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Numerological superstitions and market-wide herding: Evidence from China

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ABSTRACT

We empirically investigate the effect of traditional Chinese numerological superstitions over market-wide herding in the Shanghai and Shenzhen stock exchanges for the 2000–2020 period, based on a classification of stocks as lucky/unlucky contingent on the presence of digits deemed numerologically lucky/unlucky in their tickers. We find no compelling evidence that herding is more pronounced in those superstitious stocks, as compared to the rest of the stock market. Both superstitious stock-types herd exclusively on high-volatility days and exhibit some pronounced patterns in up vs down markets; these effects are not significantly different from the behaviour of non-superstitious stocks, however. Similarly, herding in both superstitious stock-types is largely noise-driven, but the same effect is observed for non-superstitious stocks. The similarities in herding between superstitious and non-superstitious stocks suggest that numerological superstitions do not motivate significantly stronger herding in Chinese markets.

1. Introduction

Superstitions constitute mental models based on non-scientific assumptions about how the world works, postulating the arbitrary association of certain objects with positive or negative outcomes (Risen, 2016). A key attribute of superstitions that has been confirmed in a variety of decision-settings[1] is that they tend to motivate correlated behaviour among individuals, regardless of their degree of belief in them; a setting, however, where the potential for superstition-induced correlated behaviour remains unexplored is the equity investment context. We propose that superstitions can motivate correlation (namely, herding) in investors' behaviour via the uncertainty channel. On the one hand, herding has been found (see e.g., Cui et al., 2019) to be more pronounced during periods of market stress (involving, e.g., high volatility or the potential for losses). On the other hand, superstitions' role in decision-making tends to increase in tasks/environments characterized by enhanced uncertainty (Brooks et al., 2016; Risen, 2016; Tsang, 2004; Whitson & Galinsky, 2008), either because they function as substitutes to information (Bai et al., 2020) or due to their anxiolytic properties (Tsang, 2004). As a result, it is possible that superstitions are relevant to equity market herding and our study investigates this issue for the first time in the literature.

Whether a superstition can motivate herding in equity markets or not hinges on two antithetical positions. On the one hand, if a given superstition is widely followed in a country, it is possible that many investors will factor it in their trading decisions and render this superstition capable of being detected in investors' aggregate behaviour in that market. This is likely to be the case in markets with stronger/dominant presence of retail investors (presumably less developed ones), whose lower sophistication renders them more susceptible to

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[1] Examples of such settings include: property investing, where property investors tend to avoid apartments on the (perceived as unlucky) 13th floor (Burakov, 2018) and floors where homicides/suicides have taken place (Bhattacharya et al., 2021) and prefer (avoid) properties with lucky (unlucky) numbers in their address (He et al., 2020); license-plate purchases/re-sales contingent on whether plates' numbers contain lucky/unlucky digits (Ng et al., 2010); risk-taking by corporate chairs based on their zodiac sign (Fisman et al., 2023); students not using specific pathways into buildings to avoid inviting the possibility of not graduating (Invernizzi et al., 2021).

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behaviourally biased trading patterns (Barber et al., 2009a; Barber & Odean, 2013) – and, hence also superstition-based ones.[2] If superstitions do, indeed, produce a discernible effect over aggregate market behaviour, this entails important implications for a market's efficiency (since ad hoc profitable trading strategies could be devised based on that effect) and stability (since superstitions do not constitute fundamental information, relying on them - particularly during uncertain times - can potentially destabilize the market). On the other hand, however, the popularity of a superstition in a society need not necessarily bear a footprint in investors' behaviour. It is possible, for example, that many investors in that market consider the superstition irrelevant to their decisions; that the percentage of investors who trade based on that superstition has dissipated over time (if they have grown to rely more on fundamentals or if their investment history has indicated the irrelevance of the superstition to investment success); that superstitious investors' trades are cancelled out by those of non-superstitious ones; or that superstitious individuals refrain from investing for some reason (implying that most investors are non-superstitious). Hence, whether superstitious believes could lead to market-wide herding remains unclear.

In this study we empirically address this issue for the first time in the literature by examining the effect of traditional Chinese numerological superstitions over investors' herd behaviour at the market-wide level for the 2000–2020 period in Mainland China's two stock exchanges (Shanghai and Shenzhen). We focus on Chinese markets, as they constitute an ideal testing ground for the investigation of this issue, given the sizable participation of retail investors (whose trading is largely non-information based) in their turnover (Zheng et al., 2015); the enhanced following of numerological superstitions in the Chinese population (Hirshleifer et al., 2018); and prolific evidence on these superstitions motivating particular price-regularities in these markets.[3] Drawing on the classification of stocks as lucky/unlucky contingent on the presence of digits deemed numerologically lucky/unlucky in their tickers, we first assess whether superstitious (i.e., lucky/unlucky) stocks project stronger herding than stocks with non-superstitious value (i.e., those with no/both lucky/unlucky digits in their tickers).[4] Second, given that superstitious behaviour is promoted by uncertainty, we investigate whether superstitious stocks' herding grows stronger under conditions where the potential for risk or loss looms larger in importance (i.e., periods of low returns and high volatility as opposed to periods of high returns and low volatility) – and whether non-superstitious stocks' herding interacts differently with those conditions. Third, we assess whether superstitious/non-superstitious stocks' herding[5] is motivated by fundamentals or noise.

Our findings show that superstitious stocks herd strongly in Chinese markets, yet their herding is not significantly different from that of non-superstitious ones. Unlucky stocks reveal stronger herding for days of low market returns, while lucky stocks' herding tends to grow stronger on days with high market returns. Although the above suggest that lucky (unlucky) stocks herd more on those days when the stronger gains- (loss-) expectations associated with their positive (negative) superstitious image are confirmed by the market's performance, the case for this appears weak for two reasons. On the one hand, the difference in herding between high and low market return days is insignificant for both superstitious stock-types; on the other hand, non-superstitious stocks' herding exhibits a similar pattern. Lucky, unlucky and non-superstitious stocks all herd near-exclusively when volatility is high, indicating that uncertain conditions bear a uniform effect over herding irrespective of stocks' superstitious values. We further illustrate that both superstitious and non-superstitious herding is largely noise-driven, with fundamentals playing only a minor role in its unfolding, and with no substantial differences between superstitious vs non-superstitious stocks. The impact of superstitions is further not observed during traditional festivals or for stocks traded predominantly by unsophisticated retail investors, instances when irrational beliefs would be expected to affect individuals' decisions the most. Overall, our results suggest that superstitious and non-superstitious stocks exhibit similarities in their herding, thus denoting that Chinese numerological superstitions are not significantly related to investors' herd behaviour at the aggregate level in Chinese markets. Herding appears to be driven by another behavioural force, however, irrespectively of the stocks' superstitious status, namely by investor sentiment.

Our study produces original contributions to the behavioural finance literature by investigating the relationship of a previously unexplored behavioural factor (superstition) to herding, thus introducing novel evidence to the extant literature on the role of behavioural factors in investors' herding.[6] In addition, by demonstrating the insignificant role of superstitions in market-wide herding in China, our study showcases that the impact of superstitions is not universal across all contexts of decision-making and that their role at the aggregate level is not as potent compared to the micro level (e.g., when looking at decisions of individuals within specific samples),[7] nor do they necessarily affect daily trading decisions as compared to those around unique, rare and therefore salient events such as IPOs and price crashes.

The rest of the paper is organized as follows: section 2 presents a brief theoretical overview of herding and its key drivers (section 2.1), discusses superstitions from a theoretical perspective (section 2.2.1) and outlines empirical evidence on superstitious effects from equity markets internationally (section 2.2.2.). Section 3 introduces the hypotheses tested and section 4 presents the data employed (section 4.1) and discusses the empirical design (Section 4.2), alongside some descriptive statistics (section 4.3). Section 5 discusses the results and section 6 offers concluding remarks and outlines the implications of the study's findings.

2. Theoretical background

2.1. Herding

Investors herd when they discard their priors, private signals or fundamental information in favor of imitating the actions of their peers following interactive observation of those actions (or their payoffs; Hirshleifer & Hong Teoh, 2003). Herding is a centuries-long investors' practice (de la Vega, 1688; Kindleberger & Aliber, 2005) that tends to arise primarily when there exists an asymmetry in the market, whereby some investors feel disadvantaged compared to their peers and choose to reduce this asymmetry via mimicking their behaviour. Many a time, this asymmetry is of an informational nature, when investors with limited information/processing skills track the trades of those perceived as

[2] For more on the link between sophistication and superstitious beliefs, see Risen (2016).

[3] This evidence pertains to numerological superstitions' effects over the clustering of closing prices' ending-digits (Anderson et al., 2015; Brown et al., 2002; Brown & Mitchell, 2008; Cai et al., 2007), IPO underpricing (Hirshleifer et al., 2018) and crash-risk (Bai et al., 2020). For a more detailed discussion, see section 2.2.2.

[4] The presence of lucky/unlucky digits may be seen as bestowing optimistic/pessimistic image onto a stock, which affects investors feelings about that particular stock and leads to biased financial decisions (see Lucey & Dowling, 2005, for a comprehensive review of how feelings affect financial decision making.).

[5] Throughout this paper, the term "superstitious herding" ("non-superstitious herding") will be used to refer to the herding of stocks of superstitious (non-superstitious) value, i.e., lucky/unlucky (neither lucky nor unlucky) stocks.

[6] Including the representativeness heuristic, disposition effect, overconfidence and attention-grabbing; for more on this literature, see Dorn et al. (2008), Barber et al. (2009a), Hsieh et al. (2020) and Hwang et al. (2021).

[7] The case e.g., of the decisions cited in footnote 1. Of course, the absence of any superstitious effects over herding in our study at the market-wide level does not preclude the presence of such effects at the micro-level; this could be explicitly tested for using micro data (e.g., investors' accounts/transactions), to which we have no access.

better informed in order to extract *informational payoffs* (Devenow & Welch, 1996).[8] Another source of asymmetry is often observed among investment professionals (e.g., fund managers) of differential qualities/abilities; given the relative performance assessment they are normally subject to, "bad" fund managers (those with lower quality/ability) are expected to mimic the trades of their "good" peers (those with better quality/ability) in anticipation of *professional payoffs* (e.g., in order to improve their career prospects or image; Scharfstein & Stein, 1990; Jiang & Verardo, 2018).[9] When investors herd in anticipation of informational or professional payoffs, they do so with the purpose of minimizing a perceived asymmetry (more-versus-less informed; "good"-versus-"bad" managers); hence, herding in the above cases is deemed *intentional* (Cui et al., 2019). However, investors may also herd *spuriously*, projecting correlation in their trades without necessarily imitating their peers. This is normally the case, whereby investors respond similarly to a factor to which they are jointly exposed in their environment and may be motivated via relative homogeneity,[10] style investing,[11] investigative herding,[12] behavioural biases[13] and fads.[14] The above, therefore, suggest that herding can be driven by both rational considerations as well as investors' irrationality. A particular expression of this irrationality, whose impact over investors' behaviour, in general (and herding, in particular) has not been explored to date is superstition; the next sub-section discusses superstitions from a theoretical perspective (2.2.1) and outlines the extant empirical evidence on their effects over specific aspects of equity markets' behaviour (2.2.2).

2.2. Superstitions

2.2.1. Definition, typology, and sources

Superstitions represent beliefs not based on reason, but rather hinging on arbitrary causality, stipulating that an event is capable of causing another, without these two events being linked by any physical/scientific process (Hirshleifer et al., 2018). In this case, superstitious individuals may associate (dissociate) themselves with (from) an action or object, believing it can motivate positive (negative) outcomes; if, for example, one views Friday the 13th as being an ominous day for activities, one may desist from conducting business on any such day (Lepori, 2009). By construction, superstitions allow for the subjective representation of external reality inside a person, forming mental models about how the world works; to the extent that these mental models are wrong (given their irrelevance to rationality/science),[15] the errors they generate are endogenous and cannot be ascribed to established behavioural biases (Hirshleifer et al., 2018). Superstitions can impact the probability assigned to future events (thus indirectly affecting the calculation of utility) as well as the felicity derived from a course of action, in turn, affecting individuals' mood and risk-taking (Jiang et al., 2009; Shum et al., 2014). Superstitions constitute slow-moving cultural traits, whose population frequencies vary over the centuries as a result of cultural evolution (Akçay & Hirshleifer, 2021); they have held sway in human societies for centuries, if not millennia and can vary in their effect within and across time (An et al., 2019).

From a typology perspective (Rudski, 2003), superstitions may entail a cosmological background (e.g., beliefs in the existence of heaven and hell) or a metaphysical one (e.g., believing in spirits or ghosts being able to affect our life); other superstitions may be more traditionally secular (e.g., believing in the bad luck associated with black cats) or derived through personal experience (ritual instrumentalism; Risen, 2016).[16] A lot of superstitions trace their roots to ancient belief-systems, including numerology (e.g., Feng Shui; Tsang, 2004), astrology (Lepori, 2009) and ancestral traditions (e.g., Ke et al., 2017; Suganda et al., 2020), with survey evidence (Lepori, 2009; Vyse, 2000) indicating that they are observed by a substantial fraction of the population internationally.

A key driver of superstitions is *magical thinking* (Hirshleifer, 2001; Risen, 2016), according to which an action can influence an outcome, without the two being causally connected. As mentioned previously, this implies arbitrary causality, which leads to incorrect reasoning/learning (Lepori, 2009); although the latter would suggest the presence of superstitions primarily among less sophisticated individuals, evidence to date is far from conclusive.[17] Adherence to superstition varies with age

[8] Whether this contributes to or hampers a market's informational efficiency is far from clear. If uninformed investors copy the trades of their informed peers, this can lead to an accelerated impounding of information into prices - bringing the latter closer to fundamentals (Sias, 2004; Wermers, 1999). If, however, investors tend to discard their/refrain from collecting private signals, this will render the public pool of information poorer, motivating the evolution of informational cascades (Banerjee, 1992; Bikhchandani et al., 1992).

[9] This is particularly important during market slumps, as the latter entail a substantial potential for the realization of losses (and a rise in reputational/litigation risk; Brown et al., 2014). In that case, "bad" managers can copy the portfolio-allocations of their "good" peers in order to a) come across as "good" themselves (claiming their investments were no different to those of "good" managers) and b) blame any losses on slumping markets.

[10] Investment professionals bear commonalities in their education, qualifications, the indicators they process, their processing tools and regulatory framework and these can lead them to exhibit similarities in their portfolio allocation decisions (Blake et al., 2017; Teh & de Bondt, 1997; Voronkova & Bohl, 2005).

[11] Investors employing the same style (e.g., momentum) will tend to buy and sell similar stocks (Bennett et al., 2003; Celiker et al., 2015; Grinblatt et al., 1995).

[12] The case of investors trading similarly because their information sets are correlated (e.g., because they focus on the same sector or market – see Froot et al., 1992; Hirshleifer et al., 1994).

[13] Evidence (Barber et al., 2009a; Dorn et al., 2008; Hsieh et al., 2020; Hwang et al., 2021) suggests that behavioural biases (representativeness; disposition effect; overconfidence; attention-grabbing effect) can lead to correlations among investors' trades.

[14] Fads pertain to investments that grow in popularity for (shorter or longer) periods of time, leading investors to jointly enter positions in them (see the discussion and references in Andrikopoulos et al., 2021).

[15] Although superstitions are erroneous mental models, whether individuals can learn to avoid them or correct them is far from certain. Risen (2016) cites several ways through which this correction can be fostered (based on the ability, motivation, or incentives to be rational, as well as framing/choice architecture); however, she also shows that the human mind can acquiesce to superstition, even if it knows it to be wrong. This is likely to occur when superstitions pre-empt rational processing (either because they represent compelling defaults or because the cost of ignoring intuition is high), especially in situations where an otherwise common (among people) decision is viewed as "special" for an individual.

[16] Ritual instrumentalism involves people performing rituals prior to engaging themselves in a task, due to these rituals having been found to bring benefits in people's performance in a task (Risen, 2016). This is the case e.g., of many traders wearing items they were wearing when they outperformed in their trades in the past in anticipation of this outperformance's recurrence (see the discussion in Lepori, 2009).

[17] Evidence from the US denotes that uneducated people are more prone to superstitions (see Risen, 2016 for beliefs on this issue from earlier centuries); this is in line with the tenets of deprivation theory (Torgler, 2007), which views superstitions as spiritual "aids" to socio-economically disadvantaged persons when undergoing adverse circumstances. However, superstitions have also been detected among corporate managers in Asian countries (Tsang, 2004) and the literate working population (including scientists) in India (An et al., 2019); see also the references on this issue in Hirshleifer et al. (2018). Evidence (Jahoda, 1968; Salter & Routledge, 1971) also suggests that university education does not necessarily reduce susceptibility to superstition; individuals with a background in Arts and Humanities tend to be more superstitious compared to their peers with other academic backgrounds (Smith et al., 1998). Recent evidence (Invernizzi et al., 2021) suggests that university-specific superstitions can prove strong enough among their students due to conformity.

and gender,[18] while religiosity (religious observance) bears a(n) positive (inverse) relation to superstitious tendencies (Torgler, 2007). Superstitions also constitute *coping heuristics* (Lepori, 2009), helping individuals tackle situations involving important outcomes and entailing high uncertainty due to lack of (perceived) control over these outcomes. In that sense, superstitions bear anxiolytic properties (Tsang, 2004), foster illusion of control (as they help people make sense of otherwise random situations; Risen, 2016) and boost performance (Brooks et al., 2016; Damisch et al., 2010). In that vein, superstitions are strongly triggered during periods of negative mood (Risen, 2016; Whitson & Galinsky, 2008), as they can help people cope with grief (Brooks et al., 2016). As superstitions are reinforced over time (be it through personal experience, or social dynamics[19]), they become habits, which help economize on cognitive resources (thus potentially contributing to satisficing, rather than optimal, decisions).[20] For example, superstitions can help individuals with their *mental accounting*; Risen (2016) showed that individuals can process the costs/benefits of superstitious actions and adopt them if the cost (benefit) incurred (anticipated) is low (great). Evidence further suggests that superstitions can be motivated by established *cognitive biases* and *heuristics* as a means of helping individuals simplify difficult problems (Risen, 2016).[21]

2.2.2. Superstitions in equity markets

To the extent that equity investing involves uncertainty in its outcomes, it stands to reason that some investors may resort to superstitions in order to tackle this uncertainty (and render investment decision-making more manageable from a cognitive load viewpoint). This possibility has motivated a growing literature over the past twenty years which has largely focused on the impact of numerological superstitions over equity market returns internationally. A series of studies have investigated the effect of Feng-Shui-designated (un)lucky numbers[22] in (primarily East Asian)[23] equity markets drawing on a) the ending digits of closing prices and trading lots, b) day-number combinations of calendar days and c) the tickers of listed stocks. Results based on closing prices' ending-digits suggest that any clustering around (away from) lucky (unlucky) numbers observed in closing prices is clientele-dependent (Brown & Mitchell, 2008; Cai et al., 2007; Ke et al., 2017),[24] dissipates with learning/experience/information (Chen et al., 2020; Ke et al., 2017) or as markets grow more sophisticated (Anderson et al., 2015; Brown & Mitchell, 2008) and tends to amplify during (in)auspicious celebrations (Brown et al., 2002; Ke et al., 2017; Raesita & Mahadwartha, 2020). Evidence from day-number combinations of calendar days is both limited and very mixed (Chung et al., 2014; Haggard, 2015), with (un)lucky day-numbers often found to reveal market returns of a sign opposite to what their superstitious value would suggest. Conversely, the findings from studies using tickers of listed stocks clearly suggest that stocks listed in the equity markets of China (Hirshleifer et al., 2018) and Taiwan (Weng, 2018) are more likely to experience an abnormally high IPO-premium, if at least one lucky number is included in their ticker (with the premium found to rise in the number of the ticker's lucky digits); in addition, Chinese listed firms with unlucky numbers in their ticker entail enhanced crash risk, particularly during volatile or down markets (Bai et al., 2020).

The above evidence suggests that numerological superstitions can give rise to return-regularities in equity markets; nevertheless, no evidence to date exists as per whether these superstitions can prompt correlated trades among investors (despite the wealth of evidence from other decision settings – see footnote 1). In addition, while IPOs and price crashes, which were shown to be affected by superstitions, are relatively rare and salient events, we investigate the impact of superstitious believes on a continuous phenomenon of herding driven by day-to-day investors' decisions. Lastly, while price clustering may lead to miniscule and temporary inefficiencies for individual stocks, these would most likely cancel out in the cross-section and over time; in contrast, we study market-wide herding which could manifest a more persistent inefficiency, and on the aggregate level. To that end, our study fills this gap in the literature by assessing the effect of numerological superstitions on investors' herding in Chinese equity markets; we test for a series of hypotheses based on the literature, which we present in the next section.

3. Hypotheses

Evidence from non-equity investment contexts (see footnote 1) suggests that a superstition shared by many individuals can prompt them to exhibit correlation in their behaviour, regardless of how strongly they themselves believe in the superstition[25]; social transmission mechanisms can further foster this correlation (e.g., Benvenuti et al., 2018). In the equity investment context, the designation of stocks as "lucky" or "unlucky" by virtue of superstition introduces an element of homogeneity among them; in addition, adherence to a commonly held superstition among investors also adds an element of homogeneity to them. Taken together, the above can foster correlation in superstitious investors' trades in "superstitious" stocks, leading them to herd when trading lucky/unlucky stocks.[26] In this case, superstitious ("lucky" or

[18] Although one would expect people to grow more superstitious with age (due e.g., to a greater belief in the supernatural as one grows older), younger adults can be more superstitious than their older peers. With regards to gender, women tend to exhibit superstitious traits more often than men. For more on these, see the discussion in Mowen and Carlson (2003) and Torgler (2007) and references therein.

[19] For more on how social dynamics reinforce superstitions, see Henslin (1967) and Scheibe and Sarbin (1965).

[20] If a superstition, for example, has proven to be successful over time, then this can foster naïve/reinforcement learning (individuals will continue using it, thinking it is correct).

[21] Representativeness (the heuristic which promotes stereotyping, by prompting people to extract inferences based on similarity) can enhance superstitions, as it allows those adopting them to accelerate the superstitious association between objects and outcomes. The availability bias (which prompts inferences about the likelihood of an event based on how easily it – or other similar events – come to mind) can also enhance superstitions, particularly in situations involving belief in tempting fate, since these situations are viewed as more "inviting" to negative outcomes. For a more detailed discussion of the above, see Risen (2016).

[22] Based on Feng Shui (Tsang, 2004), a number's sound-association in the Chinese language determines its superstitious value. For example, number 4 is considered rather inauspicious (its sound rhymes with the Chinese word for "death"), whereas for example numbers 8 and 9 are considered rather auspicious (their sounds rhyme with the Chinese words for "prosperity" and "long-lasting", respectively). Risen (2016) views this as a token of "nominal realism", whereby an object's name/label defines people's reactions to it.

[23] Unlike their East Asian counterparts, evidence of numerological superstitions is less pronounced in Western markets. The well-known superstition surrounding Friday the 13th has motivated ample research on its effect, yet with results largely refuting its presence (see the review of the literature in Borowski, 2019).

[24] Cai et al. (2007) and Brown and Mitchell (2008) find that Chinese A-shares (dominated by domestic, mainly retail, investors) project higher (lower) clustering around lucky (unlucky) numbers compared to B-shares (mainly held by overseas investors). Ke et al. (2017)'s results from Taiwan suggest an avoidance of number 4 – which, nevertheless, is not observed among institutional investors in that market.

[25] Evidence suggests that "half-believers" can also project superstitious behaviour without necessarily (strongly) believing in a superstition; for more on this (also known as quasi-magical thinking; Shafir & Tversky, 1992) and how superstitious practice need not reflect superstitious belief, see Risen (2016).

[26] From a theoretical point of view, the correlation in investors' trades due to superstitions would be treated as spurious herding (since it is the common adherence to the superstition that would motivate this correlation), though of course it is not unlikely that social interactions among superstitious investors also contribute to this (see the discussion on the social dynamics of superstitions in Torgler, 2007 and Lepori, 2009).

"unlucky") stocks are expected to exhibit stronger herding compared to their non-superstitious peers (i.e., stocks with no singular superstitious property). Whether this holds, however, depends on the population frequency of the superstition's following among investors, since the higher (lower) the number of superstitious investors, the more (less) likely this is to hold. Superstitious stocks, for example could exhibit weaker herding if many of their investors are not superstitious or if their trades are cancelled out by those of non-superstitious ones; on the other hand, herding among both superstitious and non-superstitious stocks may be motivated by intentional/spurious herding drivers, in which case their herding may be insignificantly different. In addition, superstitions may not motivate herding, if many investors consider superstitions irrelevant to their decisions, if superstitious individuals refrain altogether from investing for some reason, or if the percentage of investors who trade based on a superstition has dissipated over time (if their investment history has indicated the irrelevance of the superstition to investment success). To that end, we propose our first hypothesis:

Hypothesis 1. Superstitious stocks' herding is stronger compared to that of non-superstitious ones.

Stocks with lucky superstitious value are likely to engender a positive image among investors; to the extent that positive image reduces an investment's perceived riskiness and motivates the employment of heuristics in decision-making (Forgas, 1998; Schwarz, 1990), this implies a higher (lower) potential for herding in the trading of lucky (unlucky) stocks. In turn, this suggests that lucky stocks with "excessive luck" features in their superstitious image (i.e., "very lucky" stocks) should command even stronger herding. We therefore propose our next hypotheses:

Hypothesis 2a. Herding is stronger among lucky stocks than unlucky stocks.

Hypothesis 2b. Herding is stronger among very lucky stocks than lucky stocks.[27]

Theoretical literature (Brooks et al., 2016; Risen, 2016; Tsang, 2004; Whitson & Galinsky, 2008) has confirmed that superstitions tend to be fueled more aggressively during periods of enhanced uncertainty, where the potential for risk or loss looms larger in importance. Under such conditions, superstitions are more likely to be adopted, either because they function as substitutes to information (Bai et al., 2020)[28] or due to their anxiolytic properties (Tsang, 2004). As a result, one would expect individuals to exhibit more distinct superstitious behaviour in their investments when the latter entail the prospect of enhanced risk or loss.

To begin with, lucky (unlucky) stocks command a positive (negative) superstitious image associated with gain- (loss-) expectations, which render it more likely that superstitious investors will buy (sell or not buy[29]) them. If superstition, indeed, motivates herding, then we would expect stronger herding among both lucky and unlucky stocks during times of negative market performance or high market volatility (since both would suggest higher potential for risk or loss). To cope with the uncertainty of such market conditions, superstitious investors would herd more toward (away) from lucky (unlucky) stocks, in order to associate (dissociate) themselves with (from) assets they believe to be linked to positive (negative) outcomes.

However, the interplay between market performance and superstitious herding may vary between lucky and unlucky stocks, if the superstitious value of lucky/unlucky stocks is reinforced by the prevailing market conditions. If so, lucky (unlucky) stocks' herding should be stronger during bullish (bearish) markets, since the positive (negative) sentiment the latter accommodate can enhance the positivity (negativity) of these stocks' superstitious image.[30]

An alternative possibility is that bullish (bearish) conditions motivate herding across lucky, unlucky and non-superstitious stocks alike, since they are associated with market-wide gains (losses), in which case all stocks would win (lose) on average and investors would simply buy (sell) them on the upside (downside) to enjoy (reduce) gains (losses).[31] It is also possible that superstitious investors underreact in the face of a bearish market and refuse to sell their lucky stocks even when they are losing money, either to avoid experiencing cognitive dissonance (by not selling, they are not actively challenging their superstitious beliefs) or due to believing that holding lucky stocks can help see them through the market slump. In this case, lucky stocks' herding will likely be dampened during bearish markets. Finally, as low volatility periods are associated with reduced uncertainty, one would expect during them a less pronounced effect of superstitions, overall, in the decision to herd. In view of the above, we propose the following hypotheses:

Hypothesis 3a. Lucky stocks' herding is significantly different between bullish and bearish markets.

Hypothesis 3b. Unlucky stocks' herding is stronger during bearish markets.

Hypothesis 4a. Lucky stocks' herding is stronger during high-volatility markets.

Hypothesis 4b. Unlucky stocks' herding is stronger during high-volatility markets.

To assess the impact of superstitions, these hypotheses will be evaluated vis-à-vis analogous effects in neutral stocks.

Superstitions tend to be particularly appealing to less sophisticated individuals, since by providing their adherents with (an often over-simplified) understanding about how the world works (Hirshleifer, 2020; Hirshleifer et al., 2018), they help them economize on cognitive resources. This is particularly important in environments as complex and volatile as equity markets; if a stock, for instance, is classified by

[27] Again here, lucky/very lucky/unlucky stocks may exhibit insignificant superstition-driven herding (if many of their investors are not superstitious or if many of their investors are superstitious yet do not rely on superstitions for their trades) or their herding may be insignificantly different from that of non-superstitious stocks (if it is motivated by intentional/spurious herding drivers).

[28] High volatility can be due to high flow of information or the presence of noise in the market; coping with either (processing the high flow of information; navigating through noise) constitutes a laborious task (it requires considerable cognitive effort), which superstition, as a mental shortcut, helps simplify.

[29] Loss/regret-aversion would likely nudge superstitious investors toward refraining from buying unlucky stocks.

[30] More so since bullish (bearish) markets breed gains (losses); if lucky (unlucky) stocks win (lose) during bullish (bearish) markets, superstitious investors may attribute these gains (losses) to their lucky (unlucky) superstitious image (thus reinforcing their superstitious beliefs). This is expected to be particularly strong for unlucky stocks, since the loss-expectations associated with their superstitious image are likely to interact with loss-aversion in motivating their superstitious holders to sell them during bearish markets (in order to curtail their losses). Along these lines, Bai et al. (2020) found that unlucky stocks in Chinese markets tended to project enhanced crash risk versus other stocks, particularly during periods of high volatility or down-markets.

[31] Specifically with respect to bearish markets, the realization of losses may prompt superstitious investors to discard their superstitions (lucky stocks losing money will induce cognitive dissonance) and start disposing of lucky stocks, in order to mitigate further losses (thus giving rise to increased herding among lucky stocks during bearish markets). A similar dissonance, of course, would be experienced for unlucky stocks winning during bullish markets, although the realization of profits in that case would probably be rationalized by superstitious investors as the product of bullish markets turning most stocks into winners.

investors subscribing to a specific superstition as "lucky" or "unlucky", this immediately endows that stock with an image that entails emotional valence[32] and simplifies its evaluation. To the extent, therefore, that superstitious investors are likely to be less sophisticated, with limitations both in their information sets and their processing skills, superstitions help them cope with the uncertainties of equity investing by reducing investment decision-making from a complex activity into something much more tractable.[33] As it is retail investors that tend to be less sophisticated, superstitious herding would be expected to be more strongly motivated by noise (i.e., non-fundamentals),[34] considering the propensity of retail investors toward noise trading (Barber et al., 2009a, 2009b; Barber & Odean, 2013). To that end, we propose the following hypotheses:

Hypothesis 5a. Herding in lucky stocks is driven by non-fundamental factors

Hypothesis 5b. Herding in unlucky stocks is driven by non-fundamental factors.

To assess the impact of superstitions, both hypotheses will be evaluated vis-à-vis analogous effects in neutral stocks.

4. Data and methodology

4.1. Data

Our sample consists of daily data of closing prices of all publicly listed A-share stocks in the Shanghai (1639 stocks) and Shenzhen (1513 stocks) stock exchanges for the 05/01/2000–29/12/2020 period. To mitigate the possibility of survivorship bias, our sample includes data on stocks that are currently active as well as delisted/suspended during our sample period. All data is obtained from the China Stock Market and Accounting Research (CSMAR) database. To distinguish between superstitious and non-superstitious stocks we follow the approach proposed by Hirshleifer et al. (2018), which identifies lucky and unlucky digits within the tickers/listing numbers of stocks. The latter are classified as a) lucky, if their ticker contains at least one lucky number (6, 8, 9) and no unlucky number (4), b) unlucky, if they include number 4 and no lucky number, and c) neutral (i.e., non-superstitious), if they do not include any lucky/unlucky number, or if they include both.[35] In the case of the Shanghai stock exchange, all tickers begin with the number 6, so this digit is dropped before the classification of stocks.

4.2. Methodology

To assess the effect of superstition over herding, we draw on the empirical design proposed by Chang et al. (2000). Their model aims at capturing market-wide herding using securities' returns based on the assumption (initially put forth by Christie & Huang, 1995) that the presence of herding can be inferred via the relationship between the cross-sectional return dispersion and the absolute market performance. In the context of the rational asset pricing paradigm (Black, 1972) this relationship is expected to be linearly positive,[36] thus suggesting that (assuming the absence of herding) the cross-sectional return dispersion grows with the market's absolute return. If, however, investors herd during periods of extreme absolute market returns, this would prompt broader convergence of stocks to the market consensus; as the latter is reflected via the average market return, this would imply a reduction in the cross-sectional return dispersion. This would challenge the above mentioned expected linearly positive relationship between the cross-sectional return dispersion and absolute market returns and Chang et al. (2000) tested for this empirically via the following specification:

$$CSAD_{m,t} = \beta_0 + \beta_1 \left|R_{M,t}\right| + \beta_2 R_{M,t}^2 + e_t. \tag{1}$$

In the above equation, $R_{M,t}$ represents the market return of each of the two stock exchanges (Shanghai; Shenzhen) for which herding is estimated; as per $CSAD_{m,t}$, its calculation follows the following specification:

$$CSAD_{m,t} = \frac{\sum_{i=1}^{n}\left|R_{i,t} - R_{m,t}\right|}{n}. \tag{2}$$

where n corresponds to the number of securities used in the calculation of $CSAD_{m,t}$ that are actively traded on day t; $R_{i,t}$ is the first log-differenced return of stock i on day t; and $R_{m,t}$ is the average performance of all securities used in the calculation of $CSAD_{m,t}$ that are actively traded on day t.[37] If investors adhere to the rational paradigm and refrain from herding, the value of β_1 will be significantly positive (reflecting a linearly positive relationship between $CSAD_{m,t}$ and $\left|R_{M,t}\right|$) and that of β_2 insignificant (rational asset pricing would preclude the nonlinear relationship between $CSAD_{m,t}$ and $\left|R_{M,t}\right|$). If, however, investors herd when the market exhibits large absolute price movements, this would introduce nonlinearity in the relationship between $CSAD_{m,t}$ and $\left|R_{M,t}\right|$ and lead to significantly negative values of β_2.[38]

Eq. (1) is employed to test for hypotheses 1 and 2a/2b, where herding is estimated unconditionally; to test for hypotheses 3a/3b and

[32] A stock's image can induce emotions among investors and affect their investments; superstitious investors may buy a "lucky" stock simply because its "lucky" image motivates positive emotions courtesy of their superstitious beliefs. For more on the role of image in investments, see Lucey and Dowling (2005) and references therein.

[33] To the extent that buying a stock involves choosing from among the universe of listed stocks, this constitutes a hard task for unsophisticated investors (Barber et al., 2009a); by being able to capture (superstitious) investors' attention, a lucky/unlucky feature of a stock (e.g., the presence of lucky/unlucky numbers in its ticker) can simplify the stock-selection process. In that sense, superstition can help serve as a substitute for information (Bai et al., 2020). Instead of assessing a stock's fundamental value (a task arguably harder for less sophisticated investors – particularly during times of rising uncertainty, such as when markets are highly volatile or falling), a superstitious investor judges that stock based on the information emitted via its superstitious value ("lucky" stock is "good"; "unlucky" stock is "bad") – an arguably easier task.

[34] It is not unlikely, however, that superstitions can also impact the conduct of more sophisticated investors, who may choose to cater to or exploit the beliefs of their superstitious peers. This is the case e.g., of corporate managers avoiding unlucky numbers when setting offer prices for their firms' IPOs (Ke et al., 2017) or ensuring their firms obtain tickers with lucky numbers (Hirshleifer et al., 2018).

[35] Chinese numerological superstitions are based on homophony. It is a tradition where the meaning of some numbers is connected to their homophonic words or relevant expressions. The pronunciation of number "6" in Mandarin Chinese sounds similar to the word for "blessing" or "emoluments". Number "8" is pronounced like the word "prosperity"; number "9" is pronounced like "long time" and is considered as "longevity". However, the pronunciation of number "4" is like "death". Consequently, the Chinese will consider numbers "6", "8", and "9" to be auspicious and "4" inauspicious.

[36] The positive expected sign is predicated (Black, 1972) on the fact that publicly listed securities vary in their sensitivities to the movements of the market.

[37] Chang et al. (2000) infer herding in their model via $CSAD_{m,t}$'s negative and nonlinear relation to the market return; however, as they showcase, when $CSAD_{m,t}$ is calculated for subsets of a market's stocks (as, in this paper's case, for lucky and unlucky stocks), the $R_{m,t}$ in Equation (2) is the specific subset's average return.

[38] The negative value here would be the result of herding dampening the cross-sectional return dispersion.

4a/4b, we re-estimate it for each of the following subsamples of days:

High-return days; defined as those for which $R_{M,t}$ lies above its 30−/60−/252-day moving average value.

Low-return days; defined as those for which $R_{M,t}$ lies below its 30−/60−/252-day moving average value.

High-volatility days; defined as those for which $R^2_{M,t}$ lies above its 30−/60−/252-day moving average value.

Low-volatility days; defined as those for which $R^2_{M,t}$ lies below its 30−/60−/252-day moving average value.

The selection of the 30−/60−/252-day moving averages is performed to assess how herding varies when utilizing horizons of various length as reference points in the designation of high−/low-return/volatility days. As regards volatility, we calculate it by assuming the squared value of $R_{M,t}$, in line with the literature (e.g., Cui et al., 2019). We estimate Eq. (1) for each of the above four subsamples of days for lucky, unlucky and non-superstitious stocks separately for each of the two Chinese stock exchanges.

Hypotheses 5a/5b require to empirically identify non-fundamentals-(noise-)driven herding; to empirically assess this, we first regress the $CSAD_{m,t}$ of lucky/unlucky/non-superstitious stocks on China's Fama and French (2015)'s five factors,[39] as follows:

$$CSAD_{m,t} = a_0 + a_1\left(R_{M,t} - r_{f,t}\right) + a_2HML_t + a_3SMB_t + a_4RMW_t + a_5CMA_t + \varepsilon_t. \quad (3)$$

Where: $R_{M,t} - r_{f,t}$ represents the excess stock market return, HML_t the High Minus Low return (i.e., "value") factor, SMB_t the Small Minus Big return (i.e., "size") factor, RMW_t the Robust Minus Weak return (i.e., "profitability") factor, and CMA_t the Conservative Minus Aggressive (i.e., "investment") factor. Eq. (3) is employed here to remove the fundamentals-driven component of $CSAD_{m,t}$ (in line with earlier research: Galariotis et al., 2015; Cui et al., 2019; Andrikopoulos et al., 2021), with the error term (ε_t) reflecting the variations of $CSAD_{m,t}$ due to non-fundamentals:

$$CSAD_{NF,t} = \varepsilon_t \quad (4)$$

To calculate the component of $CSAD_{m,t}$ due to fundamentals, we subtract its non-fundamental component from it as follows:

$$CSAD_{F,t} = CSAD_{m,t} - CSAD_{NF,t} \quad (5)$$

Having partitioned $CSAD_{m,t}$ into its fundamental and non-fundamental components, we can now assess whether herding is fundamentals- or non-fundamentals-driven by re-estimating Eq. (1) employing each of the two components ($CSAD_{F,t}$; $CSAD_{NF,t}$) in turn, as the dependent variable, for lucky, unlucky and non-superstitious stocks separately.

Our general testing approach is as follows. To assert if herding differs between stock-types or market conditions as per relevant hypotheses, we will estimate model (1) for each type/condition first, to test if herding prevails in each in the first place. If this is the case, or if herding is significant at least in the type/condition hypothesized to exhibit more pronounced flocking-together, we then test if herding coefficients differ between these two types/conditions. For instance, when testing hypothesis 4a predicting stronger herding among lucky stocks in high-volatility periods, we obtain herding measures for, e.g., lucky (L) Shanghai (SH) stocks under high-volatility ($\beta_2^{L,SH,HighVol}$) and low-volatility ($\beta_2^{L,SH,LowVol}$) conditions, and test if $(\beta_2^{L,SH,HighVol} - \beta_2^{L,SH,LowVol}) = 0$ (we report p-values from the corresponding Wald test in relevant tables, denoted as "Wald test"). If this hypothesized herding difference is of predicted sign and statistically significant, we further test if it is significantly different from the analogous effect in non-superstitious (i.e., neutral (N)) stocks, i.e.: if $\left(\beta_2^{L,SH,HighVol} - \beta_2^{L,SH,LowVol}\right) - \left(\beta_2^{N,SH,HighVol} - \beta_2^{N,SH,LowVol}\right))$ is significantly different from zero and of correct sign (we report the resulting values of such difference-of-differences as well as the corresponding p-values in relevant tables, denoted as "Wald test vs neutral"). We can attribute any herding effects to superstitious trading only if they are significantly more intensive than what is observed in non-superstitious stocks, otherwise they are most likely to be a manifestation of market-wide phenomena driven by factors other than superstitions.

4.3. Descriptive statistics

Panel A in Table 1 presents the frequencies of lucky, unlucky, and neutral stocks in our sample. In Shanghai (Shenzhen), 31.8% (31.5%) of the stocks are classified as neutral, 64.18% (57.6%) are classified as lucky and 4.02% (10.9%) are classified as unlucky. Panel B presents a series of descriptive statistics pertaining to $CSAD_{m,t}$ and $R_{m,t}$ for both markets and each category of stocks. According to these results, the average return of all three categories is very small in magnitude and negative, with minor differences among them, for both stock exchanges, while all series exhibit significant leptokurtosis and negative skewness. The series of $CSAD_{m,t}$ also depart from normality as they exhibit significant leptokurtosis and positive skewness, while the average return dispersion does not appear to differ substantially across stock types and trading venues.

5. Results-discussion

5.1. Unconditional herding

We begin the discussion of our results with the estimates from Eq. (1) which are presented in Table 2; as the estimates there suggest, herding is pervasive (reflected through consistently negative β_2-values) across both superstitious and neutral stocks (Panel A), as well as among lucky and unlucky stocks (Panel B) for both stock exchanges. At first sight, there appear to be meaningful differences in herding across stock types: superstitious (neutral) stocks exhibit stronger herding[40] than neutral (superstitious) ones in Shenzhen (Shanghai), with lucky (unlucky) stocks' herding being more pronounced in Shanghai (Shenzhen) compared to that of unlucky (lucky) stocks. However, there is no systematic pattern in the relative herding strength which would be supportive of our prior expectations, and in all of the above cases herding is not significantly different (as the relevant Wald test results denote) between superstitious-vs-neutral and lucky-vs-unlucky stocks, thus prompting us to reject hypotheses 1 and 2a.

It may be that the effect of superstitions is only apparent in extreme cases; we therefore identify "very lucky" stocks (defined as those containing at least two lucky numbers: 6, 8, 9, and no unlucky number) and compare herding among them vs among their lucky counterparts. Results (Panel C) indicate that very lucky stocks appear to herd more strongly than their lucky peers in both markets, without herding being significantly different between the two, however, leading us to reject hypothesis 2b. Taken together, the results outlined in Table 2 suggest that, in the aggregate, numerological superstitions do not motivate significantly stronger herding in Chinese markets; a possible explanation for this is that herding in China may be primarily motivated by intentional/spurious herding factors (see the discussion in section 2.1), irrespective of a stock's superstitious value. It may also be that numerological superstitions are irrelevant to many investors when making trading decisions (irrespective of whether they are superstitious or not); alternatively, most investors in Chinese markets may be non-superstitious (and their trades may cancel out those of superstitious ones), or superstitious individuals refrain from investing for some

[39] Source: https://www.factorwar.com/data/factor-models/.

[40] Their β_2 is more strongly negative.

Table 1
Summary statistics.

	Shanghai ($N = 1639$)		Shenzhen ($N = 1513$)	
Panel A: Frequency of neutral/ lucky/unlucky stocks	(%)		(%)	
Neutral	31.80		31.50	
Lucky	64.18		57.60	
Unlucky	4.02		10.90	
Total	100.00		100.00	
Panel B: Neutral stocks	$CSAD_{m,t}$	$R_{M,t}$	$CSAD_{m,t}$	$R_{M,t}$
Mean	0.0156	−0.0001	0.0164	−0.0003
Standard deviation	0.0055	0.0192	0.0056	0.0200
Skewness	1.4797	−0.7809	1.5659	−0.7460
	(0.000)	(0.000)	(0.000)	(0.000)
Excess kurtosis	7.4107	7.5716	8.2797	7.0562
	(0.000)	(0.000)	(0.000)	(0.000)
Min	0.0026	−0.1026	0.0020	−0.1025
Max	0.0585	0.0941	0.0632	0.0944
Panel C: Lucky stocks				
Mean	0.0157	0.0000	0.0164	−0.0002
Standard deviation	0.0055	0.0189	0.0056	0.0197
Skewness	1.6066	−0.7425	1.4433	−0.7675
	(0.000)	(0.000)	(0.000)	(0.000)
Excess kurtosis	7.9858	7.4421	7.2911	7.2800
	(0.000)	(0.000)	(0.000)	(0.000)
Min	0.0038	−0.1018	0.0036	−0.1041
Max	0.0615	0.0934	0.0635	0.0935
Panel D: Unlucky stocks				
Mean	0.0160	−0.0002	0.0163	−0.0002
Standard deviation	0.0064	0.0196	0.0062	0.0198
Skewness	1.5603	−0.7605	1.5779	−0.7391
	(0.000)	(0.000)	(0.000)	(0.000)
Excess kurtosis	8.0415	7.1230	7.7981	7.0284
	(0.000)	(0.000)	(0.0000)	(0.000)
Min	0.0035	−0.0992	0.0003	−0.1030
Max	0.0710	0.0914	0.0637	0.0952

Notes: Panel A presents the frequency of neutral, lucky and unlucky stocks of our sample. Panels B—D present selected descriptive statistics (mean; standard deviation; skewness; excess kurtosis; min; max) for the $CSAD_{m,t}$ and $R_{M,t}$ values of neutral (panel B), lucky (panel C) and unlucky (panel D) stocks listed on the Shanghai and Shenzhen stock exchanges for the 05/01/2000–29/12/2020 period. Parentheses include p-values.

reason.

It is important to note, however, that the above results hail from unconditional herding estimations and the latter do not allow us to control for the fact that conditions of differential emotional valence can lead to variations in superstitions' effects over individuals (see the discussion in section 2.2). Since conditions of uncertainty, entailing risk and loss potential, tend to amplify superstitious behaviour, we investigate this possibility in the next section by conditioning superstitious stocks' herding on the market's performance and volatility.

5.2. Superstitious herding and uncertainty

5.2.1. Herding and market performance

Panels A-C in Tables 3 and 4 present the estimates for lucky and unlucky stocks, respectively, when herding is conditioned on days of high and low market returns. Firstly, we observe that herding in both the Shanghai and Shenzhen markets is present for days of both high and low returns for both stock-types ($\beta_2 < 0$ and significant throughout). Lucky stocks exhibit stronger herding for days of high market returns (Table 3), with unlucky stocks projecting more intense herding always for days of low market returns (Table 4). Since high-return (low-return) days reflect bullish (bearish) conditions, this suggests that lucky (unlucky) stocks herd more on days when the stronger gains- (loss-) expectations associated with their positive (negative) superstitious image are confirmed by the market's performance. Although this would imply a connection between market performance and superstitious herding, this relationship is rather weak: the Wald tests' p-values indicate that the difference in herding between high- and low-return days is never significant for either lucky or unlucky stocks. In view of the above, we conclude that superstitions do not generate a significantly distinct pattern in market-wide herding and reject hypotheses 3a and 3b.

5.2.2. Herding and market volatility

The impact of volatility over herding across both lucky and unlucky stocks is rather uniform. Results in Panels D—F of Tables 3 and 4 illustrate an overwhelming herding presence for high-volatility days only, with low-volatility days revealing no herding whatsoever,[41] with the difference of herding between high- and low-volatility days being consistently significant in all cases. A priori, the exclusive presence of herding for lucky/unlucky stocks on high-volatility days is a very interesting finding here, considering the role of uncertain conditions in amplifying superstitious tendencies among individuals (Brooks et al., 2016; Risen, 2016; Tsang, 2004; Whitson & Galinsky, 2008). A possibility here is that lucky (unlucky) stocks' image offers superstitious investors a summary information indicator that helps them cope with the uncertainty of volatile markets. Irrespective of whether high volatility is the result of information-flow or noise, processing either involves considerable cognitive effort - and superstition, as a mental shortcut, can help simplify this task. If they believe that lucky (unlucky) stocks - courtesy of their lucky (unlucky) image - can see them through (are undesirable to hold during) this high volatility, superstitious investors can end up herding more on them during volatile times.[42] Nevertheless, the same pattern of stronger herding is also observed in neutral stocks, to the effect that the high-vs-low volatility effects in superstitious stocks tend to not differ significantly from their neutral counterparts; only for two cases of Shanghai lucky stocks (Table 3, Panel D and E) do we find that herding is stronger in high volatility conditions, and significantly so as compared to neutral stocks. The fact that the herding-volatility effects in superstitious stocks tend to not differ significantly from those in neutral stocks renders it more likely that the volatility-herding relationship documented here is market-wide,[43] rather than superstition-motivated. This leads us to reject hypotheses 4a and 4b, as these hypotheses were derived on the premise of superstitions exerting a unique influence on relevant subsets of stocks.

5.3. Superstitious herding: fundamentals- or noise-driven?

To the extent that superstitious investors are expected to be less so-

[41] The significantly positive values of β_2 for low volatility-days indicate that low volatility in Chinese markets motivates an increase in $CSAD_{m,t}$ over and above what rational asset pricing would predict (since it does not allow for non-linearities; see section 4.2). Gebka and Wohar (2013) ascribed such positive nonlinearities to investors' overconfidence. In our specific case, investors may rely more on their own private signals during low volatility periods, since the latter's lower implied uncertainty reduces the need for tracking the trades of other investors for information. In turn, this suggests greater divergence of opinion among investors regarding company-valuations and a reduced potential for herding.

[42] Although our data does not allow us to verify the direction of unlucky stocks' herding during high-volatility days, the fact that unlucky stocks in China bear enhanced crash risk during high-volatility periods (Bai et al., 2020) suggests the possibility that this herding is likely associated with the sell-side.

[43] The presence of market-wide herding exclusively during high volatility days may be due to investors using herding as a tool to cope with uncertainty; alternatively, it may be due to uninformed investors mimicking the trades of their informed peers (if this high volatility is the product of information-based trading).

Table 2
Unconditional herding.

	Shanghai				Shenzhen			
	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
Panel A: Superstitious vs. Neutral								
Superstitious	0.0136***	0.254***	−2.073***	0.108	0.0140***	0.229***	−1.717***	0.103
	(0.000)	(0.014)	(0.250)		(0.000)	(0.014)	(0.245)	
Neutral	0.0135***	0.244***	−2.142***	0.095	0.0142***	0.223***	−1.690***	0.097
	(0.000)	(0.014)	(0.250)		(0.000)	(0.014)	(0.247)	
Wald test	[0.650]				[0.806]			
Panel B: Lucky vs. Unlucky								
Lucky	0.0135***	0.255***	−2.084***	0.109	0.0141***	0.225***	−1.661***	0.101
	(0.000)	(0.014)	(0.250)		(0.000)	(0.014)	(0.246)	
Unlucky	0.0140***	0.238***	−1.895***	0.073	0.0139***	0.243***	−1.895***	0.091
	(0.000)	(0.017)	(0.295)		(0.000)	(0.016)	(0.274)	
Wald test	[0.326]				[0.224]			
Panel C: Very Lucky vs. Lucky								
Very lucky	0.0133***	0.260***	−2.127***	0.106	0.0134***	0.231***	−1.890***	0.059
	(0.000)	(0.015)	(0.260)		(0.000)	(0.018)	(0.322)	
Lucky	0.0135***	0.255***	−2.084***	0.109	0.0141***	0.225***	−1.661***	0.101
	(0.000)	(0.014)	(0.250)		(0.000)	(0.014)	(0.246)	
Wald test	[0.589]				[0.338]			

Notes: The table presents estimates from model (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 Shanghai- and Shenzhen-listed stocks. The above equation is estimated for each category (neutral/lucky/unlucky/very lucky) of stocks listed on the Shanghai or the Shenzhen stock exchange. The significance of the difference between the β_2 values in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

phisticated, they are likely to be of retail background and, if so, their investment patterns will reflect noise trading (Barber & Odean, 2013). As a result, superstitious herding would be expected to be more strongly motivated by noise (i.e., non-fundamentals) and we now turn to gauge whether this is indeed the case by re-estimating Eq. (1) for fundamental and non-fundamental herding separately for the Shanghai and Shenzhen markets. We begin with Tables 5 and 6, which contain unconditional herding estimates for each of the two stock exchanges; as the estimates in both tables suggest, herding is non-fundamentals- (i.e., noise-) driven across the board (β_2 estimates all negative and highly significant), with no evidence of fundamentals-driven herding surfacing. This result preliminarily points toward acceptance of hypotheses 5a and 5b, i.e., superstitious stocks experience herding only in the noise-related components of their price movements. However, and similarly to Table 2, noise-driven herding appears insignificantly different between superstitious-vs-neutral, lucky-vs-unlucky and very lucky-vs-lucky stocks. These initial results clearly denote the role of noise in motivating herding in Chinese markets, in line with research (Cheng et al., 2022; Li, 2017; Mei et al., 2009; Xiong & Yu, 2011; Zheng et al., 2015) on noise investors in China.[44] More relevant to our study, however, these results also indicate that superstitions have no unique and significantly elevated impact on investors' market-wide herding behaviour, leading us to reject hypotheses 5a and 5b.

Having established that herding only prevails in non-fundamental price behaviour in Chinese market, we further explore this aspect in the conditional setting. Tables 7 and 8 present results from estimations conditioning noise-driven herding on market performance and volatility for lucky (Table 7) and unlucky (Table 8) stocks. Several observations can be made. Firstly, noise-driven herding is present for both high- and low-return days, tending to grow stronger for high-return days in the majority of cases, albeit less so for unlucky Shenzhen stocks (Panels A-C in Tables 7 and 8). However, these differences in herding tend to be statistically insignificant. Where they are significant (two cases of lucky Shenzhen stocks), the pattern they exert is not significantly different from that prevailing among neutral stocks; hence it cannot be attributed to the unique impact of superstitions. In further support of our findings in Table 3, these results lead us to reject hypotheses 3a and 3b for noise-driven herding in lucky and unlucky stocks traded in both Shanghai and Shenzhen.

Furthermore, noise-driven herding is also evident for high-volatility days and absent for low-volatility ones for both stock types; the significance of the difference in its presence between high- and low-volatility days is confirmed in all cases (Panels D—F in Tables 7 and 8). However, when compared to the analogous phenomenon among neutral stocks, the superstitions-driven effects do not appear to be significantly stronger. The only exception are lucky Shanghai stocks for 30- and 60-MA volatility measures which tend to herd more in high- vs low-volatility conditions, also as compared to their neutral counterparts. Overall, however, the evidence to support the notion that superstitions (lucky and unlucky stock features) cause uniquely stronger herding in high-volatility conditions for both stock types and in both trading locations is very weak indeed; this tallies with our previous inference in section 5.2.2. and supports the overall rejection of hypotheses 4a and 4b.

The above results denote that noise-driven herding is prevalent in both lucky and unlucky stocks. However, to the extent that neutral stocks' herding is also motivated by noise, this suggests that noise-driven herding is not the exclusive property of superstitious stocks, but rather constitutes a market-wide phenomenon, in line with earlier findings (see, for example, Zhu et al., 2020, and references therein) on the dominant retail clientele of Chinese markets being herding-prone. This leads us to reject hypotheses 5a and 5b as universally valid propositions (although a pocket of their validity, in form of Shanghai lucky stocks under high volatility conditions, exists; this could be purely due to change, however).

5.4. Superstitions' irrelevance to market-wide herding: possible explanations

Overall, the evidence presented here suggests that superstitious and

[44] As Zheng et al. (2015) note: "…[China's] stock market is still full of inexperienced, less-educated retail investors, who are likely to herd after institutional investors or other sophisticated investors. According to a recent SWUFE China Household Finance Survey, 60% of new stockholders have junior high as their highest education level and 5.8% cannot read" (p. 62).

Table 3
Herding of lucky stocks and uncertainty.

	Shanghai				Shenzhen			
	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
Panel A: Above 30-day MA returns vs. Below 30-day MA returns								
Above 30-day MA	0.0130***	0.206***	−2.632***	0.056	0.0134***	0.208***	−3.023***	0.051
	(0.000)	(0.018)	(0.332)		(0.000)	(0.018)	(0.351)	
Below 30-day MA	0.0140***	0.329***	−2.418***	0.186	0.0146***	0.308***	−2.272***	0.184
	(0.000)	(0.021)	(0.356)		(0.000)	(0.020)	(0.336)	
Wald test	[0.692]				[0.108]			
Wald test vs neutral	−0.366 [0.209]				−0.118 [0.614]			
Panel B: Above 60-day MA returns vs. Below 60-day MA returns								
Above 60-day MA	0.0131***	0.205***	−2.639***	0.054	0.0135***	0.199***	−2.892***	0.048
	(0.000)	(0.018)	(0.333)		(0.000)	(0.018)	(0.347)	
Below 60-day MA	0.0139***	0.328***	−2.392***	0.187	0.0146***	0.311***	−2.318***	0.183
	(0.000)	(0.021)	(0.357)		(0.000)	(0.021)	(0.340)	
Wald test	[0.648]				[0.222]			
Wald test vs neutral	−0.284 [0.328]				−0.153 [0.510]			
Panel C: Above 252-day MA returns vs. Below 252-day MA returns								
Above 252-day MA	0.0132***	0.198***	−2.563***	0.051	0.0136***	0.190***	−2.778***	0.043
	(0.000)	(0.018)	(0.333)		(0.000)	(0.018)	(0.348)	
Below 252-day MA	0.0138***	0.334***	−2.451***	0.191	0.0145***	0.320***	−2.421***	0.189
	(0.000)	(0.021)	(0.358)		(0.000)	(0.021)	(0.340)	
Wald test	[0.837]				[0.448]			
Wald test vs neutral	−0.445 [0.125]				−0.125 [0.592]			
Panel D: Above 30-day MA volatility vs. Below 30-day MA volatility								
Above 30-day MA volatility	0.0085***	0.495***	−4.517***	0.260	0.0084***	0.496***	−4.426***	0.224
	(0.000)	(0.028)	(0.365)		(0.000)	(0.032)	(0.407)	
Below 30-day MA volatility	0.0136***	0.266***	4.288**	0.118	0.0141***	0.238***	2.958*	0.106
	(0.000)	(0.042)	(1.845)		(0.000)	(0.038)	(1.541)	
Wald test	[0.000]				[0.002]			
Wald test vs neutral	−1.738 [0.018]				0.848 [0.260]			
Panel E: Above 60-day MA volatility vs. Below 60-day MA volatility								
Above 60-day MA volatility	0.0085***	0.500***	−4.602***	0.234	0.0080***	0.519***	−4.691***	0.202
	(0.000)	(0.030)	(0.396)		(0.001)	(0.036)	(0.449)	
Below 60-day MA volatility	0.0139***	0.147***	9.693***	0.111	0.0145***	0.114***	8.735***	0.105
	(0.000)	(0.042)	(1.974)		(0.000)	(0.039)	(1.689)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	−2.458 [0.004]				0.765 [0.376]			
Panel F: Above 252-day MA volatility vs. Below 252-day MA volatility								
Above 252-day MA volatility	0.0082***	0.543***	−5.169***	0.186	0.0082***	0.532***	−4.924***	0.153
	(0.001)	(0.038)	(0.471)		(0.001)	(0.043)	(0.521)	
Below 252-day MA volatility	0.0140***	0.110**	8.862***	0.063	0.0145***	0.110**	6.803**	0.059
	(0.000)	(0.047)	(2.492)		(0.000)	(0.045)	(2.207)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	−0.393 [0.666]				0.613 [0.487]			

Notes: The table presents estimates from model (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 Shanghai- and Shenzhen-listed stocks. The above equation is estimated for each market state (high/low market returns/volatility) for stocks listed on the Shanghai or the Shenzhen stock exchange. The significance of the difference between the β_2 values (Above-minus-Below) in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). "Wald test vs neutral" refers to the test of the difference in β_2 differences in each panel vs analogous β_2 differences in corresponding neutral stocks (the resulting difference of differences is reported, *p*-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

non-superstitious stocks exhibit similarities in their herding, thus denoting that numerological superstitions do not motivate significantly stronger herding in Chinese markets. This may be due to herding in China being primarily motivated by intentional/spurious herding factors (irrespective of a stock's superstitious value), or Chinese investors discarding numerological superstitions (irrespective of whether they believe in them or not) when making trading decisions. Alternatively, most investors in Chinese markets may be non-superstitious (and their trades may cancel out those of superstitious ones), or superstitious individuals in China may refrain altogether from investing for some reason. In this section, we make several empirical attempts to investigate some of the likely causes of the documented irrelevance of superstitions for market-wide herding.[45]

Firstly, to investigate whether the lack of significant superstitious effects over herding is due to Chinese investors discarding their numerological superstitions in everyday trading decisions, we hypothesize that those superstitions, deeply embedded into Chinese investors' culture and tradition, would be most likely affecting investment decisions around days when traditions and culture play an elevated role in peoples' lives. To that end, we identify traditional Chinese festivals

[45] We thank an anonymous referee for suggesting to explore those alternatives.

Table 4
Herding of unlucky stocks and uncertainty.

	Shanghai				Shenzhen			
	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
Panel A: Above 30-day MA returns vs. Below 30-day MA returns								
Above 30-day MA	0.0137***	0.160***	−2.117***	0.023	0.0133***	0.200***	−2.570***	0.040
	(0.000)	(0.022)	(0.402)		(0.000)	(0.021)	(0.405)	
Below 30-day MA	0.0142***	0.343***	−2.620***	0.151	0.0142***	0.342***	−2.873***	0.165
	(0.000)	(0.024)	(0.414)		(0.000)	(0.022)	(0.370)	
Wald test	[0.371]				[0.624]			
Wald test vs neutral	0.352 [0.507]				0.937 [0.033]			
Panel B: Above 60-day MA returns vs. Below 60-day MA returns								
Above 60-day MA	0.0137***	0.162***	−2.160***	0.023	0.0133***	0.197***	−2.513***	0.041
	(0.000)	(0.022)	(0.402)		(0.000)	(0.020)	(0.396)	
Below 60-day MA	0.0142***	0.340***	−2.563***	0.150	0.0143***	0.341***	−2.868***	0.159
	(0.000)	(0.024)	(0.415)		(0.000)	(0.023)	(0.377)	
Wald test	[0.474]				[0.566]			
Wald test vs neutral	0.366 [0.490]				0.775 [0.076]			
Panel C: Above 252-day MA returns vs. Below 252-day MA returns								
Above 252-day MA	0.0138***	0.159***	−2.129***	0.022	0.0135***	0.187***	−2.394***	0.037
	(0.000)	(0.021)	(0.401)		(0.000)	(0.020)	(0.396)	
Below 252-day MA	0.0141***	0.343***	−2.583***	0.151	0.0142***	0.350***	−2.974***	0.164
	(0.000)	(0.024)	(0.418)		(0.000)	(0.023)	(0.378)	
Wald test	[0.421]				[0.346]			
Wald test vs neutral	0.121 [0.819]				0.812 [0.063]			
Panel D: Above 30-day MA volatility vs. Below 30-day MA volatility								
Above 30-day MA volatility	0.0091***	0.472***	−4.264***	0.177	0.0077***	0.526***	−4.760***	0.212
	(0.000)	(0.034)	(0.450)		(0.001)	(0.034)	(0.441)	
Below 30-day MA volatility	0.0140***	0.258***	3.778	0.080	0.0139***	0.266***	3.118	0.103
	(0.000)	(0.049)	(2.168)		(0.000)	(0.043)	(1.726)	
Wald test	[0.003]				[0.003]			
Wald test vs neutral	−0.976 [0.508]				0.355 [0.707]			
Panel E: Above 60-day MA volatility vs. Below 60-day MA volatility								
Above 60-day MA volatility	0.0090***	0.476***	−4.326***	0.168	0.0073***	0.551***	−5.050***	0.192
	(0.001)	(0.036)	(0.469)		(0.001)	(0.039)	(0.485)	
Below 60-day MA volatility	0.0142***	0.143**	9.136***	0.074	0.0142***	0.142**	8.667***	0.098
	(0.000)	(0.050)	(2.349)		(0.000)	(0.044)	(1.903)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	−1.625 [0.366]				0.474 [0.654]			
Panel F: Above 252-day MA volatility vs. Below 252-day MA volatility								
Above 252-day MA volatility	0.0086***	0.525***	−4.951***	0.141	0.0073***	0.576***	−5.403***	0.151
	(0.001)	(0.043)	(0.543)		(0.001)	(0.046)	(0.557)	
Below 252-day MA volatility	0.0143***	0.141**	6.346**	0.040	0.0142***	0.123**	7.722***	0.059
	(0.000)	(0.056)	(2.980)		(0.000)	(0.051)	(2.494)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	2.342 [0.211]				−0.784 [0.613]			

Notes: The table presents estimates from model (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 Shanghai- and Shenzhen-listed stocks. The above equation is estimated for each market state (high/low market returns/volatility) for stocks listed on the Shanghai or the Shenzhen stock exchange. The significance of the difference between the β_2 values (Above-minus-Below) in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). "Wald test vs neutral" refers to the test of the difference in β_2 differences in each panel vs analogous β_2 differences in corresponding neutral stocks (the resulting difference of differences is reported, p-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

which are most likely to carry an elevated emotional load and could be triggering superstitious behaviours among investors. These are further divided into auspicious and inauspicious events, depending on their fortuitous (or otherwise) connotation.[46] We estimate model (1) separately for observations around the relevant festival type and for the rest of the sample. Results (Table 9) indicate that even these "super-superstitious" subperiods do not generate more superstitions-driven herding. Specifically, Shanghai-traded lucky stocks (Panel A) show no evidence of herding at all during auspicious festivals ($\beta_2 > 0$ and insignificant), while for their unlucky counterparts (Panel C), they do not herd significantly during inauspicious festivals ($\beta_2 < 0$ but insignificant), with this effect not being significantly stronger than outside of inauspicious festivals (p-value of 0.557), and not significantly stronger (p-value of 0.328) than among neutral stocks (Panel D). With respect to Shenzhen-listed stocks, we observe qualitatively similar patterns. Overall, even if one focuses on times of the year when individuals' decisions could be affected by irrational superstitions embedded in their culture and tradition the most (i.e., traditional festivals), those superstitions still show no effect on investors' propensity to herd. These results

[46] The auspicious festivals include Spring, Lantern, Duanwu, and Mid-Autumn festival, while the inauspicious festivals are Qingming and Zhongyuan festival (DuBois, 2014).

Table 5
Fundamentals/Non-fundamentals-driven herding in superstitious and neutral stocks (Shanghai).

	Shanghai-fundamental				Shanghai-nonfundamental			
	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
Panel A: Superstitious vs. Neutral								
Superstitious	0.0156***	0.0079*	0.231***	0.018	−0.0020***	0.246***	−2.304***	0.097
	(0.000)	(0.005)	(0.081)		(0.000)	(0.013)	(0.240)	
Neutral	0.0155***	0.0063	0.224**	0.018	−0.0019***	0.238***	−2.366***	0.085
	(0.000)	(0.004)	(0.074)		(0.000)	(0.014)	(0.241)	
Wald test	[0.673]				[0.678]			
Panel B: Lucky vs. Unlucky								
Lucky	0.0156***	0.0081*	0.224***	0.018	−0.0021***	0.247***	−2.309***	0.098
	(0.000)	(0.004)	(0.080)		(0.000)	(0.013)	(0.240)	
Unlucky	0.0159***	0.0047	0.290***	0.018	−0.0019***	0.233***	−2.186***	0.064
	(0.000)	(0.005)	(0.082)		(0.000)	(0.016)	(0.285)	
Wald test	[0.041]				[0.524]			
Panel C: Very Lucky vs. Lucky								
Very lucky	0.0154***	0.0098**	0.206**	0.019	−0.0021***	0.250***	−2.333***	0.094
	(0.000)	(0.005)	(0.082)		(0.000)	(0.014)	(0.249)	
Lucky	0.0156***	0.0081*	0.224***	0.018	−0.0021***	0.247***	−2.309***	0.098
	(0.000)	(0.004)	(0.080)		(0.000)	(0.013)	(0.240)	
Wald test	[0.004]				[0.766]			

The table presents estimates from the following equations (modified model (1)):

$CSAD_{FUND,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R^2_{M,t} + e_t$

$CSAD_{NONFUND,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R^2_{M,t} + e_{t.}$

$R_{M,t}$ is the market return for Shanghai-listed stocks. $CSAD_{FUND,t}$ is the part of the variation of $CSAD_{m,t}$ due to fundamentals; $CSAD_{NONFUND,t}$ is the part of the variation of $CSAD_{m,t}$ due to non-fundamentals (i.e., due to noise). The above equation is estimated for each category (neutral/lucky/unlucky/very lucky) of stocks listed on the Shanghai stock exchange. The significance of the difference between the β_2 values in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Fundamentals/Non-fundamentals-driven herding in superstitious and neutral stocks (Shenzhen).

	Shenzhen-fundamental				Shenzhen -nonfundamental			
	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
Panel A: Superstitious vs. Neutral								
Superstitious	0.0164***	−0.0221***	0.862***	0.053	−0.0023***	0.251***	−2.578***	0.095
	(0.000)	(0.004)	(0.074)		(0.000)	(0.013)	(0.236)	
Neutral	0.0165***	−0.0225***	0.856***	0.052	−0.0023***	0.246***	−2.546***	0.089
	(0.000)	(0.004)	(0.073)		(0.000)	(0.014)	(0.237)	
Wald test	[0.181]				[0.767]			
Panel B: Lucky vs. Unlucky								
Lucky	0.0164***	−0.0224***	0.867***	0.053	−0.0023***	0.247***	−2.528***	0.092
	(0.000)	(0.004)	(0.075)		(0.000)	(0.014)	(0.236)	
Unlucky	0.0163***	−0.0194***	0.814***	0.053	−0.0024***	0.262***	−2.709***	0.082
	(0.000)	(0.004)	(0.072)		(0.000)	(0.015)	(0.265)	
Wald test	[0.002]				[0.328]			
Panel C: Very Lucky vs. Lucky								
Very lucky	0.0157***	−0.0203***	0.791***	0.053	−0.0023***	0.251***	−2.673***	0.053
	(0.000)	(0.004)	(0.068)		(0.000)	(0.018)	(0.315)	
Lucky	0.0164***	−0.0224***	0.867***	0.053	−0.0023***	0.247***	−2.528***	0.092
	(0.000)	(0.004)	(0.075)		(0.000)	(0.014)	(0.236)	
Wald test	[0.003]				[0.519]			

The table presents estimates from the following equations (modified model (1)):

$CSAD_{FUND,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R^2_{M,t} + e_t$

$CSAD_{NONFUND,t} = \beta_0 + \beta_1 |R_{M,t}| + \beta_2 R^2_{M,t} + e_t$

$R_{M,t}$ is the market return for Shenzhen-listed stocks. $CSAD_{FUND,t}$ is the part of the variation of $CSAD_{m,t}$ due to fundamentals; $CSAD_{NONFUND,t}$ is the part of the variation of $CSAD_{m,t}$ due to non-fundamentals (i.e., due to noise). The above equation is estimated for each category (neutral/lucky/unlucky/very lucky) of stocks listed on the Shenzhen stock exchange. The significance of the difference between the β_2 values in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Non-fundamental herding of lucky stocks and uncertainty.

	Shanghai				Shenzhen			
	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
Panel A: Above 30-day MA returns vs. Below 30-day MA returns								
Above 30-day MA	−0.0025***	0.281***	−2.707***	0.133	−0.0030***	0.300***	−3.104***	0.139
	(0.000)	(0.017)	(0.324)		(0.000)	(0.018)	(0.351)	
Below 30-day MA	−0.0016***	0.213***	−1.911***	0.071	−0.0016***	0.200***	−1.995***	0.060
	(0.000)	(0.021)	(0.356)		(0.000)	(0.020)	(0.336)	
Wald test	[0.147]				[0.018]			
Wald test vs neutral	−0.410 [0.158]				−0.168 [0.472]			
Panel B: Above 60-day MA returns vs. Below 60-day MA returns								
Above 60-day MA	−0.0025***	0.278***	−2.687***	0.129	−0.0029***	0.290***	−2.962***	0.133
	(0.000)	(0.017)	(0.325)		(0.000)	(0.018)	(0.349)	
Below 60-day MA	−0.0016***	0.215***	−1.914***	0.074	−0.0016***	0.204***	−2.059***	0.062
	(0.000)	(0.021)	(0.356)		(0.000)	(0.021)	(0.339)	
Wald test	[0.160]				[0.055]			
Wald test vs neutral	−0.323 [0.267]				−0.196 [0.400]			
Panel C: Above 252-day MA returns vs. Below 252-day MA returns								
Above 252-day MA	−0.0023***	0.269***	−2.586***	0.121	−0.0028***	0.280***	−2.837***	0.125
	(0.000)	(0.017)	(0.327)		(0.000)	(0.018)	(0.351)	
Below 252-day MA	−0.0018***	0.223***	−2.003***	0.078	−0.0018***	0.214***	−2.169***	0.067
	(0.000)	(0.021)	(0.357)		(0.000)	(0.021)	(0.338)	
Wald test	[0.290]				[0.156]			
Wald test vs neutral	−0.476 [0.101]				−0.169 [0.469]			
Panel D: Above 30-day MA volatility vs. Below 30-day MA volatility								
Above 30-day MA volatility	−0.0068***	0.461***	−4.425***	0.267	−0.0078***	0.500***	−5.062***	0.221
	(0.000)	(0.024)	(0.318)		(0.000)	(0.028)	(0.357)	
Below 30-day MA volatility	−0.0020***	0.248***	5.734**	0.131	−0.0022***	0.251***	3.260**	0.122
	(0.000)	(0.041)	(1.804)		(0.000)	(0.038)	(1.517)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	−1.866 [0.010]				0.852 [0.257]			
Panel E: Above 60-day MA volatility vs. Below 60-day MA volatility								
Above 60-day MA volatility	−0.0069***	0.471***	−4.549***	0.239	−0.0082***	0.525***	−5.339***	0.201
	(0.000)	(0.027)	(0.349)		(0.001)	(0.031)	(0.393)	
Below 60-day MA volatility	−0.0018***	0.158***	9.399***	0.118	−0.0019***	0.132***	8.930***	0.121
	(0.000)	(0.041)	(1.933)		(0.000)	(0.039)	(1.668)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	−2.478 [0.003]				0.741 [0.394]			
Panel F: Above 252-day MA volatility vs. Below 252-day MA volatility								
Above 252-day MA volatility	−0.0071***	0.509***	−5.070***	0.186	−0.0080***	0.537***	−5.573***	0.150
	(0.001)	(0.033)	(0.420)		(0.001)	(0.038)	(0.459)	
Below 252-day MA volatility	−0.0016***	0.0953**	10.230***	0.070	−0.0019***	0.117***	7.647***	0.071
	(0.000)	(0.046)	(2.450)		(0.000)	(0.045)	(2.196)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	−0.477 [0.601]				0.548 [0.536]			

Notes: The table presents estimates from model (1): $CSAD_{NONFUND,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2 R_{M,t}^2 + e_t$. $CSAD_{NONFUND,t}$ ($R_{M,t}$) is the daily non-fundamentals driven cross-sectional absolute deviation of returns (market return) for Shanghai- and Shenzhen-listed stocks. The above equation is estimated for each market state (high/low market returns/volatility) for stocks listed on the Shanghai or the Shenzhen stock exchange. The significance of the difference between the β_2 values (Above-minus-Below) in each panel and for each market is tested using the Wald test (*p*-values are shown in square brackets). "Wald test vs neutral" refers to the test of the difference in β_2 differences in each panel vs analogous β_2 differences in corresponding neutral stocks (the resulting difference of differences is reported, *p*-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

show that superstitions fail to produce distinct effects over herding even around superstitiously charged days, and align with the notion that Chinese investors may be discarding their numerological superstitions in everyday trading decisions (or superstitions-driven trades are not substantial enough to affect market-wide outcomes), this being a potential explanation as to why our study does not find compelling empirical evidence of the impact of numerological superstitions on market-wide herding.

To further investigate whether Chinese investors refrain from trading on superstitions, or do not uphold such beliefs at all, as a potential explanation for our findings of irrelevance of superstitions for market-wide herding, we propose that, if superstitions play any role in herding at all, their impact should be most visible in stocks traded predominantly by retail investors, as they have been shown elsewhere to be most likely to engage in noise trading (Barber et al., 2009a, 2009b; Barber & Odean, 2013). To empirically capture this effect, we collect data on institutional ownership of Chinese firms from CSMAR and divide our sample into three equal groups: the lowest tercile encompasses those stocks where the fraction of retail investors is the highest (as the fraction of institutional shareholders is the lowest). If superstitious beliefs only manifest themselves in the trades of irrationality-prone retail investors, we should observe stronger herding in superstitious stocks in the low-

Table 8
Non-fundamental herding of unlucky stocks and uncertainty.

	Shanghai				Shenzhen			
	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
Panel A: Above 30-day MA returns vs. Below 30-day MA returns								
Above 30-day MA	−0.0022***	0.246***	−2.194***	0.078	−0.0029***	0.286***	−2.658***	0.109
	(0.000)	(0.021)	(0.398)		(0.000)	(0.021)	(0.405)	
Below 30-day MA	−0.0016***	0.221***	−2.141***	0.053	−0.0019***	0.237***	−2.589***	0.062
	(0.000)	(0.024)	(0.414)		(0.000)	(0.022)	(0.370)	
Wald test	[0.924]				[0.910]			
Wald test vs neutral	0.332 [0.531]				0.871 [0.046]			
Panel B: Above 60-day MA returns vs. Below 60-day MA returns								
Above 60-day MA	−0.0022***	0.246***	−2.213***	0.076	−0.0029***	0.282***	−2.593***	0.111
	(0.000)	(0.021)	(0.398)		(0.000)	(0.020)	(0.397)	
Below 60-day MA	−0.0017***	0.220***	−2.112***	0.053	−0.0019***	0.237***	−2.598***	0.060
	(0.000)	(0.024)	(0.415)		(0.000)	(0.023)	(0.377)	
Wald test	[0.857]				[0.993]			
Wald test vs neutral	0.349 [0.511]				0.712 [0.102]			
Panel C: Above 252-day MA returns vs. Below 252-day MA returns								
Above 252-day MA	−0.0021***	0.240***	−2.159***	0.073	−0.0028***	0.271***	−2.464***	0.105
	(0.000)	(0.021)	(0.397)		(0.000)	(0.021)	(0.398)	
Below 252-day MA	−0.0018***	0.225***	−2.159***	0.055	−0.0020***	0.247***	−2.712***	0.064
	(0.000)	(0.024)	(0.416)		(0.000)	(0.023)	(0.377)	
Wald test	[0.999]				[0.684]			
Wald test vs neutral	0.106 [0.841]				0.747 [0.086]			
Panel D: Above 30-day MA volatility vs. Below 30-day MA volatility								
Above 30-day MA volatility	−0.0065***	0.439***	−4.213***	0.167	−0.0083***	0.527***	−5.333***	0.200
	(0.000)	(0.031)	(0.409)		(0.000)	(0.031)	(0.400)	
Below 30-day MA volatility	−0.0019***	0.243***	5.180**	0.089	−0.0024***	0.280***	3.289*	0.115
	(0.000)	(0.048)	(2.133)		(0.000)	(0.042)	(1.706)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	−1.099 [0.453]				0.552 [0.559]			
Panel E: Above 60-day MA volatility vs. Below 60-day MA volatility								
Above 60-day MA volatility	−0.0066***	0.447***	−4.314***	0.159	−0.0087***	0.553***	−5.635***	0.183
	(0.000)	(0.033)	(0.427)		(0.001)	(0.035)	(0.439)	
Below 60-day MA volatility	−0.0017***	0.157***	8.769***	0.079	−0.0021***	0.161***	8.701***	0.111
	(0.000)	(0.050)	(2.311)		(0.000)	(0.044)	(1.883)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	−1.613 [0.369]				0.675 [0.523]			
Panel F: Above 252-day MA volatility vs. Below 252-day MA volatility								
Above 252-day MA volatility	−0.0069***	0.491***	−4.883***	0.133	−0.0088***	0.578***	−5.996***	0.144
	(0.001)	(0.039)	(0.495)		(0.001)	(0.041)	(0.506)	
Below 252-day MA volatility	−0.0016***	0.127**	7.771***	0.044	−0.0020***	0.131***	8.463***	0.069
	(0.000)	(0.055)	(2.943)		(0.000)	(0.051)	(2.482)	
Wald test	[0.000]				[0.000]			
Wald test vs neutral	2.168 [0.252]				−0.691 [0.656]			

Notes: The table presents estimates from model (1): $CSAD_{NONFUND,t} = \beta_0 + \beta_1|R_{M,t}| + \beta_2 R_{M,t}^2 + e_t$. $CSAD_{NONFUND,t}$ ($R_{M,t}$) is the daily non-fundamentals driven cross-sectional absolute deviation of returns (market return) for Shanghai- and Shenzhen-listed stocks. The above equation is estimated for each market state (high/low market returns/volatility) for stocks listed on the Shanghai or the Shenzhen stock exchange. The significance of the difference between the β_2 values (Above-minus-Below) in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). "Wald test vs neutral" refers to the test of the difference in β_2 differences in each panel vs analogous β_2 differences in corresponding neutral stocks (the resulting difference of differences is reported, p-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

institutional-ownership subsample.

Results (Table 10) demonstrate that superstitions-driven herding is not confined to stocks mostly traded by retail investors. While for lucky stocks (Panel A) we do find significant herding, it is not significantly different compared to the high institutional ownership subsample (p-value of 0.717), and this pattern is not different from neutral stocks (p-value of 0.658), either (Panel B). For unlucky stocks (Panel C), there is even less evidence of herding among low-institutional-ownership stocks (β_2 is insignificant). Overall, these results do not support the notion that superstitions make any difference to how investors herd, hence are in line with the notion that Chinese investors refrain from trading on superstitions, or do not uphold such beliefs sufficiently strongly in the context of everyday stock market herding.

Given the universal presence of irrational investor herding documented in this study, an issue arising is what other forces of irrationality, superstitions aside, could be driving that market phenomenon. We propose that investors' sentiment, as documented in numerous studies (Baker & Wurgler, 2006; Han & Li, 2017; Huang et al., 2015), could be the dominant behavioural force behind their trades and the resulting market behaviour in form of herding: sentiment could dominate any trading motives and/or observed price patterns over those potentially resulting from decisions based on superstitious beliefs, even if those

Table 9
Herding and auspicious/inauspicious festivals.

	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
	Shanghai				Shenzhen			
Panel A: Lucky stocks								
Auspicious festivals	0.0136***	0.177	0.610	0.114	0.0149***	0.073	2.997	0.132
	(0.001)	(0.134)	(2.429)		(0.001)	(0.133)	(2.836)	
Rest of the sample period	0.0135***	0.256***	−2.112***	0.109	0.0141***	0.226***	−1.690***	0.101
	(0.000)	(0.014)	(0.252)		(0.000)	(0.014)	(0.247)	
Wald test	[0.165]				[0.020]			
Wald test vs neutral	2.171 [0.000]				0.103 [0.880]			
Panel B: Neutral stocks								
Auspicious festivals	0.0130***	0.251*	−1.596	0.088	0.0151***	0.071	2.866	0.141
	(0.001)	(0.133)	(2.414)		(0.001)	(0.123)	(2.628)	
Rest of the sample period	0.0136***	0.244***	−2.147***	0.095	0.0142***	0.224***	−1.718***	0.097
	(0.000)	(0.014)	(0.252)		(0.000)	(0.014)	(0.248)	
Wald test	[0.771]				[0.015]			
Panel C: Unlucky stocks								
Inauspicious festivals	0.0129***	0.329	−5.179	0.056	0.0128***	0.306	−4.455	0.070
	(0.002)	(0.277)	(6.077)		(0.001)	(0.213)	(4.081)	
Rest of the sample period	0.0140***	0.238***	−1.886***	0.073	0.0139***	0.242***	−1.882***	0.091
	(0.000)	(0.017)	(0.296)		(0.000)	(0.016)	(0.274)	
Wald test	[0.557]				[0.504]			
Wald test vs neutral	3.630 [0.328]				0.472 [0.782]			
Panel D: Neutral stocks								
Inauspicious festivals	0.0120***	0.506**	−9.050*	0.136	0.0141***	0.253	−4.725	0.034
	(0.001)	(0.226)	(4.969)		(0.001)	(0.216)	(4.149)	
Rest of the sample period	0.0136***	0.244***	−2.127***	0.094	0.0142***	0.223***	−1.680***	0.098
	(0.000)	(0.014)	(0.251)		(0.000)	(0.014)	(0.247)	
Wald test	[0.107]				[0.421]			

Notes: The table presents estimates from model (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 Shanghai- and Shenzhen-listed stocks. The above equation is estimated for each stock type (lucky/unlucky/neutral) and regime (auspicious/inauspicious festivals and their respective remaining sub-samples) for stocks listed on the Shanghai or the Shenzhen stock exchange. The significance of the difference between the β_2 values in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). "Wald test vs neutral" refers to the test of the difference in β_2 differences in each panel vs analogous β_2 differences in corresponding neutral stocks (the resulting difference of differences is reported, p-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

beliefs affect other aspects of individuals' lives and manifest themselves in specific instances such as, e.g., IPOs (Hirshleifer et al., 2018; Weng, 2018). To that end, we employ a measure of investor sentiment, the consumer sentiment index (CCI) following the literature (e.g., Lemmon & Portniaguina, 2006; Schmeling, 2009; Bathia & Bredin, 2013; Wang et al., 2021; El Hajjar et al., 2024), obtained from Refinitiv. To account for the well documented sentiment's persistence (e.g., Schmeling, 2009; Wang et al., 2021) and therefore predictability (hence, a weak "surprise" content of the observed levels of sentiment), we use a measure of *unexpected* sentiment, computed as the monthly value of CCI minus its 12-months moving average value. This variable is then used to split the sample into observations with high (above the median of the unexpected sentiment) and low (below median) sentiment "regimes", and model (1) is fitted into each regime. If sentiment is the behavioural force affecting market-wide herding, we should observe significant herding differences between high- vs low-sentiment regimes; if sentiment dominates superstitious beliefs as the behavioural factor behind herding, we should observe impactful sentiment across all types of stocks (lucky/unlucky/neutral), with this effect not being significantly stronger for superstitious stocks.

Table 11 presents the results of this sentiment-focused analysis. Firstly, taking all stock types together (Panel A), for both Shanghai and Shenzhen we observe that herding is present in both sentiment regimes, but significantly stronger when unexpected sentiment is low (i.e., pessimistic). To the extent that low sentiment coincides with bear markets and periods of high uncertainty/volatility, this result is in line with research showing that herding is stronger in down markets (e.g.: Gavriilidis et al., 2013; Goodfellow et al., 2009; Holmes et al., 2013) and when volatility is high (e.g.: Blasco et al., 2012; Economou et al., 2015). Herding in superstitious stocks specifically (Panel B) is significant and lower (β_2 less negative) for high unexpected sentiment, but the same pattern is observed for non-superstitious (neutral) stocks (Panel C), with the difference in how sentiment affects herding between these two stock types not being statistically significant (*p*-value of 0.404). This observation also generally holds when lucky and unlucky stocks are considered separately (Panels D and E) and compared to their neutral counterparts. Hence, the result is that irrational sentiment is a strong and omnipotent force behind investor herding, however, given that it does not tend to affect superstitious stocks differently from non-superstitious stocks, the results seem to align with our prior reasoning that it is investor sentiment, not superstitious beliefs, which drives herding in Chinese stocks.

The above analysis offers some compelling insights into how numerological superstitions do not motivate investor herding, with this result being in line with several existing studies showing lacking or mixed evidence for the superstitions-market outcomes nexus (Chung et al., 2014; Haggard, 2015) as well as with the literature demonstrating a diminishing impact of superstitions with investors' learning/experience, information availability, and overall market sophistication (see Section 2.2.2. for details). However, future research could explore this issue further using alternative methods. For instance, surveys could be employed to better measure investors' attachment to superstitious beliefs, and whether, and under what circumstances, these are important in financial decision making. The impact of superstitions on trading

Table 10
Herding and institutional stock ownership.

	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
	Shanghai				Shenzhen			
Panel A: Lucky stocks								
Low institutional ownership	0.0135***	0.272***	−2.226***	0.022	0.0144***	0.208***	−1.139*	0.022
	(0.000)	(0.036)	(0.642)		(0.000)	(0.034)	(0.587)	
High institutional ownership	0.0130***	0.303***	−2.050***	0.046	0.0140***	0.240***	−1.072**	0.044
	(0.000)	(0.030)	(0.528)		(0.000)	(0.029)	(0.507)	
Wald test	[0.717]				[0.856]			
Wald test vs neutral	−0.203 [0.658]				0.106 [0.853]			
Panel B: Neutral stocks								
Low institutional ownership	0.0138***	0.245***	−1.875***	0.018	0.0142***	0.200***	−0.996*	0.021
	(0.000)	(0.037)	(0.663)		(0.000)	(0.035)	(0.605)	
High institutional ownership	0.0135***	0.297***	−1.903***	0.042	0.0145***	0.218***	−0.823	0.039
	(0.000)	(0.031)	(0.553)		(0.000)	(0.029)	(0.514)	
Wald test	[0.960]				[0.821]			
Panel C: Unlucky stocks								
Low institutional ownership	0.0139***	0.178***	−0.630	0.014	0.0144***	0.115***	0.0125	0.011
	(0.000)	(0.039)	(0.704)		(0.001)	(0.036)	(0.638)	
High institutional ownership	0.0137***	0.252***	−0.848	0.024	0.0137***	0.249***	−1.187**	0.038
	(0.000)	(0.042)	(0.756)		(0.000)	(0.032)	(0.562)	
Wald test	[0.896]				[0.542]			
Wald test vs neutral	0.191 [0.896]				1.373 [0.327]			

Notes: The table presents estimates from model (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 Shanghai- and Shenzhen-listed stocks. The above equation is estimated for each stock type (lucky/unlucky/neutral) and level of institutional ownership (low for bottom tercile and high for top tercile of institutional ownership) for stocks listed on the Shanghai or the Shenzhen stock exchange. The significance of the difference between the β_2 values in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). "Wald test vs neutral" refers to the test of the difference in β_2 differences in each panel vs analogous β_2 differences in corresponding neutral stocks (the resulting difference of differences is reported, p-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

behaviour and market-wide outcomes could further be explored in laboratory experiments (see Duxbury, 2015, for a review).

6. Conclusions

Although superstitions have been found to give rise to correlated behaviour in several decision-settings, the potential for such correlation arising in the equity investment context has been largely underexplored to date. This is especially the case for everyday trading behaviour leading to market inefficiency at the aggregate level, rather that superstitions affecting micro-level idiosyncratic price patterns or individual decisions, and/or only at times of rare, salient events. We address this issue by examining how traditional Chinese numerological superstitions relate to investors' herd behaviour in Mainland China's two equity markets (Shanghai and Shenzhen) for the 2000–2020 period by relying on a classification of stocks as "lucky" or "unlucky" based on the presence of digits deemed numerologically lucky/unlucky in their tickers. Overall, there is no compelling evidence that these superstitions affect market-wide investors' herding. We find that superstitious (lucky and unlucky) stocks herd strongly in Chinese markets, yet their herding is not significantly different from that of non-superstitious (neutral) ones. Lucky/unlucky stocks' herding tends to be insignificantly different between high-versus-low market return days, yet significantly different between high-versus-low volatility days (with its presence being identified exclusively on high volatility days); however, these patterns are not more pronounced than those in neutral stocks and, hence, cannot be attributed to the impact of superstitions. The herding of all three stock-types (lucky/unlucky/neutral) is predominantly noise-driven.

Overall, the evidence presented here suggests that superstitious and non-superstitious stocks exhibit similarities in their herding, thus denoting that numerological superstitions do not motivate significantly stronger herding in Chinese markets. This may be due to herding in China being primarily motivated by intentional/spurious herding factors (irrespective of a stock's superstitious value), or Chinese investors discarding numerological superstitions (irrespective of whether they believe in them or not) when making trading decisions. Alternatively, most investors in Chinese markets may be non-superstitious (and their trades may cancel out those of superstitious ones), or superstitious individuals in China may refrain altogether from investing for some reason. Our additional tests reveal that herding in superstitious stocks is not stronger for those mostly traded by retail investors (who are most likely to be affected by superstitions), nor is it elevated during traditional festival periods (when cultural aspects such as superstitions should be manifesting themselves most), supporting the notion that numerical superstitions are not a sufficiently relevant factor in Chinese stock market trading. Instead, we document that an alternative behavioural factor, namely investor sentiment, is a dominant force significantly driving herding in Chinese stocks, both superstitious and neutral ones.

Our findings reveal a more complex relationship between superstitions and financial decisions than hitherto documented in this branch of the literature: while prior studies almost unanimously show that superstitions matter in financial context[47] (leading to price clustering toward (away from) lucky (unlucky) numbers, higher IPO premia and lower crash risk for stocks with lucky tickers, as per discussion in Section 2.2.2), we demonstrate that the impact of superstitions is not necessarily universally dominant in all aspects of investors' decisions, or at least that

[47] Of course, one cannot rule out that the picture the literature paints is not unbiased, as it is well documented that studies reporting weak magnitudes of analysed effects and finding insignificant results are less likely to be published (e.g., Harvey et al., 2016; Ioannidis et al., 2017). Our results are largely insignificant for most hypotheses of interest and are therefore not indicative of such potential p-hacking.

Table 11
Herding and investor sentiment.

	β_0	β_1	β_2	R^2	β_0	β_1	β_2	R^2
	Shanghai				Shenzhen			
Panel A: All stocks								
High sentiment	0.0138***	0.200***	−0.805**	0.103	0.0141***	0.188***	−0.513	0.118
	(0.000)	(0.019)	(0.396)		(0.000)	(0.019)	(0.397)	
Low sentiment	0.0134***	0.282***	−2.717***	0.109	0.0141***	0.242***	−2.117***	0.094
	(0.000)	(0.020)	(0.337)		(0.000)	(0.020)	(0.333)	
Wald test	[0.012]				[0.038]			
Panel B: Superstitious stocks								
High sentiment	0.0138***	0.202***	−0.866**	0.101	0.0141***	0.189***	−0.550	0.114
	(0.000)	(0.020)	(0.399)		(0.000)	(0.020)	(0.402)	
Low sentiment	0.0133***	0.288***	−2.703***	0.114	0.0141***	0.243***	−2.114***	0.094
	(0.000)	(0.020)	(0.341)		(0.000)	(0.021)	(0.336)	
Wald test	[0.001]				[0.043]			
Wald test vs neutral	−0.220 [0.404]				−0.100 [0.652]			
Panel C: Neutral stocks								
High sentiment	0.0137***	0.196***	−0.701*	0.101	0.0143***	0.184***	−0.418	0.112
	(0.000)	(0.020)	(0.401)		(0.000)	(0.020)	(0.405)	
Low sentiment	0.0134***	0.270***	−2.758***	0.093	0.0143***	0.235***	−2.083***	0.086
	(0.000)	(0.020)	(0.400)		(0.000)	(0.021)	(0.337)	
Wald test	[0.007]				[0.033]			
Panel D: Lucky stocks								
High sentiment	0.0138***	0.203***	−0.839**	0.102	0.0141***	0.185***	−0.479	0.112
	(0.000)	(0.020)	(0.402)		(0.000)	(0.020)	(0.404)	
Low sentiment	0.0133***	0.289***	−2.723**	0.115	0.0141***	0.240***	−2.060***	0.092
	(0.000)	(0.020)	(0.340)		(0.000)	(0.021)	(0.337)	
Wald test	[0.014]				[0.046]			
Wald test vs neutral	−0.173 [0.502]				−0.083 [0.717]			
Panel E: Unlucky stocks								
High sentiment	0.0140***	0.186***	−1.125**	0.056	0.0139***	0.203***	−0.894**	0.091
	(0.000)	(0.023)	(0.468)	0.081	(0.000)	(0.022)	(0.455)	
Low sentiment	0.0140***	0.273***	−2.425***		0.0139***	0.261***	−2.294***	0.087
	(0.000)	(0.024)	(0.403)		(0.000)	(0.023)	(0.371)	
Wald test	[0.129]				[0.048]			
Wald test vs neutral	−0.757 [0.094]				−0.265 [0.492]			

Notes: The table presents estimates from model (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 Shanghai- and Shenzhen-listed stocks. The above equation is estimated for each stock type (superstitious/lucky/unlucky/neutral) and investor sentiment level subsample for stocks listed on the Shanghai or the Shenzhen stock exchange. The significance of the difference between the β_2 values in each panel and for each market is tested using the Wald test (p-values are shown in square brackets). "Wald test vs neutral" refers to the test of the difference in β_2 differences in each panel vs analogous β_2 differences in corresponding neutral stocks (the resulting difference of differences is reported, p-values are shown in square brackets). Parentheses include standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

it does not inevitably lead to biased aggregate outcomes and market inefficiency (while acting on superstitions can still be financially detrimental on individual level).

Although the evidence presented in this study hails from China, we would also argue that it bears particular implications for other markets. The fact that numerological superstitions were found to generate no distinct herding at the market-level in the retail-dominated setting of Chinese markets suggests that widely shared irrational beliefs need not necessarily motivate correlation in noise investors' trades, thus denoting that not all irrational (and correlated) beliefs are likely to stimulate destabilizing outcomes in capital markets. As this suggests that irrational beliefs contribute non-uniformly to investors' herding, this denotes that the latter may be affected by differences in such beliefs across different markets; an initial implication, therefore, of this is that it is necessary to place more focus on the detection of noise drivers in each market - beyond simply confirming the presence of noise trading. What is more, the fact that China is dominated by retail investors further suggests that superstitious effects over herding may also be absent in other retail-dominated markets; if so, this would indicate that prevailing superstitions need not necessarily be acted upon in investment decisions, thus pointing toward a potential cognitive dissonance in the practice of investors. In this case, for example, we would be faced with investors subscribing to a superstitious belief, yet not acting on it in all domains of their life and would raise the question of why this is so; this issue would be best addressed in the context of qualitative frameworks (e.g., via investors' surveys), as it would allow for investors the opportunity of elaborating on the role of those beliefs in their trades and why they may/not follow them in their investments.

Future research could investigate further if the "pocket of superstition" identified in some of our results, i.e., lucky stocks in Shanghai herding stronger on high-volatility days, is just a statistical artefact, or if it reveals a genuine underlying impact of superstitious attitudes. Assuming availability of investor-level transaction data, one could also investigate individual, rather than market-wide, herding as a potential function of superstitious believes. Furthermore, it is possible that superstitious attitudes affect investment decisions in assets other than stocks, e.g., those which are more difficult to value such as cryptocurrencies or NFTs. In addition, it is possible that superstitions affect other behavioural patterns, herding aside. An example here is feedback trading, which relies on extrapolating from historical prices; assuming that some feedback traders rely on numerological superstitions similar to those outlined here and their presence is conditioned on whether the previous trading day's closing prices bear lucky/unlucky ending-digits, this can give rise to novel market dynamics. We hope that our paper will spur further interest in this area of research.

Data availability

No

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