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Sentiment Indicators and Market Dynamics

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1. Introduction

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 and Welch 1996). This can result from investors abandoning a rational asset pricing approach and copying others. Despite the apparent irrationality of this behaviour, in a wider market context it can have both rational and irrational motivations.

Rational herding is a response from investors with limited information who "follow the herd" as they believe the crowd have superior knowledge or information and they (rationally) copy others (Bikhchandani et al. 1998). Irrational herding exists when behavioural biases overcome the rational decision-making processes of investors, 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". Under uncertainty and asymmetric information, individuals will not make rational decision based on fundamentals but rather on assets that will retain (or increase) their value in the short-run.

When individual investors do not make purely individual choices and instead follow some collective metric, then returns will cluster around some market average, meaning that the dispersion of returns, or cross-sectional absolute deviation (CSAD), will be smaller than in "normal" conditions (Chang et al. 2000). If individuals make their own decisions based on market signals, then "incorrect" bubble-type market conditions will give them skewed signals and therefore their responses will be skewed, leading to an irrational loop. Herding can then be seen to lead to bubble formations and resulting price reinforcing collapses with knock on asset and economic losses, and systemic issues in the wider financial and economic systems.

Conversely, under some market conditions, individual returns will not cluster around the market return but will in fact disperse more widely, leading to reverse-herding (Bekiros et al. 2017). This is intuitively the opposite of herding, which means that individuals act against the consensus and a greater cross-sectional dispersion of returns is observed. Not only are individuals not suppressing their own opinions in favour of the market consensus, but they are ignoring information coming from wider market signals and following their own opinion, or the opinions of a small group, and actively deviating from the market direction. Overall, as Griffin et al. (2003) conclude, herding is neither universal nor similar across assets and markets.

Several possible concepts could explain why, in a market with a large increase in returns, cross-sectional dispersion is greater than would be estimated by a rational asset pricing analysis (Gebka and Wohar 2013). Firstly, localised herding is present when small groups of investors move in and out of assets against the wider market direction in some attempt to take advantage of market movements, which leads to greater dispersion as they are going against the main consensus. However, the illiquidity and transactions costs in real estate make this impractical and costly.

More possible is a flight to safety, where investors liquidate assets to rebalance their portfolios into safe assets, which is often associated with housing. This could be a rational behaviour on an individual basis, conditional on the individual risk tolerance and capacity for loss, as they rebalance portfolios in up and down markets. If assets are coming from non-housing liquidations, the money could be redeployed quite quickly into property. However, fairly limited numbers of people have liquid assets sufficient to buy an additional house. In addition, housing is not a costless or quick asset to liquidate if market conditions justify rebalancing into other asset classes.

Lastly, investor overconfidence can exist if returns have recently been strong and individuals feel this will continue, which can take place at the expense of market signals. If these reactions to market signals are heterogeneous this will result in a greater cross-sectional dispersion in returns. Ekholm and Pasternack (2008) present evidence that individuals may be less likely to herd as they are supremely confident in their own abilities. Daniel et al (1998) show that in an overconfident context, individuals overreact to private information and underreact to public information. As private information is local, this leads to local overreaction and heterogeneous price movements and dispersion, which will lead to reverse herding. In the context of metropolitan housing markets, this local argument gives a framework for the activation of overconfidence in determining return dispersions.

Unintentional herding exists when people react similarly but independently to some market information, unlike rational herding where investors consciously mimic others. This information may be house prices, economic growth, national and local news, but would be hard to specifically isolate. Therefore, sentiment can serve as a proxy of investors' attitudes resulting from this market information. Investor sentiment can then be seen to drive herding, as it can be argued that sentiment may create a form of unintentional herding as people react similarly but independently to general market conditions (Gebkar and Wohar 2013). The behaviour and cognitive decisions of individuals cannot be directly observed, however a sufficient market sample can be measured as a proxy to make some inferences on these mechanisms.

There is extensive evidence of the importance of sentiment in determining price dynamics across a range of asset classes, and in determining house price returns, and so its inclusion in this analysis adds to its role in determining individual responses to market dynamics, specifically investors' cross-sectional responses to large changes in the market return.

Much empirical work on herding has been on equities, and so the use direct prices in a sample of large metropolitan housing markets allows an analysis of direct investors' herding tendencies without having to isolate general equity-induced behaviour. Also, investigating a largely owner-occupier market assesses how herding plays out in uniformed or "unsophisticated" investors who are also consumers of the investment good.

An interesting aspect of the spatial scale used is that the same asset is measured in distinct geographies within one national jurisdiction, so the informational framework is more nuanced. Sentiment is measured at a national level, and so non-standard i.e. heterogeneous responses to sentiment can be expected. In a regression framework, the sensitivity betas are expected to be statistically different between cities.

Previous literature (Ngene et al. 2017, Bekiros et al. 2017) show the role of uncertainty or fear in explaining the presence of herding as peoples' state of mind will impact their response to changes in market returns, and so it follows that expectations for the future will also determine responses. In times of overconfidence, an increase in market returns should lead to greater than linear and an increase in cross-sectional dispersion. It can then be seen that overconfidence and greater dispersion, whilst the opposite to suppressed reactions and herding (i.e. lower cross-sectional dispersion), are similar irrational responses to market returns.

In an equity context, the herding behaviour takes place in one central marketplace, with easily observable pricing and securitised assets. However, housing lacks both a central market and homogenous assets, so that behaviour is highly specific to the location and the property.

There is some argument that, whilst 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 mutual funds) then in a market such as housing that is predominantly held by individual investor-occupiers, more irrational responses would be apparent. However, in a localised context people may be very well informed about local house markets and therefore are more efficient and therefore rational than first assumed, and so the motivations for herding may differ from those found in equity-style dynamics, in addition to the structural market issues of real estate which lacks the observable actions of others, easily accessible and frequent pricing, homogenous assets and easily tradeable positions seen in securities.

The remainder of the paper is structured as follows; section 2 (Empirical Approach) introduces dispersion measurements and herding testing, the market analysed, market data and descriptive statistics, section 3 (Empirical Results) covers a base herding analysis, herding under different market conditions, and results for sentiment as an explanatory power, and section 4 (Conclusion) concludes the paper and recommends further research.

2. Data and Methodology

Market

Unlike a stock market which exists as a central clearing place, housing is more local and there is an extensive argument that there is no "national" housing market. 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 USA, 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. Previous empirical studies have also found that herding behaviour is more prevalent in individuals than in institutions, hence why housing may be a suitable market.

The markets consist of the 20 largest MSAs by population in 2019 (the latest year for which population estimates are available). These MSAs (Table 1) represent cities of least almost 3 million inhabitants and are generally more mature and have more diversified socio-economic bases, and so would exclude high-growth or dominant industry urban areas.

Data

The house price data used to calculate both the returns and dispersions comes from the MSA-level and ZIP-level Zillow Price Index, which is an appraisal-based index estimated via an automated valuation model for the 35th to 65th percentiles of price data, and allows for the construction of MSA-level price dispersion. 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.

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”. Sentiment can be measured directly via a survey or indirectly via market factors such as price discounts. As herding is a market-wide behaviour, a market survey of investor beliefs and expectations is a good proxy measure of sentiment.

The empirical analysis is based on cross-sectional housing market returns and follows the method primarily developed by 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 squared deviations aspect) then CCK modified this to use the cross-sectional absolute deviation (CSAD);

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |R_{i,t} - R_{m,t}| \quad (1)$$

Where N is the number of observations (the number of ZIPs in each MSA at the respective time period *t*), $R_{i,t}$ is the return of any ZIP in month t and $R_{m,t}$ is the equally-weighted simple average of all ZIPs in the MSA. As can be seen, this is broadly similar to the concept of the standard deviation and 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.

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

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

Equation 2

Where P_t denotes the ZIP level price index.

Then the CSAD for each MSA is calculated on a monthly basis with the MSA as the market and the ZIPs as the individual observations (Table 2).

Herding is not a directly measurable phenomena, however the relationship between cross-sectional dispersion (CSAD) and market returns can be estimated to test for evidence of herding behaviour, via the testing model proposed by CCK (2000);

$$CSAD_t = \alpha_t + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$$

Equation 3

Where CSAD is the previously discussed measure of dispersion and $R_{m,t}$ is the equally-weighted simple average of all ZIP returns i.e the MSA average return.

Rational asset-pricing models predict that as the absolute value of the market return increases then so will the dispersion of individual returns as individual sensitivities (i.e. the betas) are specific to individuals. Chang et al (2000) showed that, if the market return results from a rational asset pricing model such as the CAPM, 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 homogenously, 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 ($R_{m,t}^2$) 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, CSAD reduces with is interpreted as less dispersion and evidence for herding.

Likewise, a significant positive estimated coefficient would give evidence of reverse herding, 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 then there is no evidence to reject the existence of a rational pricing model for generating market returns.

It is likely that herding will be present in extreme market conditions as people are somewhat overwhelmed by extreme conditions and instead default to the market consensus, for example in a flight to safety or irrational exuberance. It is also expected that there will be weaker evidence of herding across the entire time period as previous evidence in other literature has shown that. Behavioural motivators may only be evident under certain market conditions. For example, if herding may exist in "large" absolute market returns, there would be no evidence in "normal" conditions as a quarter century will average out to "normal" and so evidence of herding (i.e. strong behavioural dynamics) would be surprising.

3. Empirical Results

1. Initial herding analysis

To ensure the robustness of the estimated results, the parameters are estimated using quantile regression (QR), 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.

$$Q_t(\tau|CSAD_t) = \theta_\tau + \gamma_{1,\tau}\left|R_{m,t}\right| + \gamma_{2,\tau}R_{m,t}^2 + \varepsilon_{t,\tau}$$

Equation 4

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. Table 3 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 is statistically significant. The initial analysis estimates responses for the entire period of available price data.

The estimated coefficient γ_2 is significantly negative in at least one quantile in seven MSAs, and indeed two markets show evidence in only one quantile. Conversely, γ_2 is significantly positive in 16 markets and is more persistent across quantiles within the MSAs. For example, there is evidence in 10 or more quantiles out of 13 quantiles for Chicago, Atlanta, Riverside, Detroit and Minneapolis. Overall, there are 18 quantiles of herding and 83 quantiles of reverse herding. When not accounting for market conditions, there is more than three times 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. As 101 out of 260 quantiles overall show some non-linear response, there is evidence that around three-fifths of responses can be explained by a rational asset-pricing model.

As previously discussed, the local scale of markets being analysed allows for a relatively high degree of information efficiency and so the majority of responses to absolute increases in the market return are not statistically significant and suggest a rational behaviour.

2. *Herding under different market conditions*

As extensive previous literature finds evidence of asymmetric price responses to market conditions, the model is adjusted to account for individual responses dependent on whether house prices are increasing or decreasing. This allows some understanding of how investors' responses to large absolute movements in the market return depend on the market conditions.

This can be most effectively modelled using a dummy variable approach to test for herding under up and down markets;

$$Q_t(\tau|CSAD_t) = \theta_\tau + \gamma_{1,\tau}D^{down}\left|R_{m,t}\right| + \gamma_{2,\tau}D^{up}\left|R_{m,t}\right| + \gamma_{3,\tau}D^{down}R_{m,t}^2 + \gamma_{4,\tau}D^{up}R_{m,t}^2 + \varepsilon_{t,\tau}$$

Equation 5

Where D^{down} is 1 where $R_{m,t}<0$ and D^{up} is 1 where $R_{m,t}>0$.

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.

In at least one quantile (Table 4), there is evidence for herding in 10 down markets and seven up markets and evidence of reverse herding in six down markets and in 15 up markets. In terms of intensity, there is more evidence of persistence of herding in down markets and reverse herding in up markets. As herding seems most likely to exist when house prices are falling, this may be rationally motivated when uniformed investors observe a declining market and decide, as they are unsure of the exact scale of the market turbulence, to copy what actions they can observe. The result is that during a market downturn the cross-sectional dispersions are lower than in an upturn which gives support to the idea of a "flight-to-safety".

Conversely and logically, in up markets people diverge from the market return as they may be experiencing overconfidence and feel they can outperform the market. It can clearly be seen how these behaviours link with market sentiment (although the causality of sentiment and returns is difficult to disentangle and the direction may not be clear). This suggests that the incorporation of sentiment into the estimations may give additional explanatory power to the presence of both herding and reverse herding. If sentiment is high, positive or increasing, then overconfidence may be present and result in reverse herding.

3. GFC-based Estimates

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 Global Financial Crisis (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. The occurrence of reverse herding after the GFC is almost double the prevalence before (Table 5), which suggests that (if overconfidence is the motivator for reverse herding) then there was some reason this became stronger after the GFC.

Confidence could have been negatively affected by the housing-driven GFC but the period since has been characterised by almost globally strong housing markets, due in part to the record low interest rates that resulted from financial and monetary responses to the crisis, potentially exacerbated by low housing supply and high liquidity and easy access to credit. Returns have been almost consistently positive since the housing market recovered and so there has been very strong persistence which could act as the market characteristic that activates the overconfidence mechanism. In addition, the pre-GFC housing boom was relatively short lived and so perhaps did not have time to create the necessary level of persistence that would have led to more widespread reverse herding.

As with previous estimates, herding is much less common than reverse herding but shows a marked decline after the GFC which may reveal a permanent change in structural market dynamics.

Some markets have shown persistent evidence of herding or reverse herding both before and after the GFC (Table 6). On the contrary, some cities saw marked changes in behaviour after the crisis, such as Detroit which went from strong evidence of reverse herding to showing no irrational market responses after. This may result from the context that the pre-GFC housing bubble was national (driven partly by the fact it was a sub-prime issue) the recovery has been more geographically varied, and indeed it seems that Detroit never recovered in housing or economic terms as opposed to other major MSAs.

It may be that the GFC caused a collective reluctance to follow the crowd again. Alternatively, pre-GFC there was a substantial amount of sub-prime lending in the housing market, which predominantly went to unsophisticated borrowers (almost by definition – they were low-income, insecure employment, no assets, often unaware of the repayment structure). After the GFC, new regulations restricted credit to this sub-section of borrowers and so they were to some extent removed from the housing market (and in fact homeownership rates did decline in almost all markets). It could be argued that these unsophisticated borrowers were more likely to herd (and in fact the rationale for sub-prime borrowing was largely based on the idea of constant asset price appreciation in the housing market) as they lacked the skills and information to make more rational assessments of the housing market. Therefore, post-GFC the lack of these unsophisticated borrowers removed the agents who caused the herding which would explain its much reduced prevalence. The more restrictive regulations applied more generally in the housing credit market may have also spread this effect across borrowers who could still access mortgages, beyond sub-prime borrowers specifically.

4. *Volatility Estimates*

Volatility was defined as the standard deviation of the previous 12 months of returns. Unlike sentiment, volatility is local and so not all periods are the same but they are roughly equal as expected. Volatility can be perceived as risk and therefore an important signal to investor occupiers as they try to understand and process market price signals. Higher volatility means market signals are harder to process and therefore motivates rational herding.

If low volatility is expected to create some overconfidence as conditions are unchanging and investors become complacent then it explains why reverse herding is 50% more common in low volatility than high volatility markets (94 against 64 quantiles) (Table 7). Herding is (as in all models) less common but a 50% increase (23 against 16 quantiles) in the occurrence of herding exists when volatility is high, which may result from volatile market conditions causing investor confusion and uncertainty toward market information. As a result, investors rationally follow the lead of others that they believe may be better informed, often referred to as "the wisdom of the crowd". This latter result fits with our expectations.

However, this cannot be overstated and herding is still only present in around 10% of quantiles. It is possible that in structures where market 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 high heterogeneous investment asset.

Although herding can result from information asymmetry, the investor needs a minimum level of market information to actually copy.

5. *Sentiment Estimates*

Having analysed the role of direct market conditions (price movement and volatility) in determining the existence of herding and reverse herding, it is useful to understand further the more direct measures such as market agents' expectations and confidence in determining their responses to large absolute increase in the market return. The former direct conditions are the external rational components of the marker whereas beliefs or sentiment can be seen as the internal and classically irrational components of agent behaviour. The role of sentiment in herding would result from unintentional herding, where investors herd based on similar but independent responses to some market metric. As the specific metric cannot be easily identified, sentiment provides a proxy for investor attitudes. In periods of positive sentiment, investors are feeling generally bullish and so herd almost coincidentally rather than because they instinctively copy others. Although sentiment is not the metric they respond to, it provides a good proxy of peoples' interpretation of other metrics that they can directly observe, for example news media.

This model uses the University of Michigan Consumer Sentiment data to gauge people's expectations of future house price growth. It is based on the percentage of people with positive expectations. By simply measuring the long-term average of sentiment and defining periods above and below (which are roughly equal as expected - 157 and 143 months respectively), the responses in Table 8 were estimated.

The much greater prevalence of herding in high sentiment markets would give support for the idea of unintentional herding. The presence of more reverse herding in low than high sentiment conditions is somewhat unexpected as reverse herding was hypothesised to result from bullish sentiment. The low prevalence of herding in low sentiment conditions suggests that investors may act more rationally and not have the same urge to follow the crowd as low sentiment may produce a conservatism (although the presence of reverse herding under low sentiment suggests some motivation for irrational behaviour), although a flight-to-safety behaviour could also have been expected.

Confidence Analysis

In the GFC analysis (Table 5), it could be seen that herding and reverse herding differ clearly before and after the recession. Some potential explanation is the difference in confidence and market structure between the two periods, and so deeper analysis of the role of confidence could give some explanation for the differing behaviour. Confidence can be measured via housing, economic and political scores from media sources (and their divergence on an MSA-level from the national score).

MSAs are ranked (Table 9) by confidence for the whole period and also split into pre- and post-GFC periods, with counts of herding and reverse herding. Much as with the concept of sentiment providing a framework for unintentional herding, higher levels of confidence are expected to coincide with more common herding. However, it could also be argued that lower levels of confidence will motivate herding as investors indulge in a flight-to-safety. Conversely, the concept of overconfidence in individual investors would suggest that greater confidence would activate belief in the possibility of outperformance and result in statistically significant reverse herding.

The motivation for looking at confidence in the time-variant context based around the GFC is that substantially more reverse herding has been observed post-GFC and therefore it is of interest to analyse if this was motivated by greater confidence.

As with the sentiment analysis, the MSAs are ranked by economic sentiment (mean ess score) from 2000 onwards due to data availability and analysed in three periods.

Herding Groupings by Economic, Housing and Political Confidence

Pre-GFC, two clear patterns appear (Table 9); high economic confidence is associated with herding, and low economic confidence is associated with reverse herding, the latter of which differs from expectations.

Replicating this analysis with housing sentiment measures (Table 10), post-GFC there is some pattern with higher housing confidence leading to herding and lower housing confidence leading to reverse herding, in line with previous pre-GFC economic results. Only ten MSAs have observations pre-GFC (with low frequency) therefore the result should be treated with caution.

Finally, none of the periods (Table 11) show any significant relationship between political sentiment and herding or reverse herding. In part this may result from the fact that sentiment variation is very low, in that it is very similar across time and between MSAs as political sentiment is likely to be heavily national and so will not show any strong correlation with any local market dynamics.

Although there is evidence that confidence levels may work much like sentiment in determining the existence of herding, the role of confidence in reverse herding is less clear. As it has been argued that it is overconfidence that motivates reverse herding as opposed to the level of confidence, then further analysis of MSA-specific differences from the national level may yield some insight into this phenomenon by investigating how locally specific variations from the "norm" explain responses to large absolute changes in market returns.

Overconfidence Analysis

The same time-based analysis is employed and for each MSA the difference from the national value is calculated (Tables 12, 14 and 16) such that a positive value represents overconfidence, that is confidence greater than the national level.

Herding Groupings by Economic, Housing and Political Overconfidence

Although limited by patchy data pre-GFC as 5 MSAs (Atlanta, Dallas, Riverside, San Diego and Tampa have no observations for this period and many others have incomplete series), economic overconfidence is associated with herding (Table 13). If the availability of sub-prime lending did lead to a greater relative level of unsophisticated investor-occupier activity, then the psychological biases that this represents could explain a form of irrational herding as these investors did not make investment decisions based on any rational framework.

The association of reverse herding with lower than national confidence is harder to explain. It may be that in markets with lower confidence there was less connection with the national market and as investors were not following the national trend they looked to perform on some other metrics and dispersed their behaviour. These MSAs (Detroit, Minneapolis, Phoenix, San Francisco and Seattle) are mixed in economic terms but it could be argued that each is a one-industry city (automotive, software etc.) and so maybe markets are less connected to the overall national sentiment. Post-GFC, the relationship reverses. Reverse herding is now more prevalent in more overconfident MSAs (almost twice as common) and low confidence markets are more likely to experience herding.

In respect of housing overconfidence, the behaviour over the whole period is fairly evenly distributed and so it is hard to draw any conclusion about the role of housing overconfidence (Table 15). Pre-GFC, herding behaviour is fairly evenly distributed over the levels of confidence and reverse herding is possibly more weighted to lower levels of confidence, similar to but weaker than the situation with economic sentiment. Again, the lack of data pre-2011 may limit the significance of any conclusions. Post-GFC (where data is more frequent and available for more MSAs) then it appears that herding is seen in overconfident markets and reverse herding is possibly more common in less confident markets, which is the opposite pattern of economic sentiment.

In terms of political sentiment, there is some evidence that over the whole period greater confidence is associated with herding (Table 17), and there is a fairly even distribution of reverse herding across all levels of confidence suggesting that reverse herding is not driven by political confidence. Pre-GFC, although again restricted by the issue of data frequency and MSA-availability, herding seems unclear in correlation with confidence, but reverse herding does generally seem more common in confident markets. The issue here is that almost all MSAs were on average less confident than the USA national average, which suggests that herding was associated with general low confidence. 22 cases of reverse herding were in markets with greater than national confidence and 30 cases were in markets with lower than national confidence, so the story is much less clear. Relative confidence is more evenly distributed post-GFC and whilst herding is not strongly related to any level of confidence, reverse herding can be seen to have a much clearer and stronger relationship with political confidence (and in fact the numbers are almost identical to economic confidence) which gives some support for the overconfidence context argued for the existence of reverse herding.

Outperformance and Persistence of Returns

In addition to measures of confidence derived from new media, price return data can be used to categorise MSAs by relative performance which may be a powerful motivator of local confidence and overconfidence. In addition, if positive returns are persistent then this may also motivate confident sentiment.

The difference of each MSA return from the benchmark national figure (Table 19) can be ranked which shows only one strong pattern pre-GFC (Table 20) where underperformance has a relationship with reverse herding, contrary to expectations. However, some of this behaviour is already captured by the positive and negative return analysis in the market condition framework which measures the link between returns and herding.

Return persistence in terms of a simple measure of unbroken price appreciation may also encourage confidence in local markets. By November 2012, all the top 20 MSAs had returned to house price growth and six markets have not experienced a single month of house price decline since then. After counting the longest unbroken period of growth since November 2012 for each MSA, there is little pattern in persistence (Table 21), which suggests in fact that it is not return persistence that is the trigger for reverse herding, whether through overconfidence or some other mechanism.

So overall the evidence from confidence is mixed and somewhat contrary to my expectations – the persistence idea also fails to provide robust results. Therefore, the determinants of market responses are not necessarily the current market dynamics but something deeper and more structural – the beliefs of the inhabitants themselves.

4. Conclusion

Evidence of irrational responses to large increases in market returns can be found across metropolitan markets, across market conditions and across the conditional distribution. This suggests that, whilst individuals may generally in around two-thirds of cases follow a rational approach to large return increases, there are also fairly widespread situations where this relationship does not hold. More specifically, there is more evidence of reverse-herding than herding (both more prevalent and more persistent within MSAs), and most herding is present pre-GFC.

However, it was apparent from previous empirical studies that there is wide spatial and temporal variation in herding behaviour and it is not a widespread or persistent phenomenon. As substantial evidence of rational responses to market returns has been found, the local nature of the markets analysed gives some suggestion that individuals may be better informed than supposed and possess significance local knowledge and information. If so, this supports rational behaviour via information efficiency in the local housing market structure. In addition, the low level of institutional involvement in housing suggests that informational asymmetries may not be as great as first thought, and that most owners have fairly similar levels of information and understanding of housing as an asset. In addition, unlike equity markets, individuals are not competing with better informed institutions and so information asymmetries may not exist that could potentially provoke rational herding.

Ngene et al. (2017) found more substantial evidence of herding in regionally-based housing markets, however the range of dispersion in each MSA is quite low relative to regional markets. This may be because the cross-section is quite homogenous in construction as prices within one urban area are likely to move largely in sync. The states within each region can be expected to show quite marked cross-sectional differences, and economic integration within regions should not be overstated as wide disparities can exist even within states, and there is also arguably no national housing market. It is also clear when referencing results to previous equity-based studies that individual stocks or industry-defined indices will exhibit much larger dispersion than housing within one contiguous urban area. This merits more consideration on how the underlying range of dispersions impacts linearity of responses to market returns.

Finally, consumption is the primary driver and so the investment aspect must always be secondary, at least for owner-occupiers. Consumption driven expenditure can be heavily influenced by behavioural factors, but herding is an investment-based concept.

Lastly, there is relatively extensive existence of reverse herding, which is more consistent across GFC-based conditions, sentiment and volatility. This consistently is very interesting and suggests some intrinsic permanent behavioural mechanism that leads to reverse herding. This may result from the existence of a core of investors who are susceptible to overconfidence as an innate personal or social psychological trait and are therefore unaffected by sentiment, market conditions or return volatility.

Sub-analysis

Further asymmetric modelling revealed herding behaviour skewed to up markets and reverse herding skewed to down markets, the former potentially from a flight-to-safety mechanism and the latter maybe resulting from overconfidence. There was a significant increase in reverse herding post-GFC, whilst declining occurrences of herding may reasonably have resulted from the reduction of rational or irrational behaviour as unsophisticated investors were removed from the market along with sub-prime lending.

Post-GFC, the new regulatory and internal business restrictions on lending quality meant the virtual disappearance of sub-prime residential mortgage lending in the USA. Rational and irrational herding can be seen to link strongly with unsophisticated borrowers. In turn, sophisticated borrowers have more information and more analytical skills to process information, so they will have less reason to depend on copying others as they have their own resources to fall back on. Secondly, it may be assumed reasonably that sophisticated agents are more aware of behavioural biases and are therefore less susceptible to falling for them, and can better separate reason from emotion when it comes to investment and consumption decision making (both pertinent to housing). So it could be argued that the herding seen before the GFC was driven to some extent by the mortgages going to unsophisticated investors, and the increase in investor sophistication post-GFC has led to a decline in herding. However, although one type of irrationality has declined, another type has increased in the form of reverse herding. Reverse herding should also decline as the market should be more analytically driven and therefore rational. However, reverse herding, although an irrational response to market returns, does not have the same psychological basis and is therefore present in different types of investors than herding.

Sophisticated investors may be more susceptible to overconfidence because there may be an element of intellectual arrogance – “a little bit of knowledge is dangerous” – as they have the skills and information to analyse the market and so feel they can justify an expectation of outperformance. However, this innate psychological factor would not explain the increased presence of reverse herding after the GFC, unless the crisis caused some structural change to investor attitudes. This suggests reverse herding is not dependent on cyclical issues such as volatility, returns, sentiment, and persistence but on more permanent structural characteristics.

Finally, the direct sentiment and confidence analysis shows some mixed results (and is hampered by data availability, quality and construction) such that there is evidence for unintentional herding, and some strong results that economic confidence can be linked to irrational responses. High sentiment may cause herding (which is perhaps an unintentional motivation for herding), and there are some interesting (but not overwhelming) results from the confidence analysis. Economic overconfidence shows a clear pattern that switches for reverse herding as result of the GFC, but there should be some caution about pre-GFC data.

Overconfidence may not be sentiment driven but rather an innate part of some people and therefore is present regardless of wider conditions. If reverse herding is driven by overconfidence, this means investors feel market conditions are irrelevant and that they can outperform the market because of their internal superior abilities. Sentiment is a market wide measure of expectations of the future whereas overconfidence is innate to individuals and these individuals are relatively more prevalent post-GFC due to the market being more sophisticated in aggregate.

What can be said broadly is that herding is dependent on the behavioural or conditional context, specifically that high sentiment leads to unintentional herding, high volatility lead to rational herding or a flight to safety, herding was common pre-GFC due to unsophisticated investors and that the GFC caused a structural change in the incidence of reverse herding.

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MSA	Population	Per capita income ($)	House price ($)
New York	19,216,182	76,681	521,485
Los Angeles	13,214,799	63,913	755,509
Chicago	9,458,539	61,089	261,271
Dallas	7,573,136	55,886	275,161
Houston	7,066,141	56,077	233,519
Washington	6,280,487	72,483	481,196
Miami	6,166,488	57,228	326,199
Philadelphia	6,102,434	64,440	281,425
Atlanta	6,020,364	52,473	267,696
Phoenix	4,948,203	46,125	343,830
Boston	4,873,019	78,694	543,455
San Francisco	4,731,803	99,424	1,181,198
Riverside	4,650,631	40,486	439,809
Detroit	4,319,629	53,086	200,871
Seattle	3,979,845	74,620	600,497
Minneapolis	3,654,908	62,889	323,869
San Diego	3,338,330	61,386	700,502
Tampa	3,194,831	47,240	261,372
Denver	2,967,239	64,287	494,108
St Louis	2,803,228	55,883	198,797

Table 1: MSA Descriptive 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

Table 2: Descriptive and Distributional Statistics

MSA	Herding	Reverse Herding
New York	4	
Los Angeles		2
Chicago		12
Dallas		7
Houston		
Washington	3	2
Miami	1	1
Philadelphia	3	
Atlanta		10
Phoenix		
Boston		4
San Francisco		3
Riverside		11
Detroit		11
Seattle	4	1
Minneapolis		11
San Diego		2
Tampa		2
Denver	1	2
St Louis	2	2
Total	**18**	**83**

Table 3: Base Results

MSA	Down Herding	Up Herding	Reverse Down Herding	Reverse Up Herding
New York		1		
Los Angeles			1	2
Chicago	1			11
Dallas		1		9
Houston				2
Washington	9	1		1
Miami	12	7		
Philadelphia	1	3		
Atlanta	9			9
Phoenix	8			9
Boston			3	7
San Francisco				6
Riverside	2		4	7
Detroit			3	5
Seattle	6	6		2
Minneapolis			4	11
San Diego			10	
Tampa	4			
Denver	1			4
St Louis		3		4
Total	**53**	**22**	**25**	**89**

Table 4: Up and Down Market Results

	Pre-GFC (142)		GFC (19)		Post-GFC (139)	
MSA	**Herding**	**Reverse**	**Herding**	**Reverse**	**Herding**	**Reverse**
New York	1					6
Los Angeles	1		4			3
Chicago		7				4
Dallas		6		2	1	8
Houston		5				2
Washington	8				5	
Miami	7				1	1
Philadelphia	6				2	1
Atlanta		2				10
Phoenix		5			1	7
Boston		4			2	
San Francisco		8				11
Riverside	1	2			1	6
Detroit		9				
Seattle	9					11
Minneapolis		11				10
San Diego	3			2		4
Tampa						5
Denver	9			8		7
St Louis	2					11

Total	47	59	4	12	13	107

Table 5: GFC Results

Consistent Herding	Consistent Reverse Herding
Miami	Atlanta
Philadelphia	Chicago
Riverside[1]	Dallas
Washington	Houston
	Minneapolis
	Phoenix
	Riverside[1]
	San Francisco

Table 6: Herding Consistency

[1]Riverside, although showing much more prevalence of reverse herding, still exhibits some evidence of herding in both periods.

	Low volatility		High volatility	
MSA	**Herding**	**Reverse**	**Herding**	**Reverse**
New York	9			6
Los Angeles		7		1
Chicago		11		8
Dallas		7		6
Houston		4	1	
Washington	1		1	1
Miami		5	10	
Philadelphia	6			
Atlanta		10		7
Phoenix		8	2	2
Boston		5		3
San Francisco		5		5
Riverside		5		11
Detroit		4		6
Seattle		3	3	
Minneapolis		10		5
San Diego		1		3
Tampa		1		
Denver		7	4	
St Louis		1	2	
Total	**16**	**94**	**23**	**64**

Table 7: Market Volatility Results

	Low sentiment (143)		High sentiment (157)	
MSA	**Herding**	**Reverse**	**Herding**	**Reverse**

New York	3	2	4	
Los Angeles		6	1	4
Chicago		11		1
Dallas		1	2	8
Houston	1			8
Washington		2	13	
Miami	2	9	13	
Philadelphia			8	
Atlanta		7		10
Phoenix		6	2	6
Boston		2	1	4
San Francisco		3		3
Riverside		11	7	1
Detroit		9	1	5
Seattle			2	4
Minneapolis	1	8		9
San Diego	1	3		1
Tampa		13	10	
Denver	2		1	5
St Louis				3
Total	**10**	**93**	**65**	**72**

Table 8: Relative Housing Sentiment Results

	Average		Average pre-GFC		Average post-GFC	
	Herding	**Reverse Herding**	**Herding**	**Reverse Herding**	**Herding**	**Reverse Herding**
High	4	27	24	4	3	43
Middle	7	39	10	12	7	29
Low	7	17	9	33	3	35

Table 9: Economic Sentiment Ranked Herding

	Average		Average pre-GFC		Average post-GFC	
	Herding	**Reverse Herding**	**Herding**	**Reverse Herding**	**Herding**	**Reverse Herding**
High	5	25	9	4	9	17
Middle	9	27	16	7	3	41
Low	4	20	2	10	0	43

Table 10: Housing Sentiment Ranked Herding

	Average		Average pre-GFC		Average post-GFC	
	Herding	**Reverse Herding**	**Herding**	**Reverse Herding**	**Herding**	**Reverse Herding**
High	6	25	17	12	2	39
Middle	9	24	13	24	7	37
Low	3	34	16	16	4	31

Table 11: Political Sentiment Ranked Herding

MSA	Average	Average pre-GFC	Average post-GFC
New York	1.16	-4.16	4.28

Los Angeles	0.60	8.40	3.5
Chicago	-1.47	-0.41	-3.23
Dallas	16.21	---	16.21
Houston	1.15	-9.27	2.31
Washington	2.08	10.23	2.40
Miami	10.60	-1.26	11.06
Philadelphia	-1.10	3.81	-2.26
Atlanta	2.92	---	2.92
Phoenix	2.27	-10.58	1.52
Boston	6.22	6.77	5.34
San Francisco	-2.41	-20.64	-1.00
Riverside	34.20	---	34.20
Detroit	5.25	-11.55	9.12
Seattle	5.05	-11.90	5.20
Minneapolis	2.51	-42.61	11.54
San Diego	3.73	---	3.73
Tampa	7.78	---	7.78
Denver	12.41	46.56	11.18
St Louis	10.52	-7.70	13.65
Average	**5.98**	**-2.96**	**6.97**

Table 12: Economic Overconfidence

	Average		Average pre-GFC		Average post-GFC	
	Herding	**Reverse Herding**	**Herding**	**Reverse Herding**	**Herding**	**Reverse Herding**
High	4	25	24	4	3	43
Middle	7	41	10	12	2	39
Low	7	17	9	33	8	25

Table 13: Economic Overconfidence Ranked Herding

MSA	**Average**	**Average pre-GFC**	**Average post-GFC**
New York	6.26	5.36	7.16
Los Angeles	4.10	16.29	9.04
Chicago	-0.46	11.24	0.44
Dallas	17.39	---	17.39
Houston	-5.22	-16.26	-3.17
Washington	11.86	29.14	13.30
Miami	14.05	---	14.38
Philadelphia	2.40	-14.86	10.49
Atlanta	-0.43	---	-0.43
Phoenix	4.88	-39.94	4.21
Boston	4.91	14.45	2.15
San Francisco	-2.28	-2.52	-2.86
Riverside	---	---	---
Detroit	15.27	---	16.42
Seattle	7.72	-13.80	7.81
Minneapolis	-7.15	---	-7.15

San Diego	-4.00	---	-4.00
Tampa	-5.65	---	-5.65
Denver	14.72	---	14.45
St Louis	4.56	---	4.56
Average	**4.36**	**-1.09**	**5.19**

Table 14: Housing Overconfidence

	Average		Average pre-GFC		Average post-GFC	
	Herding	**Reverse Herding**	**Herding**	**Reverse Herding**	**Herding**	**Reverse Herding**
High	9	24	9	4	9	17
Middle	9	18	10	15	3	42
Low	0	30	6	10	0	42

Table 15: Housing Overconfidence Ranked Herding

MSA	Average	Average pre-GFC	Average post-GFC
New York	0.30	-0.27	0.52
Los Angeles	-0.29	-1.08	-0.27
Chicago	-0.17	-0.76	0.02
Dallas	-1.34	-1.13	-1.14
Houston	0.05	-0.24	0.22
Washington	-0.40	-0.62	-0.11
Miami	0.30	-0.36	0.59
Philadelphia	-0.88	-1.92	-0.65
Atlanta	0.85	0.17	1.03
Phoenix	0.72	---	0.86
Boston	-0.19	-0.83	-0.21
San Francisco	-0.50	-2.07	0.00
Riverside	-6.31	---	-6.31
Detroit	-1.05	0.16	-1.42
Seattle	0.70	-0.27	0.82
Minneapolis	0.36	3.21	0.33
San Diego	-2.36	-3.20	-2.37
Tampa	-0.13	---	0.07
Denver	-0.11	2.55	-0.21
St Louis	0.91	-1.24	0.95
Average	**-0.48**	**-0.47**	**-0.36**

Table 16: Political Overconfidence

	Average		Average pre-GFC		Average post-GFC	
	Herding	**Reverse Herding**	**Herding**	**Reverse Herding**	**Herding**	**Reverse Herding**
High	10	24	9	27	2	46
Middle	5	25	26	11	7	39
Low	3	34	11	14	4	22

Table 17: Political Overconfidence Ranked Herding

	Average		Average pre-GFC		Average post-GFC	
	Herding	**Reverse Herding**	**Herding**	**Reverse Herding**	**Herding**	**Reverse Herding**
High					3	33

Middle					10	38
Low						36

Table 18: Combined Sentiment Ranked Herding

MSA	**Average**	**Average pre-GFC**	**Average post-GFC**
New York	-0.02	0.10	-0.20
Los Angeles	0.16	0.27	0.12
Chicago	-0.15	-0.12	-0.24
Dallas	-0.05	-0.31	0.10
Houston	-0.08	-0.28	-0.01
Washington	-0.03	0.07	-0.14
Miami	0.01	0.16	0.01
Philadelphia	-0.08	-0.03	-0.23
Atlanta	-0.06	-0.15	0.00
Phoenix	0.03	0.05	0.16
Boston	0.05	0.07	-0.03
San Francisco	0.15	0.17	0.15
Riverside	0.07	0.19	0.15
Detroit	-0.11	-0.25	0.06
Seattle	0.07	0.07	0.09
Minneapolis	-0.01	-0.01	-0.06
San Diego	0.11	0.17	0.11
Tampa	0.01	0.08	0.03
Denver	0.06	-0.11	0.14
St Louis	-0.12	-0.15	-0.22

Table 19: MSA Return Outperformance

	Average		**Average pre-GFC**		**Average post-GFC**	
	Herding	**Reverse Herding**	**Herding**	**Reverse Herding**	**Herding**	**Reverse Herding**
High	5	21	13	10	2	38
Middle	8	27	32	20	4	37
Low	5	35	2	29	7	32

Table 20: Return Persistence Ranked Herding

	Average post-GFC	
	Herding	**Reverse Herding**
High	3	30
Middle	3	47
Low	7	30

Table 21: Return Persistence Count