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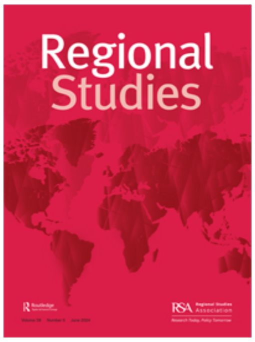

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Herding and reverse herding in US housing markets: new evidence from a metropolitan-level analysis

Matthew Pollock[a*], Masaki Mori[b] and Yi Wu[a]

ABSTRACT

This study is the first to examine herding and reverse herding in US metropolitan housing markets based on Zillow ZIP-level house price indices. Reverse herding is found to be more prevalent than herding, which differs markedly from equity markets and outcomes derived from less granular house price indices. The results suggest that the interaction between price appreciation and overconfidence may drive reverse herding. Also, herding and reverse herding show strong dependency on market conditions. Wide spatial and temporal variation in herding and reverse herding suggests the importance of local characteristics as determinants of the rationality of market responses.

KEYWORDS

Herding; reverse herding; housing; overconfidence

JEL D82, R31, R32

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1. INTRODUCTION

This study is the first to examine herding and reverse herding in the United States (US) housing markets at the metropolitan statistical area (MSA)-level, which allows identification of local variation in herding and reverse herding. Housing markets exhibit unique characteristics, such as local variation, high information acquisition costs and information inefficiency, which are distinct from equity markets. These characteristics suggest the importance of examining the possible evidence of reverse herding as well as herding at the local level. The environments under which herding and reverse herding are observed are examined, focusing on market conditions (up and down markets), a major crisis period and the interaction of overconfidence with price appreciation. These sub-analyses shed some light on the determinants of herding and reverse herding behaviours.

This paper contributes to the existing literature in several ways. Firstly, this study adds to the fairly limited research on herding in direct real estate and housing in particular. Also, investigating a largely owner-occupier market assesses herding behaviours among retail investors who are also consumers of the investment good. Secondly, this study advances the understanding of herding in housing markets by analysing it at a new spatial level. A unique database of local house price indices is employed to proxy the behaviour of individuals and test irrational responses at the city level. Thirdly, this study delves into the phenomenon of reverse herding, which is an underexplored topic in investment markets generally. By considering the context of its prevalence in real estate, the study highlights the significance of reverse herding as an outcome worth investigating and understanding. Finally, a unique measure of individual overconfidence is proposed by combining a national-level economic sentiment measure with a national-level housing market sentiment measure. This facilitates an examination of the potential role of overconfidence as one of the driving factors behind reverse herding under specific market conditions.

A significant part of equity ownership is through institutions who are sophisticated and less prone to irrational psychological biases (although there is evidence of herding in funds (Cui et al., 2019; Zhou & Anderson, 2013)). However, in a market such as housing that is predominantly held by individual owner-occupiers, more irrational responses would be apparent (Flynn, 2012). Within the irrational responses identified, as housing clearly demonstrates the characteristics of an inefficient market, and as the US is a developed economy, previous

CONTACT Matthew Pollock matthew.pollock@ntu.ac.uk, m.a.pollock@pgr.reading.ac.uk
[a] School of Real Estate & Planning, Henley Business School, University of Reading, Reading, UK
[b] EHL Hospitality Business School, HES-SO University of Applied Sciences and Arts Western Switzerland, Lausanne, Switzerland
[*] Now at Property Management and Development, School of Architecture, Design and the Built Environment, Nottingham Trent University, Nottingham, UK, NG1 4FQ.

studies would suggest that reverse herding will be relatively more prevalent than herding. Following the existing literature, a potential change in responses after the Global Financial Crisis (GFC) is expected.

In line with previous findings, evidence is found that markets often react irrationally to large increases in price. Specifically, this study identifies significantly more reverse herding than herding, which may be due to the innate overconfidence of homeowners, the presence of strong private information in local housing markets, the general level of market maturity or the high cost of acquiring information for new market entrants. Herding is found to be more prevalent in down markets and before the GFC. Conversely, reverse herding is more common in up markets and after the GFC. Immediately prior to the GFC, the combination of strong price appreciation and overconfidence resulted in elevated levels of reverse herding. In contrast, similar appreciation in later years did not trigger similar levels of reverse herding, potentially due to much lower levels of housing confidence measured during that period.

2. LITERATURE REVIEW

Herding has been defined as the existence of correlated behaviour across individuals, especially where it leads to sub-optimal investment decisions and bubble formation (Devenow & Welch, 1996). This can result from investors abandoning a rational asset pricing approach and copying others (Banerjee, 1992).

Rational herding is a response from investors with limited information who 'follow the herd' as they believe the crowd has superior knowledge or information and they rationally copy others (Bikhchandani et al., 1992; Bikhchandani et al., 1998; Welch, 1992). Irrational herding exists when behavioural biases overcome the rational decision-making processes of investors (Barber et al., 2009), for example, where a social or personal requirement to keep up with some defined cultural group causes them to copy others, e.g., the much-discussed 'keeping up with the Joneses'.

When individual investors follow a collective metric, returns will cluster around the market average, meaning the dispersion of returns will be smaller than expected under a rational asset-pricing model (Chang et al., 2000). Herding can then lead to bubble formation, resulting in price collapse and systemic issues in broader financial and economic systems (Lux, 1995).

The evidence for herding in previous studies is largely dependent on exogenous factors (Goodfellow et al., 2009). For example, there is evidence that herding exists around major data releases (Galariotis et al., 2015) and that this behaviour can spill over into other countries, the latter finding aligning with evidence of significant co-movement in herding across European markets (Economou et al., 2011). Chang and Lin (2015) found herding to be dependent on local culture and market sophistication, whilst Lam and Qiao (2015) showed a decline in herding over a 30-year period. Herding has been also reported in real estate investment trust (REIT) markets (Lantushenko & Nelling, 2017; Philippas et al., 2013; Zhou & Anderson, 2013). Thus, herding is consistently identified in various asset classes and geographical markets. However, as Griffin et al. (2003) conclude, herding is neither universal nor similar across assets and markets and is heavily influenced by country and time-specific factors (Galariotis et al., 2015).

The US housing market was estimated to exceed $52 trillion in June 2023. Given that a home purchase represents the largest lifetime financial decision for most individuals, there is valid motivation to examine herding behaviour that can lead to bubble formation. Housing also differs from securitised markets because real estate markets are local and possess significant information asymmetries, which will impact the nature and motivation of mimetic actions.

While research for herding in housing is limited, Hott (2012) looked at housing and found movements beyond those justified by the fundamentals. Ngene et al. (2017) looked at regional US housing markets and found that almost half of estimated responses were significantly irrational, which varied across market conditions and regions. Lan (2014) finds herding in the Chinese national housing market.

Ngene et al. (2017) established some evidence of variation between regions. However, the examination at the MSA-level is more appropriate considering the body of research on MSA-level dynamics and its role as an integrated real estate market and economic unit. In a huge but fragmented market such as housing, as information acquisition costs for real estate are high, then purchasers within their own metropolitan area may, by benefiting from lower costs, have an information advantage. This advantage will be reduced at larger geographical regional levels. Therefore, this possession of local knowledge on a very localised asset may generate different market dynamics. Additionally, when considering the potential immobility of homeowners due to employment, the substitutability of housing within urban areas is significant, as the MSA may provide opportunities for substitution of assets not found at the regional level (Ren et al., 2023).

Finally, larger geographical units such as census regions are combinations of more granular units, so regional price information must be smoothed and display reduced volatility. Common structures are more likely to be identified between series when they are smoothed (Kettunen & Keltikangas-Järvinen, 2001), resulting in spurious correlations. The data reduction resulting from averaging or aggregating data can dampen any noise, leading to false correlation from coincidentally aligned smoothed series. Lastly, if information is lost from aggressive smoothing then significant patterns in the series may be removed, also leading to potentially spurious results. These issues in the data structure suggest that testing for irrational behaviour at the regional level may lead to an over-detection of herding and an under-detection of reverse herding, motivating an analysis at the smaller MSA-level.

Prior studies suggest the importance of local variation in housing (Gray, 2018; Hortas-Rico & Gómez-Antonio, 2020; Lerbs & Oberst, 2014; Palomares-Linares & van Ham, 2020; Tsai, 2015; Zhang & Fan, 2019) and the smaller spatial scale allows identification of local variation in herding. This is the first study to investigate herding at the MSA-level.

Under some market conditions, rather than assigning more weight to the market consensus, investors follow their own opinion and actively deviate from the market average. As individual returns will not cluster around the market return but will disperse more widely, greater cross-sectional dispersion of returns will be observed, leading to reverse herding (Bekiros et al., 2017). Hwang and Salmon (2004) state that reverse herding must exist by definition if herding exists, and so it should be equally considered.

This reverse herding behaviour has been identified in equity markets (Chang et al., 2000; Galariotis et al., 2015; Hwang & Salmon, 2004) and in REIT markets (Philippas et al., 2013; Zhou & Anderson, 2013). When exploring herding behaviour in housing at a sub-national level, Ngene et al. (2017) discovered both herding and reverse herding phenomena. Nevertheless, it is essential to note that reverse herding occurred significantly less frequently than herding, and Ngene et al. did not give specific attention to reverse herding behaviour in their study.

Prior studies suggested possible motivators for the existence of reverse herding. Firstly, there may be a significant number of uniformed noise traders who misunderstand the market consensus (Gebka & Wohar, 2013). Secondly, reverse herding may be driven by the presence of overconfidence (Bekiros et al., 2017; Hwang & Salmon, 2004). The trading costs and illiquidity present in real estate transactions make noise trading impractical. In addition, purchasing a home is a much larger commitment of time and money than buying listed equities. Therefore, homeowners are unlikely to make purchasing decisions based on noisy information and rather will commit when they are more certain, or overconfident. Furthermore, the localised spatial scale allows for heterogeneity of information which can promote overconfidence (Daniel et al., 2004), suggesting overall that reverse herding in housing markets is likely to result from overconfidence rather than noisy trading.

In addition, much like mutual funds, individual home purchasers exhibit heterogeneity which is likely to preclude herding behaviours (Bikhchandani & Sharma, 2000). Secondly, in an illiquid market such as housing, the trading volumes in any given period may not be sufficient to allow for mimetic behaviour (Grinblatt et al., 1995). Combined, these factors will impede rapid information diffusion, therefore suggesting a low observation of herding.[1]

Thus, it is likely that reverse herding will be identified more than herding at a granular spatial scale such as across MSAs, and reverse herding is expected to be more common when overconfidence can be observed.

The motivation for reverse herding may be reputational (Effinger & Polborn, 2001; Levy, 2004), due to strong private information (Avery & Chevalier, 1999) or result from bullish sentiment (Sibande et al., 2021). In line with Avery and Chevalier (1999), Hwang et al. (2020) make the argument that the importance assigned to information in trading decisions is dependent on whether the information is public or private, as profit can be derived from private information in inefficient markets. An investor could be rational to deviate from the public information represented by the market average when they possess strong private information. Assigning more weight to private information and trading on it would lead to greater dispersions, resulting in reverse herding.

However, due to the trading costs and illiquidity of real estate, these trading-style explanations may be limited in relevance. Rather, another important consideration is the role of information acquisition costs.[2] As mentioned, housing is a fragmented and localised market which requires time and transport costs to acquire relevant information about properties. Therefore, investors may rely on broader market signals, personal contacts or informational cascades to acquire information, and the inaccuracy or bias of these mechanisms may result in irrational market outcomes (Bikhchandani et al., 1992; Bikhchandani et al., 1998; Welch, 1992).

Christie and Huang (1995) and Gleason et al. (2004) found more evidence of reverse herding in developed markets which, combined with Chang et al. (2000) identifying reverse herding in similarly developed US, Japanese and Hong Kong markets, suggests that while herding is more common in developing markets, reverse herding is more prevalent in developed markets. Klein (2013) proposes that behaviour is linked to market sophistication and that markets may progress in the long-term from herding to reverse herding as they mature, a development also seen by Lam and Qiao (2015).

As market maturity may be accompanied by relatively more reverse herding (Klein, 2013), this phenomenon is expected to be present in the US housing market which is considered as a developed market. In addition, the existence of more prevalent reverse herding specifically in a housing context can come from the nature of the market itself, which is characterised by low transparency and a lack of easily accessible and frequent pricing, culminating in strong private information.

In addition to evidence that prices respond asymmetrically to market conditions (Bekaert & Wu, 2000; Conrad et al., 1991; Hong et al., 2006), herding also displays asymmetry (Hyun & Milcheva, 2018; Lan, 2014; Ro et al., 2018; Ro & Gallimore, 2014).

Herding may be more present in extreme market conditions (Christie & Huang, 1995) as people are somewhat overwhelmed by noisy information and struggle to process price signals. As a result, people follow the lead of others believing they are better informed, often referred to as ‘the wisdom of the crowd’ (Bikhchandani et al., 1992; Welch, 1992).

However, it is possible that in markets where signals are clearer, it is easier for traders to herd around the index as the index is published and current, whereas house market prices are much more lagged and not always for the exact asset as housing is a highly heterogeneous investment asset. Although herding can result from information asymmetry, the investor needs a minimum level of market information to actually copy. Indeed Hwang and Salmon (2004) find herding in tranquil market conditions, and Zhou and Anderson (2013) suggest that market conditions are also a determinant of whether herding exists in turbulent markets.

Low volatility may create some complacency as conditions are unchanging and investors become overconfident, which has been theorised as a motivator for reverse herding. However, significant reverse herding is found also in turbulent periods by Philippas et al. (2013) with REITs and Chang et al. (2000) in equity markets.

In the cryptocurrency market, Coskun et al. (2020) found the existence of herding under low volatility conditions and reverse herding under high volatility states. The market structure of housing is more akin to cryptocurrency with high levels of individual ownership and information asymmetries. Hwang and Salmon (2004) also said that herding can take place under non-extreme conditions of normality, and so as with previous studies (Griffin et al., 2003), no behaviour is completely unobserved under any conditions. Overall, the role of volatility is clear in importance if not direction, and so testing for herding behaviours requires accounting for its impact.

Ekholm and Pasternack (2008) present evidence that individuals may be less likely to herd as they are supremely confident in their abilities. Daniel et al. (1997) show that in an overconfident context, individuals overreact to private information and underreact to public information. Bao and Li (2020) find a conspicuous overconfident effect during booms and inefficient periods, and simulations suggest that this leads to excessive trading. Chuang et al. (2014) and Griffin et al. (2006) find that inefficient markets are prone to overconfident, excessive trading, which can lead to reverse herding. In addition, Hwang et al. (2020) state that homeowners are generally overconfident in the United Kingdom (UK), a market similar in maturity to the US housing market. By November 2012, all the top 20 MSAs had returned to consistent house price appreciation, which would trigger the overconfident response for the post-GFC period.

Reverse herding, along with traditional herding, plays a significant role in the emergence of speculative bubbles. According to Hong and Sraer (2013), instances of investor disagreement, denoted as reverse herding, coupled with constraints on short sales prevalent in housing markets, contribute to episodes of equity overpricing. Essentially, the phenomenon of reverse herding, fuelled by overconfidence, initiates a ripple effect leading to overpricing, as elucidated by Hong and Sraer (2013). This surge, akin to a wave, attracts a multitude of individuals exhibiting herding behaviours. Consequently, the wave gains momentum, escalating into a substantial force that eventually gives rise to speculative bubbles. Recognising that herding alone does not lead to speculative bubbles in the absence of a driving force, it becomes evident that identifying and comprehending reverse herding is equally crucial. This perspective aligns with the insights of Harrison and Kreps (1978), Miller (1977), Chen et al. (2002) and Scheinkman and Xiong (2003).

3. ANALYTICAL FRAMEWORK

The empirical method is based on cross-sectional housing market returns and follows Christie and Huang (1995) and Chang et al. (2000), the latter commonly referred to as CCK. As the initial cross-sectional standard deviation approach developed by Christie and Huang was found to be sensitive to outliers due to the use of squared deviations, then CCK modified this to use the cross-sectional absolute deviation (CSAD);

$$CSAD_t = \frac{1}{N}\sum\nolimits_{i=1}^{N} |R_{i,t} - R_{m,t}|, \qquad (1)$$

where N is the number of individual assets in the market in month t, $R_{i,t}$ is the return of any individual asset in month t, and $R_{m,t}$ is the equally-weighted average return over all assets in the market. This measure is similar to the standard deviation.

Firstly, returns are calculated by differences in the natural logs;

$$R_t = 100 \text{ x } (\log(P_t) - \log(P_{t-1})), \qquad (2)$$

where P_t denotes the asset level price index.

Herding is not a directly measurable phenomenon, however, the relationship between the CSAD and market returns can be estimated to test for evidence of herding behaviour via the CCK testing model proposed by Chang et al. (2000);

$$CSAD_t = \alpha_t + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t, \qquad (3)$$

where CSAD is the previously discussed measure of dispersion (Equation (1)) and $R_{m,t}$ is the equally-weighted average return over all assets in the market.

Chang et al. (2000) showed that, if the market return results from a rational asset pricing model such as the capital asset pricing model, the cross-sectional absolute deviation is a linear function of these market returns. If there is a large absolute increase in the market return, individual investors may react homogeneously, which would be classed as herding behaviour. As individual asset returns will be more correlated, then the cross-sectional dispersion will not increase as much as the market return (or even decline), so the relationship will now be non-linear and so violate the assumptions of the rational asset-pricing framework.

As the rational asset-pricing framework assumes a linear response of dispersion to increases in the market return, then (as per CCK) a non-linear market return term ($R^2_{m,t}$) is included. This allows testing for the presence of herding under the condition that the coefficient for this estimated non-linear coefficient γ_2 is negative and significant. This would give evidence that as market returns increase, the CSAD reduces which is interpreted as less dispersion and evidence for herding.

Likewise, a significant positive estimated coefficient would give evidence of reverse herding, as it suggests an increase in dispersion when there is a large increase in the market return. Reverse herding is also an irrational response to increases in the market return, as the same non-linear response exists in the opposite direction, suggesting that returns are driven systematically by factors other than the market risk. On the contrary, if the estimated coefficients for γ_2 are not statistically different from zero, there is no evidence to reject the existence of a rational pricing model for generating market returns.

Following previous literature (Avery & Chevalier, 1999; Bikhchandani et al., 1992; Daniel et al., 1997), the information asymmetries, costs of acquiring information and spatial scale suggest that reverse herding will be commonly identified:

> Hypothesis 1: Reverse herding will be more prevalent than herding in MSA-level housing markets.

Price dynamics, including herding, respond asymmetrically to market conditions (Hyun & Milcheva, 2018; Ro & Gallimore, 2014), and house buyers may feel greater confidence during periods of price appreciation, leading to reverse herding (Bekiros et al., 2017; Hwang & Salmon, 2004):

> Hypothesis 2: Reverse herding will be more prevalent in up markets and herding will be more prevalent in down markets.

The relative occurrence of reverse herding has increased over time with market sophistication (Klein, 2013; Lam & Qiao, 2015) and the GFC caused significant disruption in housing markets, therefore the relative balance of herding and reverse herding will change over the period investigated:

> Hypothesis 3: Reverse herding will be relatively more common after the GFC, whilst the occurrence of herding will have decreased.

Finally, as reverse herding is likely to be present when house buyers are confident (Bekiros et al., 2017; Hwang & Salmon, 2004) due to the commitment of time and money, reverse herding is expected to be more common when there is measurably higher confidence in the housing market:

> Hypothesis 4: The interaction between price appreciation and house-buying sentiment will impact the relative prevalence of herding and reverse herding.

4. EMPIRICAL IMPLEMENTATIONS

4.1. Study area

Unlike the central clearing place of a stock market, housing is local and therefore, rather than testing for national-level herding, a smaller spatial scale is employed, namely the metropolitan statistical area (MSA). Herding has been tested on the regional-level in the US, however, herding has not been tested on the MSA-level before. Due to the interconnected socio-economic nature of MSAs, much empirical analysis of housing dynamics is done on an MSA-level. Table 1 presents the list of the 20 largest MSAs by population with basic market descriptions.

Strong population growth in southern and western cities has not translated into the greatest price appreciation, which has been in California and other technology-centred economies such as Denver and Seattle. Other variations may derive from states such as California possessing stronger regulatory and geographical impediments to development.

4.2. Data

House price data is drawn from Zillow Research, a source now used extensively in peer-reviewed research (Baldauf et al., 2020; Bernstein et al., 2019; Damianov & Escobari, 2016; Giglio et al., 2021; Holt & Borsuk, 2020; Joshi, 2016; Rivas et al., 2019). The data points are 'Zestimates' estimated via a neural network-based automated valuation model (AVM) with feeds of public records, user-generated data, and multiple listings services, which can therefore account for individual property specifications and location.[3] For approximately 90,000 regions in the US, a Zillow Home Value Index (ZHVI) is created by a weighted average of applicable Zestimates.

The All Homes ZHVI mid-tier series is used for model estimation, which represents the typical value for homes in the 35th to 65th percentile range in the area. This is referred to as the 'flagship' ZHVI and is used for most consumer-focused ZHVI material as well as being the basis of Zillow's forecasts.

Returns and dispersions are measured on a monthly frequency and on a month-to-month basis. Data is available from January 1996 to January 2021, and losing one observation to calculate differences leaves 300 observations for each MSA. For each MSA, the MSA itself is defined as the *market* and the ZIPs that aggregate to form the MSA are defined as the *individuals*.

CSAD, illustrated in Equation (1), specifically measures the cross-sectional deviation of returns in any MSA at one time period, and so a monthly time series can be constructed for each of the 20 MSAs. The 20 largest MSAs cover urban areas with populations greater than 3 million inhabitants and account for approximately 45% of the total urban population. Whilst there may be some ZIP-level estimation errors, these MSAs have at least 71 ZIPs within their boundaries in January 1996, and data coverage increases significantly over time. Table 2 shows that the aggregation will compensate for any local estimation errors and provides enough observations to make robust estimates of herding behaviour. This data is extracted from Zillow as it is the sole provider of ZIP-level house price estimates.

Table 1. MSA descriptive statistics.

	Population			Real per capita income ($)			House price ($)			Ownership (%)	ZIPs
MSA	1996	2020	%	1996	2020	%	1996	2020	%	2020	2021
New York	17,681,708	19,124,359	8	53,574	82,322	54	308,039	509,356	65	51	939
Los Angeles	11,771,038	13,109,903	11	42,852	69,805	63	304,629	735,356	141	48	362
Chicago	8,782,253	9,406,638	7	47,952	67,671	41	243,076	257,714	6	68	387
Dallas	4,622,564	7,694,138	66	43,728	61,554	41	185,483	274,597	48	64	267
Houston	4,314,589	7,154,478	66	42,664	59,893	40	181,549	232,626	28	62	237
Washington	4,549,151	6,324,629	39	54,711	76,771	40	295,432	471,701	60	66	322
Miami	4,652,414	6,173,008	33	44,818	64,190	43	183,825	321,994	75	61	182
Philadelphia	5,602,154	6,107,906	9	46,179	69,705	51	198,865	274,637	38	71	388
Atlanta	3,765,817	6,087,762	62	44,470	58,773	32	200,935	264,610	32	67	206
Phoenix	2,855,711	5,059,909	77	38,982	51,851	33	187,034	326,891	75	68	154
Boston	4,265,564	4,878,211	14	52,503	85,724	63	275,812	535,789	94	60	284
San Francisco	3,923,208	4,696,902	20	57,510	111,050	93	419,320	1,178,986	181	52	168
Riverside	2,990,316	4,678,371	56	32,395	45,365	40	205,586	422,649	106	66	149
Detroit	4,433,102	4,304,136	−3	45,302	58,356	29	171,830	198,541	16	72	209
Seattle	2,856,795	4,018,598	41	48,579	80,420	66	273,083	583,855	114	59	159
Minneapolis	2,846,496	3,657,477	28	48,083	67,214	40	197,545	319,088	61	72	231
San Diego	2,651,549	3,332,427	26	42,215	66,266	57	289,310	678,553	135	56	99
Tampa	2,256,460	3,243,963	44	39,732	52,291	32	147,493	253,548	72	69	130
Denver	1,959,552	2,991,231	53	47,885	69,822	46	241,171	484,473	101	67	127
St Louis	2,640,161	2,805,473	6	43,481	60,844	40	161,032	196,929	22	69	220
USA	269,390,000	331,500,000	23	42,588	61,674	45	177,761	268,690	51	66	

Notes: This table shows descriptive statistics for the twenty largest urban areas in the USA by population, using the metropolitan statistical area defined by the Census Bureau. The population and per capita income data are provided by the Bureau of Economic Analysis and house prices by Zillow Research, and the homeownership rate by the Census Bureau. Per capita income and house price figures are all in 2020 dollars using the Consumer Price Index for all Urban Consumer from the Bureau of Labor Statistics. ZIPs are the number of ZIP codes with price data in the MSA in January 2021. MSA, metropolitan statistical area.

Table 2. Descriptive and distributional statistics.

MSA	Metric	Mean	Median	Min	Max	SD	Skewness	Kurtosis	Obs
NYC	Return	0.33	0.30	−0.81	1.30	0.54	−0.12	2.13	300
	CSAD	0.39	0.38	0.20	0.57	0.05	0.28	3.48	300
LAX	Return	0.50	0.65	−2.47	2.50	0.86	−0.79	4.29	300
	CSAD	0.29	0.27	0.13	0.93	0.12	2.40	10.35	300
CHC	Return	0.20	0.32	−1.30	1.39	0.52	−0.96	3.31	300
	CSAD	0.36	0.32	0.18	0.89	0.13	1.29	4.56	300
DFW	Return	0.29	0.26	−0.78	1.31	0.39	−0.09	3.12	300
	CSAD	0.22	0.20	0.10	0.62	0.08	1.54	6.32	300
HOU	Return	0.26	0.26	−0.67	0.98	0.32	−0.28	3.43	300
	CSAD	0.32	0.31	0.20	0.53	0.05	0.91	4.15	300
WDC	Return	0.32	0.25	−1.47	1.87	0.63	−0.06	3.45	300
	CSAD	0.37	0.35	0.14	0.68	0.11	0.77	3.10	300
MIA	Return	0.35	0.52	−2.76	2.35	0.98	−1.05	4.30	300
	CSAD	0.31	0.29	0.10	0.73	0.13	1.09	3.95	300
PHD	Return	0.26	0.21	−0.83	1.30	0.47	0.13	2.63	300
	CSAD	0.33	0.34	0.16	0.49	0.05	−0.18	3.35	300
ATL	Return	0.28	0.41	−1.51	1.27	0.57	−1.44	4.70	300
	CSAD	0.35	0.30	0.15	0.86	0.14	1.11	3.65	300
PHN	Return	0.37	0.48	−2.71	3.53	1.05	−0.38	4.55	300
	CSAD	0.33	0.28	0.15	0.86	0.14	1.49	5.14	300
BOS	Return	0.39	0.46	−0.70	1.44	0.52	−0.29	2.33	300
	CSAD	0.34	0.33	0.17	0.65	0.08	0.73	3.50	300
SFR	Return	0.49	0.62	−1.61	1.96	0.75	−0.46	2.62	300
	CSAD	0.48	0.45	0.20	1.01	0.15	0.73	3.01	300
RIV	Return	0.42	0.50	−3.24	2.46	1.04	−1.27	5.48	300
	CSAD	0.38	0.35	0.16	0.87	0.14	1.37	4.70	300
DTR	Return	0.24	0.39	−1.65	1.66	0.65	−1.03	3.78	300
	CSAD	0.39	0.35	0.17	1.08	0.15	1.14	4.53	300
STL	Return	0.42	0.58	−1.78	1.64	0.70	−1.01	3.43	300
	CSAD	0.28	0.26	0.11	0.61	0.10	1.05	3.94	300
MNN	Return	0.33	0.46	−1.05	1.21	0.53	−0.98	3.22	300
	CSAD	0.33	0.30	0.18	0.73	0.11	0.99	3.43	300
SDG	Return	0.45	0.60	−2.19	2.18	0.86	−0.69	3.22	300
	CSAD	0.29	0.25	0.12	0.93	0.13	2.78	11.56	300
TMP	Return	0.36	0.58	−2.07	2.31	0.88	−0.93	3.63	300
	CSAD	0.31	0.29	0.13	0.64	0.08	0.94	4.41	300
DNV	Return	0.40	0.42	−0.64	1.22	0.45	−0.25	2.33	300
	CSAD	0.26	0.24	0.11	0.59	0.08	1.12	4.64	300
SLS	Return	0.22	0.27	−0.70	0.82	0.32	−0.79	2.94	300
	CSAD	0.39	0.38	0.25	0.60	0.06	0.51	3.22	300

Notes: For each MSA, descriptive and distributional statistics for both price returns (from Equation (2)) and the cross-sectional absolute deviation (CSAD) (from Equation (1)) are calculated from Zillow data for the period January 1996 to January 2021 on a month-to-month basis and on a monthly frequency (authors' own calculations). MSA, metropolitan statistical area; SD, standard deviation; Obs, observations.

4.3. Estimation approach

The unclear information signals resulting from price volatility may motivate rational herding as market agents follow signals they can observe. As a quantile regression is used to account for the non-normality of the data, Equation (3) is adjusted further to control for idiosyncratic volatility. This is measured by the estimated conditional variance from a GARCH(1,1) model, following Ngene et al. (2017);

$$\delta^2_{m,t} = \omega_0 + \omega_1 \propto^2_{m,t-1} + \beta\delta^2_{m,t-1} \qquad (4)$$

where δ^2 is the estimated conditional variance, $\omega_1\alpha^2_{m,t-1}$ captures information about the previous period's volatility, and the model's fitted variance from the previous period is captured by $\beta\delta^2_{m,t-1}$.

The estimated conditional variance is then added as a regressor to Equation (3);

$$CSAD_t = \alpha_t + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3\hat{\delta}^2_{m,t} + \varepsilon_t, \quad (5)$$

Firstly, the initial herding analysis outlined by Ngene et al. (2017) is closely replicated. However, the approach is enhanced by employing more granular house price indices. This ensures that any disparities in outcomes do not arise from variations in methodologies or potential model misspecifications, thereby contributing valuable supplementary insights. The assessment encompasses the complete time span for each MSA and employs a two-state switching model based on Equation (5) to estimate both herding and reverse herding. Importantly, this model also incorporates the influence of idiosyncratic volatility.

Further, to ensure the robustness of the estimated results, quantile regression (QR) is employed, which better accounts for observations in the extreme tails of the distribution than the standard ordinary least squares (OLS) approach. This is more appropriate for non-normal distributions and investigating non-linear relationships, as the theory suggests herding is more commonly observed in extreme tails of the distributions. Whilst OLS coefficients are estimated by minimising the squared deviations from the conditional sample mean, QR coefficients are estimated by minimising the weighted sum of absolute errors, where weights are defined by the quantiles. All the following quantile regressions include idiosyncratic volatility estimated by a GARCH(1,1) model as a control variable;

$$Q_t(\tau|CSAD_t) = \theta_\tau + \gamma_{1,\tau}|R_{m,t}| + \gamma_{2,\tau}R^2_{m,t} + \gamma_{3,\tau}\hat{\delta}^2_{m,t} + \varepsilon_{t,\tau} \quad (6)$$

A range of percentiles are used to perform the quantile estimation; 0.025, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95 and 0.975. As irrational and non-normal behaviour, herding is assumed to take place in the tails and so estimating responses across the full range of quantiles identifies the exact presence of irrational behaviour.

4.4. Testing for asymmetric responses to market conditions

Having established that responses to market conditions are often asymmetric, estimating the role of market conditions can be most effectively modelled using a dummy variable approach to test for herding under up and down markets;

$$\begin{aligned} Q_t(\tau|CSAD_t) = \theta_\tau &+ \gamma_{1,\tau}D^{down}|R_{m,t}| \\ &+ \gamma_{2,\tau}D^{up}|R_{m,t}| + \gamma_{3,\tau}D^{down}R^2_{m,t} \\ &+ \gamma_{4,\tau}D^{up}R^2_{m,t} + \gamma_{5,\tau}\hat{\delta}^2_{m,t} + \varepsilon_{t,\tau}, \end{aligned} \quad (7)$$

where D^{down} is 1 when $R_{m,t} \leq 0$ and D^{up} is 1 when $R_{m,t} > 0$.

Estimated via a quantile regression, the significance and sign of the respective quadratic coefficients (γ_3 and γ_4) will give evidence for the existence of herding or reverse herding under either market condition. As market states are MSA-specific, there is some variation in sample size in each estimation. These range from 46 down months (15% of months) for Houston to 86 months (29%) for San Diego. The average for all MSAs is around 67 (22%) months.

This same model is employed for the further sub-analysis, with the definition of the dummies being changed appropriately.

For the GFC-based analysis, the data set is split into before and after the Federal Reserve definition of the recession which provides nearly equal samples (142 months pre-GFC and 139 months post-GFC).

4.5. Overconfidence measure

A unique measure of individual overconfidence is proposed by combining a national-level economic sentiment measure with a national-level housing market sentiment measure. Baker and Wurgler (2007) define sentiment as 'a belief about future cash flows and investment risks that is not justified by the facts at hand'. Economic sentiment is measured by the Daily News Sentiment Index produced by the Federal Reserve Bank of San Francisco (FRBSF) (Shapiro et al., 2020). The news aggregator service Factiva collects articles of at least 200 words from 24 major US newspapers where the main topic was US economics. These sources cover all major regions and include several national papers. Publicly available lexicons are combined with a news-specific lexicon created by the FRBSF and trained on a historical archive of 16 major US newspapers to create a newspaper-specific sentiment-scoring model.

This model correlates highly with human-derived sentiment scores and outperforms some current machine-learning techniques. The index is produced daily and converted to monthly averages for this analysis.

House-buying sentiment is measured by the Survey Research Center at the University of Michigan, which surveys a minimum of 500 households monthly to ask around 50 core questions. The core questions cover personal finances and business and buying conditions. To measure house-buying sentiment specifically, the percentage of respondents who believe that now is a good time to buy a house is collected.

To allow comparison between the measures, each observation is transformed into a percentile ranking based on the whole period. The ratio of house buying sentiment to economic sentiment then serves as a proxy for how overconfident prospective house purchasers are relative to the broader economy. Specifically, if the ratio is greater than one, the market is classed as overconfident and if the ratio is less than one then it is classed as unconfident.

$$\text{Sentiment ratio} > 1\text{, housing market is overconfident} \quad (8)$$

$$\text{Sentiment ratio} < 1\text{, housing market is unconfident} \quad (9)$$

Based on this overconfidence measure, the data is split first into overconfident and unconfident groups dependent on the ratio of house-buying to economic sentiment, assuming that overconfidence (unconfidence) is present when house-buying sentiment is more positive (negative) than economic sentiment. As naturally expected, there is strong correlation between 'overconfident' periods and periods marked as 'up markets'.[4] However, two noteworthy phases are uncovered; the first (spanning from June 2001 to May 2005) features pronounced house price appreciation alongside overconfidence, whilst the second (spanning from October 2016 to January 2021) also showcases substantial house price appreciation but lacks accompanying overconfidence. These distinct periods are leveraged to analyse the potential moderating influence of overconfidence on the relationship between house price appreciation and the phenomena of herding and reverse herding.

5. EMPIRICAL FINDINGS

5.1. Descriptive statistics

The CSAD for each MSA is calculated on a monthly basis with the MSA as the market and the ZIPs as the individual observations. As expected, Table 2 shows that house price growth is high in urban areas such as San Francisco and Seattle, which have been outsized beneficiaries of growth in technology-based industries. In addition, the geographic constraints in these urban areas restrict land available for development, and local regulations also significantly determine the supply of new housing, further complicating the dynamics of demand and price appreciation. The relationship with dispersion measured by CSAD is less clear, as Los Angeles, despite being the fastest-growing city, has seen relatively low dispersion of responses whereas Chicago has seen low growth but much higher dispersion than Los Angeles. This may suggest that responses are not purely driven by pricing but also other market conditions and motivates further analyses.

Table 3. Two-state switching model.

	Base model	
	State 1	State 2
New York		Reverse herding
Los Angeles		Reverse herding
Chicago	Reverse herding	Reverse herding
Dallas	Reverse herding	
Houston		Reverse herding
Washington	Reverse herding	Reverse herding
Miami		
Philadelphia		
Atlanta	Reverse herding	
Phoenix	Reverse herding	
Boston		Herding
San Francisco	Reverse herding	Reverse herding
Riverside	Reverse herding	
Detroit	Reverse herding	
Seattle	Herding	
Minneapolis	Reverse herding	
San Diego	Herding	Herding
Tampa		
Denver		Reverse herding
St Louis		
Total	H:2 RH:9	H:2 RH:7

Note: Estimated using Equation (5) across two states for each MSA, with herding or reverse herding identified at the 10% significance level.

5.2. Initial herding analysis

Following Ngene et al. (2017), herding and reverse herding is estimated over the entire time period for each MSA via a two-state switching model using Equation (5). Table 3 shows, across the forty states (two states across twenty MSAs), that four states of herding and sixteen states of reverse herding are observed.

This result is consistent with expectations that the presence of information heterogeneity and low trading volumes at the localised spatial scale foster overconfidence. Consequently, the prevalence of reverse herding surpasses that of herding, highlighting a noteworthy deviation from the findings reported by Ngene et al. Their study, which reported almost twice as much herding as reverse herding, starkly contrasts with the results in Table 3. The significant difference in results at different geographical levels suggests that the spatial scale is important.

Table 4 demonstrates the range of herding and reverse herding, as well as rational responses, across the data distributions for each MSA. Panel A of Table 5 is a summary of quantiles with significant evidence of herding or reverse herding for each MSA, collated by the count of quantiles where the γ_2 response coefficient on the non-linear term in Equation (6) is statistically significant. The initial analysis estimates responses for the entire period of available price data.

The estimated coefficient γ_2 is significantly negative, suggesting herding, at the 10% level in at least one quantile in eight out of twenty MSAs, and indeed four markets show evidence in only one quantile. Conversely, γ_2 is significantly positive, suggesting reverse herding, in 11 markets and is more persistent across quantiles within the MSAs. For example, there is significantly positive evidence in 10 or more out of 13 quantiles in Chicago and Minneapolis. Overall, there are 20 quantiles of herding and 52 quantiles of reverse herding. When not accounting for market conditions, there is more than twice as much evidence that cross-sectional dispersion increases non-linearly in response to increases in market returns as there is evidence of decreases in cross-sectional dispersion, and so there is substantially more evidence of reverse herding than of herding, supporting Hypothesis (1). This differs markedly from Ngene et al. (2017) who found approximately three times as much herding as reverse herding in the US regional house markets using 50 states as individuals and nine census regions as markets. This may result

Table 4. Base results.

	$\tau = 0.025$	$\tau = 0.05$	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.3$	$\tau = 0.4$	$\tau = 0.5$	$\tau = 0.6$	$\tau = 0.7$	$\tau = 0.8$	$\tau = 0.9$	$\tau = 0.95$	$\tau = 0.975$
NYC	0.027	−0.037	−0.044	−0.044	−0.069	−0.051*	−0.030	−0.027	−0.039	−0.035	−0.039	−0.028	−0.045
	(0.056)	(0.036)	(0.034)	(0.047)	(0.073)	(0.026)	(0.025)	(0.043)	(0.029)	(0.034)	(0.045)	(0.052)	(0.070)
LAX	−0.014	−0.002	0.000	−0.001	0.010	0.009	−0.003	0.005	0.006	0.027	0.064**	0.058***	0.038
	(0.013)	(0.013)	(0.009)	(0.011)	(0.012)	(0.021)	(0.023)	(0.018)	(0.030)	(0.033)	(0.025)	(0.022)	(0.056)
CHC	0.028	0.257***	0.270**	0.297***	0.320***	0.367***	0.390***	0.370***	0.280***	0.219**	0.216*	0.255	0.038
	(0.128)	(0.097)	(0.104)	(0.053)	(0.068)	(0.090)	(0.072)	(0.075)	(0.076)	(0.088)	(0.113)	(0.170)	(0.244)
DFW	0.080	0.099**	0.134**	0.115*	0.175***	0.145***	0.105**	0.066	0.071	−0.007	−0.097	−0.017	−0.051
	(0.057)	(0.039)	(0.060)	(0.062)	(0.055)	(0.034)	(0.044)	(0.052)	(0.060)	(0.055)	(0.075)	(0.104)	(0.083)
HOU	−0.083	−0.008	−0.017	−0.060	−0.014	−0.016	0.022	0.015	−0.030	0.050	0.113	0.051	0.130
	(0.075)	(0.080)	(0.104)	(0.074)	(0.056)	(0.047)	(0.054)	(0.078)	(0.104)	(0.093)	(0.099)	(0.155)	(0.179)
WDC	−0.003	−0.025	−0.061	−0.014	−0.037	−0.020	−0.028	−0.039**	0.046***	−0.047*	−0.077***	−0.099***	−0.081***
	(0.038)	(0.041)	(0.044)	(0.032)	(0.023)	(0.025)	(0.028)	(0.019)	(0.017)	(0.025)	(0.028)	(0.020)	(0.021)
MIA	−0.022	−0.032	−0.020	−0.027	−0.013	−0.013	−0.023	−0.008	−0.008	−0.010	−0.008	−0.066*	−0.074**
	(0.031)	(0.023)	(0.016)	(0.020)	(0.019)	(0.020)	(0.019)	(0.016)	(0.013)	(0.018)	(0.023)	(0.038)	(0.034)
PHD	−0.039	−0.006	−0.019	−0.021	−0.014	−0.025	−0.016	−0.033	−0.026	−0.028	−0.049	−0.067	0.112
	(0.061)	(0.053)	(0.052)	(0.024)	(0.023)	(0.031)	(0.029)	(0.024)	(0.019)	(0.027)	(0.035)	(0.089)	(0.101)
ATL	−0.042	0.051	0.085	0.035	0.002	−0.073	−0.122	−0.121	−0.166**	−0.111	−0.006	0.092	0.033
	(0.084)	(0.106)	(0.111)	(0.083)	(0.087)	(0.090)	(0.094)	(0.106)	(0.071)	(0.086)	(0.098)	(0.084)	(0.110)
PHN	0.015*	0.009	0.008	0.008	0.005	0.009	0.006	0.010	0.006	0.007	−0.005	−0.017	−0.024
	(0.009)	(0.008)	(0.008)	(0.011)	(0.013)	(0.012)	(0.009)	(0.008)	(0.010)	(0.013)	(0.013)	(0.013)	(0.015)
BOS	0.079	0.107**	0.123***	0.024	0.047	0.022	−0.017	−0.037	−0.014	−0.030	−0.073	−0.151	0.086
	(0.050)	(0.051)	(0.046)	(0.026)	(0.032)	(0.037)	(0.046)	(0.051)	(0.045)	(0.056)	(0.085)	(0.116)	(0.135)
SFR	0.062	0.026	0.060**	0.038*	0.062**	0.073**	0.060*	0.031	0.035	−0.002	−0.021	0.013	0.146
	(0.079)	(0.032)	(0.019)	(0.022)	(0.019)	(0.025)	(0.031)	(0.037)	(0.033)	(0.037)	(0.042)	(0.085)	(0.132)
RIV	0.025**	0.015**	0.023**	0.020	0.000	−0.009	−0.012	−0.001	0.001	0.010	0.014	0.012	0.058
	(0.009)	(0.007)	(0.009)	(0.015)	(0.018)	(0.015)	(0.017)	(0.018)	(0.023)	(0.024)	(0.019)	(0.047)	(0.071)
DTR	0.141**	0.080**	0.036	0.016	−0.007	−0.021	−0.018	−0.056	−0.025	−0.044	−0.073*	−0.066	0.118
	(0.055)	(0.035)	(0.023)	(0.038)	(0.034)	(0.037)	(0.044)	(0.052)	(0.046)	(0.033)	(0.043)	(0.133)	(0.182)
STL	−0.088***	−0.088**	−0.127***	−0.135***	−0.109***	−0.081*	−0.085	−0.037	0.033	−0.006	0.027	0.098	0.233
	(0.018)	(0.034)	(0.025)	(0.028)	(0.035)	(0.047)	(0.062)	(0.076)	(0.075)	(0.072)	(0.085)	(0.123)	(0.174)

MNN	0.169***	0.220***	0.188***	0.181***	0.162***	0.172***	0.179***	0.105**	0.120*	0.063	0.220***	0.168***	0.118
	(0.032)	(0.039)	(0.028)	(0.053)	(0.062)	(0.039)	(0.048)	(0.044)	(0.069)	(0.083)	(0.068)	(0.039)	(0.105)
SDG	−0.041**	−0.011	−0.021	−0.029**	−0.023	0.003	−0.005	−0.015	−0.010	−0.010	−0.011	0.007	−0.002
	(0.020)	(0.026)	(0.017)	(0.014)	(0.018)	(0.018)	(0.012)	(0.012)	(0.018)	(0.024)	(0.033)	(0.026)	(0.031)
TMP	−0.010	−0.012	−0.002	−0.019	0.007	−0.008	0.001	−0.001	−0.011	−0.022	0.023	0.014	0.073
	(0.026)	(0.020)	(0.013)	(0.020)	(0.021)	(0.027)	(0.019)	(0.011)	(0.017)	(0.022)	(0.036)	(0.053)	(0.071)
DNV	0.112**	0.045	0.076**	0.063**	0.066*	0.049*	0.026	0.0463*	0.010	0.002	−0.015	0.044	−0.062
	(0.052)	(0.039)	(0.038)	(0.025)	(0.036)	(0.030)	(0.022)	(0.026)	(0.039)	(0.062)	(0.082)	(0.098)	(0.094)
SLS	−0.328*	−0.173	0.017	0.103	0.194*	0.154**	0.092	0.089	0.181	0.181	0.257*	0.321*	0.094
	(0.188)	(0.222)	(0.231)	(0.207)	(0.117)	(0.067)	(0.083)	(0.150)	(0.132)	(0.176)	(0.142)	(0.192)	(0.230)

Notes: Estimated via Equation (6) for a range of quantiles across the distribution, with standard errors provided in parenthesis. * denotes 10%, ** denotes 5%, *** denotes 1% significance. A significantly negative (positive) coefficient provides evidence of (reverse) herding, cumulative counts for each MSA are also provided.

from the existence of stronger private information in locally defined markets (i.e., MSAs used in this study instead of regions used in Ngene et al. (2017)), leading to greater reverse herding, as well as the potentially stronger impact of more disaggregated housing markets. As 72 out of 260 quantiles overall show some non-linear response, there is evidence that around three-quarters of responses can be explained by a rational asset-pricing model. Ngene et al. (2017) found that more than half of market responses in total were irrational. Chiang and Zheng (2010) also found around half of the equity responses to be rational but all are herding, and indeed this may support the idea that the specific market characteristics of real estate tend toward reverse herding.

Concerning the fairly low persistence of herding across quantiles, Ngene et al. (2017) found weak evidence of persistent herding in the US regional housing markets across long periods, and behavioural motivators may only be evident under certain market conditions. Therefore, further analysis to examine the effects of market conditions is required as suggested by previous studies.

5.3. Herding under different market conditions

5.3.1. Up and down markets

Panel B of Table 5 shows that, in at least one quantile, there is evidence for herding in 47 down markets and 21 up markets and evidence of reverse herding in eight down markets and in 65 up markets, supporting Hypothesis (2). In terms of intensity, there is more evidence of persistence of herding in down markets and reverse herding in up markets. The latter point is in line with Duffee (2001) who found that stock returns are more dispersed in a rising stock market than when the market falls. When markets appreciate, investors diverge from the market return as they may be experiencing overconfidence and feel they can outperform the market. It may be that in benign market conditions, investors assign more weight to any private information they possess.

Herding in a down market may be rationally motivated when uninformed investors observe a declining market and, as they are unsure of the exact scale of the market disruption, copy the actions they can observe. In an environment of poor market conditions, investors may feel that any private information is not worth trading on and is overwhelmed by the negative signals shown in public information.

Lan (2014) finds herding in up markets, not down, as do Hyun and Milcheva (2018) under a different empirical framework. However, Lan looks at China, one large national market, which may not possess the same structure as a metropolitan housing market, and previous studies have suggested that herding is more common in developing markets such as China. In addition, Lan did find evidence of herding in a down market if it was also turbulent.

Whilst herding and reverse herding are observed in both market conditions, there is a clear pattern which could imply the need to incorporate asymmetric effects into any risk measures. In addition, if herding drives price bubble formation, which would be a concern for

Table 5. Market condition results.

	Panel A – Base model		Panel B – Up and down markets			
	Estimated over whole period		Down		Up	
	Herding	Reverse	Herding	Reverse	Herding	Reverse
New York	1		1	1	1	
Los Angeles		2				2
Chicago		10	1			6
Dallas		6				9
Houston						1
Washington	6		10		2	
Miami	2		5		7	
Philadelphia				2		
Atlanta	1		9		1	4
Phoenix		1	3			6
Boston		2		1		5
San Francisco		5	2			5
Riverside		3				6
Detroit	1	2	2		2	2
Seattle	6		6		6	1
Minneapolis		11		4		12
San Diego	2				2	
Tampa			7			
Denver		6	1			5
St Louis	1	4				1
Total	20	52	47	8	21	65

	Panel C – GFC				Panel D – Overconfidence interactions			
	Pre-GFC		Post-GFC		Overconfidence		Unconfidence	
	Herding	Reverse	Herding	Reverse	Herding	Reverse	Herding	Reverse
New York		2		8		7		
Los Angeles				1				
Chicago		5		6	3			
Dallas		8		7		1	4	
Houston		3						
Washington	10		4			5		
Miami	1		3	1	3			
Philadelphia	3		2	1				
Atlanta		2		10	2	3	2	
Phoenix		5		5		4		
Boston		3	1	1				3
San Francisco		3		8		8	2	4
Riverside				5				
Detroit		1						
Seattle	11			7		1		
Minneapolis		8		10		1		
San Diego	6			4	1			6
Tampa		1		3		10		
Denver	8			8	2			
St Louis	3			8				
Total	42	41	10	93	11	40	8	13

Notes: Panel A aggregates the results from Table 4 and Panel B estimates responses to market returns in up and down markets. A cumulative count is presented due to space limitations. The coefficients and standard errors can be produced on request. Panel C aggregates the results split between pre- and post-GFC periods, and Panel D estimates behaviour according to overconfidence or unconfidence. A cumulative count is presented due to space limitations. The coefficients and standard errors can be produced on request.

investors, especially in illiquid property assets, then identification of the conditions herding appears under is required.

5.3.2. Global financial crisis

There is evidence of long-term changes in herding behaviour (Klein, 2013) which may be related to the level of market sophistication. However, previous studies found evidence of change in behaviour after the GFC (Zhou & Anderson, 2013), an event that may have served as a catalyst as the fiscal and monetary action was accompanied by regulatory change.

Using the Federal Reserve definition of the recession lasting from December 2007 until June 2009, estimated results for cross-sectional responses demonstrate the existence of irrational behaviour both before and after the GFC. The 'during' period is too short to draw any significant economic conclusions from, but the pre- and post-GFC periods are almost identical in size (142 and 139 months, respectively), which allows for easy comparison of behaviour.

As anticipated, both herding and reverse herding behaviours changed significantly after the GFC, supporting Hypothesis (3). Panel C from Table 5 shows a marked decline in herding from 42 to 10 quantiles, suggesting the GFC did cause some general structural changes to house market behaviour. The occurrence of reverse herding more than doubled after the GFC as seen by the increase in quantile evidence from 41 to 93, such that more than nine times as much reverse herding as herding was recorded post-GFC.

There is persistent evidence of herding in Miami, Philadelphia and Washington both before and after the GFC, whilst persistent reverse herding is observed both before and after the GFC in Atlanta, Boston, Chicago, Dallas, Minneapolis, New York, Phoenix, San Francisco and Tampa. On the contrary, some cities saw marked changes in behaviour after the crisis, such as Denver, San Diego, Seattle and St Louis which followed the general pattern and switched from herding pre-GFC to reverse herding post-GFC. This may result from the context that the pre-GFC housing bubble was national whilst the recovery has been more geographically varied. This suggests variation between MSAs that motivates further research on the impact of local characteristics.

This local variation has clear implications for any investor constructing a diversified national portfolio of residential real estate. Whilst diversification benefits come from the addition of less than perfectly correlated assets, the lack of consistency between MSAs may lead to unmeasured exposure to localised irrational dynamics.

5.3.3. Overconfidence

Previous studies (Avery & Chevalier, 1999; Chuang et al., 2014; Griffin et al., 2006; Hwang et al., 2020) suggest that both market structure and inherent behavioural characteristics lead to generally overconfident conditions in housing markets. The results in Panels A, B and C of Table 5 also suggest the potential effect of overconfidence, especially on reverse herding behaviour. Following prior studies (Blasco et al., 2012; Liao et al., 2011; Philippas et al., 2013; Vieira et al., 2015) that suggest sentiment may determine herding behaviour, an innovative combination of sentiment measures is used as a proxy for overconfidence.

The data is split into overconfident and unconfident groups based on the ratio of house buying to economic sentiment, assuming that overconfidence (unconfidence) is present when house buying sentiment is more positive (negative) than economic sentiment. An analysis of the overconfidence levels shows that, in the immediate pre-GFC period, housing confidence was on average around twice the relative general level of economic confidence. Conversely, prior to the COVID-19 pandemic and during its early stages, housing confidence was relatively little more than half that of the confidence in economic conditions. However, in both periods, consistent price appreciation continued.

When isolating these two particular scenarios, Panel D of Table 5 shows evidence that herding is largely consistent in both states. Consistent with expectations, more than three times as much reverse herding is observed in the overconfident pre-GFC period. As with previous sub-analyses, there is still herding and reverse herding in both market states and indeed prior findings (Choi & Yoon, 2020; Ngene et al., 2017; Vieira et al., 2015) are mixed.

Whilst these results may look contrary to the broader GFC-based perspective seen in Panel C, it does demonstrate that it is, in fact, the interaction between price appreciation and overconfidence that may lead to the observation of reverse herding, supporting Hypothesis (4).

Note that Panel D shows broad disparities between MSAs, as they respond heterogeneously to overconfidence in a manner suggestive of local variation in behaviour. Previous literature (Carlino & DeFina, 1998; Carlino & DeFina, 1999; Giannakis & Bruggeman, 2017; Gupta & Kabundi, 2010; Hwang & Quigley, 2006) shows that, due to differing economic structures, sub-national markets react heterogeneously to exogenous shocks, motivating further research into local measures of overconfidence.

6. CONCLUSION

This paper examines herding and reverse herding at the MSA-level and found extensive evidence of potentially irrational responses to large increases in absolute market returns. Analysing the phenomena on an appropriate spatial level, and across a variety of market conditions, has contributed to herding research.

As expected from the review of existing literature, herding exists primarily in downturns whereas reverse herding exists under more bullish market conditions. In terms of temporal change, the GFC may have caused some permanent change in behaviour as herding became sparse whilst the occurrences of reverse herding doubled. Wide spatial and temporal variation in herding and reverse herding behaviour warrants further investigation to isolate the MSA-specific characteristics that determine the rationality of market responses.

The existing theory (Avery & Chevalier, 1999; Bekiros et al., 2017; Daniel et al., 1997; Hwang et al., 2020) demonstrates that inefficient markets and innate homeowner overconfidence may contribute to reverse herding, as home purchasing is a costly commitment that requires strong confidence to deviate from the consensus. The results of this study suggest that overconfidence, when combined with price appreciation, does lead to reverse herding. Future research into the potential link between confidence and irrational behaviour is motivated, especially by establishing a good measure of confidence at the MSA-level, if possible.

In this relatively local geographical context, individuals may be better informed than stylised facts on real estate information asymmetries suggest, and indeed it can be assumed they possess significant knowledge on local housing markets. It would follow then that, due to strong private information, markets are more overconfident than expected, therefore motivating reverse herding. The high costs of information acquisition in heavily localised markets will also trigger irrational responses to market dynamics. Additionally, housing markets still exhibit a low level of institutional involvement relative to securitised investment classes, and so homeowners are not at an informational disadvantage.

Lastly, consumption is always the primary driver for housing, and therefore investment must take a secondary role, especially for the owner-occupiers who still constitute around two-thirds of the asset holders. Therefore, further research should consider herding not only relative to investment considerations but also in the context of consumption-driven behaviour, especially homeownership. Also worthy of consideration is that regional variation may be due to spatial constraints common in real estate markets.

These findings have policy implications as, because cities display these irrational behaviours under certain market conditions, these results may have use as leading indicators, especially considering the link between herding and bubble formation. These behaviours, therefore, operate as important warning signs for lenders, investors and policymakers.

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NOTES

1. The authors thank an anonymous reviewer for this insight.
2. The authors thank an anonymous reviewer for this insight.
3. The data inputs incorporate property characteristics such as size and location, on-market data such as listing prices and days on the market, off-market data such as tax valuations and prior sales and market trends such as seasonality. Zillow calculates a Zestimate for 104 million individual homes across the US. Zillow's own internal research finds the nationwide median error rate for Zestimates for on-market homes is 1.9% and 6.9% for off-market homes. In order to ensure data quality, values are only produced where at least 2 years of data is available. ZHVI captures only market-based appreciation and removes appreciation that results from property changes in order to measure the price change for the typical property. The index is seasonally adjusted via a locally estimated scatterplot smoothing (LOESS)-based seasonal decomposition and then chained backwards. In addition, a 3-month moving average is applied to smooth the index.
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ORCID

Matthew Pollock http://orcid.org/0000-0003-2185-7698
Masaki Mori http://orcid.org/0000-0003-3269-0715
Yi Wu http://orcid.org/0000-0003-0354-5658

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