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Herding and market volatility

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ABSTRACT

In this paper, we explore the impact of investor herding behavior on stock market volatility. We adopt a direct herding measure based on the variation of cross-sectional stock betas. The measure can be readily separated into positive and adverse components, whereby investors herd towards and away from the market portfolio, respectively. Using A-shares listed in the Chinese equity market from August 2005 to March 2021, we show that the market volatility is Granger caused by the measure, and that there exists an asymmetric effect between positive and adverse herding on volatility. Furthermore, we provide robust evidence that the information contained in the herding measure helps generate significantly improved volatility forecasts and add economic value to investors. Our paper not only contributes to the volatility forecasting literature but also advances our understanding of herding in the equity market.

1. Introduction

In the literature, herding has gradually come to be recognized as a widespread decision-making behavior in international markets (Dang & Lin, 2016; Demirer et al., 2010; Fei et al., 2019; Hudson et al., 2020; Kremer & Nautz, 2013) and across different asset classes (Andrikopoulos et al., 2017; Cai et al., 2019; Demirer et al., 2015; Galariotis et al., 2016; Jiang & Verardo, 2018; Philippas et al., 2013). Investors herd by following each other into or out of the same securities regardless of their own information or judgment (Sias, 2004). Great efforts have been exerted on theorizing the causes and examining the empirical evidence of herding (see Bikhchandani et al., 1992; Brown et al., 2013; Falkenstein, 1996; Guo et al., 2020, for example) because it not only impacts asset returns but also contains significant implication for stock market stability.

There is mixed evidence in the literature on the latter issue, i.e., whether herding (de)stabilizes stock markets. On the one hand, Scharfstein and Stein (1990) argue from a theoretical perspective that institutional investors herd to avoid reputation damage. It gives rise to bubbles and subsequent price corrections thus destabilizing the stock market. On the other hand, Hirshleifer et al. (1994) motivate herding as a result of sequential flow of information arrival and show that it stabilizes stock markets. Empirically, Lakonishok et al. (1992) and Wermers (1999) document little evidence of institutional herding at the aggregate stock market level. More recently, Choi and Skiba (2015) examine institutional herding in 41 countries and conclude that herding stabilizes stock prices, whereas Jiao and Ye (2014) provide evidence that mutual funds herd hedge funds into or out of the same stocks resulting in sharp price reversal in the following quarter. These studies examine the (de)stabilizing effect in terms of stock return dynamics, but the same effect can be analyzed via the second moment of the return distribution, i.e., volatility.

Meanwhile, from the perspective of whether herding is (un)intentional, it impacts differently on market volatility (Bikhchandani & Sharma, 2001). Intentional herding usually involves the blind imitation of others (Banerjee, 1992; Bikhchandani et al., 1992) or is due to manager reputation (Scharfstein & Stein, 1990). It leads to excess volatility and destabilizes the market. This is often contrary to unintentional herding when rational investors rely on the same factors and arrive at the same investment decision (Hirshleifer et al., 1994) or are attracted by stocks with similar characteristics (Falkenstein, 1996). Furthermore, in terms of information quality, the theoretical framework in Wang and Wang (2018) suggest that herding will lead to either market efficiency and lower market volatility or deviation from fundamentals and higher market volatility depending on the quality of the private information from opinion leaders, i.e., gurus. Finally, in a recent paper, building upon investor behavioral biases, Hwang et al. (2021) argue that excessive trading of overconfident investors also contributes to positive beta herding.

Motivated by the debate and evidence in the existing literature, we address two related questions in this paper. First, does herding reduce or increase stock market volatility? Put differently, does herding stabilize or destabilize the market? Second and importantly, does the information contained in the investor herding behavior help improve market volatility prediction?

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To address these questions, we adopt a direct herding measure developed in Hwang and Salmon (2004) (hereafter HS). HS make a careful distinction between two forms of herding in a stock market: one which potentially leads to market inefficiency, and the other which reflects an efficient reallocation of assets on the basis of common fundamental news. By conditioning on observed price movements in the fundamentals as those expressed in pricing models, the paper separates adjustment to fundamental news from the latent herding behavior. Hence, if investors herd towards (away from) the market portfolio, the cross-sectional dispersion of the estimated stock beta will decrease (increase) relative to the equilibrium beta. The latent herding measure is thus obtained by modeling the difference between estimated and equilibrium stock betas.

This direct herding measure enjoys clear advantages over the cross-sectional deviation measures in Chang et al. (2000) and Christie and Huang (1995). First, it is a direct measure of herding, whereas the cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) *reflect* return dispersion by looking at the statistical significance of CSSD and CSAD regression coefficients. Second, this measure allows adverse herding, namely investors herding away from the market portfolio, which represents a systematic adjustment back towards the long-term risk and return equilibrium. In this way, we are able to obtain and plot the time series of the herding measure and gain a clearer understanding. Together, positive and adverse herding provide a comprehensive description and enable us to analyze herding direction and intensity, i.e., the magnitude of herding, and their respective implication on market stability.[1] The main assumption for the herding measure is that a specific asset pricing model is needed and that herding leads to biases in the short-term risk and return relation described by equilibrium pricing models.

Empirically, we examine the relation between herding and market stability in the Chinese equity market. We are interested in this market mainly because it is the largest emerging market in the world, and its disproportionately large number of retail investors exhibit strong behavior biases such as the disposition effect, overconfidence, and herding (see Chen et al., 2014; Feng & Seasholes, 2005; Hilliard & Zhang, 2015; Kim & Nofsinger, 2008, for example). Our sample includes all listed A-shares traded in the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE).[2] The sample period for our daily data is from August 2005 to March 2021 covering the Great Recession of 2007–08, the recent Chinese stock market turbulence in 2015–2016, and the Covid-19 pandemic in 2020.

Our empirical analyses offer a host of interesting findings. First, we show in the in-sample estimation that herding, positive herding, and adverse herding all play a significant role in explaining the Chinese stock market volatility. Interestingly, herding intensity is insignificant suggesting that herding direction matters. Second, there exists a distinct asymmetric herding effect on market volatility: positive (adverse) herding is associated with heightened (reduced) level of market volatility, and that adverse herding is not as substantial as positive herding but the impact is more long-lasting. Furthermore, the Granger causality test suggests that a potential causality relation exists between herding and market volatility, as the null hypothesis that volatility is not Granger caused by herding is overwhelmingly rejected up to 22 lags. Third, the information content in the herding measure proves useful for predicting future volatility at the one-, five-, and 22-day ahead horizons: when we incorporate the herding measure in the HARQ model of Bollerslev et al. (2016), we find that the prediction errors are significantly reduced. Fourth, we investigate whether the improved volatility forecasts are able to deliver economic gains to mean–variance utility investors in a portfolio setting across different levels of risk aversion. Using three different performance measures, we show that the augmented model consistently offers more economic value to investors than the benchmark model. Finally, we perform a number of robustness checks and show that the baseline results are not due to specific choices we make in the econometric framework: it does not matter which specific asset pricing models or time span we use for estimating stock betas upon which the herding measure is based; and the results are not affected by alternative volatility model, true volatility proxy, or whether we include leverage effect and return jumps. Our baseline results are also robust with respect to the subsample analysis.

Our paper is related to two strands of the literature. First, it contributes to the literature on the information content of herding for volatility prediction. Blasco et al. (2012) conclude that the magnitude of herding increases with historical, realized, and option-implied volatilities of the market in-sample, and it is useful for predicting out-of-sample volatility under certain conditions. More recently, Fei et al. (2019) outline clear channels through which the CSSD and CSAD measures may impact asset volatility. One of the channels is the association between these return dispersion measures and herding. The paper provides comprehensive empirical evidence that the information contained in CSSD and CSAD helps improve volatility prediction at the market and industry levels. Our results are in line with evidence in the prior literature: when the herding measure is added to the HARQ model, it helps generate significantly more accurate volatility forecasts.

Our paper also contributes to the debate in the literature on the (de)stabilizing effect of investor herding. In addition to the studies that analyze the (de)stabilizing effect in terms of stock returns, Kremer and Nautz (2013), Venezia et al. (2011), and Voukelatos and Verousis (2019) document empirical evidence that herding and market volatility are positively and significantly related. Our paper brings a new perspective to this strand of literature. We argue that herding can both increase and decrease market volatility depending on its direction. Specifically, we show that there have been long spells of adverse herding in 2009–2010 and from mid-2016 to early-2018, during which herding substantially reduces volatility and stabilizes the Chinese equity market.

The rest of the paper is organized as follows. In Section 2, we outline the econometric framework for estimating the herding measure from cross-sectional stock betas, and the volatility models used for in- and out-of-sample exercises. Section 3 introduces data, discusses empirical results, and performs robustness tests. Finally, Section 4 concludes.

2. Econometric framework

In this section, we outline the state-space model that leads to a direct measure of herding following HS. Volatility models, proxy for the *true* volatility dynamics, and prediction metrics are discussed in turn.

2.1. A state-space model of herding measure

Consider the CAPM in equilibrium (Lintner, 1965; Sharpe, 1965)[3]:

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt}), \tag{1}$$

where $E_t(\cdot)$ is the conditional expectation at time t, r_{it} denotes excess returns to asset i at time t, r_{mt} is the market risk premium at time t, and β_{imt} is the sensitivity of excess returns to asset i with respect to

[1] We have performed the baseline analyses with the CSSD and CSAD measures and our main findings remain unchanged, i.e., herding exists in the Chinese equity market, and the cross-sectional stock return dispersions impact on market volatility. The in- and out-of-sample results show a positive relation between CSSD/CSAD and market volatility. However, in this case, we could only conclude that there is a positive relation between future market-level volatility and the cross-sectional stock return dispersion, and we cannot establish a relation between herding and volatility. These results are available upon request from the authors.

[2] Due to data constraint, we are unable to use direct transaction-based measure of herding.

[3] This subsection largely follows HS.

market returns at time t. Given the presence of herding, the equilibrium relation in Eq. (1) no longer holds, as β_{imt} and expected asset returns will be biased as shown below:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1), \tag{2}$$

where $E_t^b(\cdot)$ is the biased short-run conditional expectation, β_{imt}^b is the short-term biased market beta at time t, and h_{mt} is a time-varying latent herding parameter conditional on market fundamentals. If $h_{mt} = 0$, $\beta_{imt}^b = \beta_{imt}$ and no herding is observed in the market. If $h_{mt} = 1$, this indicates perfect (positive) herding towards the market portfolio when all individual assets move in the same direction with the same magnitude as the market portfolio. If $0 < h_{mt} < 1$, this suggests some degree of positive herding based on the magnitude of h_{mt}. Finally, $h_{mt} < 0$ indicates adverse herding whereby investors herd towards firm fundamentals. As β_{imt} and h_{mt} are latent variables not observed in the market, the standard deviation of β_{imt}^b can be formulated as follows:

$$\begin{aligned}\mathrm{Std}_c(\beta_{imt}^b) &= \sqrt{E_c((\beta_{imt} - h_{mt}(\beta_{imt}-1)-1)^2)}\\ &= \sqrt{E_c((\beta_{imt}-1)^2)}(1-h_{mt})\\ &= \mathrm{Std}_c(\beta_{imt})(1-h_{mt}),\end{aligned} \tag{3}$$

where $E_c(\cdot)$ and $\mathrm{Std}_c(\cdot)$ are the cross-sectional expectation and standard deviation, respectively. Taking the logarithm on both sides of Eq. (3) gives the following:

$$\log(\mathrm{Std}_c(\beta_{imt}^b)) = \log(\mathrm{Std}_c(\beta_{imt})) + \log(1-h_{mt}), \tag{4}$$

where $\mathrm{Std}_c(\beta_{imt}^b)$ is allowed to be stochastic to reflect the level of herding in the market over a time interval. Furthermore, let the relative herding measure $H_{mt} = \log(1-h_{mt})$ and $\log(\mathrm{Std}_c(\beta_{imt})) = \mu_m + v_{mt}$, where $\mu_m = E[\log(\mathrm{Std}_c(\beta_{imt}))]$ and $v_{mt} \sim i.i.d.(0, \sigma_{mv}^2)$, we have the following:

$$\log(\mathrm{Std}_c(\beta_{imt}^b)) = \mu_m + H_{mt} + v_{mt}. \tag{5}$$

Following HS, we let the relative herding variable, H_{mt}, follow an AR(1) process with zero mean:

$$\log(\mathrm{Std}_c(\beta_{imt}^b)) = \mu_m + H_{mt} + v_{mt}, \tag{6}$$

$$H_{mt} = \phi H_{mt-1} + \eta_{mt}, \tag{7}$$

where $\eta_{mt} \sim i.i.d.(0, \sigma_{m\eta}^2)$. Eq. (7) describes the dynamic pattern of the latent state variable, H_{mt}. If $\sigma_{m\eta}^2 = 0$, this standard state-space model can be expressed as follows:

$$\log(\mathrm{Std}_c(\beta_{imt}^b)) = \mu_m + v_{mt}, \tag{8}$$

where $H_{mt} = 0$, i.e., there is no herding at t. Hence, a significant $\sigma_{m\eta}^2$ indicates the existence of herding in the market. This specification allows us to observe relative changes in herding activity, H_{mt}, as well as the direct herding measure, h_{mt}, across the market.

An attractive feature of the model is that it can accommodate additional variables, such as the market premium, to reflect market and macroeconomic conditions. We follow HS and consider the market premium, size (SMB), and book-to-market (HML) factors of Fama and French (1992), and market log-volatility as follows:

$$\log(\mathrm{Std}_c(\beta_{imt}^b)) = \mu_m + H_{mt} + c_1 r_{mt} + c_2\mathrm{SMB}_t + c_3\mathrm{HML}_t + c_4\log\sigma_{mt} + v_{mt}, \tag{9}$$

$$H_{mt} = \phi H_{mt-1} + \eta_{mt}. \tag{10}$$

Empirically, this standard state-space model can be estimated via the Kalman filter.

To obtain the daily cross-sectional standard deviation of β_{imt}^b, we use a four-month rolling window of daily data and adopt the CAPM, Fama–French 3-factor model (Fama & French, 1992), and Fama–French 5-factor model (Fama & French, 2015) as follows[4]:

$$r_{it} = \alpha_{it}^b + \beta_{imt}^b r_{mt} + \varepsilon_{it}, \tag{11}$$

$$r_{it} = \alpha_{it}^b + \beta_{imt}^b r_{mt} + \beta_{iSt}^b\mathrm{SMB}_t + \beta_{iHt}^b\mathrm{HML}_t + \varepsilon_{it}, \tag{12}$$

$$r_{it} = \alpha_{it}^b + \beta_{imt}^b r_{mt} + \beta_{iSt}^b\mathrm{SMB}_t + \beta_{iHt}^b\mathrm{HML}_t + \beta_{iRt}^b\mathrm{RMW}_t + \beta_{iCt}^b\mathrm{CMA}_t + \varepsilon_{it}. \tag{13}$$

The herding measure h_m is subsequently obtained via the Kalman filter.

2.2. Volatility modeling and forecasting

The HARQ and HARQ-X models

We employ the HARQ model proposed by Bollerslev et al. (2016), which includes realized quarticity terms in the heterogeneous autoregressive (HAR) model developed by Corsi (2009). The HAR model is a simple AR-type model in realized volatility that considers different volatility components realized over different time horizons, and capable of capturing the main empirical characteristics of financial time series such as long memory, fat tails, heteroskedasticity in the error and multi-scaling which cannot be handled by traditional short-memory models such as the popular generalized autoregressive conditional heteroskedasticity model (GARCH) of Bollerslev (1986) and Engle (1982). Most importantly, it exhibits remarkable forecasting performance (Bollerslev et al., 2016; Corsi, 2009) and is widely adopted in the literature (see Dimpfl & Jank, 2016; Fei et al., 2019; Fernandes et al., 2014; Jiang et al., 2019, for example).

The HARQ model innovates the HAR model as the quarticity terms address measurement error of the realized volatility estimator. It includes additive cascade of volatility components defined over different time horizons and the realized quarticity, $RQ_t \equiv \frac{N}{3}\sum_{n=1}^{N} r_{n,t}^4$, as follows:

$$RV_{t:t+h-1} = \alpha + (\beta_d + \beta_{dQ}RQ_{t-1}^{1/2})RV_{t-1} + \beta_w RV_{t-5:t-1} + \beta_m RV_{t-22:t-1} + \varepsilon_t, \tag{14}$$

where $N = 1/\Delta$, $r_{n,t}$ is the Δ-period intraday returns, $\mathrm{RV}_{t:t+h-1}$ aggregates h terms of the logarithmic forms of realized volatility as follows:

$$RV_{t_1:t_2} = \frac{1}{(t_2 - t_1 + 1)}\sum_{t=t_1}^{t_2} RV_t, \qquad t_2 > t_1, \tag{15}$$

and $\mathrm{RV}_{t-5:t-1}$ and $\mathrm{RV}_{t-22:t-1}$ are weekly and monthly aggregations of RV_t.

The HAR family of models is able to include additional variables as different participants perceive volatility in a non-homogeneous way. A number of studies have adopted this approach and included additional components, such as the leverage effect (Corsi & Reno, 2012), jumps (Anderson & Vahid, 2007), and lunch-break returns (Wang et al., 2015). In this paper, we include the herding measure, h_{mt}, into the HARQ model to form a HARQ-X model as follows:

$$\begin{aligned}RV_{t:t+h-1} = \alpha &+ (\beta_d + \beta_{dQ}RQ_{t-1}^{1/2})RV_{t-1} + \beta_w RV_{t-5:t-1}\\ &+ \beta_m RV_{t-22:t-1} + \gamma h_{mt-1} + \varepsilon_t.\end{aligned} \tag{16}$$

In addition to h_{mt}, we also incorporate the absolute value of h_{mt}, $|h_{mt}|$, to investigate the impact of herding intensity on volatility without considering herding direction.

[4] We show in Section 3.4 that our baseline results remain qualitatively the same when the herding measure is based on the cross-sectional standard deviation of β_{imt}^b obtained from the three-/five-month rolling window scheme.

Table 1
Descriptive statistics of the dataset. In Panel A, we provide summary statistics of the daily cross-sectional standard deviation of β^b_{imt} obtained from the CAPM, Fama–French 3-factor model, and Fama–French 5-factor model. We use both the value- (VW) and equal-weighting (EW) schemes. In Panel B, we report descriptive statistics of daily returns and volatility series for the CSI 300 index, SSE composite index, and SZSE composite index. These include the mean, median, maximum (Max), minimum (Min), standard deviation (Stdev), skewness, and excess kurtosis (Excess kurt). The sample period is from 1 August 2005 to 31 March 2021.

Panel A: The cross-sectional standard deviation of β^b_{imt}						
	CAPM		Fama–French 3-factor model		Fama–French 5-factor model	
	VW	EW	VW	EW	VW	EW
Mean	0.369	0.328	0.334	0.325	0.332	0.329
Median	0.360	0.313	0.334	0.319	0.331	0.322
Max	0.770	0.694	0.666	0.654	0.597	0.681
Min	0.168	0.171	0.159	0.156	0.160	0.150
Stdev	0.112	0.097	0.092	0.090	0.090	0.092
Panel B: Returns and volatility series						
	CSI 300 index		SSE composite index		SZSE composite index	
	Return	Volatility	Return	Volatility	Return	Volatility
Mean (%)	0.060	19.33	0.043	17.93	0.058	21.23
Median (%)	0.098	16.06	0.088	14.46	0.091	18.21
Max (%)	9.342	110.2	9.455	105.1	9.594	123.8
Min (%)	−9.240	4.199	−8.841	4.074	−9.290	4.924
Stdev (%)	1.708	11.64	1.593	11.26	1.841	11.99
Skewness	−0.434	2.219	−0.492	2.220	−0.427	2.140
Excess kurt	3.697	7.929	4.495	7.588	2.843	7.701

Finally, we separate the herding measure h_{mt} into positive (h^+_{mt}) and adverse herding (h^-_{mt}). The in-sample volatility estimation is performed separately as follows:

$$\begin{aligned} RV^+_{t:t+h-1} =& \alpha + (\beta_d + \beta_{dQ} RQ^{1/2+}_{t-1}) RV^+_{t-1} + \beta_w RV^+_{t-5:t-1} + \beta_m RV^+_{t-22:t-1} \\ &+ \gamma h^+_{mt-1} + \varepsilon_t, \quad h_{mt} \geq 0 \end{aligned} \tag{17}$$

$$\begin{aligned} RV^-_{t:t+h-1} =& \alpha + (\beta_d + \beta_{dQ} RQ^{1/2-}_{t-1}) RV^-_{t-1} + \beta_w RV^-_{t-5:t-1} + \beta_m RV^-_{t-22:t-1} \\ &+ \gamma h^-_{mt-1} + \varepsilon_t, \quad h_{mt} < 0 \end{aligned} \tag{18}$$

where $RV^+_{t:t+h-1}$ ($RV^-_{t:t+h-1}$), $RV^+_{t-1}, RV^+_{t-5:t-1}, RV^+_{t-22:t-1}$ ($RV^-_{t-1}, RV^-_{t-5:t-1}, RV^-_{t-22:t-1}$), and $RQ^{1/2+}_{t-1}$ ($RQ^{1/2-}_{t-1}$) are the h-day ahead aggregation of realized volatility, the daily, weekly and monthly volatility components, and the square root of realized quarticity, respectively, when $h_{mt} \geq 0$ ($h_{mt} < 0$).

<u>Proxy for latent volatility dynamics</u>

Since volatility is unobservable, we follow Andersen and Bollerslev (1998) and construct the realized volatility (RV) based on 5-minute return series as the *true* volatility proxy. RV is a widely used non-parametric volatility estimator (see Bandi & Russell, 2006; Chortareas et al., 2011; Jiang et al., 2019, for example), and can be obtained by aggregating intraday squared returns as follows:

$$RV^2_t = \sum_{n=1}^{N} r^2_{n,t}, \tag{19}$$

where RV^2_t is the day t realized variance, and $r^2_{n,t}$ ($n = 1, 2, \ldots, N$) is the 5-minute squared returns on day t with $r_{n,t} = \ln P_{n,t} - \ln P_{n-1,t}$. We use this proxy to evaluate the out-of-sample volatility predictive performance.

<u>Forecast evaluation</u>

To evaluate the predictive accuracy of volatility models, we compare the forecasting performance of HARQ-X model with the benchmark HARQ model. We follow Bollerslev et al. (2016) and use the first one-third of the sample period for the in-sample estimation and the remaining data for out-of-sample prediction. We implement a rolling window scheme and compute one-, five- and 22-day ahead forecasts. The forecasting accuracy is evaluated using three popular loss functions: the root mean squared error (RMSE), the mean absolute percentage error (MAPE), and the mean absolute error (MAE) as follows:

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\widehat{RV}^2_{t+h} - RV^2_{t+h})^2}, \tag{20}$$

$$\text{MAPE} = \frac{100}{T}\sum_{t=1}^{T}\left|\frac{\widehat{RV}^2_{t+h} - RV^2_{t+h}}{RV^2_{t+h}}\right|, \tag{21}$$

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}\left|\widehat{RV}^2_{t+h} - RV^2_{t+h}\right|, \tag{22}$$

where T is the number of days in the out-of-sample period, $\widehat{RV}^2_{t+h}$ is the predicted variance over horizon h, where $h = 1$, 5, or 22, and RV^2_{t+h} is the proxy for *true* variance, i.e., the 5-minute RV.

We perform the Diebold and Mariano (1995) test because a smaller forecasting error does not necessarily indicate that the forecasting performance is statistically superior to its competitor. This test conducts a pairwise comparison to assess whether the difference between two forecast errors is statistically significantly. The t-statistic is defined as follows:

$$DM = \frac{\overline{\Delta l}}{\sqrt{\widehat{LRV}_{\overline{\Delta l}}/T}}, \tag{23}$$

where the loss differential process $\{\Delta l_t : t = 1, 2, 3, \ldots, T\}$ is equal to $L(\varepsilon^{(i)}_{t+h|t}) - L(\varepsilon^{(j)}_{t+h|t})$ and $L(\cdot)$ is the loss function, $\bar{l}$ is the mean of the loss differential process $\{\Delta l_t\}^T_{t_0}$, and $LRV_{\overline{\Delta l}} = \gamma_0 + 2\sum_{j=1}^{\infty}\gamma_j, \gamma_j = cov(\Delta l_t, \Delta l_{t-j})$.

Finally, we conduct the Mincer and Zarnowitz (1969) regression test. Known as the *predictive power test*, the regression is specified as follows:

$$RV^2_{t+h} = \alpha + \beta\widehat{RV}^2_{t+h} + \varepsilon_{t+h}, \tag{24}$$

where RV_{t+h} is the *true* volatility proxy at time $t + h$, and $\widehat{RV}^2_{t+h}$ is the forecasted variance at time $t + h$. The higher the R^2 from the Mincer–Zarnowitz regression, the better the volatility prediction.

3. Data and empirical analyses

We obtain daily prices for all A-shares listed in the SSE and SZSE and daily Fama and French factors from 1 August 2005 to 31 March

2021 from the China Stock Market & Accounting Research (CSMAR) database. The sample period covers three market downturns: the Great Recession of 2007–2008, the Chinese stock market crash from late 2015 to early 2016, and the COVID-19 pandemic in 2020. The Chinese national bond yield is taken as the risk-free rate to obtain excess stock returns. Meanwhile, we use intraday returns series to compute realized volatility as the proxy for *true* volatility dynamics in the out-of-sample tests.

Table 1 Panel A reports the mean, median, maximum, minimum, standard deviation, skewness, excess kurtosis of the daily cross-sectional standard deviation of β_{imt}^{b}, which are the loading of the market risk in the CAPM (Eq. (11)), Fama–French 3-factor model (Eq. (12)), or Fama–French 5-factor model (Eq. (13)). We use both value- and equal-weighting schemes for constructing the cross-sectional β_{imt}^{b} from individual stocks and they yield similar beta estimates. For instance, the average value for β_{imt}^{b} is between 0.32 and 0.37 across asset pricing models and different weighting schemes. The median values are of similar magnitude. Panel B tabulates descriptive statistics of daily returns and volatility dynamics of the three stock indices. Over the sample period, the CSI 300 index offers the highest daily average return (0.060%) but the SZSE composite index is the most volatile with an average annualized volatility of 21.2%. It is interesting to note that the annualized realized volatility ranges from less than 10% to over 100% for the indices. Hence, our sample includes both quiet and turbulent periods and allows us to investigate the impact of herding on stock market volatility in divergent market conditions.

3.1. The herding measure

Table 2 summarizes parameter estimates for state-space models via the Kalman filter for the relative herding measure. In Panel A, the relative herding measure H_{mt} is based on β_{imt}^{b} from the CAPM in Eq. (11). Results in the first column are obtained from the standard state-space model of Eqs. (6) and (7) via the value-weighting scheme without additional control variables. We observe that the relative herding measure is highly persistent as ϕ is large and statistically significant. More importantly, $\sigma_{m\eta}$ is highly significant, suggesting the existence of herding in the cross section of stock returns.

The second to fifth columns contain estimation results of Eqs. (9) and (10), which include the market premium (r_m), size (SMB) and value (HML) factors of Fama and French (1992), and the market log-volatility ($\ln V_m$) as control variables. The inclusion of these additional variables enables us to take macroeconomic and market fundamentals into account and we observe that incorporating these control variables does not qualitatively change the baseline results in the first column. We find that $\sigma_{m\eta}$ continues to be highly significant so the herding measure continues to be significant and persistent. It is worth noting that the coefficients for market premium (r_m), size (SMB) and value (HML) factors of Fama and French (1992), and market log-volatility ($\ln V_m$) are all statistically insignificant, indicating that herding is not affected by these macro and market variables. As a result, we observe similar log likelihood value (LL), the Akaike information criterion (AIC), and Bayesian information criterion (BIC). The last column contains estimation results based on Eqs. (9) and (10) via the equal-weighting scheme. These results are qualitatively the same as those with the value-weighting scheme and support the presence of herding behavior. In the empirical tests below, we use the set of results obtained via the value-weighting scheme since it yields higher LL and lower AIC and BIC values.

In Panels B and C, we tabulate the estimation results when β_{imt}^{b} is obtained from the Fama–French 3- and 5-factor models, respectively. Results continue to support the existence of herding in the Chinese stock market. Furthermore, the presence of control variables adds little as they are always insignificant.

In Fig. 1, we plot the time series of realized volatility and herding measure based on the CSI 300 index over the entire sample period. The

Table 2
The herding measure estimated via state-space models. This table reports the relative herding measure H_{mt} estimated from state-space models via the Kalman filter. The relative herding measure is obtained based on stock beta from the CAPM (Eq. (11)), Fama–French 3-factor model (Eq. (12)), and Fama–French 5-factor model (Eq. (13)) in Panels A, B, and C, respectively, using both the value- (VW) and equal-weighting (EW) schemes. We also include the market premium (r_m), size (SMB), and value (HML) factors of Fama and French (1992), and the market log-volatility ($\ln V_m$). The sample period is from 1 August 2005 to 31 March 2021. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: CAPM						
	VW					EW
μ_m	−1.032***	−1.032***	−1.032***	−1.032***	−1.035***	−1.157***
	(0.131)	(0.132)	(0.132)	(0.133)	(0.133)	(0.081)
ϕ	0.997***	0.997***	0.997***	0.997***	0.997***	0.993***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
σ_{mv}	0.1E−04	0.0E−04	0.1E−04	0.2E−04	0.1E−04	0.2E−04
	(0.564)	(1.286)	(0.258)	(0.130)	(0.257)	(0.728)
$\sigma_{m\eta}$	0.024***	0.024***	0.024***	0.024***	0.024***	0.034***
	(2.5E−04)	(2.6E−04)	(2.6E−04)	(2.7E−04)	(2.7E−04)	(0.001)
r_m		−0.016	−0.017*	−0.017	−0.020	−0.010
		(0.010)	(0.010)	(0.011)	(0.012)	(0.022)
SMB			0.014	0.012	0.001	0.028
			(0.028)	(0.033)	(0.034)	(0.051)
HML				−0.009	−0.006	−0.011
				(0.045)	(0.046)	(0.104)
$\ln V_m$					−0.002	−0.003
					(0.001)	(0.002)
LL	8838	8838	8838	8838	8839	7477
AIC	−17,668	−17,667	−17,665	17,663	−17,663	−14,938
BIC	−17,643	−17,635	−17,627	−17,619	−17,613	−14,888
Panel B: Fama–French 3-factor model						
	VW					EW
μ_m	−1.141***	−1.141***	−1.141***	−1.141***	−1.144***	−1.169***
	(0.110)	(0.110)	(0.112)	(0.112)	(0.112)	(0.069)
ϕ	0.996***	0.996***	0.996***	0.996***	0.996***	0.990***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
σ_{mv}	0.004***	0.004***	0.004***	0.004***	0.004***	0.5E−04
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.451)
$\sigma_{m\eta}$	0.026***	0.026***	0.026***	0.026***	0.026***	0.039***
	(3.5E−04)	(3.6E−04)	(3.6E−04)	(3.6E−04)	(3.6E−04)	(0.001)
r_m		0.003	0.002	0.002	−0.001	−0.013
		(0.012)	(0.012)	(0.013)	(0.015)	(0.027)
SMB			0.019	0.019	0.009	0.007
			(0.034)	(0.038)	(0.039)	(0.061)
HML				0.001	0.004	−0.039
				(0.061)	(0.061)	(0.128)
$\ln V_m$					−0.002	−0.003
					(0.001)	(0.002)
LL	8439	8439	8439	8439	8440	6950
AIC	−16,869	−16,867	−16,866	−16,864	−16,863	−13,884
BIC	−16,844	−16,836	−16,828	−16,820	−16,813	−13,834
Panel C: Fama–French 5-factor model						
	VW					EW
μ_m	−1.145***	−1.145***	−1.145***	−1.145***	−1.146***	−1.158***
	(0.112)	(0.113)	(0.114)	(0.114)	(0.114)	(0.071)
ϕ	0.996***	0.996***	0.996***	0.996***	0.996***	0.991***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
σ_{mv}	0.007***	0.007***	0.007***	0.007***	0.007***	0.5E−04
	(3.1E−04)	(3.2E−04)	(3.2E−04)	(3.2E−04)	(3.3E−04)	(0.327)
$\sigma_{m\eta}$	0.025***	0.025***	0.025***	0.025***	0.025***	0.038***
	(1.8E−04)	(1.9E−04)	(1.9E−04)	(1.9E−04)	(1.9E−04)	(0.001)
r_m		−0.012	−0.013	−0.012	−0.014	−0.006
		(0.011)	(0.011)	(0.012)	(0.013)	(0.025)
SMB			0.007	−0.007	−0.012	−0.042
				(0.037)	(0.039)	(0.063)
HML				−0.045	−0.043	−0.112
				(0.061)	(0.061)	(0.118)
$\ln V_m$					−0.001	−0.002
					(0.001)	(0.002)
LL	8425	8426	8426	8426	8426	7017
AIC	−16,843	−16,841	−16,839	−16,838	−16,836	−14,018
BIC	−16,818	−16,810	−16,802	−16,794	−16,786	−13,968

dashed line with axis on the right shows the time series variation of the herding measure h_{mt}, which is related to the relative herding measure via $H_{mt} = \log(1 - h_{mt})$, based on the CAPM β^b_{imt}. The horizontal line corresponds to $h_{mt} = 0$. We also include the daily realized volatility of the CSI 300 index constructed from 5-minute return series in the solid line with axis on the left. There are a few interesting observations. First, we can see that the largest value of h_{mt} is around 0.5, indicating moderate positive herding ($h_{mt} > 0$) during the sample period despite episodes of extreme market stress. Consistent with evidence in the prior literature, the positive herding mainly takes place during market downturns, specifically during the Great Recession and the Chinese stock market crash. Second, we find that these two heightened spells of positive herding are followed by extended periods of adverse herding. In particular, from the first half of 2016, the magnitude of adverse herding increases and goes below −1 in late 2017. Economically, this prevalent adverse herding suggests that market participants are trading towards firm fundamentals, and it tends to accompany much reduced market volatility.

To summarize, our initial results add to the prior literature which predominately identifies the existence of herding behavior using return dispersion measures based on stock prices (see Christie & Huang, 1995; Demirer et al., 2010; Yao et al., 2014, among others) or the LSV measure using institutional trading data (see Lakonishok et al., 1992; Zheng et al., 2015, for example).

3.2. In-sample volatility estimation

Table 3 reports the in-sample volatility estimation results of the HARQ and HARQ-X models for the CSI 300 index, SSE composite index, and SZSE composite index. The X variable is the absolute herding measure $|h_{mt}|$ or the herding measure h_{mt} obtained from the CAPM β^b_{imt}.

We report the estimation results over the full sample period in the first three columns across the panels. We find that the coefficient of $|h_{mt}|$ is not statistically significant for any index, indicating that, without considering herding direction, the herding intensity *per se* exhibits no significant impact on the volatility dynamics. Meanwhile, the coefficient of h_{mt}, which captures investor herding with direction, is positive and significant at the 1% level for all indices. The positive coefficient for h_{mt} suggests that, when $h_{mt} > 0$, positive herding is associated with increased market volatility, whereas when $h_{mt} < 0$, adverse herding is negatively related to market volatility.

We further divide h_{mt} into positive and negative herding and separately tabulate the in-sample estimation results based on Eqs. (17) and (18) in the final two columns across the panels. This allows us to gain a comprehensive understanding of the (de)stabilizing effect of positive and adverse herding. Consistent with the results over the full sample, we obtain positive and significant coefficients for both positive and adverse herding across the indices, which support the hypothesis of asymmetric herding effect on the volatility dynamics. For example, the coefficient for positive herding is 0.068, 0.050, and 0.061, respectively, for the CSI 300 index, SSE composite index, and SZSE composite index, and significant at the 1% level. Economically, this suggests that the stronger the positive herding, the higher the market volatility. Similarly, the stronger the adverse herding the lower the market volatility. Moreover, the coefficient of positive herding is on average six times larger than that of negative herding. For instance, the coefficient for positive and negative herding for the SSE composite index is 0.050 and 0.008, respectively, and significant at the 1% and 5% level, respectively. This implies that the destabilizing effect of positive herding tends to be much stronger than the stabilizing effect of adverse herding. Thus, it takes longer for adverse herding to bring the volatility level back to a relatively stable level after a period of agitation in the financial market. This is the pattern that we observe in Fig. 1, in which adverse herding persists in the market for a longer period than positive herding.

Table 3
In-sample volatility estimation. This table reports the in-sample volatility estimation of the HARQ and HARQ-X models for the CSI 300 index, SSE composite index, and SZSE composite index. The additional X variable is the absolute herding measure ($|h_{mt}|$) or the herding measure (h_{mt}). The first three columns summarize the results over the full sample based on Eq. (16). The last two columns separately tabulates the results for positive (Eq. (17)) and adverse (Eq. (18)) herding. The sample period is from 1 August 2005 to 31 March 2021. The Newey and West (1987) HAC-robust standard errors are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: CSI 300 index					
	Full sample period			Positive	Adverse
α	0.010***	0.008**	0.019***	0.015**	0.013***
	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)
β^d	0.432***	0.433***	0.420***	0.449***	0.417***
	(0.047)	(0.047)	(0.047)	(0.064)	(0.058)
β^w	0.357***	0.357***	0.356***	0.315***	0.442***
	(0.059)	(0.059)	(0.059)	(0.072)	(0.085)
β^m	0.168***	0.168***	0.136***	0.119**	0.093
	(0.042)	(0.042)	(0.043)	(0.051)	(0.074)
β^d_Q	−0.946	−0.974	−0.747	−0.682	−5.296***
	(0.955)	(0.955)	(0.961)	(1.033)	(1.708)
$\lvert h_{mt}\rvert$		0.006			
		(0.005)			
h_{mt}			0.019***	0.068***	0.009**
			(0.004)	(0.018)	(0.004)
Adj. R^2	0.6643	0.6644	0.6659	0.6195	0.5525
Panel B: SSE composite index					
	Full sample period			Positive	Adverse
α	0.005*	0.004	0.012***	0.007	0.013***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
β^d	0.483***	0.484***	0.472***	0.516***	0.410***
	(0.046)	(0.046)	(0.045)	(0.061)	(0.067)
β^w	0.316***	0.315***	0.316***	0.275***	0.415***
	(0.063)	(0.063)	(0.064)	(0.078)	(0.084)
β^m	0.183***	0.183***	0.156***	0.144**	0.108
	(0.045)	(0.044)	(0.046)	(0.057)	(0.073)
β^d_Q	−1.834**	−1.861**	−1.625**	−1.834**	−3.784
	(0.797)	(0.797)	(0.795)	(0.839)	(2.495)
$\lvert h_{mt}\rvert$		0.005			
		(0.004)			
h_{mt}			0.015***	0.050***	0.008**
			(0.004)	(0.018)	(0.003)
Adj. R^2	0.6874	0.6874	0.6884	0.6390	0.5541
Panel C: SZSE composite index					
	Full sample period			Positive	Adverse
α	0.011***	0.009**	0.021***	0.015**	0.022***
	(0.003)	(0.004)	(0.004)	(0.006)	(0.005)
β^d	0.458***	0.459***	0.447***	0.497***	0.365***
	(0.042)	(0.042)	(0.041)	(0.054)	(0.061)
β^w	0.286***	0.285***	0.284***	0.214***	0.458***
	(0.060)	(0.060)	(0.059)	(0.069)	(0.086)
β^m	0.213***	0.214***	0.18***	0.191***	0.080
	(0.040)	(0.040)	(0.041)	(0.050)	(0.075)
β^d_Q	−0.923	−0.943	−0.774	−0.904	−2.155
	(0.684)	(0.684)	(0.671)	(0.697)	(1.863)
$\lvert h_{mt}\rvert$		0.005			
		(0.005)			
h_{mt}			0.020***	0.061***	0.012***
			(0.004)	(0.018)	(0.004)
Adj. R^2	0.6360	0.6360	0.6376	0.5878	0.5400

By separately examining positive and adverse herding, our in-sample estimation results shed new light on the (de)stabilizing effect of investor herding on market volatility. We are the first to reveal an asymmetric impact of herding on the volatility dynamics in an important emerging stock market. This contributes to the literature in which most existing studies identify a one-directional destabilizing effect of herding, i.e., there exists a positive relation between herding and market volatility (see Blasco et al., 2012; Venezia et al., 2011, for example).

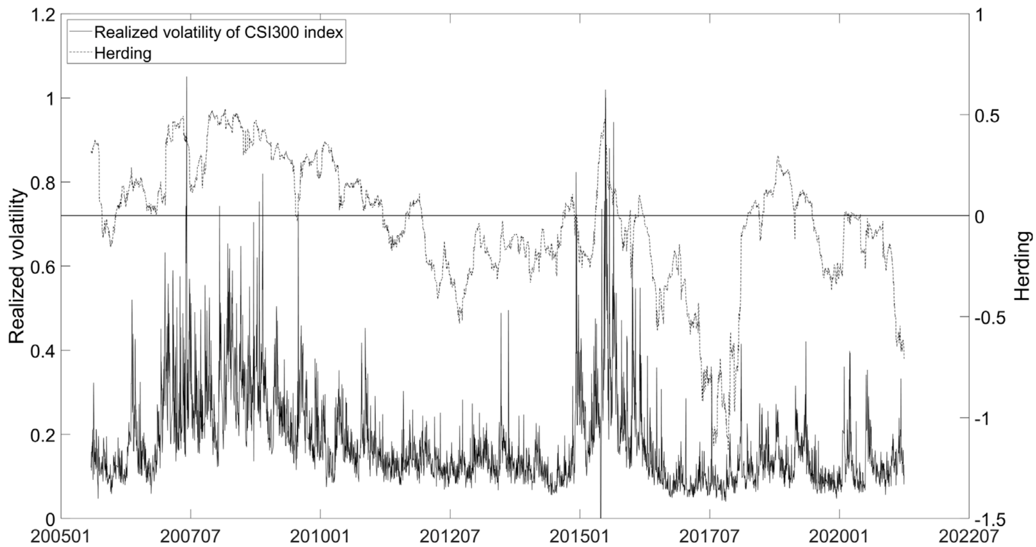

Fig. 1. The time series of the herding measure h_{mt}. This figure shows the daily realized volatility of the CSI 300 index (left axis) and the herding measure (h_{mt}) (right axis) for the Chinese stock market. The sample period is from 1 August, 2005, to 31 March, 2021.

3.3. Granger causality test

The evidence that herding and market volatility are significantly related does not imply a causal relation between the two. To further investigate the bidirectional causality between herding and volatility, we undertake a conventional two-way Granger causality test (Granger, 1969) as follows:

$$RV_t = \alpha + \sum_{j=1}^{K_1} \beta_j RV_{t-j} + \sum_{j=1}^{K_2} \gamma_j h_{mt-j}, \tag{25}$$

$$h_{mt} = \alpha + \sum_{j=1}^{K_2} \gamma_j h_{mt-j} + \sum_{j=1}^{K_1} \beta_j RV_{t-j}, \tag{26}$$

where K_1 and K_2 are the maximum lags for volatility and herding, respectively. We summarize the results in Table 4 Panel A for the SSE composite index.[5] We first determine the optimal lags for herding and volatility via the BIC score. The null hypothesis that herding does not Granger cause volatility is overwhelmingly rejected with the optimal lag at 16 for volatility and 1 for herding at the 1% level, indicating that herding Granger causes market volatility and (de)stabilizes the market. Furthermore, if we set the maximum volatility lag K_1 and K_2 for up to 22 lags, i.e., one-month horizon, instead of using the optimal lag, we again observe similar results. Meanwhile, we fail to reject the null hypothesis that volatility does not Granger cause herding either at the optimal lag or for the majority of cases when we set maximum lags.

In addition to the standard Granger causality test, we further conduct the Toda and Yamamoto (1995) Granger non-causality test. This modified version of the Granger causality test provides valid statistics irrespective of whether the time series are integrated or co-integrated. Furthermore, it allows variables to be employed in their levels, avoiding potential information loss due to data differencing (Alexander, 2001). Consistent with evidence in Panel A, results for the Toda–Yamamoto Granger non-causality test in Panel B show that herding significantly Granger causes market volatility with significant p-values when the optimal lags are chosen by either the AIC or BIC score and (de)stabilizes the market; whereas volatility does not Granger cause herding.

[5] Results based on the CSI 300 index and the SZSE composite index are qualitatively the same and available upon request from the authors.

3.4. Out-of-sample forecasting

Does the significant role played by the herding measure in in-sample tests help improve out-of-sample volatility prediction? To address this question, we perform out-of-sample prediction exercises to explore the forecasting performance of the HARQ and augmented HARQ-X models over one-, five-, and 22-day ahead horizons. Table 5 summarizes the prediction results for the three indices. The root mean square error (RMSE), the mean absolute percentage error (MAPE), and the mean absolute error (MAE) are used as the evaluation metrics. We implement the Diebold and Mariano (1995) pairwise comparison to assess the statistical significance of differences between predictions from the benchmark and augmented models with an additional herding measure, h_{mt}. We also report the adjusted R^2 of the Mincer–Zarnowitz regression to show the predictive power of volatility predictions.

We find that the HARQ-X model generates significantly more accurate volatility predictions overall and outperforms the HARQ model for all evaluation metrics and across all indices. For example, in Panels A and C for the CSI 300 index and SZSE composite index, respectively, the Diebold and Mariano t-statistics over one-, five-, and 22-day ahead horizons for the RMSE, MAPE, and MAE are all significant at the 1% level when the HARQ model is augmented by h_{mt} except for the one-day ahead forecast for the RMSE. Similar results are observed for Panel B for the SSE composite index. In addition, the Mincer–Zarnowitz adjusted R^2 also improves across board when h_{mt} is included. The improvement becomes more substantial when we move to five- and 22-day ahead horizons, highlighting the overall superior performance of the augmented HARQ-X model.[6]

3.5. Discussion

To summarize, our baseline results suggest that the herding behavior in the stock market substantially impacts market volatility both in- and out-of-sample, and the direction of herding is of great relevance as investors are shown to herd towards and away from the market over time. These findings extend recent empirical evidence by Blasco et al. (2012), which documents a strong contemporaneous linear relationship

[6] For robustness, we conduct the same exercises using GARCH and GARCH-X models and obtain consistent results that the GARCH-X model with the herding measure generates significantly improved volatility predictions. These results are available upon request from the authors.

Table 4
Granger causality test between volatility and herding measure. This table summarizes results of the Granger (1969) causality test and Toda and Yamamoto (1995) non-causality test in Panels A and B, respectively, between realized volatility for the SSE composite index and the herding measure h_{mt}. The sample period is from 1 August 2005 to 31 March 2021.

Herding does not Granger-cause volatility			Volatility does not Granger-cause herding		
Panel A: Granger causality test					
	F-Stat.	Sig. level		F-Stat.	Sig. level
Optimal lag:			Optimal lags		
$RV_t = 16$ lags and $h_{mt} = 1$ lag	16.751	0.000	$RV_t = 1$ lag and $h_{mt} = 1$ lag	5.002	0.124
Fixed RV_t and h_{mt} lags			Fixed RV_t and h_{mt} lags		
1	158.95	0.000	1	5.880	0.015
2	45.868	0.000	2	3.130	0.044
3	21.950	0.000	3	2.126	0.095
4	14.431	0.000	4	1.789	0.128
5	10.993	0.000	5	1.511	0.183
10	4.005	0.000	10	1.381	0.183
22	2.363	0.000	22	1.193	0.242
Panel B: Toda–Yamamoto Granger causality test					
	χ^2-Stat.	Sig. level		χ^2-Stat.	Sig. level
Akaike Information Criterion (AIC)					
Optimal lags:			Optimal lags:		
16	30.841	0.014	16	19.442	0.246
Bayesian Information Criterion (BIC)					
Optimal lags:			Optimal lags:		
4	13.984	0.007	4	6.908	0.141

Table 5
Out-of-sample volatility forecasting performance. This table reports the out-of-sample forecasting performance between the HARQ and HARQ-X models for the CSI 300 index, SSE composite index, and SZSE composite index in Panels A, B, and C, respectively. The additional X variable is the herding measure (h_{mt}). The root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) are used. The t-statistic of the Diebold and Mariano (1995) (DM) test between forecasts by the benchmark and augmented models, and the adjusted R^2 of the Mincer–Zarnowitz (MZ) regression are also reported. The sample period is from 1 August 2005 to 31 March 2021. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	RMSE	DM t-stat	MAPE	DM t-stat	MAE	DM t-stat	Adj. R^2 of MZ regression
Panel A: CSI 300 index							
HARQ							
1-day ahead	4.490		47.28		1.621		0.563
5-day ahead	3.410		38.77		1.325		0.595
22-day ahead	3.017		44.32		1.414		0.451
HARQ-h_{mt}							
1-day ahead	4.467	2.389**	44.60	8.348***	1.596	5.143***	0.569
5-day ahead	3.317	3.885***	36.66	5.014***	1.286	5.312***	0.616
22-day ahead	2.750	5.743***	42.70	2.588***	1.326	6.644***	0.538
Panel B: SSE composite index							
HARQ							
1-day ahead	4.176		46.54		1.400		0.568
5-day ahead	3.055		39.10		1.168		0.622
22-day ahead	2.739		44.83		1.239		0.517
HARQ-h_{mt}							
1-day ahead	4.160	1.994**	44.22	7.656***	1.38	5.549***	0.573
5-day ahead	2.981	4.078***	37.61	3.557***	1.141	4.561***	0.640
22-day ahead	2.525	5.848***	44.27	0.921	1.179	5.572***	0.581
Panel C: SZSE composite index							
HARQ							
1-day ahead	5.202		46.14		1.982		0.492
5-day ahead	3.766		38.00		1.578		0.516
22-day ahead	2.877		41.66		1.569		0.492
HARQ-h_{mt}							
1-day ahead	5.181	2.090**	43.91	7.634***	1.956	4.651***	0.498
5-day ahead	3.679	3.481***	36.12	4.585***	1.542	4.020***	0.538
22-day ahead	2.629	6.197***	39.58	3.677***	1.461	7.392***	0.573

between herding and market volatility. Meanwhile, herding is a double-edged sword in that it can be either rational or irrational (Bekiros et al., 2017), and less sophisticated investors who invest by simple imitation are also considered undertaking rational herding since the cost of collecting and processing their own information would be higher than that of following others. Therefore, rather than considering herding as rational or irrational, we evaluate its impact on market stability. Our findings support that positive herding, which drives market inefficiency (Hwang & Salmon, 2004), leads to higher future volatility and destabilizes the market; whereas adverse herding, which reflects efficient asset reallocation, lowers future volatility and stabilizes the market. Hence, as positive or adverse herding causes higher or lower in-sample volatility, respectively, and helps better predict out-of-sample volatility, investors gain a better understanding of it in the market. Investors would also be more wary of positive herding as it causes excess volatility and is considered one of the most important drivers of financial distress (Bikhchandani & Sharma, 2001; Gebka & Wohar, 2013).

3.6. Economic value

Do improved volatility forecasts offer economic value and lead to economic gains to investors? To address this question, we follow Wang et al. (2016) and implement a simple portfolio exercise measured by three performance metrics: the mean annualized portfolio excess returns (Ret), the Sharpe ratio (SR), and the certainty equivalent return (CER). Assuming a mean–variance utility framework whereby investors allocate their wealth between a stock index and the risk-free asset, we construct a portfolio with different pre-specified levels of risk aversion (Γ) as follows:

$$U_t(\tilde{r}_t) = E_t(w_t\tilde{r}_t + r_{t,f}) - \frac{1}{2}\Gamma\ \mathrm{var}_t(w_t\tilde{r}_t + r_{t,f}), \tag{27}$$

where $\tilde{r}_t$ and $r_{t,f}$ are the stock index excess returns and the risk-free rate, respectively, at time t, and w_t is the weight of the portfolio at time t. We maximize the utility function, $U_t(\tilde{r}_t)$, with respect to w_t and obtain the *ex ante* optimal weight, w_t^*, at time $t+1$ as follows[7]:

$$w_t^* = \frac{1}{\Gamma}\left(\frac{\hat{r}_{t+1}}{\widehat{RV}^2_{t+1}}\right), \tag{28}$$

where $\widehat{RV}_{t+1}$ denotes the volatility forecast, and $\hat{r}_{t+1}$ is the excess return forecasts proxied by the historical average returns following Neely et al. (2014) and Rapach et al. (2010). Since the expected returns to individual assets are their historical average, the optimal weight and portfolio returns hinge upon the accuracy of volatility forecasts given pre-specified level of investor risk aversion. Hence, we evaluate the portfolio performance via the average annualized portfolio excess returns, $\mathrm{Ret} = \frac{1}{T}\sum_{t=1}^{T}(w_t^*\hat{r}_{t+1} + r_{t+1,f})$, the Sharpe ratio, $\mathrm{SR} = \frac{\hat{\mu}_p}{\hat{\sigma}_p}$, and the certainty equivalent return, $\mathrm{CER} = \hat{\mu}_p - \frac{\Gamma}{2}\hat{\sigma}_p^2$, where $\hat{\mu}_p$ and $\hat{\sigma}_p$ are the mean and standard deviation of portfolio returns.

In Table 6, we report these three performance metrics across three risk aversion levels, $\Gamma = 3$, 6, and 9. We use the bold font to highlight the better performance between the benchmark (HARQ) and augmented (HARQ-X) model. Our results are consistent with the out-of-sample forecasting performance in that volatility forecasts generated by the augmented model offer economic gain to mean–variance utility investors. For example, in Panel A for the CSI 300 index, we obtain higher portfolio returns, Sharpe ratio, and certainty equivalent return across all three risk aversion levels for the augmented model. Furthermore, we also observe that the CSI 300 index exhibits better economic performance among the three indices. Hence, the information contained in the herding measure not only helps yield more accurate volatility forecasts statistically but these forecasts also add economic value to investors.

3.7. Robustness checks

We perform a series of robustness tests to show that our baseline results discussed above are not due to specific choices in the empirical analyses. In the first robustness test, we demonstrate that β^b_{imt} estimates based on three- and five-month of daily data lead to a herding measure with similar in-sample volatility estimation performance. In the second test, the in-sample volatility estimation employs the herding measure based on β^b_{imt} obtained from the Fama–French 3- or 5-factor models instead of the CAPM. The next robustness test adopts different volatility model and proxy and shows that the information in herding adds to volatility prediction for an alternative model with the *leverage effect* and jumps.[8] The fourth robustness check is the subsample analysis.

[7] We restrict the optimal weight up to 50% leverage and rule out short sale ($0 \le w_t^* \le 1.5$).

[8] We only report results based on the SSE composite index for the first three robustness tests in Tables 7–10 to save space. Results based on the CSI 300 index and SZSE composite index are qualitatively the same and available upon request from the authors.

Table 6
Economic value of volatility forecasts. This table reports the annualized average portfolio excess returns (Ret), Sharpe ratio (SR), and certainty equivalent returns (CER) of portfolios under a mean–variance utility framework with Γ as investor risk aversion level. The bold font highlights the better economic performance between the benchmark and augmented models. The sample period is from 1 August 2005 to 31 March 2021.

	$\Gamma = 3$			$\Gamma = 6$			$\Gamma = 9$		
	Ret	SR	CER	Ret	SR	CER	Ret	SR	CER
Panel A: CSI 300 index									
HARQ	8.964	0.502	4.173	7.409	0.631	3.269	6.740	0.783	3.408
HARQ-h_{mt}	**9.225**	**0.522**	**4.541**	**7.752**	**0.667**	**3.705**	**8.218**	**0.928**	**4.685**
Panel B: SSE composite index									
HARQ	2.190	0.171	−0.261	1.439	0.170	−0.713	1.587	0.254	−0.175
HARQ-h_{mt}	**2.307**	**0.182**	**−0.092**	**2.004**	**0.239**	**−0.107**	**2.536**	**0.388**	**0.613**
Panel C: SZSE composite index									
HARQ	−0.831	−0.051	−4.859	−0.108	−0.010	−3.762	0.508	0.061	−2.603
HARQ-h_{mt}	**−0.349**	**−0.022**	**−4.249**	**0.734**	**0.066**	**−2.978**	**2.269**	**0.255**	**−1.308**

In the final robustness check, volatility forecasts are generated based on the herding measures obtained via Fama–French 3- and 5-factor models. These robustness checks offer qualitatively the same results as our baseline findings.

1. Different estimation window for β^b_{imt}

In the baseline test, we use four months of daily returns to calculate β^b_{imt}. In our first robustness check, we use different estimation window, including three and five months of daily data to determine β^b_{imt} and obtain the herding measure based on the variance of these cross-sectional β^b_{imt} estimates. We summarize the in-sample estimation results for the SSE composite index in Table 7. In the first three columns for the full sample, the coefficients of $|h_{mt}|$ continues to be insignificant, whereas those for h_{mt} remain positive and significant as in Table 3. The last two columns tabulate the estimation results for positive and adverse herding. Similarly, our main findings remain qualitatively unchanged as coefficients of the herding measure h_{mt} are positive and statistically significant in all cases, and the magnitude of positive herding coefficient tends to be greater than that of adverse herding. Overall, our results are not affected by the specific estimation window for the cross-sectional stock beta β^b_{imt}.

2. Alternative factor models for β^b_{imt}

Our baseline test implements the CAPM to obtain the cross section of stock β^b_{imt}. We further adopt the Fama–French 3- and 5-factor models via the value-weighting scheme to obtain β^b_{imt}. The results for the SSE composite index from the state-space models are summarized in Panels B and C of Table 2 already. In our second robustness test, we perform the in-sample volatility estimation results which are based on the stock beta of these multi-factor pricing models. The results over the full sample and separately for positive and adverse herding are shown in Table 8.

Over the full sample, the results are very similar to those documented in Table 3. When we separately test for positive and adverse herding, however, we notice that for the Fama–French 5-factor model, the coefficients are positive but only significant at the 10% level for adverse herding. One possible explanation is that the β^b_{imt} obtained from the CAPM better specifies the state-space model with higher LL and lower AIC and BIC.

3. Alternative volatility model and proxy

It is well documented in the literature that negative returns exhibit a stronger effect on volatility than positive returns of similar magnitude. This is known as the *leverage effect* (see Black, 1976; Bollerslev et al., 2006; Engle & Ng, 1993; Glosten et al., 1993, for example). Furthermore, there exists ample evidence that jumps in asset returns also impact volatility (see Andersen et al., 2012; Eraker et al., 2003; Huang & Tauchen, 2005, for example). To show that our baseline results are robust in the presence of leverage effect and return jumps, we

Table 7
Robustness: Different estimation periods for β^b_{imt}. This table reports the in-sample volatility estimation for the SSE composite index when herding measures are obtained based on the cross-sectional standard deviation of β^b_{imt} estimated over a rolling window of three months (Panel A) and five months (Panel B). The first three columns summarize the results over the full sample based on Eq. (16). The last two columns tabulate separately the results for positive (Eq. (17)) and adverse Eq. (18)) herding. See also notes to Table 3.

Panel A: 3-month rolling window

	Full sample period			Positive	Adverse
α	0.005*	0.005	0.012***	0.008*	0.014***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
β^d	0.483***	0.483***	0.472***	0.515***	0.429***
	(0.046)	(0.046)	(0.045)	(0.060)	(0.057)
β^w	0.316***	0.316***	0.316***	0.290***	0.365***
	(0.063)	(0.063)	(0.063)	(0.071)	(0.080)
β^m	0.183***	0.183***	0.158***	0.146***	0.130*
	(0.045)	(0.045)	(0.046)	(0.054)	(0.073)
β^d_Q	−1.834**	−1.834**	−1.626**	−1.944***	−4.437*
	(0.797)	(0.800)	(0.790)	(0.751)	(2.306)
$\lvert h_{mt}\rvert$		1.67E−04			
		(0.004)			
h_{mt}			0.014***	0.033**	0.009**
			(0.004)	(0.017)	(0.003)
Adj. R^2	0.6874	0.6873	0.6883	0.6287	0.5369

Panel B: 5-month rolling window

	Full sample period			Positive	Adverse
α	0.005*	0.004	0.013***	0.009*	0.010**
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
β^d	0.483***	0.484***	0.471***	0.522***	0.407***
	(0.046)	(0.046)	(0.045)	(0.062)	(0.070)
β^w	0.316***	0.315***	0.315***	0.281***	0.379***
	(0.063)	(0.063)	(0.064)	(0.081)	(0.034)
β^m	0.183***	0.182***	0.153***	0.117**	0.163***
	(0.045)	(0.044)	(0.046)	(0.059)	(0.048)
β^d_Q	−1.834**	−1.870**	−1.619**	−1.875**	−3.618
	(0.797)	(0.794)	(0.795)	(0.830)	(2.203)
$\lvert h_{mt}\rvert$		0.007			
		(0.005)			
h_{mt}			0.017***	0.058***	0.006*
			(0.005)	(0.020)	(0.003)
Adj. R^2	0.6874	0.6875	0.6886	0.6400	0.5647

Table 8
Robustness: Alternative factor models for β^b_{imt}. This table reports the in-sample volatility estimation for the SSE composite index when herding measures are obtained based on the cross-sectional standard deviation of β^b_{imt} estimated from the Fama–French 3-factor (Panel A) and 5-factor (Panel B) models. The first three columns summarize the results over the full sample based on Eq. (16). The last two columns tabulate separately the results for positive (Eq. (17)) and adverse (Eq. (18)) herding. See also notes to Table 3.

Panel A: Fama–French 3-factor model

	Full sample period			Positive	Adverse
α	0.005*	0.004	0.014***	0.010*	0.013***
	(0.003)	(0.004)	(0.004)	(0.006)	(0.005)
β^d	0.483***	0.484***	0.473***	0.525***	0.450***
	(0.046)	(0.046)	(0.045)	(0.061)	(0.049)
β^w	0.316***	0.316***	0.318***	0.284***	0.402***
	(0.063)	(0.063)	(0.064)	(0.077)	(0.095)
β^m	0.183***	0.182***	0.144***	0.120**	0.092
	(0.045)	(0.045)	(0.048)	(0.06)	(0.072)
β^d_Q	−1.834**	−1.859**	−1.651**	−1.983**	−7.110***
	(0.797)	(0.798)	(0.792)	(0.84)	(1.924)
$\lvert h_{mt}\rvert$		0.004			
		(0.005)			
h_{mt}			0.019***	0.048***	0.010**
			(0.005)	(0.017)	(0.004)
Adj. R^2	0.6874	0.6873	0.6884	0.6128	0.4997

Panel B: Fama–French 5-factor model

	Full sample period			Positive	Adverse
α	0.005*	0.005	0.014***	0.011*	0.011**
	(0.003)	(0.004)	(0.004)	(0.006)	(0.005)
β^d	0.483***	0.484***	0.474***	0.524***	0.421***
	(0.046)	(0.046)	(0.046)	(0.058)	(0.057)
β^w	0.316***	0.316***	0.319***	0.281***	0.453***
	(0.063)	(0.063)	(0.064)	(0.074)	(0.089)
β^m	0.183***	0.182***	0.145***	0.133**	0.070
	(0.045)	(0.045)	(0.048)	(0.057)	(0.083)
β^d_Q	−1.834**	−1.858**	−1.666**	−1.956**	−7.114***
	(0.797)	(0.799)	(0.795)	(0.836)	(2.169)
$\lvert h_{mt}\rvert$		0.003			
		(0.006)			
h_{mt}			0.018***	0.035**	0.006*
			(0.005)	(0.016)	(0.003)
Adj. R^2	0.6874	0.6873	0.6882	0.5952	0.4798

follow Corsi and Reno (2012) and adopt an alternative volatility model, the leverage heterogeneous autoregressive with continuous volatility and jumps (LHAR-CJ) model, which incorporates these two features:

$$\begin{aligned} TBPV_{t:t+h-1} =& \alpha + \beta_d \widehat{TC}_{t-1} + \beta_w \widehat{TC}_{t-5:t-1} + \beta_m \widehat{TC}_{t-22:t-1} \\ &+ \theta_d \log(\widehat{TJ}_{t-1}+1) + \theta_w \log(\widehat{TJ}_{t-5:t-1}+1) \\ &+ \theta_m \log(\widehat{TJ}_{t-22:t-1}+1) \\ &+ \omega_d r^-_{t-1} + \omega_w r^-_{t-5:t-1} + \omega_m r^-_{t-22:t-1} + \varepsilon_t, \end{aligned} \tag{29}$$

where $\widehat{TC}_t = RV_t - \widehat{TJ}_t$ denotes the continuous part of the quadratic variation, $\widehat{TJ}_t$ represents the jump component is obtained by employing the threshold bipower variance (TBPV) estimate $\widehat{TJ}_t = I_{\{C\text{-}Tz > \Phi_\alpha\}} \cdot (RV_t - TBPV_t)^+$,[9] $\widehat{TC}_{t:t+h-1}$ and $\widehat{TJ}_{t:t+h-1}$ are aggregations of logarithmic forms of realized volatility as in Eq. (15). In addition, $r_{t_1:t_2} = \frac{1}{(t_2-t_1+1)}\sum_{t=t_1}^{t_2} r_t$, r_t are the day-t stock returns, and $r^-_t = \min(r_t, 0)$. This is our benchmark model. Our augmented model includes the herding measure h_{mt} as follows:

$$\begin{aligned} TBPV_{t:t+h-1} =& \alpha + \beta_d \widehat{TC}_{t-1} + \beta_w \widehat{TC}_{t-5:t-1} + \beta_m \widehat{TC}_{t-22:t-1} \\ &+ \theta_d \log(\widehat{TJ}_{t-1}+1) + \theta_w \log(\widehat{TJ}_{t-5:t-1}+1) \\ &+ \theta_m \log(\widehat{TJ}_{t-22:t-1}+1) \\ &+ \omega_d r^-_{t-1} + \omega_w r^-_{t-5:t-1} + \omega_m r^-_{t-22:t-1} + \gamma h_{mt-1} + \varepsilon_t. \end{aligned} \tag{30}$$

Table 9 Panel A reports the in-sample estimation results for the SSE composite index. We observe an obvious leverage effect in our estimation results as the coefficient for daily negative returns ω_d is consistently positive and highly significant at the 1% level across board, indicating that the more negative the returns, the higher the volatility.[10] The coefficients for daily jumps are also positive and often significant at the 1% level, highlighting the existence of jumps in the return series. Interestingly, despite significant leverage and jump effects, the herding measure still comes out positive and significant at the 1% level, and we also observe similar results for positive and adverse herding. This provides clear evidence that the herding measure possesses information that is not contained in the leverage and price jumps.

Does this information help predict future volatility in the presence of leverage effect and return jumps? To answer this question, we perform volatility prediction comparison between the benchmark and

[9] Φ_α is the cumulative distribution function of the normal distribution at confidence level α, and C-Tz is the test statistic used to identify jumps with the confidence level $\alpha = 99.9\%$.

[10] Although the coefficient for monthly negative returns is positive, their impact on volatility is weaker. See Harvey and Lange (2018) for example.

Table 9
Robustness: Alternative volatility proxy and model. This table reports the in-sample volatility estimation (Panel A) and out-of-sample forecasting performance (Panel B) based on the leverage heterogeneous autoregressive model with continuous volatility and jumps (LHAR-CJ) of Corsi and Reno (2012). The threshold bipower variance (TBPV) of Corsi et al. (2010) is adopted as the *true* volatility proxy for the SSE composite index. See also notes to Tables 3 and 5.

Panel A: In-sample estimation

	Full sample period			Positive	Adverse
α	−0.061	−0.061	−0.132*	−0.231***	−0.062
	(0.058)	(0.058)	(0.074)	(0.076)	(0.132)
β^d	0.219***	0.219***	0.217***	0.173	0.279***
	(0.063)	(0.063)	(0.063)	(0.113)	(0.037)
β^w	0.484***	0.485***	0.485***	0.481***	0.475***
	(0.051)	(0.051)	(0.051)	(0.085)	(0.056)
β^m	0.279***	0.280***	0.242***	0.252***	0.217***
	(0.045)	(0.045)	(0.039)	(0.065)	(0.054)
θ^d	0.463***	0.463***	0.460***	0.486	0.394
	(0.142)	(0.142)	(0.142)	(0.319)	(0.255)
θ^w	0.662	0.660	0.639	0.293	1.174**
	(0.619)	(0.619)	(0.614)	(0.898)	(0.519)
θ^m	0.378	0.392	0.041	0.577	−0.265
	(0.833)	(0.828)	(0.788)	(1.152)	(0.997)
ω^d	−7.216***	−7.217***	−7.193***	−7.251***	−6.978***
	(0.449)	(0.449)	(0.447)	(0.846)	(0.989)
ω^w	0.934	0.952	1.070	0.209	2.057
	(1.849)	(1.833)	(1.794)	(2.113)	(3.165)
ω^m	12.078***	12.131***	11.583***	10.610***	17.404***
	(2.545)	(2.492)	(2.518)	(2.874)	(4.807)
$\lvert h_{mt}\rvert$	0.010	0.010			
	(0.023)	(0.023)			
h_{mt}			0.080***	0.196***	0.039**
			(0.028)	(0.067)	(0.017)
Adj.R^2	0.7174	0.7173	0.7184	0.6315	0.631

Panel B: Out-of-sample prediction

	RMSE	DM t-stat	MAPE	DM t-stat	MAE	DM t-stat	Adj.R^2 of MZ regression
LHAR-CJ							
1-day ahead	3.803		40.97		1.157		0.642
5-day ahead	2.663		32.32		0.873		0.650
22-day ahead	2.033		36.18		0.869		0.607
LHAR-CJ-h_{mt}							
1-day ahead	3.772	2.064**	39.67	9.075***	1.144	4.767***	0.649
5-day ahead	2.594	2.968***	30.72	7.775***	0.851	5.775***	0.677
22-day ahead	1.890	5.095***	32.63	10.46***	0.812	9.116***	0.688

augmented models described above and tabulate the results in Table 9 Panel B. We find that over the 1-, 5-, and 22-day ahead horizons, the augmented model exhibits significantly smaller forecast errors for all three loss functions. These results show that the herding measure contains incremental information relative to the leverage effect and return jumps, and this information is helpful for forecasting future volatility.

4. Subsample forecasting analysis

Our fourth robustness check involves breaking the full sample period into three subsamples. The first subsample is from August 2005 to December 2012 covering the Great Recession of 2007/08; the second period is from January 2013 to December 2018 covering the Chinese stock market crash of 2015/16; and the third period is from January 2019 to the end of the sample of March 2021 that contains the COVID-19 pandemic.

We report the performance of the subsample forecasting exercises in Table 10. Panels A, B, and C contain the results for the three subsamples for the SSE composite index, respectively. We observe that the subsample analysis comprehensively corroborates the baseline findings that the inclusion of the herding measure h_{mt} adds useful information that helps generate more precise volatility predictions, regardless of market conditions.

5. Forecasting based on alternative herding measures

In our final robustness test, we extend the second robustness check in the in-sample estimation and perform out-of-sample volatility prediction when the herding measure is obtained from stock β^b_{imt} based on the Fama–French 3- or 5-factor models. In Table 11, we tabulate the RMSE and the t-statistic of the Diebold and Mariano (1995) (DM) test. It is worth noting that the forecasting results based on h_{mt} are consistently with those in Table 5, as the t-statistic for the DM pairwise comparison is significant at the 5% level or the 1% level suggesting superior volatility prediction by the HARQ-X model. When the HARQ model is augmented by the h_{mt}, it continues to generate more accurate volatility forecasts over the one-, five- and 22-day ahead horizons. These results attest to the importance of augmenting herding in volatility forecasting.[11]

4. Conclusion

In this paper, we focus on investor herding behavior in the stock market and explore its impact on the volatility dynamics. We employ the state-space approach developed in Hwang and Salmon (2004), which allows the herding measure to be separated into positive and adverse herding. Using data on all listed A-shares in China, our findings support the existence of both positive and adverse herding in China. Furthermore, contrary to evidence in the prior literature, we show that there exists an asymmetric impact of investor herding on volatility dynamics, i.e., positive herding tends to push up volatility, whereas adverse herding reduces market volatility. Finally, we provide robust evidence that the information content of herding helps improve volatility forecasting accuracy over the daily, weekly, and monthly horizons and offer economic gains to mean–variance utility investors. Overall, our paper shows that the investor herding behavior exhibits

[11] Results based on the MAPE and MAE, not reported to conserve space, are also consistent with the baseline findings and available upon request.

Table 10
Robustness: Out-of-sample volatility forecasting over subsamples. This table reports the out-of-sample forecasting performance over subsamples based on the SSE index. The first subsample is from 1 August 2005 to 31 December 2012; the second is from 1 January 2013 to 31 December 2018; and the third is from 1 January 2019 to 31 March 2021. See also notes to Table 5.

	RMSE	DM t-stat	MAPE	DM t-stat	MAE	DM t-stat	Adj.R^2 of MZ regression
Panel A: 08/2005–12/2012							
HARQ							
1-day ahead	4.625		45.483		2.225		0.530
5-day ahead	3.115		38.121		1.855		0.648
22-day ahead	2.691		46.207		1.935		0.651
HAQR-h_{mt}							
1-day ahead	4.606	1.853*	43.597	9.265***	2.203	3.313***	0.534
5-day ahead	3.043	4.299***	35.999	8.525***	1.798	5.876***	0.663
22-day ahead	2.526	6.650***	41.717	11.00***	1.808	8.176***	0.688
Panel B: 01/2013–12/2018							
HARQ							
1-day ahead	5.995		49.619		2.103		0.606
5-day ahead	4.542		49.077		1.883		0.643
22-day ahead	4.144		56.839		1.968		0.536
HARQ-h_{mt}							
1-day ahead	5.917	2.373**	45.865	5.273***	2.068	3.150***	0.618
5-day ahead	4.265	3.382***	45.048	3.928***	1.803	4.068***	0.684
22-day ahead	3.237	5.074***	50.545	3.957***	1.664	6.359***	0.716
Panel C: 01/2019–03/2021							
HARQ							
1-day ahead	1.332		45.127		0.700		0.530
5-day ahead	1.004		36.674		0.588		0.495
22-day ahead	0.864		40.159		0.590		0.353
HARQ-h_{mt}							
1-day ahead	1.313	1.201	42.949	2.950***	0.684	1.656*	0.546
5-day ahead	0.959	4.061***	31.394	6.628***	0.536	5.381***	0.540
22-day ahead	0.695	4.996***	35.466	4.182***	0.482	6.237***	0.549

Table 11
Robustness: Out-of-sample volatility forecasting with alternative herding measures. This table reports the out-of-sample forecasting performance when the herding measure is obtained from the cross-sectional standard deviation of β^b_{imt} based on the Fama–French 3- or 5-factor models. The root mean square error (RMSE) is used. See also notes to Table 5.

	Fama–French 3-factor model		Fama–French 5-factor model	
	RMSE	DM t-stat	RMSE	DM t-stat
Panel A: CSI300 index				
HARQ				
1-day ahead	4.490		4.490	
5-day ahead	3.410		3.410	
22-day ahead	3.017		3.017	
HARQ-h_{mt}				
1-day ahead	4.464	2.905***	4.469	2.735***
5-day ahead	3.332	4.276***	3.347	4.215***
22-day ahead	2.834	5.597***	2.874	5.548***
Panel B: SSE composite index				
HARQ				
1-day ahead	4.176		4.176	
5-day ahead	3.055		3.055	
22-day ahead	2.739		2.739	
HARQ-h_{mt}				
1-day ahead	4.158	2.503**	4.163	2.182**
5-day ahead	2.987	4.555***	3.002	4.233***
22-day ahead	2.580	5.788***	2.618	5.466***
Panel C: SZSE composite index				
HARQ				
1-day ahead	5.239		5.239	
5-day ahead	3.785		3.785	
22-day ahead	2.863		2.863	
HARQ-h_{mt}				
1-day ahead	5.214	2.929***	5.219	2.693***
5-day ahead	3.705	4.426***	3.721	4.228***
22-day ahead	2.656	7.074***	2.698	6.922***

a significant impact on the stock volatility dynamics, and is highly relevant for the prediction of future volatility.

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