FPE); iii) the Akaike information criterion (AIC); iv) the Bayesian information criterion (BIC); and v) the Hannan-Quinn information criterion (HQ). The following vector autoregression (VAR) model is estimated to test for cross-market herding:

$$h_{mt} = \delta_m + \sum_{m=1}^{q} \sum_{j=1}^{p} \omega_{mt-j} h_{mt-j} + \vartheta_t \tag{10}$$

where, h_{mt} refers to the series extracted from Equations (7) and (8) for each market *m* in month *t*; δ_m is the constant term of the equation; ω_{mt-j} is a vector containing the regression coefficients; h_{mt-j} reflects the h_{mt} series extracted from Equations (7) and (8) for each market *m* in month *t-j*; and, finally, ϑ_t is the model's error term.

We further assess whether cross-market herding is impacted when controlling for the performance of major international markets as well as key crisis-episodes. Specifically, with respect to the effect of the latter over herding, evidence from the literature appears rather mixed. While some studies conclude that herding increases during periods of market stress (Kim and Wei, 2002; Chiang and Zheng, 2010; Mobarek et al., 2014; BenMabrouk and Litimi, 2018), others discover that herding diminishes during major global crises[15] (Choe et al., 1999; Hwang and Salmon, 2004; Andrikopoulos et al., 2017; Bekiros et al., 2017). To control for the effect

[14] Results from the Dickey-Fuller stationarity tests are not reported here in the interest of brevity and are available on request from the authors.
[15] Perhaps due to crises revealing groundbreaking fundamentals that render the pre-crisis consensus (and, hence, its herding) obsolete; see Andrikopoulos et al. (2017).

of crisis-episodes, alongside the effect of major international markets' returns, the following VAR model is estimated:

$$h_{mt} = \delta_m + \sum_{m=1}^{q} \sum_{j=1}^{p} \omega_{mt-j} h_{mt-j} + \gamma_1 D_{Asia,t} + \gamma_2 D_{Global,t} +$$

$$\gamma_3 D_{S\&PCOMP,t} + \gamma_4 D_{COVID,t} + \vartheta_t \tag{11}$$

where, h_{mt}, δ_m, ω_{mt-j}, ϑ_t and h_{mt-j} are defined same as in Equation (10); $D_{Asia,t}$ is a dummy variable assuming the value of one for the July 1997 – July 1998 period (corresponding to the Asian crisis), zero otherwise; $D_{Global,t}$ is a dummy variable assuming the value of one for the October 2008 – March 2009 period (corresponding to the global financial crisis), zero otherwise; $D_{S\&PCOMP,t}$ is a dummy variable assuming the value of one for those months for which the Standard & Poor's Composite Index (a proxy for the US stock market's performance) [16] generated a negative return, zero otherwise; and $D_{COVID,t}$ is a dummy variable assuming the value of one from March 2020 until the end of our sample window (corresponding to the global pandemic).

2.2.3 Descriptive statistics

Table 2 presents a series of descriptive statistics pertaining to the logarithmic cross-sectional standard deviation of the betas - log $[Std_c(\beta_{imt}^b)]$ - for each of our ten sample markets (panel A) as well as the correlation matrix among the log $[Std_c(\beta_{imt}^b)]$ of all ten markets (panel B). As the table illustrates, the highest (lowest) mean value of log $[Std_c(\beta_{imt}^b)]$ is observed for Malaysia (Shanghai), with log $[Std_c(\beta_{imt}^b)]$ appearing the most (least) volatile (as the standard deviation values indicate) in Shanghai (Japan). Overall, we notice that log $[Std_c(\beta_{imt}^b)]$ exhibits great variability across our sample markets, with its maximum and minimum value detected in Shanghai. The correlations among the ten markets' log $[Std_c(\beta_{imt}^b)]$ values vary in

[16] US market returns have been found to motivate herding internationally in several studies (Chiang and Zheng, 2010; Economou et al., 2015a; Guney et al., 2017).

magnitude, with their coefficients ranging from as high as 0.6676 (the Malaysia-Singapore pair) to as low as -0.0820 (the Shanghai-Philippines pair). ***[Table 2 near here]***

3. Results – Discussion

3.1 Is herding present in our sample markets?

We begin our discussion with the presentation of our findings from the estimation of Equations (7) and (8) for each of our ten sample markets. Results are outlined in Table 3 and denote that herding is significant ($\sigma^2_{m,\eta}$ is always significant at the 1 percent level) and persistent (ϕ_m is always significant at the 1 percent level) for all markets, in line with evidence from a host of studies (Choe et al., 1999; Kim and Wei, 2002; Chiang and Zheng, 2010; Chen, 2013; Chiang et al., 2013; Bui et al., 2015; Lam and Qiao, 2015; Chong et al., 2017) confirming the presence of herding in Asia-Pacific markets. Herding appears the most persistent in Malaysia, Singapore and Shanghai (ϕ_m there is just over 0.99), followed by Hong Kong, Taiwan, the Philippines, Thailand, South Korea, Japan and Indonesia (for which ϕ_m assumes its lowest value, 0.66). The bottom row of the table presents us with the signal-to-noise ratio, which, as Hwang and Salmon (2004) showed, is calculated by dividing $\sigma_{m,\eta}$ by the time series standard deviation of the log[$Std_c(\beta^b_{imt})$]) and indicates the fraction of the variability of the log [$Std_c(\beta^b_{imt})$] accounted for by herding. High (low) values of that ratio suggest a less (more) smooth evolution of herding; as we can see from Table 3, the ratio assumes its minimum value – 17.2% - in Singapore, and its maximum one in Taiwan – 73%). ***[Table 3 near here]***

3.2 Are our sample markets' "herds" related to each other?

Having established the presence of herding in each of our sample markets, we now assess whether their "herds" are significantly related to each other. Before we begin with the presentation of our results from the VAR and causality tests, we first construct the correlation matrix for all markets' h_{mt} in Table 4. Herding across Asia-Pacific markets is positively correlated in the vast majority (38/45 correlation coefficients) of cases; negative correlations are encountered for some pairs involving primarily the Philippines (and, in one case, Japan). Correlation coefficients exhibit variability, ranging from a maximum value of 0.8278 (Malaysia-Singapore) to a minimum one of -0.2667 (Philippines-Shanghai). **[Table *4 near here]***

To assess the relationships among our sample markets' "herds" in a multivariate setting, we draw on the extracted h_{mt} values from Equations (7) and (8) and estimate Equations (10) and (11) using one lag in their specification as indicated by the diagnostic tests for the preferred VAR model with and without controls. Results from the estimations of Equations (10) and (11) are presented in Tables 5 and 6, respectively, and, overall, indicate that herding in each market is related to both that market's own lagged herding as well as the lagged herding of the other sample markets. Each market's herding is always positively and significantly related to its lagged value, with this first-order autocorrelation being consistently in excess of 0.5; this suggests a strong inter-temporal dependence of herding, in line with the relevant literature (see e.g., Sias, 2004; Choi and Sias, 2009).

With respect to the links among our sample markets' "herds", we notice that their sign is positive in most cases (59% in Table 4; 53% in Table 6), with all cross-market coefficients being consistently statistically significant at the 10 percent level. Controlling for the Asian crisis, global financial crisis, global pandemic and US market returns prompts occasional switches in sign in Table 6 (compared to Table 5), without however, this affecting the significance of the estimates. What is more, the maximum (i.e., most positive) and minimum (i.e., most negative) cross-market herding coefficients are identified for the same market-pairs in both tables. The most negative (positive) cross market herding coefficient for whole sample, overall is observed for the South Korean (Shanghai) market with regards to Japan's

(Thailand's) lagged herding. The market with the strongest evidence of cross-market herding is Thailand, whose lagged herding reveals the highest coefficient in the estimates (see Table 5) of Equation (10) for Shanghai, Hong Kong and Indonesia (and also for Japan, Singapore, South Korea and Taiwan for their estimates from Equation (11) in Table 6). Singapore's lagged herding generates the most negative cross market herding coefficients for Indonesia (Table 5 only), Japan and the Philippines; what is more, Singapore's herding is positively related to all other markets' herds in Table 5, without however this holding in Table 6. ***[Tables 5 and 6 near here]***

The results presented in Tables 5 and 6 suggest that herding in each of the ten markets is significantly related to the herding of the rest, thus confirming the presence of cross-market herding among Asia-Pacific markets. With regards specifically to the coefficients of the control variables in Equation (11), they are found to be collectively significant. γ_1 is found to be positive for 6 markets, with γ_3 bearing positive values for almost all markets (except Thailand); these results suggest that most Asia-Pacific markets in our sample witnessed a herding increase during the Asian crisis and also tend to herd more during months of negative US market performance. As per γ_2, it appears positive in eight markets, denoting that the global financial crisis prompted significant herding in the Asia-Pacific region. These results are in line with evidence on herding in Asian markets during the Asian (Kim and Wei, 2002; Chiang et al., 2007; Chiang and Zheng, 2010), and global financial crises (Chong et al., 2017). With regards to γ_4, its sign appears positive in eight markets, thus showcasing that the ongoing pandemic has culminated in substantial herding across the region's markets, in line with previous studies (Aslam et al, 2021).

In view of the significant herding interrelations among our ten sample markets, we now turn to assess the presence of causality in these interrelations, i.e., whether herding in a market motivates herding in other markets. To that end, we perform Granger causality tests based on the estimates of the VAR models from Equations (10) and (11), with their results appearing in Table 7, panels A and B, respectively. As we observe from the results in both panels of Table 7, causality is evident for a minority (about 15%) of market-pairs. ***[Table 7 near here]***

As results in Table 7 denote, Thailand is the market whose herding motivates herding in more markets (Shanghai, Hong Kong and Taiwan in both tables; Indonesia and South Korea in Table 6 only), followed by Shanghai and Singapore (the herding of each generates herding in two or three other markets, depending on the table). As for the rest of the markets' herds, they are found to motivate herding in two or fewer markets in both tables.[17].

These results denote that cross-market herding is present among Asia-Pacific markets, thus showcasing that, return-dynamics aside (Masih and Masih, 1999), investors' behavior in the region's markets is also highly correlated. Nevertheless, causality is not particularly widespread in the structure of cross-market herding, suggesting that Asia-Pacific markets' "herds" are persistently interlinked, yet not widely motivating each other. A possible explanation here is that Asia-Pacific markets' investors herd as a response to (fundamental or non-fundamental) factors largely common to their region (this would account for the consistent herding-links), without, however, the herding of their region's markets *per se* being informative or important enough to command broad following or attention (hence, the lower causality levels observed). This may partially be attributed to the relatively moderate size of some Asia-Pacific markets that can, indeed, render their herding less important to follow; in other cases, the presence of institutional restrictions (e.g., in foreign ownership) may well constrain their

[17] Extracting herding from the cross-section of the betas of a market's stocks necessitates accounting for the potential impact of non-synchronous trading over beta-estimates. If a stock is infrequently traded and its price occasionally remains stale, the covariance estimate between that stock and the market will be downwardly biased, leading the estimated beta itself to be downwardly biased as well. As this issue has been observed among Asia-Pacific markets (e.g., Levine and Schmukler, 2006), we adjusted all betas estimated from Equation (9) for non-synchronous trading based on the methodologies of Scholes and Williams (1977) and Dimson (1979) and herding has been re-estimated. Results (not reported here in the interest of brevity and available on request from the authors) are clearly indicative of herding across all sample markets, thus denoting that the significance of the estimated single-market herding used for the cross-market herding tests holds when correcting for thin trading.

investors from herding on other markets' herds (and vice versa).[18] Additionally, to the extent that retail investors bear a larger average participation in Asia-Pacific markets (Barber et al., 2007; 2009; Chou et al., 2011; Kuo et al., 2015) compared to Western ones, this suggests the stronger potential for (given retail investors' proclivity for noise trading) and possibility of similarities in (due e.g., to cultural factors; see Chen and Yau, 2014) herding in the region's markets. However, retail investors tend to project lower sophistication *vis-à-vis* their institutional peers (Barber et al., 2009), thus rendering tracking the herding of other regional markets perhaps too involved a task for them. To the extent that a larger average retail participation implies lower average foreign institutional investors' presence, the latter denotes that any foreign portfolio allocations/rebalances in the region's markets may contribute to cross-market herding among its markets, yet their impact may not be sufficient enough to motivate widespread causal relations among herding across these markets.

4. Conclusion

We study the structure of cross-market herding in the Asia-Pacific region, in terms of whether regional markets' "herds" are related to each other and whether they motivate each other. We assess this issue drawing on a sample of ten markets from the region for the February 1995 – March 2022 period and report findings denoting that all ten markets' "herds" project significant relationships with each other, with causality being identified within a minority of those relationships. The results presented here denote that cross-market herding is evident among Asia-Pacific markets, yet causality is not particularly widespread in its structure; these results

[18] In that respect, if intra-regional portfolio investment is low (or varying among markets), this would suggest a less significant impact of each market's investors on other markets' equity trading in the region - and help account for the limited evidence of causality unearthed in our study. The lack of data-availability on intra-region equity trades in the Asia-Pacific, however, renders it impossible to verify this. One might argue that herding from more "open" markets in the region (such as Hong Kong and Singapore) would be more receptive to/influential for herding in other markets; this, however, is not confirmed via our results in Table 6. In addition, when considering the aggregate influence of the other nine markets' herding on each market's herding (see the last row of panels A and B in Table 6), we find that it is only significant for the herding of 6-7 countries (Indonesia, Malaysia, South Korea, Taiwan and Thailand for both panels, and Shanghai (Hong Kong) only in panel A (B)).

are robust when controlling for crisis-episodes (Asian; global financial; global pandemic) and US market returns and we verify that the initial herding estimates' significance is not affected when controlling for the thin trading bias.

The evidence presented in this study is of key interest to the investment community, in particular to investors with international portfolio allocations. Given the empirical design utilized for the investigation of cross-market herding, an investor could, for example, rely on it to assess the structure of cross-market herding among markets of relevance to her investments and use any output to inform her trading strategy. A plausible possibility here would involve investing in two markets (let A and B), with A's herding found to Granger-cause B's; in that case, any increase in market A's herding would predict a forthcoming rise in B's and the investor could employ this information as input for her asset allocation between the two markets. With respect to regulatory authorities, the findings outlined here are clearly important; to the extent that herding can be destabilizing (e.g., it can increase a market's systemic risk) within a market, the presence of cross-market herding indicates the potential for the interactive transmission of such behavior across markets. This raises the need for closer monitoring of such cross-market transmission and we propose an empirical framework that can offer insights into the structure of this transmission-mechanism. To the extent that globalization renders cross-market herding a reality, policy makers could launch *ad hoc* initiatives to monitor it (such as indices capturing cross-market herding between their market and key foreign markets); they could also attempt to moderate its potentially adverse consequences by promoting measures aiming at rendering the impact of herding-spillovers shorter-lived (and, hence, reduce the potential for destabilization). One possibility here is to ensure that their equity markets adopt sophisticated trading systems allowing for enhanced information flow, so that any overseas signals are quickly absorbed by domestic prices and the possibility of prolonged herding on those signals is mitigated. This is particularly important for policy makers in member-countries of financial integration initiatives (such as cross-border exchanges), since the enhanced linkages between those countries' financial systems can amplify the potential for cross-market herding among them.[19] As regards the research community, the results reported here suggest that (causal or not) correlations may be present among other widely documented behavioral trading patterns internationally; a possibility here is feedback trading, a pattern which has been all too frequently encountered alongside herding in the literature. In addition, to the extent that herding in the literature has been shown to be subject to the effect of various determinants across markets, investor-types and time, the fact that our approach allows for an empirical examination of cross market herding free from the shortcomings of earlier approaches (see appendix 1) suggests the possibility that cross market herding may also have its own determinants that future research can investigate. An example in this direction would be to explore the extent to which cross market herding is fundamentals- or noise-driven, by investigating how it varies with fluctuations in macro fundamentals- or sentiment-spillovers across economies. In addition, one could also assess whether cross market herding varies with the stage of markets' integration, by examining its variations before and after markets join international economic/trade/monetary unions.

Declaration of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[19] For more on herding in cross-border exchanges' member-markets and its determinants pre and post membership, see Andrikopoulos et al. (2017) and Economou et al. (2015a).

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Appendix 1

Cross market herding has been investigated in earlier studies on the premises of the Chang, Cheng and Khorana (2000) (henceforth referred to as CCK) approach in two different ways. To begin with, CCK inferred herding via the equation $\mathrm{CSAD}_{m,t} = \alpha_0 + \alpha_1 |r_{m,t}| + \alpha_2 r_{m,t}^2 + e_t$, where CSAD is the cross-sectional dispersion of returns and $r_{m,t}$ is the average market return. The rationale underlying their model is that the relationship between the cross-sectional dispersion of returns and the absolute market return is positive and linear (courtesy of the varying sensitivities of stocks to market movements) in the rational asset pricing framework, but can turn negative and nonlinear in the presence of herding (which would, thus, be reflected through a significantly negative α_2). The first approach of detecting cross market herding was presented by Economou, Kostakis, and Philippas (2011), who tested for cross market herding among four South European stock markets by adding the CSAD of the rest three on the right-hand side of the above equation when estimating herding in each market. Economou, Kostakis, and Philippas (2011) found evidence of significant co-movement among the four markets' CSADs which they interpreted as evidence of co-movement in their herding, with similar results reported by Mobarek, Mollah, and Keasey (2014) who also relied on this approach when testing for herding in a wider European context. However, an issue arising with this interpretation is that herding in the original CCK model is identified through significantly negative α_2 values, not CSAD *per se*. Furthermore, a significantly positive (negative) relationship between two countries' CSADs reveals that their trading dynamics are significantly related due to their co-varying risks (CSAD is a proxy for cross sectional return volatility; Hwang and Salmon, 2004), as Chiang and Zheng (2010) argued, not that their herding forces move *in tandem*. The second approach in detecting cross market herding was developed by Chiang et al. (2013) and is based on assuming that the α_2 coefficient in the CCK model follows an autoregressive process of order 1 (AR-1), which can be used as a state equation in a Kalman filter setting to extract the time-varying series of α_2. Since α_2 is used to detect herding in the original CCK model, Chiang et al. (2013) use its extracted time series as a proxy for herding, whose relationship with market variables is examined by including it as a variable in their regression estimations. This approach is closer to the crux of CCK's herding argument, since α_2 indeed denotes the presence of herding, if significantly negative. The issue arising with using the estimated time series of α_2 as a herding proxy is that it only shows us whether herding on a daily basis is present (herding is present for those days with negative α_2 values) or absent (herding is absent for those days with positive α_2 values), not how it evolves (rises or falls) over time. If we were to use the daily time series of α_2 in our study in our VAR or causality tests (as described above) and the time series for two of the markets, for example, assumed positive values (an indication that herding is absent) most of the time, it is possible that we would end up discovering significant evidence of the existence of (and maybe, even causality in) their relationship. This would be regarded as evidence of cross market herding, without herding being there most of the time in the first place for either of the two markets. As a result of the drawbacks of the above two approaches, we chose to study cross market herding on the premises of the Hwang and Salmon (2004) model, which allows for the direct observation of changes in herding over time.

Appendix 2

ARTICLE	AUTHORS	JOURNAL	YEAR	HERDING-SCOPE
Are Asian Stock Market Fluctuations Due Mainly to Intra-regional Contagion Effects? Evidence Based on Asian Emerging Stock Markets	Masih, A., and R. Masih	Pacific-Basin Finance Journal	1999	Asian Markets
Institutional Herding, Business Groups, and Economic Regimes: Evidence from Japan	Kim, K.A., and J.R. Nofsinger	The Journal of Business	2001	Asian Markets
Dynamic Correlation Analysis of Financial Contagion: Evidence from Asian Markets	Chiang, T.C., B.N. Jeon, and H.Li. 2007	Journal of International Money and Finance	2007	Asian Markets
Herding Behavior in Chinese Stock Markets: An Examination of A and B Shares	Tan, L., T.C. Chiang, J.R. Mason and E. Nelling	Pacific Basin Finance Journal	2008	Asian Markets
Empirical Investigation of Herding Behavior in Chinese Stock Markets: Evidence from Quantile Regression Analysis	Chiang, T.C., J. Li, and L. Tan	Global Finance Journal	2010	Asian Markets
An Empirical Analysis of Herd Behavior in Global Stock Markets.	Chiang, T.C. and, D. Zheng	Journal of Banking and Finance	2010	Asian Markets
Do Investors Herd in Emerging Stock Markets? Evidence from the Taiwanese Market	Demirer, R., A.M. Kutan, and C-D. Chen.	Journal of Economic Behavior and Organizations	2010	Asian Markets
Mutual Fund Herding and its Impact on Stock Returns: Evidence from the Taiwan Stock Market.	Hung, W., C.-C. Lu, and C.F. Lee	Pacific-Basin Finance Journal	2010	Asian Markets
Do Investors Herd in Global Stock Markets?	Chen, T. 2013.	Journal of Behavioral Finance	2013	Asian Markets
Dynamic Herding Behavior in Pacific-Basin Markets: Evidence and Implications	Chiang, T., L. Tan, J. Li, and E. Nelling	Multinational Finance Journal	2013	Asian Markets
Investor herding behavior of Chinese stock market	Ma, C. , W.P. He, and J. Yao.	International Review of Economics and Finance	2014	Asian Markets
Do ADR investors herd?: Evidence from advanced and emerging markets	Demirer, R., A. Kutan, and H. Zhang	International Review of Economics & Finance	2014	Asian Markets
Herd behaviour in Southeast Asian Stock Markets — An Empirical Investigation.	Bui, N.D., L.T.B Nguyen, and N.T.T Nguyen	Acta Oeconomica	2015	Asian Markets
Herding and Fundamental Factors: The Hong Kong Experience	Lam, K.S.K and Z. Qiao	Pacific-Basin Finance Journal	2015	Asian Markets
Investigation of Herding Behaviour in Developed and Developing Countries: Does Country Governance Factor Matters?	Fawwaz, A., A. Ariffin, H. Siong, and M. Yahya	Capital Markets Review, Malaysian Finance Association	2017	Asian Markets
What Explains Herd Behavior in the Chinese Stock Market?	Chong, T T-L, X. Liu, and C. Zhu	Journal of Behavioral Finance	2017	Asian Markets

Effects of transparency on herding behavior: evidence from the taiwanese stock market	Huang Y.S. and, K.Y. Wang	Emerging Markets Finance and Trade	2018	Asian Markets
Regime-dependent herding behavior in Asian and Latin American stock markets.	Kabir, M., and S. Shakur	Pacific-Basin Finance Journal	2018	Asian Markets
Behavior of foreign investors in the Malaysian stock market in times of crisis: A nonlinear approach	Perihan, I., and O. Tolga	Journal of Asian Economics	2019	Asian Markets
The role of overconfidence and past investment experience in herding behaviour with a moderating effect of financial literacy Evidence from pakistan stock exchange	Binti, H., H.B Mohammad, and S.A. Sabir	Asian Economic and Financial Review	2019	Asian Markets
Analysis of herding behavior in the stock market: a case study of the Asean-5 and the US	Ermawati, E. and R. Eki Rahman	Buletin Ekonomi Moneter dan Perbankan	2020	Asian Markets
The COVID Pandemic and Herding Behaviour Evidence from India's Stock Market	Dhall, R., and B. Singh	Millennial Asia	2020	Asian Markets
Herding in the Singapore stock Exchange	Arjoon,V. P. Ramlakhan, and C. Shekhar	Journal of Economics and Business	2020	Asian Markets
Does herding behavior exist in the Mongolian stock market	Batmunkh, M-U, E.Choijil, C. Espinosa-Méndez, J.P Vieito, and W-K. Wong	Pacific Basin Finance Journal	2020	Asian Markets
Social Factors and Herd Behaviour in Developed Markets Advanced Emerging Markets and Secondary Emerging Markets	Ahmad, Z. and O.K. Loang	Journal of Contemporary Eastern Asia	2020	Asian Markets
Herding behavior in the commodity markets of the Asia-Pacific region	Badhani, K.N., E. Bouri, A. Kumar, and T. Saeed	Finance Research Letters	2021	Asian Markets
Herding behavior in Hong Kong stock market during the COVID-19 period: a systematic detection approach	Jian, R., C. Wen, and Z. Yang	Journal of Chinese Economics and Business Studies	2021	Asian Markets / Crises
Investor's herding behavior in Asian equity markets during COVID-19 period	Cui, J., R. Jiang, C. Wen, and R. Zhang.	Pacific-Basin Finance Journal	2022	Asian Markets / Crises
The Global Crisis and Equity Market Contagion	Bekaert, G., M. Ehrmann, M. Fratzscher, and A.Mehl	The Journal of Finance	2014	Crises
Herding Behavior, Market Sentiment and Volatility: Will the Bubble Resume?”	Bekiros, S., M. Jlassi, B. Lucey, K. Naoui, and G.S. Uddin	The North American Journal of Economics and Finance	2017	Crises
Herding Behaviour in Australian stock market: Evidence on COVID-19 effect	Arias, J., and Espinosa-Méndez, C.	Applied Economics Letters	2020	Crises
Herding behaviour in energy stock markets during the Global Financial Crisis SARS and ongoing COVID	Chang, C.L., M.McAleer, and Y.A.Wang	Renewable and Sustainable Energy Reviews	2020	Crises

Herding behavior during the Covid-19 pandemic: a comparison between Asian and European stock markets based on intraday multifractality	Aslam, F., Ferreira, P., Ali, H., and S. Kauser	Eurasian Economic Review	2021	Crises
The effects of a black swan event COVID on herding behavior in cryptocurrency markets	Jalan, A., R. Matkovskyy, and L.Yarovaya	Journal of International Financial Markets, Institutions and Money	2021	Crises
Deaths panic lockdowns and US equity markets The case of COVID pandemic	Baig, A.S., H. A. Butt, O.Haroon, and S.A.R. Rizvi	Finance Research Letters	2021	Crises
Covid-19 and herding in global equity market	Raimundo, G., and A. Rubesam	Journal of Behavioral and Experimental Finance	2022	Crises
Together we Invest? Individual and Institutional Investors' Trading Behavior in Poland	Goodfellow, C., M. Bohl, and B. Gebka	International Review of Financial Analysis	2009	Different Markets
Do Fund Managers Herd in Frontier Markets-and why?	Economou, F., K. Gavriilidis, V. Kallinterakis, and, N. Yordanov	International Review of Financial Analysis	2015	Different Markets
Intraday Herding on a Cross-border Exchange	Andrikopoulos, P., V. Kallinterakis, M.P. Leite Ferreira, and T. Verousis.	International Review of Financial Analysis	2017	Different Markets
Institutional Traders' Behaviour in an Emerging Stock Market: Empirical Evidence on Polish Pension Fund Investors	Voronkova, S., and M.T. Bohl	Journal of Business, Finance and Accounting	2005	Different Markets
Cross-country Effects in Herding Behavior: Evidence from Four South European Markets	Economou, F., A. Kostakis, and N. Philippas	Journal of International Financial Markets, Institutions and Money	2011	Different Markets
Investor Herds and Regime-switching: Evidence from Gulf Arab Stock Markets.	Balcilar, M., R. Demirer and S. Hammoudeh	Journal of International Financial Markets, Institutions and Money	2013	Different Markets
A Cross-country Analysis of Herd Behavior in Europe."	Mobarek, A., S. Mollah, and K. Keasey	Journal of International Financial Markets, Institutions and Money	2014	Different Markets
Herding Dynamics in Exchange Groups: Evidence from Euronext	Economou, F., K. Gavriilidis, V. Kallinterakis, and, A. Goyal	Journal of International Financial Markets, Institutions and Money	2015	Different Markets
Herding in Frontier Markets: Evidence from African Stock Exchanges	Guney, Y., V. Kallinterakis, and G. Komba	Journal of International Financial Markets, Institutions and Money	2017	Different Markets
Country herding in the global market	Chen, T.	Journal of Behavioral Finance	2019	Different Markets
Do Investors in SMEs Herd? Evidence from French and UK Equity Markets	Benkraiem, R., M. Bouattour, E. Galariotis, and A. Moloudi	Small Bus Econ	2021	Different Markets
Herding in Imperial Russia: Evidence from the St. Petersburg Stock Exchange (1865–1914)	Kallinterakis, V., and G.Konstantinos	Journal of Behavioral Finance	2021	Different Markets
Herd Behavior and Investment	Scharfstein, D.S., and J.C. Stein	American Economic Review	1990	Other
Herd on the Street: Informational Inefficiencies in a Market with Short-term Speculation.	Froot, K., D. Scharfstein, and J.C. Stein	Journal of Finance	1992	Other
Rational Herding in Financial Economics	Devenow, A., and I. Welch	European Economic Review	1996	Other

Herding Behavior and Stock Returns: An Exploratory Investigation	De Bondt, W.F.M, and L.L.Teh	Swiss Journal of Economics and Statistics	1997	Other
Mutual Fund Herding and the Impact on Stock Prices	Wermers, R.	Journal of Finance	1999	Other
An Examination of Herd Behavior in Equity Markets: An International Perspective	Chang, E.C., J.W. Cheng, and A. Khorana	Journal of Banking and Finance	2000	Other
Herd Behavior and Cascading in Capital Markets: a Review and Synthesis	Hirshleifer, D., and S.T Teoh	European Financial Management	2003	Other
Market Stress and Herding	Hwang, S., and M. Salmon	Journal of Empirical Finance	2004	Other
Institutional Herding	Sias, R.W	Review of Financial Studies	2004	Other
Herding and Information Based Trading	Zhou, R.T., and R.N. Lai	Journal of Empirical Finance	2009	Other
Institutional Industry Herding	Choi, N., and R.W. Sias	Journal of Financial Economics	2009	Other
Do Fund Managers Herd to Counter Investor Sentiment	Liao, T.-L., C.-J Huang, and C.-W. Wu	Journal of Business Research	2011	Other
Market Sentiment: a Key Factor of Investors' imitative Behaviour	Blasco, N., P. Corredor, and S. Ferreruela	Accounting & Finance	2012	Other
Institutional Industry Herding: Intentional or Spurious?	Gavriilidis, K., V. Kallinterakis, and M.P. Leite-Ferreira	Journal of International Financial Markets, Institutions and Money	2013	Other
International Herding: does it Differ Across Sectors?	Gebka, B., and M.E. Wohar	Journal of International Financial Markets, Institutions and Money	2013	Other
Herding on Ending Digits in Security Trading	Chen, T. and W.C.W. Yau	Chinese Economy	2014	Other
Do Mutual Funds Herd in Industries?	Celiker, U., J. Chowdhury, and G. Sonaer	Journal of Banking and Finance	2015	Other
The Impacts of Individual and Institutional Trading on Futures Returns and Volatility: Evidence from Emerging Index Futures Markets	Kuo, W-S, S-L Chung, and C-Y Chang	Journal of Futures Markets	2015	Other
The Market for Lemmings: The herding behavior of pension funds	Blake D., k. Sarno, and G. Zinna.	Journal of Financial Markets	2017	Other
Investors' fear and Herding in the Stock Market	Economou, F., C. Hassapis, and N. Philippas	Applied Economics	2018	Other
Does Herding Behavior Reveal Skill? An Analysis of Mutual Mund Performance.	Jiang, H., and M. Verardo	Journal of Finance	2018	Other
Cross herding between American Industries and the Oil Market	BenMabrouk, H., and H. Litimi	The North American Journal of Economics and Finance	2018	Other
Does Asymmetric Information Drive Herding An Empirical Analysis	Alhaj-Yaseen, Y.S., and X. Rao	Journal of Behavioral Finance	2019	Other
Monetary Policy and Herd Behavior: International Evidence	Krokida, S., P. Makrychoriti, and S. Spyrou	Journal of Economic Behavior and Organization	2020	Other

What Drives Herding Behavior in the Cryptocurrency Market?	Youssef, M.	Journal of Behavioral Finance	2020	Other
Does Country Matter to Investor Herding? Evidence from an Intraday Analysis.	Chen, T.	Journal of Behavioral Finance	2020	Other
Regulatory Mood-congruence and Herding: Evidence from Cannabis Stocks	Andrikopoulos, P., B, Gebka, and V. Kallinterakis.	Journal of Economic Behavior and Organization	2021	Other

Table 1: Market characteristics

	Clusters	Restrictions to foreign investors	Rating S&P	Market Classification	Market capitalization (million USD)			Number of listed companies (Total)			% of domestic companies/total		
					1996	2009	2021	1996	2009	2021	1996	2009	2021
China (Shanghai)	ASEAN+3	YES	A+	Emerging	N.D	2.704.778,46	8.154.689,12	287	870	2.037	100,0%	100,0%	100,0%
China (Hong Kong)	ASIAN TIGERS	YES	A+	Developed	449.218,77	2.305.142,81	5.434.177,12	561	1.308	2.388	96,2%	99,2%	92,8%
Indonesia	ASEAN / ANSA	NO*	BBB	Emerging	90.997,08	214.941,47	578.631,40	252	398	766	99,6%	100,0%	100,0%
Japan	ASEAN +3 / G7 / G8	YES	A+	Developed	3.019.733,73	3.306.082,05	6.544.303,49	1.766	2.320	3.818	96,3%	99,4%	99,8%
Malaysia	ASEAN /ANSA	NO*	A-	Emerging	306.164,19	289.219,39	414.285,26	615	952	940	99,5%	99,3%	99,3%
Philippines	ASEAN / ANSA	YES	BBB+	Emerging	80.648,63	86.349,43	285.423,26	216	246	273	100,0%	99,2%	98,9%
Singapore	ASEAN / ASIAN TIGERS /ANSA	NO	AAA	Developed	150.043,56	481.246,70	663.388,48	266	459	442	100,0%	59,4%	65,7%
South Korea	ASEAN +3 / ASIAN TIGERS	NO	AAA	Developed	139.121,66	834.596,86	2.218.658,14	760	1.778	2.383	100,0%	99,4%	99,0%
Taiwan	ASIAN TIGERS	NO	A++	Emerging	273.607,67	658.991,37	2.029.131,45	382	741	881	100,0%	98,1%	90,8%
Thailand	ASEAN /ANSA	YES	BBB+	Emerging	96.697,31	176.956,07	598.908,32	454	535	776	100,0%	100,0%	100,0%

* only for some sectors

The table presents some characteristics of the countries and the markets under study (belonging to different clusters of countries; restrictions to foreign investors; rating of the country in 2022 according to S&P; classification as emerging or developed; market capitalization in millions of USD; number of listed companies and percentage of domestic companies over the total number of listed companies – given the length of the sample, we show data for 1996, 2009 and 2021 for the last three items).

Table 2: Descriptive statistics for our sample markets (February 1995 – March 2022)

Panel A: Descriptive statistics for log $[Std_c(\beta^b_{imt})]$ for each of our sample markets

	China (Shanghai)	China (Hong Kong)	Indonesia	Japan	Malaysia	Philippines	Singapore	South Korea	Taiwan	Thailand
Mean	-0.2927	-0.0948	0.0227	-0.2198	0.0395	-0.0302	-0.0186	-0.1467	-0.2210	-0.0787
Standard Deviation	0.1620	0.1155	0.1336	0.0943	0.1325	0.1372	0.1539	0.1112	0.1153	0.1101
Maximum value	0.6515	0.4083	0.4102	0.1044	0.3982	0.3797	0.6235	0.2943	0.1025	0.3576
Minimum value	-0.7537	-0.4226	-0.3511	-0.5054	-0.3934	-0.3644	-0.4283	-0.4521	-0.6305	-0.3749

Panel B: Correlation matrix of log $[Std_c(\beta^b_{imt})]$ of our sample markets

	China (Shanghai)	China (Hong Kong)	Indonesia	Japan	Malaysia	Philippines	Singapore	South Korea	Taiwan	Thailand
China (Shanghai)	1.0000									
China (Hong Kong)	0.2146	1.0000								
Indonesia	0.2239	0.3293	1.0000							
Japan	0.1734	0.2771	0.2054	1.0000						
Malaysia	0.3731	0.3306	0.1811	0.0827	1.0000					
Philippines	-0.0820	0.1656	0.2609	0.0906	0.0043	1.0000				
Singapore	0.4531	0.4835	0.2528	0.0662	0.6676	0.0064	1.0000			
South Korea	0.2361	0.3929	0.2814	0.0728	0.4390	0.0367	0.4457	1.0000		
Taiwan	0.3557	0.4768	0.2870	0.2223	0.4652	0.0482	0.4621	0.5421	1.0000	
Thailand	0.4262	0.3124	0.4057	0.2162	0.2897	0.0795	0.4197	0.3101	0.3525	1.0000

The table presents some descriptive statistics (mean; standard deviation; maximum and minimum value) for the log $[Std_c(\beta^b_{imt})]$ - i.e., the logarithmic cross sectional standard deviation of monthly betas - of each of our sample markets in panel A; panel B presents the correlation matrix of log $[Std_c(\beta^b_{imt})]$ of our sample markets. All statistics refer to the February 1995 – March 2022 period.

Table 3: Herding estimates for our sample markets (February 1995 – March 2022)

	China (Shanghai)	China (Hong Kong)	Indonesia	Japan	Malaysia	Philippines	Singapore	South Korea	Taiwan	Thailand
μ_m	-0.5106	-0.1284	0.0241	-0.2208	-0.1339	-0.0303	-0.1864	-0.1476	-0.2234	-0.0816
	(0.0000)	(0.0000)	(0.0810)	(0.0000)	(0.0052)	(0.0425)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
ϕ_m	0.9919	0.9210	0.6646	0.7769	0.9957	0.8125	0.9954	0.7901	0.9162	0.8030
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\sigma^2_{m,\upsilon}$	0.0090	0.0049	0.0064	0.0045	0.0055	0.0123	0.0062	0.0031	0.0010	0.0045
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
$\sigma^2_{m,\eta}$	0.0016	0.0015	0.0064	0.0017	0.007	0.0022	0.0007	0.0035	0.0071	0.0027
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0002)	(0.0016)	(0.0000)	(0.0000)	(0.0000)
$\sigma_{m,\eta}$/ S.D. (log-CXB)	0.2469	0.3354	0.5987	0.4373	0.6313	0.3420	0.1719	0.5320	0.7305	0.4720

The table presents the coefficients from the estimation of the following system of equations for our ten sample markets:

$\log\,[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \upsilon_{mt}$

$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt}$

The estimations correspond to the period February 1995 – March 2022. $\log\,[Std_c(\beta^b_{imt})]$ is the logarithmic cross sectional standard deviation of monthly betas of each of our sample markets. S.D. (log-CXB) is the time series standard deviation of the $\log\,[Std_c(\beta^b_{imt})]$. Parentheses include p-values.

Table 4: Correlation matrix for our sample markets' "herds" (February 1995 – March 2020)

	China (Shanghai)	China (Hong Kong)	Indonesia	Japan	Malaysia	Philippines	Singapore	South Korea	Taiwan	Thailand
China (Shanghai)	1.0000									
China (Hong Kong)	0.2642	1.0000								
Indonesia	0.3091	0.3725	1.0000							
Japan	0.2362	0.2971	0.2383	1.0000						
Malaysia	0.5420	0.3772	0.1536	0.0144	1.0000					
Philippines	-0.2667	0.1746	0.2445	0.0498	-0.1757	1.0000				
Singapore	0.5884	0.5373	0.2143	0.0069	0.8278	-0.1860	1.0000			
South Korea	0.3133	0.4040	0.2945	-0.0173	0.5369	-0.0261	0.5204	1.0000		
Taiwan	0.5764	0.5599	0.3623	0.2116	0.6425	-0.1149	0.6253	0.6360	1.0000	
Thailand	0.6096	0.3429	0.4738	0.2562	0.3382	-0.0257	0.4663	0.3627	0.4790	1.0000

The table presents the correlation matrix for our sample markets' "herds" (proxied through the values of h_{mt} for each market) for the February 1995 – March 2022 period. h_{mt} refers to the dynamic, time-varying herding extracted from the Hwang and Salmon (2004) measure and is calculated as $h_{mt} = 1 - exp(H_{mt})$.

Table 5: Cross-market herding estimates based on the VAR model without control variables (February 1995 - March 2022)

	China (Shanghai), t	China (Hong Kong), t	Indonesia,t	Japan,t	Malaysia,t	Philippines,t	Singapore,t	South Korea,t	Taiwan,t	Thailand,t
$\omega_{China\ (Shanghai),t-1}$	0.8832**	-0.0134**	0.0603**	0.0307**	0.0097**	-0.0180**	0.0017**	-0.0067**	0.0150**	0.0727**
$\omega_{China\ (Hong\ Kong)\ ,t-1}$	-0.0440*	0.8818**	0.1044*	0.0479**	-0.0281**	0.0628**	0.0109**	0.0166*	0.0481**	-0.0231**
$\omega_{Indonesia,t-1}$	-0.0183**	0.0034*	0.5552**	0.0009**	0.0060**	0.0124**	0.0213**	0.0223**	0.0151**	0.0419**
$\omega_{Japan,t-1}$	-0.0206*	0.0501**	-0.0480*	0.7182**	-0.0374**	-0.0317**	0.0135**	-0.2142*	-0.0148**	-0.0452*
$\omega_{Malaysia,t-1}$	-0.0031**	0.0220**	0.0035*	0.0194**	0.9054**	0.0265**	0.0441**	0.1026**	0.0539**	-0.0380**
$\omega_{Philippines,t-1}$	-0.0844*	0.0103**	0.0420*	-0.0260**	-0.0026**	0.7586**	0.0534**	-0.0079*	-0.0461**	-0.0100*
$\omega_{Singapore,t-1}$	0.0383**	0.0100**	-0.0822*	-0.0612**	0.0810**	-0.0448**	0.9486**	-0.0116**	-0.0220**	0.0290**
$\omega_{South\ Korea,t-1}$	-0.0317**	0.0089**	-0.0319*	-0.0136**	-0.0291**	-0.0222**	0.0195**	0.6476**	0.0465**	-0.0146**
$\omega_{Taiwan,t-1}$	0.0516*	-0.0642*	0.0794*	-0.0190**	-0.0381**	-0.0264*	0.1058**	0.0677*	0.7520**	0.0233*
$\omega_{Thailand,t-1}$	0.1726*	0.0805**	0.1290*	0.0435**	0.0116**	0.0188**	0.0409**	0.0801*	0.0472**	0.6865**
δ_m	-0.0246***	-0.0008***	0.0033**	0.0009***	-0.0033***	-0.0061***	-0.0016***	0.0152***	0.0110***	0.0133***
R^2	0.9112	0.8289	0.4666	0.6150	0.9389	0.6640	0.9530	0.6464	0.8540	0.6629
Adjusted R^2	0.9084	0.8235	0.4496	0.6027	0.9369	0.6532	0.9515	0.6352	0.8494	0.6522
F-statistic	322.3653	152.1626	27.4657	50.1576	482.2379	62.0384	636.4362	57.4089	183.7238	61.7608
Log likelihood	509.2809	627.6721	421.9604	654.6060	681.6994	645.0865	652.1893	502.3141	736.1295	552.6858
AIC	-3.0663	-3.7949	-2.5290	-3.9607	-4.1274	-3.9021	-3.9458	-3.0235	-4.4623	-3.3335
BIC	-2.9383	-3.6668	-2.4009	-3.8326	-3.9993	-3.7740	-3.8177	-2.8954	-4.3343	-3.2054

The table presents the estimates of the VAR model aimed to capture cross-market herding for the February 1995 – March 2022 period represented by the following equation:

$$h_{mt} = \delta_m + \sum_{m=1}^{q}\sum_{j=1}^{p} \omega_{mt-j} h_{mt-j} + \vartheta_t$$

h_{mt} refers to the dynamic, time-varying herding extracted from the Hwang and Salmon (2004) measure; δ_m is the constant term of the equation; ω_{mt-j} is a vector containing the regression coefficients from each of the sample's ten markets; h_{mt-j} reflects the h_{mt} series of each market m for month *t-j*; and, finally, ϑ_t is the model's error term. *, **, and *** represent statistical significance at the 10%, 5%, and 1% significance levels, respectively.

Table 6: Cross-market herding estimates based on the VAR model with control variables (February 1995 – March 2022)

	China (Shanghai),t	China (Hong Kong),t	Indonesia,t	Japan,t	Malaysia,t	Philippines,t	Singapore,t	South Korea,t	Taiwan,t	Thailand,t
$\omega_{China\ (Shanghai),t-1}$	0.8729**	-0.0008**	0.0705**	0.0257**	0.0209**	-0.0198**	0.0037**	-0.0027**	0.0212**	0.0664**
$\omega_{China\ (Hong\ Kong),t-1}$	-0.0291*	0.8320**	0.0520*	0.0398**	-0.0502**	0.0462**	-0.0039**	-0.0256*	0.0252**	0.0000**
$\omega_{indonesia,t-1}$	-0.0102**	-0.0099*	0.5270**	0.0002**	-0.0050**	0.0044**	0.0184**	0.0088**	0.0138**	0.0511**
$\omega_{Japan,t-1}$	-0.0326*	0.0649**	-0.0265*	0.7136**	-0.0216**	-0.0314**	0.0156**	-0.2076*	-0.0080**	-0.0537**
$\omega_{Malaysia,t-1}$	0.0159 *	-0.0076**	-0.0511*	0.0217**	0.8768**	0.0176**	0.0385**	0.0811*	0.0430**	-0.0198**
$\omega_{Philippines,t-1}$	-0.0777*	-0.0201**	0.0173*	-0.0344**	-0.0063**	0.7425**	-0.0640**	-0.0403*	-0.0534**	0.0043*
$\omega_{Singapore,t-1}$	0.0314**	0.0529**	-0.0417*	-0.0519**	0.1017**	-0.0368**	0.9617**	0.0195**	0.0096**	0.0128**
$\omega_{South\ Korea,t-1}$	-0.0321**	-0.0130**	-0.0645*	-0.0237**	-0.0391**	-0.0325**	0.0120**	0.6258**	0.0313**	-0.0054**
$\omega_{Taiwan,t-1}$	0.0404*	-0.0601*	0.1179	-0.0232**	-0.0206**	-0.0203*	-0.1075*	0.0722*	0.7469**	0.0150*
$\omega_{Thailand,t-1}$	0.1575*	0.1016**	0.1476*	0.0405**	0.0202**	0.0274**	0.0461**	0.0985*	0.0460**	0.6736**
δ_m	-0.0241***	0.0032***	-0.0099**	-0.0010***	-0.0068***	-0.0101***	-0.0021***	-0.0107***	0.0111***	0.0158***
γ_1	-0.0172**	0.0146**	0.0411**	-0.0039**	0.0157***	0.0129**	0.0018**	0.0172**	-0.0089***	-0.0144**
γ_2	0.0104**	0.0261**	0.0278**	0.0244**	-0.0110**	0.0283**	0.0133**	0.0439**	0.0054**	-0.0108**
γ_3	0.0033***	0.0064***	0.0184***	0.0058***	0.0063***	0.0033***	0.0023***	0.0065***	0.0091***	-0.0022***
γ_4	-0.0134**	0.0331**	0.0274**	0.0010***	0.0162***	0.0062**	0.0090***	0.0232**	0.0161***	-0.0149**
R^2	0.9120	0.8373	0.4854	0.6220	0.9406	0.6703	0.9533	0.6549	0.8609	0.6657
Adjusted R^2	0.9080	0.8300	0.4621	0.6049	0.9379	0.6554	0.9512	0.6394	0.8546	0.6506
F-statistic	229.3845	113.9804	20.8854	36.4361	350.5347	45.0093	451.7404	42.0285	137.0057	44.0887
Log likelihood	510.6152	635.8455	427.7926	657.5894	686.3287	648.1661	653.1986	506.2730	743.9160	554.0057
AIC	-3.0499	-3.8206	-2.5403	-3.9544	-4.1313	-3.8964	-3.9274	-3.0232	-4.4856	-3.3170
BIC	-2.8753	-3.6460	-2.3656	-3.7798	-3.9566	-3.7218	-3.7527	-2.8486	-4.3110	-3.1423

The table presents the estimates of the VAR model aimed to capture cross-market herding for the February 1995 – March 2022 period represented by the following equation:

$$h_{mt} = \delta_m + \sum_{m=1}^{q} \sum_{j=1}^{p} \omega_{mt-j} h_{mt-j} + \gamma_1 D_{Asia,t} + \gamma_2 D_{Global,t} + \gamma_3 D_{S\&PCOMP,t} + \gamma_4 D_{COVID,t} + \vartheta_t$$

h_{mt} refers to the dynamic, time-varying herding extracted from the Hwang and Salmon (2004) measure; δ_m is the constant term of the equation; ω_{mt-j} is a vector containing the regression coefficients from each of the sample's ten markets; h_{mt-j} reflects the h_{mt} series of each market *m* for month *t-j*; $D_{Asia,t}$ = 1 for the July 1997 – July 1998 period, zero otherwise; $D_{Global,t}$ = 1 for the October 2008 – March 2009 period, zero otherwise; $D_{S\&PCOMP,t}$ = 1 for those months for which the Standard & Poor's Composite Index generated a negative return, zero otherwise; and $D_{COVID,t}$ = 1 from March 2020 until the end of our sample window; and, finally, ϑ_t is the model's error term. *, **, and *** represent statistical significance at the 10%, 5%, and 1% significance levels, respectively.

Table 7: Granger causality test (one lag)

Panel A: VAR model without control variables

	China (Shanghai)	China (Hong Kong)	Indonesia	Japan	Malaysia	Philippines	Singapore	South Korea	Taiwan	Thailand
China (Shanghai)	-	0.5212	2.9781*	3.2288*	0.3788	1.0520	0.0100	0.0603	1.2767	9.7053***
China (Hong Kong)	0.7457	-	2.4510	2.1567	0.8753	3.4991*	0.1102	0.1016	3.5926*	0.2670
Indonesia	0.2164	0.0159	-	0.0012	0.0664	0.2291	0.7074	0.3065	0.5919	1.4790
Japan	0.1054	1.2883	0.3338	-	0.9987	0.5733	0.1082	10.8796***	0.2188	0.6597
Malaysia	0.0043	0.4498	0.0032	0.4102	-	0.7246	2.0981	4.5079**	5.2432**	0.8432
Philippines	2.1553	0.0663	0.3122	0.5000	0.0057	-	2.0809	0.0179	2.6025	0.0394
Singapore	0.8163	0.1154	2.1899	5.0837**	10.5152***	2.5703	-	0.0719	1.0827	0.6102
South Korea	0.4762	0.0781	0.2812	0.2137	1.1595	0.5395	0.4356	-	4.1456**	0.1320
Taiwan	0.4618	1.4825	0.6385	0.1537	0.7271	0.2784	4.6752*	0.7522	-	0.1228
Thailand	10.3812***	4.6755**	3.3863	1.6102	0.1347	0.2840	1.4069	2.1404	3.1283*	-
All Markets	17.2910**	10.0412	17.2994**	11.7319	21.4078**	10.2088	9.0112	28.8224***	32.2653***	18.8392**

Panel B: VAR model with control variables										
	China (Shanghai)	China (Hong Kong)	Indonesia	Japan	Malaysia	Philippines	Singapore	South Korea	Taiwan	Thailand
China (Shanghai)	-	0.0020	3.7494*	2.0580	1.6174	1.1508	0.0420	0.0088	2.3722	7.2409***
China (Hong Kong)	0.2818	-	0.5410	1.3063	2.4797	1.6614	0.0119	0.2121	0.8926	0.0000
Indonesia	0.0636	0.1304	-	0.0001	0.0450	0.0276	0.5008	0.0462	0.4951	2.1034
Japan	0.2553	2.1873	0.1013	-	0.3296	0.5524	0.1416	10.0911***	0.0654	0.9062
Malaysia	0.0996	0.0499	0.6196	0.4575	-	0.2861	1.4038	2.5315	3.0677*	0.2030
Philippines	1.7030	0.2473	0.0506	0.8257	0.0326	-	2.7824*	0.4473	3.3792*	0.0070
Singapore	0.4432	2.7181*	0.4706	2.9950*	13.7187***	1.4187	-	0.1663	0.1729	0.0969
South Korea	0.4679	0.1671	1.138	0.6340	2.0485	1.1193	0.1574	-	1.8755	0.0176
Taiwan	0.2673	1.2800	1.3698	0.2179	0.2054	0.1571	4.5587**	0.8335	-	0.0481
Thailand	8.2102***	7.3852***	4.3338**	1.3435	0.3965	0.5776	1.6941	3.1295*	2.9415*	-
All Markets	13.501	17.2542**	18.7824**	9.1367	22.8095***	8.3320	9.4332	28.0464***	33.2484***	13.6202

The table presents the estimates for the Granger causality tests for the optimal lag-length (i.e., one lag) applied to h_{mt}, the dynamic, time-varying herding extracted from the Hwang and Salmon (2004) measure. The Chi-squared values of testing the null "h_{mt} from the markets in the first column do not linearly Granger cause h_{mt} in the market in the first row" are provided. The VAR model without control variables used in Panel A is as follows:

$$h_{mt} = \delta_m + \sum_{m=1}^{q} \sum_{j=1}^{p} \omega_{mt-j} h_{mt-j} + \vartheta_t$$

While the VAR model with control variables used in Panel B is as follows:

$$h_{mt} = \delta_m + \sum_{m=1}^{q} \sum_{j=1}^{p} \omega_{mt-j} h_{mt-j} + \gamma_1 D_{Asia,t} + \gamma_2 D_{Global,t} + \gamma_3 D_{S\&PCOMP,t} + \gamma_4 D_{COVID,t} + \vartheta_t$$

δ_m is the constant term of the equation; ω_{mt-j} is a vector containing the regression coefficients from each of the sample's ten markets; h_{mt-j} reflects the h_{mt} series of each market *m* for month *t-j*; $D_{Asia,t}$ = 1 for the July 1997 – July 1998 period, zero otherwise; $D_{Global,t}$ = 1 for the October 2008 – March 2009 period, zero otherwise; $D_{S\&PCOMP,t}$ = 1 for those months for which the Standard & Poor's Composite Index generated a negative return, zero otherwise; and $D_{COVID,t}$ = 1 from March 2020 until the end of our sample window; and, finally, ϑ_t is the model's error term. *, **, and *** represent statistical significance at the 10%, 5%, and 1% significance levels, respectively.