Herding and informed trading: Evidence from Chinese equity markets

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Abstract

We empirically investigate the variations in the structure of the relationship between informed trading and herding at the market-wide level in China for the 2003-2022 period. We find a negative contemporaneous relationship between informed trading and herding, which grows stronger for periods characterized by specific market/economic conditions (low market performance; low market volatility; high investors' sentiment; high traders' disagreement; low economic policy uncertainty; high consumer confidence). Herding in Chinese markets comprises a very strong noise-driven herding, alongside a distinct fundamentals-driven anti-herding, and we show that informed trading dampens the former, while boosting the latter. The negative contemporaneous relationship between informed trading and herding grows stronger following the tightening of legal enforcement of anti-insider trading laws in 2012; it is confirmed for a battery of alternative informed trading proxies, with the causal impact of informed trading over contemporaneous herding further established when employing an instrumental variable approach. Our findings hold when

* Corresponding author. Email: vasileios.kallinterakis@durham.ac.uk. We would like to thank conference participants at the 2024 Annual Conference of the Financial Markets and Institutions Special Interest Group (British Accounting and Finance Association), the 2024 Durham University International Workshop in Experimental and Environmental Economics, the 17th and 18th Behavioural Finance Working Group Conferences, the 2024 International Conference on Sustainable Development, Social Responsibility and Business Ethics, the 2024 Tunisian International Conference on Economics Finance&Accounting, the 2nd International Conference and Forum on Business and Digital Economy, the IFABS 2025 Oxford Conference, and seminar participants at the University of York for many helpful comments.

controlling for days of price-limit hits; we also study the dynamic relationship between informed trading and herding and demonstrate that informed trading Granger-causes herding over time. Our evidence suggests that informed traders motivate stronger herding over time (possibly due to noise traders chasing informed trades), while at the same time dampening it contemporaneously, suggesting that they prey on the very herding they attract.
JEL classification: G14; G40; G41

Keywords: informed trading; herding; anti-herding; noise; market states

1. Introduction

The relationship between informed trading and investors' herding has been the subject of a large volume of research, most of it theoretical, aiming at modelling this relationship via a series of proposed analytical paradigms.[1] By comparison, the number of empirical studies on this issue is smaller, primarily focusing on exploring how this relationship depends on firm-specific features, drawing on several (direct and indirect) proxies for informed trading (e.g., Zhou and Lai, 2009; Chang and Wang, 2019). Overall, evidence to date suggests that this relationship is significant, yet without any consensus as per its sign, with theoretical arguments (and empirical evidence) having been advanced in favor of both a positive, as well as a negative, relationship (e.g., Boyd et al., 2016; Zhao and Gao, 2023).

An aspect of this relationship that has received very limited attention in the relevant literature is the possibility of this relationship exhibiting variations in its structure. Evidence, for example, suggests (see Section 2.3 for a discussion of this literature) that both the presence of informed investors as well as the motivation of traders to herd exhibit variations across market/economic states; if so, it stands to reason that the relationship between informed trading and herding can also vary (in terms of its strength and/or sign) across different market/economic conditions. What is more, herding itself can be driven by rational considerations (e.g., due to correlated

[1] Herding is defined as imitation of others' actions following interactive observation of those actions (or their payoffs). For a more detailed discussion, see the excellent reviews of Hirshleifer and Teoh (2003; 2009).

responses to fundamentals; Galariotis et al., 2015) as well as behavioural ones (e.g., due to systematic noise trading; Barber and Odean, 2013); this suggests that the relationship between informed trading and herding may also vary depending on the type of herding examined. The above suggests the presence of factors (market/economic conditions; herding-types) potentially motivating variations in the structure of this relationship – an issue which has received scant attention to date.

We empirically investigate this issue in the context of the two Mainland Chinese equity markets (Shanghai Stock Exchange; Shenzhen Stock Exchange), which constitute an ideal testing ground for our investigation. Mainland Chinese equity markets comprise rather unique trading environments in terms of asymmetric information (see e.g., the discussion in Zhao and Gao, 2023), encompassing a large majority of noise traders[2] (domestic retail investors involved in herding and other behavioural trading patterns; Cui et al., 2024) and a comparatively smaller number of informed ones (primarily corporate insiders, as well as institutional investors). Under such conditions, a symbiotic relationship arises between the two investor-types, with noise traders tracking the trades of their informed peers (Zheng et al., 2015), and informed traders using their informational advantage to exploit noise investors (Copeland et al., 2009).

Our study covers the 2003-2022 period and draws on the volume-synchronized probability of informed trading (VPIN; Easley et al., 2012) to measure the presence of

[2] Evidence (Hu and Wang, 2022; Jones et al., 2024) denotes that domestic retail investors capture up to about one-third of the two Mainland Chinese stock exchanges' capitalization, dominating (over 80%) their volume of trade.

informed traders per stock at the daily frequency. We first explore the presence of herding in each stock exchange (Shanghai; Shenzhen) separately, as well as jointly, and report evidence of significant herding for all estimations, thus confirming the oft-cited presence of herding in Chinese markets.[3] We then assess the relationship between herding and VPIN and find that this relationship is significantly negative, with herding being present (absent) for low (high) VPIN levels, diminishing as informed trading intensifies. This denotes that the higher the presence of investors relying on information, the less likely it is for herding to surface, thus confirming earlier evidence both from the international literature (Alevy et al., 2007; Boyd et al., 2016; Blasco and Corredor, 2017) and that pertaining to Chinese markets (Wong et al., 2009; Wongchoti et al., 2009).

Although the relationship between informed trading and herding appears negative for the full sample period, its sign and significance may vary across different states of the Chinese market/economy. This expectation is predicated on ample literature (see Section 2.3) documenting variations of both herding and informed trading individually across different states of the market/economy, which would thus suggest that their relationship might also project such variations. To that end, we condition this relationship on different states of a series of relevant variables reflective of market (high/low market performance; high/low market volatility; high/low investor sentiment; high/low traders' disagreement) and economic (high/low economic policy uncertainty;

[3] For an overview of herding in Chinese equity markets, see the discussion in Cui et al. (2024).

high/low consumer confidence) conditions that have been found in the literature to be relevant to variations of both herding and informed trading individually. Results denote that informed trading maintains its negative relationship with herding irrespective of the state of each variable controlled for. This negative relationship appears the strongest during days of low market returns, low market volatility, low economic policy uncertainty, high traders' disagreement, high investors' sentiment and high consumers' confidence. We attribute the stronger presence of this negative relationship during these specific market/economic states to the latter more strongly either a) motivating informed investors to trade against herding, or b) increasing the propensity to trade on information (thus reducing the need to herd). Overall, our evidence suggests that different market/economic states do not affect the sign of the relationship between informed trading and herding in China, yet do produce variations in the strength and significance of this relationship.

Second, we assess whether this relationship projects variations when controlling for the possibility that investors may herd for reasons both related to fundamentals (e.g., following the processing of similar information) as well as unrelated to fundamentals (e.g., chasing noise sentiment). To that end, we partition herding into its fundamentals-driven and noise-driven components (Galariotis et al., 2015; Cui et al., 2019); preliminary unconditional herding estimations denote the presence of fundamentals-driven anti-herding (i.e., excessive divergence of traders' beliefs; Gebka and Wohar, 2013) and noise-driven herding. Noise-driven herding is by far stronger (in absolute terms) than fundamentals-driven anti-herding, thus showcasing that herding is largely noise-driven and confirming earlier evidence (e.g., Hu and Wang, 2022) on the role of noise in Chinese markets. We then assess whether the negative relationship between informed trading and herding holds for both herding types; results from the full sample reveal an interesting pattern. On the one hand, noise-driven herding follows the previously documented pattern (it maintains a negative relationship with VPIN), thus denoting that our earlier results were largely due to noise-driven herding. On the other hand, fundamentals-driven estimations reveal anti-herding, which rises as VPIN increases, implying that a higher presence of informed traders is associated with excessive divergence in investors' beliefs. With respect to the effect of different market/economic states, we observe that informed trading appears to dampen noise-driven herding the most for almost exactly the same states for which it dampened total herding the most. The relation of informed trading to fundamentals-driven anti-herding tends to be positive (i.e., a higher intensity of trades based on private information is associated with stronger dispersion in the beliefs of investors in the market), especially when market volatility, economic policy uncertainty, disagreement, and consumer confidence are high. All in all, these results confirm that the relationship between informed trading and herding (and the impact of market/economic conditions over it) varies with the type of herding.

To shed further light into the nature of the relationship between informed trading and herding, we perform a series of additional tests. First, we draw on the 2012-reform that strengthened the legal framework for tackling insider trading in Chinese markets, in order to assess its impact over the relationship between informed trading and herding, and find that the negative relationship between informed trading and herding grows even stronger in the reform's aftermath. A possible explanation for this is that the reform was successful in limiting insider trading in China, resulting in the remaining insider trades being based on private information with the highest economic value, and hence being more impactful on market participants (who would utilize such information more extensively, hence relying even less on herding). Alternatively, by barring insider trading, the reform may have encouraged outside investors to feel less informationally disadvantaged and more willing to commit resources to the acquisition/processing of information (thus culminating in a rise in fundamentals-driven informed trading and a reduced reliance on herding).

Second, we assess the relationship between informed trading and herding based on a battery of alternative informed trading proxies: the volume coefficient of variation (VCV), market capitalization (SIZE), and institutional ownership (IO). Overall, across these three alternative proxies for informed trading, we observe a general pattern of herding appearing dampened in the presence of informed trading, similar to our baseline results where VPIN was employed.

Third, we rely on an instrumental variable approach to provide additional evidence on the causal effect of informed trading over contemporaneous herding; employing a proxy for VPIN which is purely dependent on past, but not contemporaneous, information (and, hence, independent from contemporaneous herding), we confirm the causal direction from informed trading to herding.

Fourth, we move beyond the contemporaneous relationship between informed trading and herding and assess how it evolves dynamically. We find that a rise (fall) in informed trading over time Granger-causes a rise (fall) in herding. Although, at first glance, this may appear to contradict our earlier results on VPIN's inverse relationship with herding, one should note that that relationship was a contemporaneous one, entailing no lead-lag effects. The rise in herding Granger-caused by increased informed trading is in line with models of informational cascades (Banerjee, 1992; Bikhchandani et al., 1992; Lee, 1998), whereby noise investors chase the trades of their informed peers over time. Combining these results with the previous ones on the negative contemporaneous relationship between informed trading and herding indicates that high levels of informed trading motivate stronger herding over time, while at the same time dampening it contemporaneously, thus suggesting the presence of an interesting "ecology", whereby informed traders prey on the very herding they attract.

Fifth, we assess the potential impact of price-limit hits by removing stock-day observations corresponding to stock returns of ±10%. Our results denote that our earlier findings hold; herding is significant in Chinese equity markets and is dampened as informed trading rises.

Our study produces original contributions to the literature by demonstrating empirically for the first time that the relationship between informed trading and herding projects variations in its structure. By showcasing that market/economic states constitute qualitative moderators of this relationship (the latter varies across different states in terms of its strength, not sign), whereas herding-types (fundamentals-versus-noise-driven herding) impact both its sign and strength, we offer seminal evidence on the effect of a number of determinants of this relationship. More specifically, whereas informed trading and herding have been amply documented in the literature to vary individually across market/economic states, we produce novel evidence on how their relationship also varies (in terms of its strength) across such states. What is more, we further show for the first time that whether herding is fundamentals- or noise-driven leads it to project variations in its interactions with informed trading.

The rest of this study is organized as follows: Section 2 discusses herding (Section 2.1), and informed trading (Section 2.2), before outlining their relationship and the hypotheses regarding it (Section 2.3); it also provides (Section 2.4) a discussion on Mainland Chinese equity markets and why they constitute an ideal testing ground for the study of this relationship. Section 3 presents the data (Section 3.1) and the empirical design employed (Section 3.2), alongside descriptive statistics (Section 3.3). Section 4 discusses the results, while Section 5 offers concluding remarks and discusses the implications of our findings.

2. Theoretical background

2.1 Herding

Investors herd when they sideline their private signals and/or fundamentals, choosing to follow the trades of other investors instead; in effect, herding is a process involving interactive observation of other people's actions/action-payoffs culminating in behavioural convergence (Hirshleifer and Teoh, 2003). Key to the decision to herd is the presence of an actual or perceived asymmetry in the market environment. Investors, for example, who have no information, or whose information endowment and/or processing skills are poor, will feel tempted to imitate their presumed better-informed peers, in order to enjoy informational payoffs by free-riding on their trades (Devenow and Welch, 1996). To the extent that information is costly, this behaviour may lead investors to refrain from collecting information signals and resort to inferring information from other people's trades by copying them. If this persists, it will lead to fewer signals entering the public pool of information, thus motivating informational cascades (Banerjee, 1992; Bikhchandani et al., 1992; Lee, 1998). An alternative possibility pertaining to investment professionals is for those of lower quality to mimic those of higher quality. This has often been documented for fund managers, who, being subject to relative performance assessment versus their peers, are thus striving not to underperform their industry benchmark. In this case, "bad" managers opt for tracking the trades of "good" ones, in order to improve on their reputation and career prospects (Scharfstein and Stein, 1990; Jiang and Verardo, 2018). In both this case (whereby fund managers herd in anticipation of reputational payoffs) as well as the previous one (whereby investors herd in anticipation of informational payoffs), herding arises intentionally. Herding, however, need not always be intentional; investors may also converge in their trades due to them responding similarly to signals they commonly observe. In this case, the correlation in their trades is not the product of interactive observation, and this gives rise to spurious herding. The latter can be motivated by commonalities in the practice and regulatory framework of investment professionals that prompt them to exhibit similarity in their trades (Teh and DeBondt, 1997); it can also be driven by investors with correlated information sets (investigative herding – see Froot et al., 1992; Hirshleifer et al., 1994), who follow (or rotate across) similar investment styles (Santi and Zwinkels, 2023). In addition, fads (Andrikopoulos et al., 2021) as well as behavioural biases (Barber and Odean, 2013) can also motivate spurious herding.

2.2 Informed trading

Informed trading involves trading based upon information that is not common knowledge (e.g., private or insider information; Kyle, 1985) and has been associated with the activities of various types of investors, including volatility/directional traders (Chen and Wang, 2017), institutional investors (Chakravarty, 2001; Ryu et al., 2017), overnight and intraday informed traders (Fishe and Smith, 2012), and floor brokers (Cooney and Sias, 2004). A host of (direct and indirect) proxies have been proposed for informed trading, including the adverse selection component of the bid-ask spread

(Borisova and Yadav, 2015), buy-sell order imbalance (Feng et al., 2018), probability of informed trading (PIN; Easley et al., 1996), volume-synchronized PIN (Easley et al., 2012), proportion of medium-sized contrarian trades (Chang and Wang, 2019), volume coefficient of variation (Lof and Van Bommel, 2023), market capitalization (Llorente et al., 2002; Bushee and Goodman, 2007), institutional ownership (Guo and Qiu, 2015), and other institutional informed trading measures (see Gu et al., 2021, for a discussion). Informed traders exploit their informational advantage by trading strategically via stealth trading (Holden and Subrahmanyam, 1992; Foster and Viswanathan, 1994), whereby they split up their orders into smaller-sized ones and lead information to be integrated into prices gradually (Kyle, 1985).

Informed trading can be impacted by a variety of institutional factors, including liquidity (Admati and Pfleiderer, 1988; Wong et al., 2009; Karaa et al., 2014), trading regulation (Merl et al., 2023), market structure (Cai et al., 2015) and ownership structure (Borisova and Yadav, 2015). Firm-specific features (firm-size/-age; number of common shareholders; institutional ownership; analyst coverage) can exert a negative impact on informed trading (Aslan et al., 2011), while Jayaraman (2008) shows that informed trading is a function of earnings' volatility.

2.3 Informed trading and herding: hypotheses development

We will now introduce the hypotheses we test in our paper; we begin by discussing the relationship between informed trading and herding. On the one hand, the relationship would be expected to be negative for several reasons. First, in a rational expectations framework, investors trade on their private information, hence they would be less inclined to mimic the trades of others;[4] as a result, the higher the number of investors trading on their private information, the less potent herding should be (Alevy et al., 2007; Boyd et al., 2016). Second, if informed investors utilize their informational superiority to trade against noise investors (e.g., via informed contrarian trading; Chang and Wang, 2019), this can dampen the price impact of the herding of the latter (Avramov et al., 2006; Liao et al., 2011; Blasco and Corredor, 2017). Third, if noise investors' herding renders the market environment too risky for informed investors, the latter may choose to abstain from trading (De Long et al., 1990), leading to a reduced footprint of informed trading in the market.

On the other hand, a broad literature has proposed a series of reasons advocating a positive relationship. Examples of these reasons include: informed investors with lower-quality signals herding on the trades of their peers with better-quality signals in the presence of uncertainty about the fundamental value of an asset (Zhang, 1997; Zhou and Lai, 2009; Ford et al., 2013; Cipriani and Guarino, 2014; Tiniç et al., 2020); complexity of information and its taxing effects on attention and cognitive processing can also enhance herding among otherwise informed investors (Kim and Pantzalis, 2003); informed investors may analyze correlated information sets, either simultaneously (Froot et al., 1992) or at different points in time (e.g., due to gradual

[4] Herding investors sideline information signals relevant to the valuation of their investments (implying their knowledge of the structure of fundamentals is limited to none), as well as not engage in rational processing (since they "delegate" their investment decisions to the herd), thus departing from the rational expectations framework.

diffusion of information; Hirshleifer et al., 1994; Hong and Stein, 1999), thus inducing correlation in their trades; informed investors may temporarily engage in herd-like strategies, if they are more likely to profit from them (He and Zheng, 2016); observational learning (i.e., the case of noise investors herding more behind informed traders, as the identity/precision of the latter's presence rises; e.g., Chmura et al., 2022); informed investors refraining from arbitrage due to noise trader risk, choosing to herd on the market trend instead (De Long et al., 1990; Abreu and Brunnermeier, 2003; Brunnermeier and Pedersen, 2005); and informed trading contagion across markets/sectors (Zhao and Gao, 2023). In view of the lack of consensus over the direction of the relationship between informed trading and herding, we propose the following hypothesis:

Hypothesis 1: The relationship between informed trading and herding is statistically significant.

Research indicates that both herding and informed trading bear asymmetries in their presence conditional on a series of macro (market- and economy-wide) states. As far as herding is concerned, evidence suggests that it manifests itself asymmetrically conditional on market performance, market volatility, investor sentiment, economic policy uncertainty, and macroeconomic conditions, to mention but a few.[5] These asymmetries have been ascribed to several (primarily intentional) herding motives and

[5] For more on how herding varies with market performance/volatility, see Kallinterakis and Gregoriou (2017). Herding during high (low) sentiment periods has been reported in Liao et al. (2011) and Celiker et al. (2015) (Philippas et al., 2013). Cui et al. (2019) and Gavriilidis et al. (2024) show that herding is

have been documented in studies based on both micro as well as macro data (see e.g., the discussion in Andrikopoulos et al., 2021). Similar asymmetries across macro conditions have been documented for informed trading.[6] Given how both herding and informed trading individually vary with the state of the market/economy, it stands to reason that their relationship can also exhibit similar variations. To that end, we condition their relationship on the following variables:

i) Market performance: during periods of rising markets, herding can be amplified by various factors, including noise trading (e.g., Sicherman et al., 2015), euphoric social mood (e.g., Andrikopoulos et al., 2021), and fear of missing out (e.g., Potsaid and Venkataraman, 2022). In this case, informed investors may trade against - and dampen - noise investors' herding[7] (or ignore their private signals and ride on the uptrend, if noise traders have rendered the market too risky for informed traders to

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stronger when economic policy uncertainty is high. Indirect evidence on the relationship between consumer sentiment and herding is presented in Schmeling (2009). As per economic conditions, herding is amplified by adverse funding shocks (Philippas et al., 2013), macro announcements (Galariotis et al., 2015), interest rate increases, currency depreciations (Gong and Dai, 2017), expansionary policies (Krokida et al., 2020), and credit/funding liquidity deterioration (Duygun et al., 2021).

[6] For more on how informed trading varies with market performance, see, e.g., Chan et al. (2009), Alhashel (2015), and Ormos and Timotity (2016). The relationship of informed trading with market volatility has been investigated in several studies; examples include Goettler et al. (2009), Blasco et al. (2012), Easley et al. (2012), Jiang and Lo (2014), Lai et al. (2014), and Baruch et al. (2017). On the relationship between sentiment and informed trading, see Antoniou et al. (2016) and Gao et al. (2022). Chen and Karathanasopoulos (2022) and Cookson et al. (2022) offer evidence on how traders' disagreement is related to informed trading. Indirect evidence on the role of consumer sentiment over informed trading is presented in Kumar (2009). Regarding the role of economic policy uncertainty in informed trading, see Nagar et al. (2019), El Ghoul et al. (2022), and Zhao and Gao (2023). For examples on the role of corporate and macroeconomic announcements/conditions on informed trading, see Brennan et al. (2018) and Hu and Huang (2018).

[7] This behaviour would resemble rational arbitrageurs tackling correlated noise trades and would likely involve entering positions against the market trend (i.e., contrarian trading, something widely observed for informed investors; see the discussion in Chang and Wang, 2019). For such "predatory" behaviour on

perform arbitrage)[8], in which case the relationship between informed trading and herding will be negative (positive). On the other hand, herding can arise during market downturns due to loss-/risk-aversion: investors may be unloading their positions in a correlated fashion to curtail their losses. In this case, informed investors may contrarian-trade, potentially dampening this sell-herding (ride on the trend and sell too)[9], in which case the relationship between informed trading and herding will be negative (positive). Since *a priori* it is not possible to ascertain the direction of this relationship, we propose the following hypothesis:

Hypothesis 2a: The strength of the relationship between informed trading and herding is conditional on market performance.

ii) Market volatility: herding is likely to arise during highly volatile periods as a means of navigating through uncertainty. If high volatility is the result of enhanced information

behalf of informed investors to be successful, it is important that a) informed trading is of substantial size, b) informed trades are correlated in their responses to tackling herding, and c) informed traders can monitor each other in the market so that they can act synchronously (Abreu and Brunnermeier, 2002, 2003; Brunnermeier and Morgan, 2010). Of course, it is possible that informed traders exhibit divergence in their private signals and/or their overall responses to herding in the market, in which case, dampening herding will be less likely; if so (and assuming informed trading is significant in presence), this would lead its relationship with herding to be positive.

[8] If noise traders render the market environment too risky, informed traders may also abstain from trading (De Long et al., 1990); in this case the relationship between informed trading and herding will turn negative.

[9] This may happen, if their information signals align with the market-trend (i.e., if they indicate selling), or due to risk-aversion (to prevent the realization of further losses; or if the market has become too risky to arbitrage).

flow (Ross, 1989), then the relationship between informed trading and herding is likely to turn positive (negative), if the higher presence of informed investors makes it easier for noise traders to identify their trades and herd on them[10] (if informed investors dampen herding via their trades). If high volatility is the result of noise (Foucault et al., 2011; Peress and Schmidt, 2020), it is likely that the market will be too risky for informed investors, who may choose to abstain from trading (ride on the waves of noise), in which case the relationship between informed trading and herding will be negative (positive). As per low volatility periods, they can give rise to a negative relationship between informed trading and herding from two different perspectives. On the one hand, low volatility may reflect lower information flow – and, hence lower informed trading presence (Ross, 1989; Easley et al., 2012) – rendering informed traders less able to dampen herding; on the other hand, if volatility in the market is noise-driven, low volatility periods would likely witness the prevalence of rational, informed investors[11] – whose stronger presence would then suggest a diminished role for noise traders (and their herding). As the direction of this relationship is impossible to assert, we propose the following hypothesis:

Hypothesis 2b: The strength of the relationship between informed trading and herding is conditional on market volatility.

[10] For this to be possible, informed trades must be correlated. Uncorrelated informed trades are unlikely to offer noise traders clear directional cues to follow.
[11] See e.g., Avramov et al. (2006), Blasco et al. (2012) and Blasco and Corredor (2017).

iii) Investor sentiment: if sentiment in the market is strongly optimistic/pessimistic, informed investors can trade against it (in effect, contrarian-trade; see e.g., Liao et al., 2011 and Chau et al., 2016), dampening the herding predicated on that sentiment; in this case, if informed trades are correlated and their presence is strong enough, this will imply a negative relationship between informed trading and herding. If sentiment-driven herding has rendered the market too risky for them, informed investors can ride on sentiment, buying more during optimistic and selling more during pessimistic periods (desist from trading), in which case the relationship between informed trading and herding will be positive (negative). In view of the various directions this relationship can assume, we propose the following hypothesis:

Hypothesis 2c: The strength of the relationship between informed trading and herding is conditional on investor sentiment.

iv) Trader disagreement: high trader disagreement is a reflection of either heterogeneous priors or persistent divergence in beliefs/opinions among investors and has been associated with increased volatility and volume (see the discussion of the literature in Carlin et al., 2014). Disagreement can be the result of differences in information processing, valuation models and confidence in the precision of one's information. The presence of high trader disagreement implies that investors with heterogeneous priors trade on their private signals (implying informed trading is stronger; Cookson et al., 2022), so, in theory, this would be expected to act as a disincentive to herding and would imply a negative relationship between informed trading and herding. If, however, investors rationally update their beliefs, there must be a point where a learning effect will arise, leading their beliefs to gradually converge (Geanakoplos and Polemarchakis, 1982); as this would increase the potential for convergence in their trades, it would render it easier for noise traders to mimic them, thus amplifying herding. In this case, a reduction in disagreement would foster a positive relationship between informed trading and herding. Since learning is neither homogeneous, nor guaranteed among investors[12], this suggests that the impact of trader disagreement over the relationship between informed trading and herding is impossible to assert; as a result, we propose the following hypothesis:

Hypothesis 2d: The strength of the relationship between informed trading and herding is conditional on traders' disagreement.

v) Economic policy uncertainty: periods of elevated economic policy uncertainty tend to motivate stronger herding (Cui et al., 2019; Gavriilidis, et al., 2024), as a result of the information environment growing noisier during such times (Pástor and Veronesi, 2013). Under such conditions, informed investors will find it more difficult to rely on their private information and may choose to follow the market trend (abstain from trading), which implies that the relationship between informed trading and herding will be positive (negative). If economic policy uncertainty is low, the signals emanating from the economic environment will be less ambiguous, thus allowing informed traders to utilize them more confidently; as the informational environment grows less

[12] Learning may be hampered by behavioural factors (e.g., overconfidence or confirmation bias; see e.g., Menkhoff and Nikiforov, 2009) as well as persistent differences in opinions (Carlin et al., 2014).

noisy, it becomes more inviting to trading on information, thus reducing the need for peer-mimicking. Under such conditions, informed investors can trade more confidently (their signals are less noisy), something which can foster their presence in the market and confer a stronger adverse effect over herding. As it is not possible to predict the sign of this relationship *ex ante*, we propose the following hypothesis:

Hypothesis 2e: The strength of the relationship between informed trading and herding is conditional on economic policy uncertainty.

vi) Consumer confidence: if consumers' confidence in the economy's prospects is high, this is likely to be associated with a greater likelihood of investing in the capital market (Cupák et al., 2022). This may translate into more informed traders trading on the economy's positive signals, yet may also motivate greater participation by retail investors - the key candidates for noise trading (e.g., Barber and Odean, 2013) - and amplify herding (given how closely consumer confidence mirrors retail sentiment; Kumar and Lee, 2006). If, on the other hand, consumers' confidence is low, we are likely to witness a lower propensity towards equity investing, which is likely to adversely impact both informed trading (if fewer investors trade on their private signals) and herding (if many retail investors refrain from investing). As the above suggests that the sign of the relationship between informed trading and herding is impossible to ascertain,[13] we propose the following hypothesis:

[13] Indirect evidence on this issue is provided by Kumar (2009), who found that the probability of informed trading rises for US stocks with higher probability of attracting behaviourally biased trading, with the level of the latter increasing during periods of low consumer sentiment. This suggests that

Hypothesis 2f: The strength of the relationship between informed trading and herding is conditional on consumers' confidence.

Although the discussion thus far suggests that the relationship between informed trading and herding can vary in sign/strength, it can also be sensitive to the type of herding examined. Investors, for example, can herd on noise, often motivated by a series of behavioural forces (Barber and Odean, 2013), which can give rise to noise-driven herding; they can, however, also herd on fundamentals (if they respond with their trades similarly to commonly observed fundamental information, or if their fundamentals-related signals are correlated), in which case this can generate fundamentals-driven herding. Assuming noise-driven herding, its relationship with informed trading would be expected to involve very similar forms to those described so far for the relationship between informed trading and total herding[14]; with respect, however, to fundamentals-driven herding, this need not necessarily be the case. To the extent that both informed trading and fundamentals-driven herding rely on information, it is possible that their relationship can be positive, if both rely on the same correlated information signals. If, however, informed traders exhibit divergence in their signals

when consumer sentiment is low, informed trading rises in an attempt to exploit noise in the market. Nevertheless, the implications of these findings for the relationship between informed trading and herding are far from clear; although informed traders may, indeed, increase their presence during low consumer sentiment periods for noise-prone stocks, this does not necessarily mean they are successful in dampening any noise-driven herding.

[14] Herding (noise-driven herding) involves investors not trading on their own information (information in general) and, as a result, is at odds with the concept of information-based trading.

and this dampens fundamentals-driven herding, this relationship is expected to be negative. It is further possible that, in the extreme, informed traders overweight their signals to such an extent that the divergence in their trades grows so large, that this may lead fundamentals-driven herding to shift to anti-herding. As our discussion here indicates, the relationship between informed trading and herding is expected to vary with the type of herding examined, with a similar expectation arising as per the impact of different market/economic states over this relationship. To that end, we propose the following two hypotheses:

Hypothesis 3a: Noise-driven and fundamentals-driven herding each projects a different relationship to informed trading.

Hypothesis 3b: The impact of market/economic states over the relationship between informed trading and herding varies when examining noise-driven herding and fundamentals-driven herding separately.

2.4 Mainland Chinese equity markets

A persistent feature of Mainland Chinese equity markets (Shanghai Stock Exchange; Shenzhen Stock Exchange) since their inception in the early 1990s is the dominance of retail investors in their trading activity (Chen et al., 2007; Carpenter and Whitelaw, 2017; Jia et al., 2017). As evidence (Hu and Wang, 2022; Jones et al., 2024) suggests, domestic retail traders capture up to about one-third of the two stock exchanges' capitalization, dominating (over 80%) their volume of trade. Considering that retail investors have traditionally been deemed prime candidates for the role of noise traders (Black, 1986; Barber et al., 2009), it is perhaps hardly surprising that Mainland Chinese equity markets have consistently projected a series of behavioural trading phenomena, including herding [15] and other noise trading patterns (e.g., trades motivated by disposition effect and overconfidence; see Chen et al., 2007 and the discussion of the literature in Cui et al., 2024). This, in turn, implies a market environment with investors of relatively low sophistication[16] being prone to sentiment (Han and Shi, 2022), something which has been found to amplify volume (Liu et al., 2024) and return-anomalies (Liu et al., 2019; Han and Shi, 2022; Han and Zhang, 2024), while also dampening informational efficiency (Hu and Zhao, 2018).[17] This noisiness in Mainland Chinese equity markets is further exacerbated by the relatively low degree of voluntary disclosure and transparency (Morck et al., 2000; Piotroski et al., 2015), which hamper investors' protection.

Amid such a noisy environment, trading on information is expected to be both harder (given that most investors are likely to trade on no, or low-precision/-quality signals),

[15] The presence of herding in Chinese equity markets has been expounded in a host of studies, including Tan et al. (2008), Mei et al. (2009), Chiang and Zheng (2010), Xiong and Yu (2011), Lee et al. (2013), Li (2017), Zheng et al. (2021), Cheng et al. (2022), Wang et al. (2022), and Hasan et al. (2023).

[16] Evidence (Bouteska et al., 2023) suggests most Chinese retail investors are of relatively young age (around 30 years old, on average); Zheng et al. (2015, p. 62) cited evidence from the SWUFE China Household Finance Survey, according to which "[...] 60% of new stockholders have junior high as their highest education level and 5.8% cannot read". A stylized fact in Chinese markets (Zhang et al., 2014; Jones et al., 2024; Tan et al., 2024) is that retail investors' performance and information-access grow with the size of their financial resources, suggesting heterogeneity in their ranks.

[17] The impact of domestic retail traders is more pronounced among A-shares (denominated in Renminbi), which form the bulk of listed shares in Mainland Chinese equity markets (Cui et al., 2024); B-shares (traded in US Dollars on the Shanghai Stock Exchange and in Hong Kong Dollars on the Shenzhen Stock Exchange) entail a largely qualified foreign institutional following (Adcock et al., 2023).

and confined to more sophisticated market participants; the latter tend to include corporate insiders (He et al., 2023) and (foreign) institutional investors (Gu et al., 2021) in Chinese equity markets.[18] However, informed investors would be tempted to draw on their informational superiority, in order to exploit their noise counterparts (see e.g., De Long et al., 1990). In the context of Chinese markets, this has been reported with respect to corporate insiders (He and Rui, 2016). Insider trading in China has been reported in a multiplicity of domains, including e.g., stock splits (Titman et al., 2022), mergers, and acquisitions (Li et al., 2023); it can also assume various facets (trading on proprietary information; trading on bought inside information; sale of inside information to trigger insider trading among a broader set of investors), while, aside from corporate insiders, it can also involve government officials (Li et al., 2023). Domestic insiders have also been found to "camouflage" as foreign investors (to steer clear from prosecution; He et al., 2023), while corporate insiders may choose to share private information with institutional investors, in return for a reduced active monitoring by the latter (Hu et al., 2024).[19]

[18] The rising presence of foreign institutional investors is largely reflective of China's opening to more foreign investment, following the easing of some of the stringent regulations that previously governed its financial markets. This shift is particularly evident in initiatives like the Shanghai-Hong Kong Stock Connect and the Shenzhen-Hong Kong Stock Connect, which facilitate cross-border trading and influence market structure, potentially increasing the avenues for informed trading. The Shanghai-Hong Kong Stock Connect and Shenzhen-Hong Kong Stock Connect are cross-border trading links established in 2014 and 2016, respectively. They allow investors from Mainland China and Hong Kong to trade shares listed on each other's stock exchanges within set quotas. Overall, overseas funds' participation has proven to be stabilizing among Chinese A-shares (Liao et al., 2020).

[19] To mitigate the adverse effects of such conduct and improve transparency, the China Securities Regulatory Commission (CSRC) has been tightening corporate governance standards, by implementing market reforms aiming at tackling market manipulation, accounting fraud, and insider trading

The above reflect a rather unique environment in terms of asymmetric information (see e.g., the discussion in Zhao and Gao, 2023), with a large majority of noise traders and a small number of informed ones (many of whom have privileged access to corporate information). Such conditions can foster a symbiotic relationship between the two investor-types, with noise traders tracking the trades of their informed peers (Zheng et al., 2015), and informed traders using their informational advantage to exploit noise investors (Copeland et al., 2009). To that end, Mainland Chinese equity markets constitute an ideal testing ground for the assessment of the variations in the relationship between informed trading and herding.[20]

3. Data and Methodology

3.1 Data

Our data were primarily sourced from the CSMAR database for the 03/01/2003 - 30/12/2022 period and includes: daily data on closing prices, trading volume and

(Alhaj-Yaseen et al., 2017). For more on the issues related to insider trading and investors' protection in Chinese markets, see He and Rui (2016).

[20] In addition, there exists ample empirical evidence from Mainland Chinese equity markets on both the impact of market/economic states over informed trading (e.g., Gao et al., 2022) and herding (e.g., Cui et al., 2024) individually, as well as on the existence of fundamentals- and noise-driven herding (Wang et al., 2021; Cheng et al., 2022; Cui et al., 2024). This evidence confirms that the sets of factors (market/economic conditions; herding-types) on which we condition the relationship between informed trading and herding are very relevant to both herding and informed trading in China, thus further strengthening the case for selecting those markets for the purposes of our study.

market capitalisation for all A-share stocks listed on the two Mainland Chinese (Shanghai; Shenzhen) stock exchanges;[21] monthly data on the Chinese consumer confidence index (CCI) and the investor sentiment index (O_CICSI).[22] The monthly index by Huang and Luk (2020) was used to proxy for economic policy uncertainty in China (CNEPU)[23], while daily data on Chinese Fama and French (2015) five factors were obtained from https://www.factorwar.com/data/factor-models/. We obtained daily VPIN (volume-synchronized probability of informed trading) estimates for each A-share listed on the Shanghai and Shenzhen markets from CSMAR; these are based on intra-day data as explained in Section 3.2.1. below.

3.2 Methodology

3.2.1 The informed trading probability measure (VPIN)

We use the VPIN metric by Easley et al. (2012) to empirically capture the prevalence of informed trading, by averaging daily stock-level VPIN values to obtain a market-level measure. VPIN is based on the idea that order-imbalances signal the presence of informed trading (or adverse selection risk) and, therefore, requires classification of trading volume into buys and sells. Rather than using an itemized classification (i.e.,

[21] A-shares (denominated in Renminbi) are dominated by domestic (primarily retail) investors – and, hence, more noise-prone, reflective of domestic sentiment (Cui et al., 2024); B-shares (traded in US Dollars on the SSE and in Hong Kong Dollars on the SZSE) entail a largely qualified foreign institutional following (Adcock et al., 2023). In total, our sample entails 3,368 A-shares stocks (1,777 listed on SSE; 1,591 listed on SZSE).

[22] The Chinese investor sentiment index is a monthly aggregate index (mnemonic: *StdExMacroCICSI*), comprising the closed-end funds' discount rate, the market turnover rate, the number of IPOs, the weighted average yield of IPO negotiable shares, and the number of new investors' accounts, each orthogonalized to remove the impact of macroeconomic fundamentals, as in Baker and Wurgler (2006).

[23] CNEPU is constructed by textual analysis of 10 mainland Chinese newspapers and available under (values continuously updated to provide up-to-date coverage): https://economicpolicyuncertaintyinchina.weebly.com/.

the discrete Lee-Ready (1991) tick rule) to infer the order-imbalance within the traditional PIN approach, VPIN is based on a continuous bulk classification rule to distinguish between buy and sell volume by aggregating trades over short time intervals (time bars). Bulk volume classification has been shown to be more accurate than the tick rule in discerning trading intentions in modern, low-latency equity markets (Easley et al., 1996; Panayides et al., 2019).[24]

While we employ daily (derived from intra-day data) VPIN stock-level estimates provided by CSMAR, we also cross-checked the accuracy of those values by estimating VPIN values for a random sample of stocks and days; results (unreported) largely confirm the accuracy of CSMAR data. The VPIN estimation proceeds in the following steps. Firstly, the procedure performs trade-aggregation in 1-minute time bars. Then, each trading day is divided into *n* equal-sized volume buckets which represent pieces of homogeneous information content. Volume Bucket Size (VBS) is calculated by dividing the daily trading volume by the number of buckets *n*. Buckets are filled by accumulating the volume in consecutive time bars until reaching the specified VBS. Any extra volume from the last time bar (at completion of the last bucket) is allocated to the next bucket. At the same time of bucket completion, volume is categorized as buyer-initiated $\left(V_{\tau}^{B}\right)$ or seller-initiated $\left(V_{\tau}^{S}\right)$ in probabilistic terms as follows:

[24] For a detailed comparison of the VPIN versus the original PIN measure, see Abad and Yagüe (2012).

$$V_\tau^B = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \times Z\left(\frac{P_i - P_{i-1}}{\sigma} \right)$$

$$V_\tau^S = VBS - V_\tau^B$$

where $t(\tau)$ is the last time bar included in the τ-th volume bucket, V_i and P_i denote the trading volume and the price at the *i*-th time bar, respectively. Z is the cumulative distribution function (CDF) of the standard normal distribution, and σ is the standard deviation of price changes between time bars. The daily VPIN flow toxicity metric is then given by the average of intra-day order-imbalances, $OI = |V^B - V^S|$, within the trading session as follows:

$$VPIN = \frac{\sum_{\tau=1}^{n} OI_\tau}{n \times VBS}$$

Typical value of *n*, the number of buckets used to approximate the daily expected trade-imbalance, is 50.[25] We use daily stock-level VPIN estimates based on *n*=50 buckets; daily data, estimated using intraday information, aligns well with the frequency of our other core variables in the estimation of herding, while 50 buckets per day allow for a detailed identification of potentially short-lived informed trades within each day.

[25] For evidence on the choice of *n* = 50, see Easley et al. (2012), Andersen and Bondarenko (2014), Foucault et al. (2017), Abad et al. (2018), and Jiang and Lei (2023).

3.2.2 Herding measure

To assess the existence of market-wide investor herding, we employ the model by Chang et al. (2000). The model's underlying rationale is that, assuming conditions of rational asset pricing, stock prices exhibit varying sensitivity to market movements (i.e., their betas are diverse) and the relationship between the cross-sectional return dispersion and absolute market returns will, thus, be linear and positive. Whether this holds, however, for extreme (positive or negative) market returns is far from obvious. During periods of market stress, investors are more likely to suppress their private information and abide by the market consensus; if so, their trades will grow more correlated, resulting in increased similarity in the direction of stocks' returns – and a lower cross-sectional return dispersion in the process (since herding will prompt returns to shift in a singular direction; Christie and Huang, 1995). If this is the case, then the cross-sectional dispersion of returns will be an inverse function of the magnitude of absolute market returns, with the relationship between the two likely to turn non-linear as well. If, on the other hand, investors place excessive weight on their private beliefs (possibly due to overconfidence; Gebka and Wohar, 2013) more than rational asset pricing would warrant, it would lead this relationship to be non-linearly positive and be suggestive of anti-herding. To that end, Chang et al. (2000) proposed the following empirical specification:

$$CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R_{M,t}^2 + e_t \quad , \qquad (1)$$

where $CSAD_{m,t} = \frac{1}{N}\sum_{i=1}^{N}(R_{i,t} - R_{M,t})$ is the cross-sectional absolute deviation of stocks' returns ($R_{i,t}$, where *i* = 1…*N*) from the market return $R_{M,t}$ on date *t*. In the absence of herding (and other systematic deviations from the rational pricing paradigm), returns follow a rational asset pricing model (CAPM, in the case of Chang et al., 2000); in this case, $\beta_1 > 0$ and $\beta_2 = 0$, implying that the aforementioned linear and positive relationship between the cross-sectional return dispersion and absolute market returns holds. In the presence of herding during extreme market movements, however, the cross-sectional similarity of stock returns is excessively high, implying lower values for $CSAD_{m,t}$ than what the CAPM would predict, hence $\beta_2 < 0$ and significant. Alternatively, traders could resort to anti-herding, which would result in excess $CSAD_{m,t}$ values compared to those implied by the CAPM, hence $\beta_2 > 0$ and significant.

3.2.3. The relationship between informed trading and herding: empirical design

To assess if trading on private information, as captured by the cross-sectional average probability of informed trading on date *t* ($VPIN_t$), is related to market-wide herding (or anti-herding), we employ two alternative modelling approaches. First, we estimate Equation (1) within the threshold regression framework, allowing for the "herding" parameter β_2 to differ between "high" vs. "low" realizations of $VPIN_t$, with determination of the threshold value separating "high" vs. "low" regimes being accomplished endogenously (by minimizing the least squared value of the model):

$$CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2^{LOW} R_{M,t}^2 I(VPIN_t < \tau) + \beta_2^{HIGH} R_{M,t}^2 I(VPIN_t \geq \tau) + e_t, \quad (2)$$

where $I(VPIN_t < \tau)$ is an indicator variable equal to 1, if $VPIN_t$ assumes values lower than an endogenously determined threshold value τ[26], and zero otherwise. To assess Hypothesis 1 empirically, we test for the sign and statistical significance of $\beta_2^{HIGH} - \beta_2^{LOW}$ in (2).

Secondly, we assume that the herding coefficient β_2 in Equation (1) can be modelled as a linear function of $VPIN_t$, i.e.,

[26] The optimisation procedure involves estimating a given threshold model for all available values of the threshold variable ($VPIN_t$ in our case) between the 10th and 90th percentile of its distribution, and finally selecting the optimal threshold value τ as such which produces a model with the lowest value of the sum of squared residuals. The exclusion of the top and bottom tails of the threshold variable in search for potential threshold values is a standard procedure, applied to avoid atypical extreme/outlier values being identified as optimal thresholds, hence leaving more than 90% of the whole sample in one regime/region and rendering the estimation of a threshold (rather than linear) model effectively worthless.

$$\beta_2 \equiv \beta_{2,t} = \gamma_2 + \gamma_3 VPIN_t \quad .$$

(3)

Substituting (3) into (1) and simplifying yields:

$$CSAD_{m,t} = \gamma_0 + \gamma_1 |R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + e_t .$$

(4)

If herding (anti-herding) prevails, the corresponding coefficient tends to be significantly negative (positive) throughout the sample. A positive coefficient γ_3 implies that informed trading causes an upward shift of β_2 (as per Equation (3)), i.e., a reduction (intensification) in herding (anti-herding), as it implies a shift of β_2 towards less negative (more positive) values - and vice versa if $\gamma_3 < 0$. Hence, an alternative test of Hypothesis 1 is based on the sign and significance of γ_3 in Equation (4).

To investigate how the aforementioned (see Section 2.3) market/economic variables affect the relationship between $VPIN_t$ and herding/anti-herding, we again adopt two alternative approaches. In the threshold approach, we estimate the following model, which allows for the VPIN-herding nexus to vary between regimes of high vs. low values of each macro variable:

$$CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R_{M,t}^2$$

$$+ \beta_3^{LOW} R_{M,t}^2 VPIN_t I(DET_t < \tau) + \beta_3^{HIGH} R_{M,t}^2 VPIN_t I(DET_t \geq \tau) + e_t,$$

(5)

where $I(DET_t < \tau)$ is an indicator variable equal to 1, if a specific determinant variable DET_t (market return; market volatility[27]; investors' sentiment; traders' disagreement; economic policy uncertainty; consumers' confidence) assumes values lower than an endogenously determined threshold value τ, and zero otherwise. If a given variable impacts the VPIN-herding relationship, we should observe $\beta_3^{HIGH} - \beta_3^{LOW}$ to be significantly different from zero; this, in turn, will allow us to draw inferences regarding the validity of Hypotheses 2a-2f.

Alternatively, we model the link between the VPIN-herding nexus and each macro determinant as a linear relationship (similar to the reasoning above), which leads to the following model:

$$CSAD_{m,t} = \gamma_0 + \gamma_1 |R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t +$$

$$\gamma_4 R_{M,t}^2 VPIN_t DET_t + e_t. \qquad (6)$$

[27] Securities' returns are calculated as the first differences of their logarithmic closing prices. Market returns are calculated as equally-weighted averages of returns on securities which belong to a given market, in line with Chang et al. (2000). Market volatility is measured as the squared value of market return (e.g., Cui et al., 2019).

Here, γ_4 captures the estimated impact of each macroeconomic determinant on the VPIN-herding nexus; its interpretation needs to be conditional on prior results from Equation (4) regarding whether that relationship is unconditionally positive or negative, and from Equation (1) regarding whether it is herding or anti-herding that prevails. For instance, if herding prevails ($\beta_2 < 0$ in Equation (1)) and VPIN limits its magnitude ($\gamma_3 > 0$ in Equation (4)), a positive γ_4 in Equation (6) would imply that this herding-dampening effect of VPIN is stronger, the higher the values of a specific market/economic determinant DET_t. However, if anti-herding prevails ($\beta_2 > 0$ in Equation (1)) and VPIN boosts its magnitude ($\gamma_3 > 0$ in Equation (4)), a positive γ_4 in Equation (6) would imply an even stronger anti-herding-enhancing impact of VPIN when DET_t assumes higher values. Overall, the conditional analysis of γ_4 in Equation (6) will be used to conclude regarding Hypotheses 2a-2f.

While data for most of the determinants DET_t is obtained as specified in Section 3.1, values for the variable measuring disagreement among traders (DISAG) are not available and we calculate them as the unexpected standardized trading volume, broadly following Garfinkel (2009). First, the total trading volume for each market *j* is regressed on the linear and square deterministic time trends (and a constant), and the estimated residuals are extracted as detrended volume ($detV_{j,t}$). Next, the following model is estimated:

$$detV_{j,t} = \pi_0 + \pi_1|R^{UP}_{m,j,t}| + \pi_2|R^{DOWN}_{m,j,t}| + \nu_{j,t} \quad , \tag{7}$$

where $R^{UP}_{m,j,t}$ ($R^{DOWN}_{m,j,t}$) is market *j* return when it is positive (negative); the estimated values of $\nu_{j,t}$ represent unexpected (as in, not predictable using deterministic trends or the magnitude of market movements on the day) trading volume and are employed as a measure of traders' disagreement, after standardization (Garfinkel, 2009, demonstrates its superior empirical performance as a disagreement measure):

$$DISAG_{j,t} = \frac{\nu_{j,t}}{S.D.(\nu_{j,t})} \quad . \tag{8}$$

To differentiate between investors' herding due to their response to common risk factors (not captured by the CAPM)[28] and to truly irrational motives, we follow Galariotis et al. (2015) and regress $CSAD_{m,t}$ on the Chinese markets' Fama and French (2015) factors:

[28] As mentioned earlier, Chang et al. (2000) estimate herding assuming CAPM holds in the market.

$CSAD_{m,t} =$

$\omega_0 + \omega_1(RM_t - RF_t) + \omega_2 SMB_t + \omega_3 HML_t + \omega_4 RMW_t +$

$\omega_5 CMA_t + u_t,$ (9)

where RM_t and RF_t are the market and risk-free rates of return, respectively, and other factors are: SMB (Small-minus-Big size return factor), HML (High-minus-Low book-to-market return factor), RMW (Robust-minus-Weak operating profitability return factor), and CMA (Conservative-minus-Aggressive investment return factor). The fitted values of $CSAD_{m,t}$ from Equation (9) represent its fundamentals-driven component, with the estimated residuals capturing its noise-driven (non-fundamentals-driven) component; more formally:

$CSAD_{m,t}^{NONFUND} = \quad \widehat{u}_t$,

(10)

$CSAD_{m,t}^{FUND} = C\widehat{SA}D_{m,t} - CSAD_{m,t}^{NONFUND}$.

(11) Each of these two components is used in turn as the dependent variable in Equations (1)-(2) and (4)-(6) to estimate non-fundamentals- and fundamentals-based herding/anti-herding, respectively.

3.3 Descriptive statistics

Table 1 presents summary statistics for all variables utilized in our empirical design. $R_{M,t}$ assumes a very low (in magnitude) negative mean value (almost equal to zero), something perhaps hardly surprising, considering the long sample window (20 full years) which witnessed a series of market episodes (including several bubbles and crashes; see Hu and Wang, 2022); both Chinese stock exchanges maintain very similar mean $R_{M,t}$ values, with $CSAD_{m,t}$ furnishing us with a similar pattern. The mean $VPIN_t$ level hovers around 30 percent (in line with the literature, e.g., Chen and Wu, 2022; Tang and Wan, 2022; Zhou et al., 2023), while the average traders' disagreement is almost zero, by construction, again likely due to the long sample window entailing periods of varying (upward and downward) disagreement; a similar picture emerges regarding investors' sentiment (with O_CICSI's mean value being negative, yet low in magnitude) and consumer confidence (whose index-average hovers just above 100, its baseline). Economic policy uncertainty reveals a more pronounced average value and a substantial standard deviation, reflective of the enhanced uncertainty of the Chinese macroeconomic environment (Hu and Wang, 2022).

4. Results-Discussion

4.1 Informed trading and herding

We begin our empirical investigation by first gauging the presence of herding in the Shanghai and Shenzhen markets, both separately, as well as jointly. Results are presented in Table 2 and they clearly denote that herding is significant (β_2 is significantly negative) across all estimations.[29] These results confirm the oft-cited evidence (see the discussion in section 2.4) on the presence of herding in Mainland Chinese stock exchanges, a fact primarily ascribed to the dominance of these markets' turnover by retail investors (of low sophistication and strong speculative disposition; Cui et al., 2024).

Table 3 (Panel A) presents our results from the estimation of Equation (2) on how herding varies between high and low probabilities of informed trading; as the estimates presented there suggest, herding appears absent (present) for high (low) VPIN values, with the difference $\beta_2^{HIGH} - \beta_2^{LOW}$ being significantly positive across all three estimations (Shanghai; Shenzhen; Shanghai and Shenzhen). The estimates from Equation (4) (Panel B) further denote that the herding coefficient β_2 significantly

[29] We employ robust standard errors for all estimations, to account for autocorrelation and heteroskedasticity, where appropriate.

rises (falls) as VPIN rises (falls), as the significantly positive values of γ_3 indicate; this implies that β_2 becomes more (less) negative, indicating that herding rises (declines)[30] as informed trading grows less (more) potent. Taken together, these findings reveal a negative relationship between informed trading and herding.[31] As a result, the higher (lower) the participation of informed traders in the market, the lower (higher) herding is expected to be; this may be due to either an elevated informed investors' presence (leading more people to trade on fundamentals and rendering herding less potent; or due to informed traders preying on the herding of their noise peers) or a reduced informed investors' presence (if noise investors have rendered the market too risky for informed traders, in which case herding will remain unchallenged). Overall, these results are in line with earlier findings (Avramov et al., 2006; Alevy et al., 2007; Wong et al., 2009; Wongchoti et al., 2009; Liao et al., 2011; Boyd et al., 2016; Blasco and Corredor, 2017) and allow us to accept Hypothesis 1.

4.2 Informed trading and herding: the impact of market/economic states

[30] As per Equations (1) and (3), it is a significantly negative β_2 that reveals herding, *ergo*, the less negative β_2 grows, the weaker the herding. If herding weakens so much as to lead β_2-values to enter positive territory, this will give rise to anti-herding (reflective of excess divergence of investors' beliefs; Gebka and Wohar, 2013).

[31] In further (unreported) analyses, we investigate whether these baseline results are not entirely driven by specific events: the 2007-9 financial crisis; the 2015 Chinese stock market bubble; the 2018-2 China-US "trade war"; and the 2020-onwards COVID pandemic. After the exclusion of each of these episodes from the sample the baseline result of positive and significant γ_3 in Equation (4) prevails (as does the significant negativity of γ_2, except in one case), indicating that our main finding of herding being negatively related to informed trading holds, and is not driven by market stress episodes in Chinese stock markets.

Tables 4-9 present the estimates from both the threshold (Panel A, for all tables) and interaction (Panel B for all tables) models (Equations (5) and (6), respectively) on how market performance (Table 4), market volatility (Table 5), investor sentiment (Table 6), trader disagreement (Table 7), economic policy uncertainty (Table 8) and consumer confidence (Table 9) impact the relationship of informed trading with herding. To begin with, results from the threshold model for all macro variables controlled for are clearly indicative of informed trading being negatively related to herding irrespective of the state of the market/economy (both β_3^{HIGH} and β_3^{LOW} are positive). This negative relationship grows the strongest when market returns/market volatility/economic policy uncertainty are low, since β_3^{LOW} is always significant (unlike β_3^{HIGH}), with the difference $\beta_3^{HIGH} - \beta_3^{LOW}$ being consistently significantly negative. Estimates from the interaction model confirm this; γ_4 being negative and significant, this suggests that higher (lower) market performance/market volatility/economic policy uncertainty leads VPIN to bear a less (more) adverse impact over herding. On the other hand, the adverse effect of informed trading over herding grows the strongest when investor sentiment/trader disagreement/consumer confidence are high (β_3^{LOW} is always lower in magnitude than β_3^{HIGH}, with the difference $\beta_3^{HIGH} - \beta_3^{LOW}$ being consistently positive and significant). Estimates from the interaction model reveal a positive and significant γ_4 , suggesting that higher (lower) investor sentiment/ trader disagreement/ consumer confidence leads VPIN to project a more (less) adverse impact over herding. Taken together, the above findings confirm the negative relationship between informed trading and herding, showing that it grows significantly stronger during specific macro states, thus allowing us to accept hypotheses 2a-2f.

The stronger adverse effect of informed trading over herding during specific market/economic conditions invites primarily two possible explanations. The first involves informed traders dampening herding the strongest when conditions render it more likely for them to counter it. One relevant example here involves this effect growing stronger during periods of low market returns (when herding would be expected to be driven by the sell-side). The strength of this effect can be attributed to the oft-cited (see Chang and Wang, 2019, and the discussion therein) contrarian trading observed among informed traders, which could dampen that herding by going against the trend and buying stocks that have lost value during the downturn. This would be supported by arbitrage asymmetry (Stambaugh et al., 2015), according to which, it is easier to arbitrage away underpricing than overpricing. Since buying an underpriced stock can often be easier (volume permitting) compared to shorting an overpriced one (especially in a market with short-selling restrictions like China's; Hu and Wang, 2022), informed contrarian trading would be more feasible when market returns are low. A second relevant example here involves the stronger presence of this negative relationship during periods of high investors' sentiment, as this is in line with evidence (Liao et al., 2011; Chau et al., 2016) indicative of rational/informed investors trading against over-optimistic sentiment in order to profit from it; [32] a similar explanation can be proposed here for the stronger presence of this negative relationship during periods of high consumer confidence.[33] [34]

The second explanation underlying the stronger adverse effect of informed trading over herding hinges on specific conditions (low market volatility; high trader disagreement; low economic policy uncertainty) rendering the market environment more accommodating for informed traders. Assuming, for instance, that market volatility is primarily noise-driven (something that has been found to hold for Chinese markets – see e.g., Cui et al., 2024, and the discussion therein), the stronger negative

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[32] CSMAR's sentiment index used here includes in its construction two variables related to IPOs (the number of IPOs per month and the average first-day IPO return in each month). However, there exist periods of IPO suspensions in Chinese equity markets during our sample period, most notably the period October 2012 to January 2014, which was associated with reforms to the IPO approval system (Xia et al., 2024). To assess whether controlling for those periods impacts our results, we empirically removed the impact of IPO variables on the sentiment index, and also removed the subperiods with IPO bans in place. Results (unreported, and available upon request) indicate that the dampening effect of VPIN over herding remains robust. We thank an anonymous reviewer for suggesting controlling for potential IPO-effects.

[33] Evidence (Kumar and Lee, 2006) denotes a strong association of consumer confidence with retail sentiment.

[34] We further decomposed the consumer confidence index into its fundamentals- and noise-driven component, by regressing the raw CCI variable on a series of macroeconomic factors (annual percentage change in industrial production index; inflation, calculated as the annual percentage change in the consumer price index; dividend yield for the "CHINA-DS Market" index - calculated by DataStream for the entire Chinese stock market; the slope of the yield curve, calculated as the difference between the yield on 10-year government bonds and the major loan rate for financial institutions for durations of one year and below - due to unavailability of data on short-term government bonds), in line with the literature (Schmeling, 2009; Wang et al., 2021). Results (unreported, and available upon request) suggest that VPIN retains its dampening effect over herding, for the noise-driven component of CCI, with its effect over the fundamentals-driven component of CCI being the opposite. These results support our reasoning that excessively overoptimistic individuals enter the stock market, adding to the pool of irrational investors. We thank an anonymous reviewer for suggesting this decomposition.

effect of informed trading over herding during low volatility periods would then likely be due to such periods entailing a lower noise trader presence. As this would render the market less risky for informed traders (it would imply lower noise trader risk), it would help foster their participation and reduce the presence of herding in the market. With regard to high disagreement levels, they imply both a more pronounced presence of informed traders (Chen and Karathanasopoulos, 2022; Cookson et al., 2022) and a more pronounced heterogeneity in the priors/persistent divergence in the beliefs/opinions of investors in the market (Carlin et al., 2014), both of which would thus be expected to deter herding and strengthen the negative relationship between informed trading and herding (as our results confirm). As per low economic policy uncertainty, it renders the informational environment less noisy – and hence, more inviting to trading on information, thus reducing the need for peer-mimicking. Under such conditions, informed investors can trade more confidently (their signals are less noisy), something which can foster their presence in the market and confer a stronger adverse effect over herding.

Overall, our findings suggest that the negative relationship between informed trading and herding grows the strongest under macro conditions that render it easier for informed traders to either trade on their information, or trade against noise traders.[35]

[35] In addition, we explored the possibility of variations in the impact of informed trading over herding during periods corresponding to combinations of our control variables that reflect distinct phases of the economic cycle. Following the suggestion of an anonymous reviewer, we tested for this impact during periods of "solid growth" (entailing low economic policy uncertainty, low stock market volatility, high consumer confidence, and high investor sentiment) and find that during these periods informed trading exerts a strong dampening effect on herding, leading anti-herding to rise. Non-solid-growth periods, on

4.3 Fundamentals- versus noise-driven herding and informed trading

We now turn to explore whether different herding motives produce an effect over the relationship between informed trading and herding; although the relationship unveiled thus far is a negative one, it need not hold when distinguishing between different herding types. To that end, we first partition herding into fundamentals- and noise-driven based on Galariotis et al. (2015) (see Section 3.2); results are reported in Table 10 and denote the presence of noise-driven herding ($\beta_2 < 0$, Panel B) and fundamentals-driven anti-herding ($\beta_2 > 0$, Panel A), with the magnitude of the former being larger in absolute terms than that of the latter. These results indicate that herding in Chinese stock exchanges is primarily triggered by noise traders, thus confirming earlier evidence (see the discussion in Cui et al., 2024) on noise investors' dominance in Chinese markets. The coexistence of noise-driven herding with fundamentals-driven anti-herding further suggests that, on average, the latter dampens the former (and, total herding, in general, since total herding is largely noise-driven).

Conditioning each of the two herding types on informed trading further reveals (Table 11) an interesting dichotomy in the relationship between informed trading and herding. On the one hand, noise-driven herding follows the previously documented pattern of total herding (it grows stronger for low VPIN levels), thus denoting that our

the other hand (corresponding to over 90% of the total sample) reveal strong evidence of herding. We thank the reviewer for their suggestion; results are unreported due to brevity reasons and are available upon request.

earlier results from total herding were largely due to noise-driven herding (something hardly surprising, considering what we reported above on total herding being primarily motivated by noise). On the other hand, fundamentals-driven estimations reveal anti-herding (i.e., excessive divergence of traders' beliefs; Gebka and Wohar, 2013), which rises as VPIN increases, implying that a higher presence of informed traders is associated with a tendency for investors to excessively diverge in their beliefs when trading on fundamentals.[36]

In unreported results, when testing for the effect of different market/economic states over the relationship between informed trading and herding for each of the two components of herding, we find that informed trading dampens (boosts) noise- (fundamentals-) driven herding (anti-herding). Noise-driven herding results are (with the exception of tests controlling for market returns) similar to our previous results from total herding, with informed trading dampening noise-driven herding the most when market volatility and economic policy uncertainty are low, and market returns, investor sentiment, consumer confidence and trader disagreement are high. The

[36]The β_2-coefficient values in Table 11 (Panel A) indicate non-fundamental (noise-driven) herding, the intensity of which is dampened by informed trading, as β_2^{HIGH} is less negative than β_2^{LOW}. In contrast, the positive β_2 coefficients in Panel B reflect fundamentals-driven anti-herding, which grows stronger for higher VPIN, as indicated by β_2^{HIGH} exceeding β_2^{LOW}. Consistently, the negative γ_2 and positive γ_3 estimates in Panels C and D further confirm that as VPIN increases, noise-driven herding declines and fundamentals-driven anti-herding intensifies.

impact of informed trading on fundamentals-driven anti-herding is less clear-cut but tends to be positive, denoting that a higher intensity of trades based on private information is associated with excess divergence in investors' beliefs.[37] Taken together, our results confirm that the relationship between informed trading and herding (and the impact of market/economic conditions over it) varies with the type of herding examined; as a result, we accept hypotheses 3a and 3b.

4.4 Further tests

4.4.1 Informed trading and herding: the impact of the 2012 insider trading reform

Evidence (Fernandes and Ferreira, 2009) suggests that the enforcement of insider trading laws can impact informed trading in both a positive (if insider trading constrains informed trading by corporate outsiders, curtailing it can boost informed trading by prompting more investors to seek out information) as well as a negative (it can reduce informed trading, if the latter was largely insider-driven) way. If so, this suggests that changes in the legal/regulatory treatment of insider trading may impact the relationship between informed trading and herding and we now turn to explore this drawing on China's 2012-reform, which provides us with a natural testing ground to investigate this impact. The reform involved the regulatory intervention regarding insider trading that took place on March 29, 2012, when the Supreme People's Court jointly with the Supreme People's Procuratorate issued a legally binding interpretation

[37] Except for investor sentiment and market volatility (which do not significantly affect the nexus between fundamentals-driven anti-herding and informed trading) and for market performance (informed trading dampens fundamentals-driven anti-herding when market performance is high and boosts it when market performance is low).

on how insider trading cases should be handled in terms of criminal law enforcement, with this interpretation becoming legally effective by June 1, 2012 (Huang, 2020). Although Chinese market regulation included provisions for insider trading (e.g., Securities Law of 1999; 2007 Guide on Insider Trading for internal use by staff at the China Securities Regulatory Commission - CSRC), their enforcement was considered lax due to lack of sufficient clarity and enforceability. The 2012-reform's interpretation filled that gap, given its formal legal act status (which provided clearer definitions for the identification of insiders and insider information), ultimately leading to a clampdown on insider trading (Huang, 2020).[38]

A priori, the 2012-reform's interpretation would be expected to have significantly reduced the occurrence and magnitude of trades based on inside information. On the one hand, this could have led to a reduced flow of firm-specific information to the market (if informed trading was insider-dominated pre-reform); in view of the higher legal risks involved post-reform, insider traders would only risk trading on the highest-value private information, thus suggesting a lower frequency of such information in the market. This situation could either dampen herding (if the lower frequency of such information rendered it more attention-grabbing for investors, who would thus be able to trade on it, instead of herding), amplify herding (if noise traders chose to herd on the trades of those in possession of such information, as its lower frequency would enhance the visibility of informed trading in the market), or have no

[38] Li et al. (2023) report that criminal charges were filed for over 80% of detected insider trading cases in China.

effect over it (if noise traders ignored it due to its low frequency). On the other hand, this could enhance the flow of firm-specific information to the market (if the clampdown on insider trading prompted more investors to feel less informationally disadvantaged and invest more resources in the collection of firm-specific information; Fernandes and Ferreira, 2009), amplifying the presence of informed trading in the market and reducing investors' need to herd.

To assess the effect of the 2012-reform over the relationship between informed trading and herding, we first estimate Equation (4) before and after the announcement, and test for the significance of the difference in γ_3: a more (less) positive post-reform value of γ_3 would indicate a stronger (weaker) mitigating impact of informed traders on herding. Restricting the pre- and post-reform sample to 3 years each (to limit the impact of confounding effects on the VPIN-herding nexus), we find (Table 12) that the mitigating impact of informed trading on herding was significant in both subperiods, yet significantly stronger post-reform,[39] indicating that the reform's announcement

[39] Similar results were obtained when we extracted the time-varying values of γ_3 by estimating Equation (4) with a rolling window of 250 trading days, moving 20 days at a time. Regressing the estimated γ_3 values on a constant and a deterministic linear trend, we found that γ_3 tended to increase over time (in the 6 years' window around the 2012-reform), thus indicating a stronger adverse impact of informed trading over herding post-reform. We further found that the estimated time trend of γ_3 bore a structural break on the reform-date (the difference of the trend in γ_3 pre- vs. post-reform is statistically significant). When we estimated the unknown break date, those estimates were very close to the announcement date for Mainland Chinese markets, both individually and taken together, thus confirming the reform's announcement-effect on the relationship between informed trading and herding. Results are not presented here for brevity reasons and are available upon request.

magnified the attenuating impact of informed trading over herding.[40] A possible explanation for this is that the reform was successful in limiting insider trading in China, resulting in the remaining insider trades being based on private information with the highest economic value, and hence being more impactful on market participants (who would utilize such information more extensively, hence relying even less on herding). Alternatively, by curtailing insider trading, the reform may have encouraged outside investors to feel less informationally disadvantaged and more willing to commit resources to the acquisition/processing of information in the market (which would have culminated in a rise in information-based trading and a reduced reliance on herding).

4.4.2 Informed trading and herding: alternative informed trading proxies

We now turn to explore if our core result, that of investor herding being suppressed by informed trading, is generally valid and robust to diverse empirical proxies of informed trading. To that end, we identify three variables which can act as alternatives to VPIN: the volume coefficient of variation (VCV), market capitalization (SIZE), and institutional ownership (IO). The rationale for this choice is as follows. Firstly, the VCV,

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[40] We also employed a placebo approach similarly to Christensen et al. (2016): we first created a reform-dummy, equal to zero (one) before (after) the interpretation's announcement day. We then generated a set of "placebo reform dummies", which indicate a false reform date each (they assumed the value of one 3/6/9/12 months before and after the actual reform date, hence eight placebo dummies in total). We then estimated the following model:
$CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R_{M,t}^2 + + \beta_3 R_{M,t}^2 VPIN_t + \beta_4 R_{M,t}^2 VPIN_t D_t^{REFORM} + e_t$, where D_t^{REFORM} was either the genuine reform dummy or one of the placebo dummies. Results showed that models assuming that the significant shift happened prior to (after) March 2012 performed worse (better) compared to the models with the true reform-dummy, thus confirming that the reform strengthened the adverse impact of informed trading on herding. Results are not presented here for brevity reasons and are available upon request.

as proposed by Lof and Van Bommel (2023), is defined as the ratio of the standard deviation to the mean of trading volume, and has been demonstrated both theoretically and empirically to be strictly increasing in proportion to informed trading, which makes it an appropriate proxy for the latter. Secondly, size is well established in finance literature to be negatively associated with information asymmetry, with smaller stocks displaying higher prevalence of informed trading (Llorente et al., 2002; Bushee and Goodman, 2007). Lastly, we employ IO, as higher institutional ownership is associated with an improved information environment for the company, due to institutional investors having superior access to information and a capacity to process and trade on public information, resulting in stronger trading on information among high-IO firms (Guo and Qiu, 2015; Gu et al., 2021). Overall, we expect firms which are small, with high VCV, and high IO, to exhibit less herding than their large, low-VCV and low-IO counterparts (if informed trading suppresses herding).

To empirically investigate this, for each of the three proxy variables we sort the relevant market's sample into deciles according to the annual average values of that respective variable, thus forming ten portfolios. We then estimate Equation (1) for the top and bottom decile portfolios, and test whether their corresponding β_2-estimates differ significantly in the expected direction. Results are presented in Table 13 and, overall, denote strong support for our baseline finding, namely that herding is less pronounced when informed trading is stronger. For VCV as a proxy of informed trading, the highest VCV decile exhibits significantly weaker herding (less negative β_2-values) than its lowest-VCV counterpart, for both markets separately and combined. For SIZE, we also observe that stocks with stronger information asymmetry (i.e., higher likelihood of informed trading), i.e. small stocks, display lower herding levels than their large counterparts. Lastly, the same pattern is observed for IO (albeit only for the combination of Shanghai and Shenzhen), whereby stocks with higher levels of informed trading (high-IO stocks) show significantly less herding than what we observe among low-IO firms. Overall, across these three alternative proxies of informed trading, we observe a general pattern of herding declining in the presence of informed trading, in line with our baseline results where VPIN was employed. [41]

4.4.3 Informed trading and herding: causality

4.4.3.1 Contemporaneous causality

As discussed in Section 2.3, on purely theoretical grounds, it is not entirely unequivocal whether it is informed trading which leads to less intensive herding, or whether the causality is reverse (i.e., whether it is noise-driven, irrational herding which affects the magnitude of informed trading). Our baseline models utilize contemporaneous values of both VPIN and CSAD and, hence, do not empirically

[41] In unreported analyses, we additionally employed two types of the effective bid-ask spread (BAS, equally- and volume (amount)-weighted) as alternative proxies of informed trading (Ahern, 2020). The differences between high- versus low-BAS stocks were not statistically significant, but consistent with our baseline results that informed trading subdues herding, as the latter was lower for high-BAS stocks in all cases considered. This statistical insignificance should perhaps not be surprising, with BAS being a rather noisy proxy for informed trading, as it also contains other components, such as inventory and order-processing costs.

establish the causal direction. Therefore, below we further investigate whether informed trading, indeed, causes herding, rather than being caused by it, by employing a proxy for VPIN which is purely dependent on past, but not contemporaneous, information.

To obtain a proxy for contemporaneous values of VPIN which is entirely based on past information, and therefore cannot be caused by contemporaneous values of CSAD, for each of the markets investigated (Shanghai, Shenzhen, and the combination of these two), we fit an ARMA(p,q) model to their respective market-wide VPIN-measure. Optimal values of p and q are established empirically based on the log-likelihood criterion (other information criteria result in lower lag numbers, hence we adopted the highest ones to fully capture the underlying intertemporal dynamics of the autocorrelation and moving average features of the VPIN-data). The resulting fitted values of VPIN, fully driven by past, but not contemporaneous information, were employed in re-estimating Equations (2) and (4). [42]

Results are presented in Table 14 and, overall, strongly support the notion of causality running from VPIN (informed trading) to herding. In Panel A, we observe that the regime corresponding to low intensity of informed trading experiences significant

[42] The use of lagged explanatory variables as instruments is well-established in the economics and finance literature (e.g., Gupta, 2005; MacKay and Phillips, 2005; Clemens et al., 2012; however, the practice of directly inputting lagged values into the model has been recently questioned - Reed, 2015). Our two-stage ARMA approach utilizes more past information than what is contained in a single lagged value, as we employ multiple lags of the AR and the MA components, and it uses the predicted, rather than observed, lagged value as an instrument.

herding (β_2^{LOW} negative and significant), while for high informed trading days, herding is insignificant; this result is qualitatively identical to that obtained in Section 4.2, but here for a proxy of informed trading which is independent from contemporaneous herding, hence establishing the causality direction from informed trading to herding. In Panel B, we also observe results supportive of the VPIN-herding causality, as the relevant coefficients are of the correct sign ($\gamma_3 > 0$) and mostly significant.

4.4.3.2 Informed trading and herding: their dynamic relationship

Our previous analysis showcased that informed trading varies inversely with herding, with this inverse relationship growing stronger for specific market/economic states. This analysis hinged on the contemporaneous relationship between informed trading and herding (i.e., how informed trading impacts herding within-day), without assessing the dynamic evolution of this relationship over time. To that end, we first construct a daily, time-varying measure of herding by estimating Equation (1) within the state-space framework, for each market separately and both jointly (Kalman, 1960). Namely, we model β_2 as time-varying ($\beta_2 = \beta_{2,t}$), specifically as a random walk process, i.e.:

$$\beta_{2,t} = \beta_{2,\,t-1} + \mu_t, \qquad \mu_t \sim i.i.d., \qquad N(0,\sigma^2) \; .$$

(12)

The resulting time series of herding/anti-herding, β_{2t}, is tested for Granger causality *vis-à-vis* VPIN based on the following VAR model:

$$\beta_{2,t} = \sum_{j=1}^{J}\varphi_{1,j}\beta_{2,t-j} + \sum_{j=1}^{J}\varphi_{2,j}VPIN_{t-j} + \epsilon_{1,t} \qquad (13)$$

$$VPIN_{t} = \sum_{j=1}^{J}\varphi_{3,j}\beta_{2,t-j} + \sum_{j=1}^{J}\varphi_{4,j}VPIN_{t-j} + \epsilon_{2,t} \quad , \qquad (14)$$

where the optimal lag order J is based on the Bayesian Information Criterion. In this setting, VPIN ($\beta_{2,t}$) causes $\beta_{2,t}$ (VPIN), if $\varphi_{2,j} \neq 0$ ($\varphi_{3,j} \neq 0$) for any *j;* the cumulative sign and magnitude of that causal effect is measured by $\sum_{j=1}^{J}\varphi_{2,j}$ ($\sum_{j=1}^{J}\varphi_{3,j}$). Since herding is identified by negative values of $\beta_{2,t}$, assuming herding dominates, an increase (decline) in $\beta_{2,t}$ implies a movement towards less (more) negative values of $\beta_{2,t}$, and therefore less (more) intensive herding among investors.

Results are outlined in Table 15 and indicate (for both Mainland Chinese stock exchanges taken separately, as well as jointly) that VPIN negatively Granger-causes $\beta_{2,t}$, thus implying that, as VPIN rises (falls), subsequent $\beta_{2,t}$ falls (rises); as a result, a rise (fall) in informed trading leads to a rise (fall) in herding. Although at first glance this may appear to contradict our earlier results on VPIN's inverse relationship with herding, one should note that that relationship was a contemporaneous one, entailing no lead-lag effects. The rise in herding motivated by increased informed trading that our causality test depicts is in line with models of informational cascades (see the discussion in Section 2.1), whereby less/non-informed investors mimic the trades of their informed peers; as cascades tend to evolve over a period of time, this may help explain why we observe their effect in our causality tests (where the VPIN-$\beta_{2,t}$ relationship is assessed over several lags) and not in our earlier estimations from Sections 4.1-4.3 (where we focused on the contemporaneous VPIN-β_2 relationship).

Taken together, the results from our causality estimations and the earlier ones from Sections 4.1-4.3 and 4.4.3.1 denote that high levels of informed trading motivate stronger herding over time, while dampening it contemporaneously. This suggests the presence of an interesting "ecology": informed traders contemporaneously prey on the very herding they attract over time.[43]

4.4.4 The impact of price-limit hits

[43] As per the inverse causality in the relationship between herding and informed trading, results (unreported and available upon request) from Equation (14) suggest that a rise (fall) in $\beta_{2,t}$ Granger-causes a higher (lower) probability of informed trading, thus denoting that the less (more) people herd, the stronger (weaker) informed trading grows. A possible explanation for this is that, as herding grows stronger, the market environment becomes riskier and this can prompt informed investors to gradually (our causality setting allows us to assess the $\beta_{2,t}$-VPIN relationship over several lags) reduce their footprint in the market.

Chinese equity markets have maintained since their inception a price-limit mechanism, according to which, a stock ceases being traded once its price rises above/falls below the previous day's closing price by a pre-specified percentage (10%, in our sample). If information suggesting the price of a stock should rise/fall by more than 10% were to arrive at the market, price-limits would prevent the stock's price from adjusting to this information immediately; this would artificially "cap" daily returns of affected stocks and therefore reduce the cross-sectional dispersion of stock returns on days when limits are hit (most likely being days of large absolute market movements). As Chang et al. (2000) identify herding through a reduced cross-sectional return dispersion at times of high absolute market returns, such downward bias in CSAD-values (induced by price-limits) could lead to over-identification of herding.[44]

We empirically explore this possibility by removing all daily stock price observations for which the daily ±10% price-limit was hit (i.e., where the daily close-to-close percentage stock return equalled +10% or -10%, following Adcock et al., 2023). Then, we re-calculate all values of CSAD and market returns for each of the three markets (Shanghai; Shenzhen; Shanghai and Shenzhen combined), and re-estimate Equations (1), (2), and (4). Results presented in Table 16 demonstrate that the CSAD-values calculated after removing observations (stock-day) where price-limit hits occurred are very highly correlated with their pre-removal, whole sample counterparts (correlations are in excess of 98%). These results suggest that, while there was a solid number of

[44] We thank an anonymous reviewer for suggesting this possibility.

occurrences of price-limit hits in our sample, the impact of these events on our main variable of interest here, i.e. CSAD, was rather minimal.

Re-estimating Equation (1), we find (Table 17) a robustly strong presence of herding in Chinese stock markets, in line with our results for the complete sample (Table 2), as β_2 remains negative and statistically significant. When we re-estimate Equations (2) and (4) to assess the impact of VPIN on herding (in the sample without observations where daily price-limits were hit), results support our previous findings (Table 3), with higher levels of VPIN being associated with weaker market-wide herding (the herding coefficient being closer to zero), as $\beta_2^{\mathrm{HIGH}} - \beta_2^{\mathrm{LOW}}$ in Equation (2) remains positive and significant, as does γ_3 in Equation (4). The evidence presented here, therefore, suggests that price-limits confer no substantial effect over our initial findings.

5. Concluding remarks

Our study contributes to the literature on the relationship between informed trading and herding by investigating whether this relationship varies in its structure across different macro (market and economic) states and across different herding-types. Drawing on the Mainland Chinese equity markets' context for the 2003-2022 period and utilizing the volume-synchronized probability of informed trading (VPIN) to capture informed trading, we show that herding grows weaker for high contemporaneous informed trading levels. Although informed trading dampens herding irrespective of the state of the market/economy examined, its adverse effect over herding grows stronger during specific macro states, thus showcasing that the impact of macro states over the relationship between informed trading and herding is one of degree, rather than direction (i.e., this relationship varies across different states in terms of its strength, not sign). Upon partitioning herding into its noise-driven and fundamentals-driven components, we document the existence of noise-driven herding alongside fundamentals-driven anti-herding, with the former being stronger than the latter in absolute terms, thus denoting that herding in Mainland Chinese equity markets is primarily noise-motivated. Similar to total herding, informed trading produces an adverse effect over noise-driven herding, with this effect appearing the strongest for almost the same macro states as with total herding. Fundamentals-driven anti-herding, however, is boosted by informed trading, thus suggesting that the higher the probability of investors trading on information, the more likely they are to excessively diverge in their beliefs. Further tests indicate that the negative relationship of informed trading with herding persists for alternative informed trading proxies and appears stronger in the aftermath of the 2012-reform, which strengthened the legal enforcement of anti-insider trading rules in China. Employing an instrumental variable approach, we confirm the causal effect of informed trading over contemporaneous herding. Assessing the dynamic relationship between informed trading and herding, we find that higher levels of the former over time tend to increase the latter; combined with our previous results on higher levels of informed trading dampening herding contemporaneously, this suggests that informed traders prey contemporaneously on the very herding they attract over time from non-informed investors. We further show that our findings hold when controlling for days of price-limit hits by removing stock-day observations corresponding to stock returns equal to ±10%.

The evidence presented in this study bears important implications for the investment community, as it can be utilized by investors as input to inform their trading strategies. Investors, for example, with concerns about noise trader risk could choose to trade during macro states with a stronger adverse effect of informed trading over herding. Alternatively, an investor could devise an *ad hoc* model to forecast the probability of informed trading and use its forecasts to condition their trading on the anticipated effect of predicted informed trading over herding. Our findings are also of particular relevance to regulators, since they denote the need to strengthen the informativeness of the trading environment, by fostering greater transparency and a less concentrated market for information, in order to encourage investors to trade on information and rely less on herding. In this case, emphasis could be given to those macro states with the weakest adverse effect of informed trading over herding, in order to mitigate the possibility of their herding giving rise to destabilizing outcomes. Finally, the evidence presented in this study bears interesting implications for research, as it provides useful input to the extant debate (e.g., Bohl et al., 2009; Choi et al., 2015; Cao et al., 2017; Chelley-Steeley et al., 2019; Duxbury and Wang, 2024) on whether informed investors exert a stabilizing or destabilizing influence over financial markets. *A priori*, noise-driven herding has the potential of precipitating mispricing and destabilizing effects in markets; as a result, attracting it (as our dynamic results from Table 15 reveal) can render informed traders active agents of such phenomena (Choi et al., 2015), as it can lead them to trade *in tandem* with noise sentiment (Chelley-Steeley et al., 2019; Duxbury and Wang, 2024). However, we believe our findings to more likely point toward a stabilizing role of informed traders for two reasons. On the one hand, informed traders attract herding by noise traders; this noise-driven herding, however, is not left unchecked. With informed traders dampening it within-day, this denotes that its impact is reduced, thus contributing to efficient pricing (Bohl et al., 2009). On the other hand, the fact that informed trading promotes fundamentals-driven anti-herding offers further evidence in support of informed traders contributing to dampening herding in the market. The above discussion, therefore, suggests that our findings lend stronger support in favour of a stabilizing role of informed trading in Mainland Chinese equity markets.

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Table 1: Summary statistics

	Mean	SD	Skewness	Kurtosis	Min	Max
Panel A: Shanghai and Shenzhen combined						
$R_{M,t}$	-0.0001	0.0192	-0.8945	7.3253	-0.1029	0.0919
$CSAD_{m,t}$	0.0168	0.0052	1.8740	11.6332	0.0054	0.0736
$VPIN_t$	0.3046	0.0282	-0.2979	4.5685	0.1147	0.4320
$DISAG_t$	0.0000	1.0000	2.0356	10.3578	-2.8739	7.0605
Panel B: Shanghai						
$R_{M,t}$	-0.0001	0.0189	-0.9023	7.4235	-0.1024	0.0916
$CSAD_{m,t}$	0.0164	0.0054	2.2917	17.2403	0.0053	0.0834
$VPIN_t$	0.3038	0.0282	-0.0552	4.4517	0.1210	0.4318
$DISAG_t$	0.0000	1.0000	2.4417	12.9103	-2.7762	8.0389
Panel C: Shenzhen						
$R_{M,t}$	-0.0002	0.0196	-0.8951	7.1817	-0.1029	0.0920
$CSAD_{m,t}$	0.0172	0.0055	2.4647	21.2449	0.0046	0.0976
$VPIN_t$	0.3062	0.0290	-0.3453	3.8437	0.1243	0.4372
$DISAG_t$	0.0000	1.0000	1.7574	9.6153	-3.3957	7.0974
Panel D: Fama and French (2015) factors						
RF	0.0001	0.0000	0.3878	2.2673	0.0000	0.0002
MKT	0.0005	0.0159	-0.4541	7.5104	-0.0931	0.0989
SMB	0.0008	0.0153	-0.1867	17.5847	-0.1315	0.2281
HML	0.0003	0.0149	0.6370	7.6666	-0.0804	0.1225
RMW	0.0003	0.0153	-6.5904	240.1424	-0.5001	0.1144
CMA	-0.0001	0.0095	-0.3004	7.2109	-0.0835	0.0494
Panel E: Economic conditions						
CNEPU	128.9721	37.7933	0.1380	2.9695	39.5253	238.3172
CCI	104.4795	11.0930	0.4467	2.1318	85.5000	127.0000
O_CICSI	-0.0075	1.1879	-0.1037	2.7766	-2.4900	3.5900

Notes: the table presents a series of descriptive statistics (mean; standard deviation; skewness; kurtosis; minimum; maximum) for the full sample period (03/01/2003 – 30/12/2022) for the following variables: $R_{M,t}$ (the daily stock market return), $CSAD_{m,t}$ (the daily cross-sectional dispersion of returns), $VPIN_t$ (Easley et al., 2012; proxying for the daily probability of informed trading), $DISAG_t$ (estimated at the daily frequency as per Garfinkel, 2009; proxying for traders' disagreement) for each of the two Mainland Chinese equity markets (Shanghai; Shenzhen) separately as well as jointly; the daily Fama and French (2015) factors for China; and the monthly indices for economic policy uncertainty, consumer confidence and investors' sentiment for China.

Table 2: Market-wide herding (unconditional estimations)

	β_0	β_1	β_2	R^2
Shanghai and Shenzhen	0.0145***	0.199***	-0.911**	0.150

	(0.0002)	(0.025)	(0.352)	
Shanghai	0.0140***	0.203***	-0.782**	0.158
	(0.0002)	(0.026)	(0.398)	
Shenzhen	0.0149***	0.199***	-0.972**	0.134
	(0.0003)	(0.029)	(0.419)	

Notes: the table presents estimates from Equation (1): $CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R_{M,t}^2 + e_t$. $CSAD_{m,t}$ ($R_{M,t}$) is the daily cross-sectional absolute deviation of returns (market return) for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Parentheses include robust standard errors. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Informed trading and market-wide herding

Panel A: Threshold model

	β_0	β_1	β_2^{LOW}	β_2^{HIGH}	$\beta_2^{HIGH} - \beta_2^{LOW}$	R^2
Shanghai and Shenzhen	0.0145***	0.202***	-2.301***	-0.212	2.089***	0.187
	(0.0001)	(0.014)	(0.293)	(0.274)	[77.98]	
Shanghai	0.0141***	0.208***	-2.294***	-0.074	2.220***	0.195
	(0.0001)	(0.015)	(0.354)	(0.282)	[60.16]	
Shenzhen	0.0149***	0.201***	-2.127***	-0.386	1.741***	0.158
	(0.0001)	(0.016)	(0.402)	(0.287)	[30.72]	

Panel B: Interaction model

	γ_0	γ_1	γ_2	γ_3		R^2
Shanghai and Shenzhen	0.0146***	0.189***	-4.831***	12.673***		0.165
	(0.0002)	(0.022)	(1.303)	(4.044)		
Shanghai	0.0141***	0.196***	-6.399***	17.553***		0.179
	(0.0002)	(0.023)	(1.515)	(4.635)		
Shenzhen	0.0149***	0.191***	-5.924***	15.639***		0.150
	(0.0002)	(0.025)	(1.524)	(4.680)		

Notes: Panel A presents estimates from Equation (2): $CSAD_{m,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2^{LOW} R_{M,t}^2 I(VPIN_t < \tau) + \beta_2^{HIGH} R_{M,t}^2 I(VPIN_t \geq \tau) + e_t$, and Panel B from Equation (4): $CSAD_{m,t} = \gamma_0 + \gamma_1|R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Informed trading and market-wide herding controlling for high/low market performance

Panel A: Threshold model

	β_0	β_1	β_2	β_3^{LOW}	β_3^{HIGH}	$\beta_3^{HIGH} - \beta_3^{LOW}$	R^2
Shanghai and Shenzhen	0.0143***	0.237***	-4.225***	10.339***	2.507	-7.831***	0.200
	(0.0001)	(0.016)	(1.058)	(3.400)	(3.663)	[98.35]	
Shanghai	0.0139***	0.241***	-5.631***	14.829***	7.312*	-7.517***	0.208
	(0.0001)	(0.017)	(1.203)	(3.905)	(4.055)	[98.96]	
Shenzhen	0.0147***	0.241***	-5.006***	12.339***	4.194	-8.145***	0.186
	(0.0001)	(0.017)	(1.273)	(4.129)	(4.286)	[113.14]	

Panel B: Interaction model

	γ_0	γ_1	γ_2	γ_3	γ_4		R^2
Shanghai and Shenzhen	0.0144***	0.224***	-4.614***	8.943**	-32.172***		0.176
	(0.0002)	(0.021)	(1.234)	(3.798)	(6.091)		
Shanghai	0.0140***	0.228***	-6.093***	13.784***	-30.642***		0.187
	(0.0002)	(0.022)	(1.480)	(4.537)	(6.099)		
Shenzhen	0.0147***	0.230***	-5.534***	11.089**	-34.770***		0.163
	(0.0002)	(0.023)	(1.487)	(4.625)	(5.913)		

Notes: Panel A presents estimates from Equation (5): $CSAD_{m,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2 R_{M,t}^2 + \beta_3^{LOW} R_{M,t}^2 VPIN_t I(DET_t < \tau) + \beta_3^{HIGH} R_{M,t}^2 VPIN_t I(DET_t \geq \tau) + e_t$, while Panel B from Equation (6): $CSAD_{m,t} = \gamma_0 + \gamma_1|R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + \gamma_4 R_{M,t}^2 VPIN_t DET_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Informed trading and market-wide herding controlling for high/low market volatility

Panel A: Threshold model							
	β_0	β_1	β_2	β_3^{LOW}	β_3^{HIGH}	$\beta_3^{HIGH} - \beta_3^{LOW}$	R^2
Shanghai and Shenzhen	0.0143***	0.207***	-4.968***	367.905***	12.473***	-355.433***	0.168
	(0.0001)	(0.016)	(2.145)	(85.906)	(3.900)	[16.98]	
Shanghai	0.0138***	0.210***	-6.478***	85.871***	17.399***	-68.472***	0.181
	(0.0001)	(0.017)	(1.255)	(16.368)	(3.997)	[17.86]	
Shenzhen	0.0147***	0.206***	-6.028***	266.386***	15.467***	-250.919***	0.152
	(0.0002)	(0.018)	(1.247)	(72.143)	(4.087)	[11.89]	
Panel B: Interaction model							
	γ_0	γ_1	γ_2	γ_3	γ_4		R^2
Shanghai and Shenzhen	0.0154***	0.023	-1.874	19.637***	-1568.923***		0.189
	(0.0002)	(0.022)	(1.255)	(2.657)	(189.290)		
Shanghai	0.0149***	0.025	-3.094**	24.036***	-1650.046***		0.201
	(0.0002)	(0.025)	(1.482)	(2.898)	(208.830)		
Shenzhen	0.0157***	0.030**	-2.803***	21.345***	-1442.581***		0.170
	(0.0002)	(0.027)	(1.425)	(2.776)	(201.728)		

Notes: Panel A presents estimates from Equation (5): $CSAD_{m,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2 R_{M,t}^2 + \beta_3^{LOW} R_{M,t}^2 VPIN_t I(DET_t < \tau) + \beta_3^{HIGH} R_{M,t}^2 VPIN_t I(DET_t \geq \tau) + e_t$, while Panel B from Equation (6): $CSAD_{m,t} = \gamma_0 + \gamma_1|R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + \gamma_4 R_{M,t}^2 VPIN_t DET_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Informed trading and market-wide herding controlling for high/low investor sentiment

Panel A: Threshold model							
	β_0	β_1	β_2	β_3^{LOW}	β_3^{HIGH}	$\beta_3^{HIGH} - \beta_3^{LOW}$	R^2
Shanghai and Shenzhen	0.0145***	0.200***	-5.088***	11.659***	16.570***	4.912***	0.184
	(0.0001)	(0.015)	(1.116)	(3.518)	(3.538)	[20.98]	
Shanghai	0.0141***	0.208***	-6.427***	15.668***	20.644***	4.975***	0.197
	(0.0001)	(0.016)	(1.069)	(3.477)	(3.480)	[17.63]	
Shenzhen	0.0149***	0.203***	-6.109***	14.279***	19.534***	5.255***	0.172
	(0.0001)	(0.017)	(1.163)	(3.800)	(3.652)	[17.56]	
Panel B: Interaction model							
	γ_0	γ_1	γ_2	γ_3	γ_4		R^2
Shanghai and Shenzhen	0.0145***	0.212***	-4.831***	10.539***	2.145***		0.183
	(0.0002)	(0.025)	(1.101)	(3.576)	(0.418)		
Shanghai	0.0140***	0.218***	-6.119***	14.532***	2.121***		0.194
	(0.0002)	(0.026)	(1.343)	(4.258)	(0.453)		

Shenzhen	0.0148***	0.215***	-5.701***	12.783***	2.177***	0.168
	(0.0002)	(0.028)	(1.395)	(4.320)	(0.472)	

Notes: Panel A presents estimates from Equation (5): $CSAD_{m,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2 R^2_{M,t} + \beta_3^{LOW} R^2_{M,t} VPIN_t I(DET_t < \tau) + \beta_3^{HIGH} R^2_{M,t} VPIN_t I(DET_t \geq \tau) + e_t$, while Panel B from Equation (6): $CSAD_{m,t} = \gamma_0 + \gamma_1|R_{M,t}| + \gamma_2 R^2_{M,t} + \gamma_3 R^2_{M,t} VPIN_t + \gamma_4 R^2_{M,t} VPIN_t DET_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 0/12/2022). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Informed trading and market-wide herding controlling for high/low traders' disagreement

Panel A: Threshold model

	β_0	β_1	β_2	β_3^{LOW}	β_3^{HIGH}	$\beta_3^{HIGH}-\beta_3^{LOW}$	R^2
Shanghai and Shenzhen	0.0145***	0.197***	-4.844***	10.619***	15.609***	4.990***	0.188
	(0.0001)	(0.015)	(1.226)	(3.886)	(3.916)	[29.14]	
Shanghai	0.0141***	0.203***	-6.543***	16.079***	21.231***	5.151***	0.198
	(0.0001)	(0.016)	(1.281)	(3.978)	(4.157)	[18.46]	
Shenzhen	0.0150***	0.183***	-4.618***	9.187**	14.710***	5.523***	0.178
	(0.0001)	(0.016)	(1.146)	(3.597)	(3.328)	[40.50]	

Panel B: Interaction model

	γ_0	γ_1	γ_2	γ_3	γ_4	R^2
Shanghai and Shenzhen	0.0145***	0.192***	-4.141***	10.231***	1.679***	0.193
	(0.0003)	(0.027)	(1.211)	(3.664)	(0.253)	
Shanghai	0.0141***	0.201***	-5.886***	15.528***	1.433***	0.201
	(0.0002)	(0.027)	(1.594)	(4.546)	(0.219)	
Shenzhen	0.0149***	0.187***	-3.623***	8.782**	2.082***	0.179
	(0.0003)	(0.028)	(1.533)	(4.440)	(0.348)	

Notes: Panel A presents estimates from Equation (5): $CSAD_{m,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2 R_{M,t}^2 + \beta_3^{LOW} R_{M,t}^2 VPIN_t I(DET_t < \tau) + \beta_3^{HIGH} R_{M,t}^2 VPIN_t I(DET_t \geq \tau) + e_t$, while Panel B from Equation (6): $CSAD_{m,t} = \gamma_0 + \gamma_1|R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + \gamma_4 R_{M,t}^2 VPIN_t DET_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Informed trading and market-wide herding controlling for high/low economic policy uncertainty

Panel A: Threshold model

	β_0	β_1	β_2	β_3^{LOW}	β_3^{HIGH}	$\beta_3^{HIGH} - \beta_3^{LOW}$	R^2
Shanghai and Shenzhen	0.0146***	0.181***	-4.473***	13.638***	11.211***	-2.427***	0.170
	(0.0001)	(0.016)	(1.160)	(3.508)	(3.662)	[8.23]	
Shanghai	0.0142***	0.187***	-5.828***	18.059***	15.393***	-2.667***	0.184
	(0.0001)	(0.017)	(1.201)	(3.587)	(3.867)	[6.58]	
Shenzhen	0.0150***	0.177***	-5.458***	17.164***	14.046***	-3.118***	0.157
	(0.0001)	(0.017)	(1.215)	(3.617)	(3.947)	[7.2]1	

Panel B: Interaction model						
	γ_0	γ_1	γ_2	γ_3	γ_4	R^2
Shanghai and Shenzhen	-0.0150***	0.145***	-5.788	23.772	-0.049*	0.161
	(0.0002)	(0.032)	(10.861)	(28.942)	(0.029)	
Shanghai	0.0145***	0.158***	-9.962	34.711*	-0.039	0.182
	(0.0002)	(0.029)	(7.339)	(19.662)	(0.033)	
Shenzhen	0.0154***	0.145***	-8.361	32.072**	-0.056**	0.153
	(0.0001)	(0.024)	(5.637)	(15.488)	(0.027)	

Notes: Panel A presents estimates from Equation (5): $CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R_{M,t}^2 + \beta_3^{LOW} R_{M,t}^2 VPIN_t I(DET_t < \tau) + \beta_3^{HIGH} R_{M,t}^2 VPIN_t I(DET_t \geq \tau) + e_t$, while Panel B from Equation (6): $CSAD_{m,t} = \gamma_0 + \gamma_1 |R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + \gamma_4 R_{M,t}^2 VPIN_t DET_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly for the full sample period (03/01/2003-30/12/2022). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Informed trading and market-wide herding controlling for high/low consumer confidence

Panel A: Threshold model							
	β_0	β_1	β_2	β_3^{LOW}	β_3^{HIGH}	$\beta_3^{HIGH} - \beta_3^{LOW}$	R^2
Shanghai and Shenzhen	0.0146***	0.190***	-5.036***	12.607***	14.716***	2.110***	0.170
	(0.0001)	(0.015)	(1.209)	(3.809)	(3.790)	[6.19]	
Shanghai	0.0141***	0.196***	-6.663***	17.512***	20.156***	2.645***	0.189
	(0.0001)	(0.016)	(1.192)	(3.848)	(3.841)	[6.54]	
Shenzhen	0.0150***	0.184***	-6.035***	15.932***	20.628***	4.696***	0.157
	(0.0001)	(0.018)	(1.180)	(3.915)	(4.232)	[3.85]	
Panel B: Interaction model							
	γ_0	γ_1	γ_2	γ_3	γ_4		R^2
Shanghai and Shenzhen	0.0146***	0.194***	-4.683***	4.996	0.068*		0.168
	(0.0001)	(0.013)	(0.469)	(3.995)	(0.038)		
Shanghai	0.0142***	0.199***	-6.231***	4.361	0.123***		0.183
	(0.0001)	(0.014)	(0.563)	(4.165)	(0.039)		
Shenzhen	0.0150***	0.196***	-5.651***	0.196	0.141***		0.154
	(0.0002)	(0.014)	(0.557)	(4.131)	(0.037)		

Notes: Panel A presents estimates from Equation (5): $CSAD_{m,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2 R_{M,t}^2 + \beta_3^{LOW} R_{M,t}^2 VPIN_t I(DET_t < \tau) + \beta_3^{HIGH} R_{M,t}^2 VPIN_t I(DET_t \geq \tau) + e_t$, while Panel B from Equation (6): $CSAD_{m,t} = \gamma_0 + \gamma_1|R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + \gamma_4 R_{M,t}^2 VPIN_t DET_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly for the full sample period (03/01/2003-30/12/2022). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Fundamentals- and noise-driven herding (unconditional estimations)

	β_0	β_1	β_2	R^2
Panel A: Fundamentals-driven herding				
Shanghai and Shenzhen	0.0168***	-0.033***	1.050***	0.118
	(0.0000)	(0.007)	(0.142)	
Shanghai	0.0164***	-0.032***	1.023***	0.109
	(0.0000)	(0.007)	(0.148)	
Shenzhen	0.0173***	-0.034***	1.062***	0.122
	(0.0000)	(0.007)	(0.142)	
Panel B: Non-fundamentals-driven herding				
Shanghai and Shenzhen	-0.0026***	0.232***	-1.962***	0.126
	(0.0002)	(0.025)	(0.348)	
Shanghai	-0.0024***	0.233***	-1.806***	0.130

	(0.0002)	(0.026)	(0.384)	
Shenzhen	-0.0024***	0.234***	-2.034***	0.112
	(0.0002)	(0.028)	(0.404)	

Notes: The table presents estimates from Equation (1): $CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R_{M,t}^2 + e_t$. $CSAD_{m,t}$ ($R_{M,t}$) is the daily cross-sectional absolute deviation of returns (market return) for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Herding is being partitioned here into its fundamentals- and noise (non-fundamentals)-driven components as per Equations (9)-(11). Parentheses include robust standard errors. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Informed trading and fundamentals- versus noise-driven herding

Panel A: Non-fundamentals-driven herding						
	β_0	β_1	β_2^{LOW}	β_2^{HIGH}	$\beta_2^{HIGH} - \beta_2^{LOW}$	R^2
Shanghai and Shenzhen	-0.0023***	0.233***	-2.873***	-1.491***	1.382***	0.144
	(0.0001)	(0.014)	(0.273)	(0.251)	[42.28]	
Shanghai	-0.0023***	0.223***	-3.115***	-1.221***	1.894***	0.153
	(0.0001)	(0.014)	(0.316)	(0.265)	[53.58]	
Shenzhen	-0.0023***	0.225***	-3.112***	-1.604***	1.508***	0.127
	(0.0001)	(0.015)	(0.309)	(0.286)	[31.99]	
Panel B: Fundamentals-driven herding						
	β_0	β_1	β_2^{LOW}	β_2^{HIGH}	$\beta_2^{HIGH} - \beta_2^{LOW}$	R^2
Shanghai and Shenzhen	0.0169***	-0.032***	0.572***	1.291***	0.719***	0.157
	(0.0000)	(0.007)	(0.206)	(0.122)	[22.12]	
Shanghai	0.0164***	-0.027***	0.588***	1.226***	0.638***	0.138
	(0.0000)	(0.007)	(0.200)	(0.130)	[18.17]	
Shenzhen	0.0173***	-0.033***	0.706***	1.385***	0.679***	0.161
	(0.0000)	(0.007)	(0.178)	(0.121)	[27.23]	
Panel C: Non-fundamentals-driven herding						
	γ_0	γ_1	γ_2	γ_3		R^2
Shanghai and Shenzhen	-0.0023***	0.226***	-4.538***	8.330***		0.134
	(0.0002)	(0.023)	(1.025)	(3.066)		
Shanghai	-0.0023***	0.228***	-5.767***	12.380***		0.141
	(0.0002)	(0.023)	(1.272)	(3.801)		
Shenzhen	-0.0023***	0.228***	-5.231***	10.093***		0.120
	(0.0002)	(0.026)	(1.256)	(3.667)		
Panel D: Fundamentals-driven herding						
	γ_0	γ_1	γ_2	γ_3		R^2
Shanghai and Shenzhen	0.0169***	-0.037***	-0.293	4.343**		0.134
	(0.0000)	(0.006)	(0.624)	(1.760)		
Shanghai	0.0165***	-0.032***	-0.632	5.173***		0.126
	(0.0000)	(0.007)	(0.631)	(1.744)		
Shenzhen	0.0173***	-0.037***	-0.694	5.546***		0.142
	(0.0000)	(0.007)	(0.701)	(1.992)		

Notes: Panels A and B present estimates from Equation (2): $CSAD_{m,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2^{LOW} R_{M,t}^2 I(VPIN_t < \tau) + \beta_2^{HIGH} R_{M,t}^2 I(VPIN_t \geq \tau) + e_t$, while Panels C and D from Equation (4) $CSAD_{m,t} = \gamma_0 + \gamma_1|R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Herding is being partitioned here into its fundamentals- and noise (non-fundamentals)-driven components as per Equations (9)-(11). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Impact of the 2012 insider trading reform

	γ_0	γ_1	γ_2	γ_3	R^2
Panel A: Shanghai and Shenzhen					
Pre-reform	0.0151***	0.086***	-27.598***	80.265***	0.184
	(0.0002)	(0.029)	(7.098)	(20.363)	
Post-reform	0.0143***	0.184***	-69.284***	202.198***	0.325
	(0.0003)	(0.044)	(7.859)	(21.717)	
Pre- minus post-reform				121.932***	
				[16.85]	
Panel B: Shanghai					
Pre-reform	0.0145***	0.106***	-25.797***	74.505***	0.192
	(0.0002)	(0.028)	(6.870)	(19.721)	
Post-reform	0.0137***	0.174***	-59.682***	177.768***	0.306
	(0.0003)	(0.044)	(7.016)	(19.971)	
Pre- minus post-reform				103.263***	
				[13.60]	
Panel C: Shenzhen					
Pre-reform	0.0156***	0.064**	-28.596***	83.701***	0.167
	(0.0002)	(0.030)	(6.691)	(19.067)	
Post-reform	0.0147***	0.187***	-70.658***	201.842***	0.296
	(0.0003)	(0.042)	(8.684)	(23.675)	
Pre- minus post-reform				118.141***	
				[15.18]	

Notes: This table presents estimates from Equation (4): $CSAD_{m,t} = \gamma_0 + \gamma_1 |R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 VPIN_t + e_t$, pre- and post the 2012 insider trading regulatory enforcement reform, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly. Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Alternative proxies of informed trading

		β_0	β_1	β_2	$\beta_2^{HIGH} - \beta_2^{LOW}$	R^2
Panel A: VCV						
Shanghai and Shenzhen	Low	0.0144***	0.262***	-2.251***	1.520***	0.119
		(0.0001)	(0.016)	(0.179)	[16.67]	
	High	0.0146***	0.236***	-0.731***	{0.000}	0.133
		(0.0002)	(0.017)	(0.264)		
Shanghai	Low	0.0140***	0.272***	-2.267***	1.456***	0.116
		(0.0001)	(0.013)	(0.193)	[9.41]	
	High	0.0133***	0.283***	-0.811**	{0.002}	0.165
		(0.0002)	(0.018)	(0.294)		
Shenzhen	Low	0.0148***	0.267***	-2.246**	1.758***	0.104
		(0.0002)	(0.014)	(0.199)	[13.02]	
	High	0.0147***	0.243***	-0.488*	{0.000}	0.123
		(0.0002)	(0.019)	(0.289)		
Panel B: SIZE						
Shanghai and Shenzhen	Low	0.0136***	0.150***	-0.403**	-1.466***	0.107
		(0.0001)	(0.012)	(0.182)	[12.48]	
	High	0.0130***	0.286***	-1.869***	{0.000}	0.158
		(0.0001)	(0.014)	(0.232)		
Shanghai	Low	0.0133***	0.145***	-0.409**	-1.523**	0.092
		(0.0002)	(0.013)	(0.177)	[5.84]	
	High	0.0118***	0.307***	-1.932**	{0.016}	0.165
		(0.0001)	(0.015)	(0.251)		
Shenzhen	Low	0.0134***	0.153***	-0.595***	-1.734***	0.074
		(0.0002)	(0.014)	(0.195)	[9.64]	
	High	0.0144***	0.296***	-2.329**	{0.002}	0.118
		(0.0002)	(0.016)	(0.251)		
Panel C: IO						
Shanghai and Shenzhen	Low	0.0145***	0.193***	-1.214***	0.656**	0.108
		(0.0001)	(0.012)	(0.171)	[4.91]	
	High	0.0154***	0.196***	-0.558**	{0.027}	0.129
		(0.0001)	(0.014)	(0.227)		
Shanghai	Low	0.0146***	0.183***	-0.988***	-0.294	0.093
		(0.0001)	(0.026)	(0.187)	[0.76]	
	High	0.0144***	0.260***	-1.282***	{0.382}	0.136
		(0.0002)	(0.016)	(0.256)		
Shenzhen	Low	0.0144***	0.206***	-1.165***	0.540	0.096

	(0.0002)	(0.014)	(0.197)	[1.71]	
High	0.0157***	0.201***	-0.625**	{0.191}	0.104
	(0.0002)	(0.016)	(0.243)		

Notes: This table presents estimates from Equation (1): $CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R_{M,t}^2 + e_t$. $CSAD_{m,t}$ ($R_{M,t}$) is the daily cross-sectional absolute deviation of returns (market return) for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). VCV denotes the volume coefficient of variation, SIZE denotes market capitalization, and IO denotes institutional ownership. "Low" ("High") refers to the bottom (top) decile portfolio from annual sorts based on the average annual value of the relevant variable (VCV/SIZE/IO) in each panel. Parentheses include robust standard errors. Squared backets include values of the χ^2 statistic, with the corresponding p-values in curly brackets. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14: Informed trading and market-wide herding: IV estimations

Panel A: Threshold model

	β_0	β_1	β_2^{LOW}	β_2^{HIGH}	$\beta_2^{HIGH} - \beta_2^{LOW}$	R^2
Shanghai and Shenzhen	0.0145***	0.206***	-1.409***	-0.361	1.048***	0.160
	(0.0001)	(0.016)	(0.269)	(0.376)	[14.51]	
Shanghai	0.0140***	0.214***	-1.525***	-0.335	1.190***	0.169
	(0.0001)	(0.016)	(0.317)	(0.358)	[17.64]	
Shenzhen	0.0148***	0.206***	-1.419***	-0.559	0.860***	0.140
	(0.0001)	(0.017)	(0.347)	(0.370)	[8.49]	

Panel B: Interaction model

	γ_0	γ_1	γ_2	γ_3		R^2
Shanghai and Shenzhen	0.0144***	0.216***	-9.679***	26.226***		0.161
	(0.0002)	(0.023)	(3.166)	(9.547)		
Shanghai	0.0140***	0.226***	-10.866***	29.761***		0.172
	(0.0002)	(0.026)	(3.762)	(10.890)		
Shenzhen	0.0148***	0.211***	-7.046*	18.138		0.139
	(0.0003)	(0.030)	(4.262)	(12.291)		

Notes: Panel A presents estimates from Equation (2): $CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2^{LOW} R_{M,t}^2 I(\widehat{VPIN}_t < \tau) + \beta_2^{HIGH} R_{M,t}^2 I(\widehat{VPIN}_t \geq \tau) + e_t$, and Panel B from Equation (4): $CSAD_{m,t} = \gamma_0 + \gamma_1 |R_{M,t}| + \gamma_2 R_{M,t}^2 + \gamma_3 R_{M,t}^2 \widehat{VPIN}_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). $\widehat{VPIN}_t$ is the instrument for the original $VPIN_t$ for each market, estimated as the fitted value from an ARMA(*p*,*q*) model of $VPIN_t$, where *p* and *q* values are optimally chosen based on the log-likelihood function criterion for each market. Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 15: Granger-causality from informed trading to market-wide herding

Market	Sum of parameters ($\sum_{j=1}^{J} \varphi_{2,j}$)	Test statistic (χ^2)	P value
Shanghai and Shenzhen	-0.3851	296.28	0.000
Shanghai	-0.4682	256.75	0.000
Shenzhen	-0.2378	302.23	0.000

Notes: This table presents results based on Equation (13): $\beta_{2,t} = \sum_{j=1}^{J} \varphi_{1,j}\beta_{2,t-j} + \sum_{j=1}^{J} \varphi_{2,j} VPIN_{t-j} + \epsilon_{1,t}$, where $\beta_{2,t}$ is the time-varying herding measure obtained by estimating Equation (1) within the state-space framework. The cumulative sign and magnitude of the causal effect from informed trading ($VPIN_{t-j}$) to herding (β_{2t}) is measured by $\sum_{j=1}^{J} \varphi_{2,j}$.

Table 16: Correlations: The impact of price limits on cross-sectional return dispersion

	CSAD_SHSZ	CSAD_SHA	CSAD_SZA	CSAD_SHSZ_L	CSAD_SHA_L	CSAD_SZA_L
CSAD_SHSZ	1.000000					
CSAD_SHA	0.984353	1.000000				
CSAD_SZA	0.977761	0.942563	1.000000			
CSAD_SHSZ_L	0.983858	0.969169	0.977184	1.000000		
CSAD_SHA_L	0.984223	0.999974	0.942546	0.969149	1.000000	
CSAD_SZA_L	0.977559	0.942604	0.999948	0.977131	0.942600	1.000000

Notes: This table presents estimates of correlation coefficients for the full-sample CSAD values and their counterparts (denoted by ending "_L") from a sample where all stock-day observations equal to +/-10% were removed.

Table 17: Market-wide herding (unconditional estimations, price-limit (+/-10%) hit incidences removed)

	β_0	β_1	β_2	R^2
Shanghai and Shenzhen	0.0147***	0.207***	-0.914**	0.152
	(0.0002)	(0.027)	(0.409)	
Shanghai	0.0140***	0.203***	-0.763*	0.159

	(0.0002)	(0.026)	(0.399)	
Shenzhen	0.0149***	0.197***	-0.935**	0.134
	(0.0002)	(0.028)	(0.416)	

Notes: This table presents estimates from Equation (1): $CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R^2_{M,t} + e_t$. $CSAD_{m,t}$ ($R_{M,t}$) is the daily cross-sectional absolute deviation of returns (market return) for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Parentheses include robust standard errors. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 18: Informed trading and market-wide herding (price-limit (+/-10%) hit incidences removed)

Panel A: Threshold model						
	β_0	β_1	β_2^{LOW}	β_2^{HIGH}	$\beta_2^{HIGH} - \beta_2^{LOW}$	R^2
Shanghai and Shenzhen	0.0148***	0.212***	-2.338***	-0.284	2.054***	0.183
	(0.0001)	(0.015)	(0.382)	(0.272)	[44.83]	
Shanghai	0.0141***	0.207***	-2.274***	-0.052	2.222***	0.195
	(0.0001)	(0.015)	(0.356)	(0.283)	[59.83]	
Shenzhen	0.0149***	0.199***	-2.089***	-0.343	1.746***	0.158
	(0.0001)	(0.016)	(0.405)	(0.288)	[30.68]	
Panel B: Interaction model						
	γ_0	γ_1	γ_2	γ_3		R^2
Shanghai and Shenzhen	0.0148***	0.199***	-5.996***	16.139***		0.169
	(0.0003)	(0.025)	(1.584)	(4.878)		
Shanghai	0.0141***	0.195***	-6.382***	17.560***		0.179
	(0.0002)	(0.024)	(1.535)	(4.701)		
Shenzhen	0.0149***	0.189***	-5.899***	15.688***		0.150
	(0.0002)	(0.025)	(1.518)	(4.667)		

Notes: Panel A presents estimates from Equation (2): $CSAD_{m,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2^{LOW} R^2_{M,t} I(VPIN_t < \tau) + \beta_2^{HIGH} R^2_{M,t} I(VPIN_t \geq \tau) + e_t$, and Panel B from Equation (4): $CSAD_{m,t} = \gamma_0 + \gamma_1 |R_{M,t}| + \gamma_2 R^2_{M,t} + \gamma_3 R^2_{M,t} VPIN_t + e_t$, for the two Mainland Chinese equity markets (Shanghai; Shenzhen), separately as well as jointly, for the full sample period (03/01/2003 – 30/12/2022). Values in parentheses represent robust standard errors, those in squared brackets contain values of the χ^2 statistic. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.