Explaining herding and volatility in the cyclical price dynamics of urban housing markets using a large-scale agent-based model

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Abstract
Urban housing markets, along with markets of other assets, universally exhibit periods of strong price increases followed by sharp corrections. The mechanisms generating such non-linearities are not yet well understood. We develop an agent-based model populated by a large number of heterogeneous households. The agents’ behavioral rules are consistent with the concept of bounded rationality. The model is calibrated using several large and distributed datasets of the Greater Sydney region (demographic, economic and financial) across three specific and diverse periods since 2006. The model is not only capable of explaining price dynamics during these periods, but also reproduces the novel behavior actually observed immediately prior to the market peak in 2017, namely a sharp increase in the variability of prices. This novel behavior is related to a combination of trend-following aptitude of the household agents (herding) and their collective propensity to borrow. Trend-following behavior is found to be essential in replicating market dynamics.

Keywords Agent-based modeling · Housing market · Herding · Simulations · Price dynamics · Boom–bust cycles

JEL Classification C15 · C63 · D10 · E37 · G17 · R31
Introduction

Urban housing markets in developed economies around the world exhibit a key characteristic in common. There are periods when house prices rise very rapidly, which are followed by sharp falls, as illustrated in Fig. 4 in the Appendix. In common parlance, this is often referred to as the “boom–bust” cycle).

The motivation of this paper is to develop a model based on the interactions of heterogeneous agents which, as a fundamental feature, is able to generate this type of dynamics observed in housing markets. We illustrate this general feature with specific simulations of the model calibrated to the data for the housing market in Greater Sydney. We choose Sydney, because over the past 20 years—the period for which detailed and high-resolution housing market and micro-economic data has become available—the market has experienced not one but two periods of notable price corrections. The detailed data available for Sydney identify a very marked increase in the variability of monthly house prices in the period immediately prior to the most recent downturn at the end of the 2010s. This is a further key feature that an adequate model of the housing market ought to be able to generate.

We focus on three specific periods in the Australian housing market. First, the period 2006–2009, which contains the global financial crisis. Although Australia was one of the few Western economies not to experience a serious general economic recession, as Fig. 1 shows that there was a fairly marked but short-lived market downturn. We also examine the period 2011–2014, when the housing market was

![Fig. 1 Greater Sydney house price. The monthly average price (circles) and the yearly moving average price (line) of the housing sales for Greater Sydney region. Source: Securities Industry Research Centre of Asia–Pacific on behalf of CoreLogic, Inc](image-url)
recovering very slowly, to show that our model is able to reproduce a range of different features observed in housing markets.

We calibrate our model to these two periods. With one important exception, we use the parameters calibrated for these two periods and apply them to the third period, 2016–2019, which exhibits the most recent price correction preceded by substantial market volatility. The only model parameter that is changed across all three periods is the trend-following aptitude attributed to household agents, which quantifies their tendency to follow the price trend.

Our model is able to track the actual aggregate house price index based on heterogeneous budgetary constraints and buying and selling decisions of individual households. In addition, the model captures key qualitative dynamics such as market turning points and market volatility.

In the context of the market and economic conditions, we identify the parameters that affect market volatility. One of the key properties is the collective propensity to borrow, which quantifies the steepness of the observed statistical dependence between mortgage and income. The particular effect on the price volatility is observed only in a combination with the trend-following aptitude.

Our model reveals the key features of the Australian housing market and closely reproduces the actual non-linear market dynamics. In this model each household’s budget is individually represented: their income, tax, discretionary spending, housing expenses as well as a range of housing market and macro-economic factors. The transition of a household from renting to home ownership to owning an investment property, or in the other direction divesting to owning one home or renting, is modeled heterogeneously based on the individual household’s ability to afford the mortgage costs and the willingness of the bank to provide a mortgage for the purchase. Heterogeneity of the households is accounted for by sampling their individual properties from distributions, rather than assigning them the same fixed value.

Related works

Boom–bust cycles have been studied in general (Reinhart and Rogoff 2009), but little consideration has been given to the feedbacks which generate the sensitivity of the cyclical behavior with respect to both exogenous and endogenous factors. In line with previous works focusing on financial markets (Kirman 1993; Cont and Bouchaud 2000; Alfarano et al. 2005; Alfarano et al. 2008; Carro et al. 2015; Chen et al. 2015; Barde 2016; Yang and Carro 2020; Barde 2016), we argue in this paper that herding, or the trend-following behavior of households, is a prominent feature of such feedback dynamics in housing markets, often leading to non-linear amplification of price fluctuations (Axtell et al. 2012; Case et al. 2003; Geanakoplos 2010; Kaplan et al. 2017).

Agent-based models (ABM) are one of the most significant developments to emerge in economic modeling in recent years and they have been proposed as an alternative solution to the modeling of complex economic dynamics that formal or aggregate level models are not well suited for (Arthur 2006; Farmer and Foley 2009; Dawid and Gatti 2018; Haldane and Turrell 2017; Haldane and Turrell 2019). Their
strength lies in the micro-interactions between individual decision-making agents (Tesfatsion 2006) each with their own characteristics; for example, businesses, households, or consumers, as well as spatial characteristics that geographically localize these interactions (Barthelemy 2016; Crosato et al. 2018). These interactions can, in turn, be affected by banks’ policies (Teglio et al. 2012; Dosi et al. 2013; Banwo et al. 2019) and macroeconomics conditions (Cardaci 2018; Guilmi 2017; Mérő 2019). These agent-to-agent interactions produce complex (Jensen 2010), non-linear effects such as tipping-points (Brock and Durlauf 2001; Harré et al. 2019), boom-bust cycles (Geanakoplos et al. 2012), and chaos (Brock and Hommes 1998, Xin and Huang 2017), as well as the equilibrium dynamics predicted by classical models. More recently, an ABM was shown to outperform predictions made by several benchmark models which were based on vector auto-regression and dynamic stochastic general equilibrium approaches (Poledna et al. 2019). Such approaches are prominent in mainstream economics, commonly used by central banks for policy decision-making, providing motivation for the use of ABMs to complement current economic modeling and forecasting techniques.

A key advantage is that, unlike formal approaches that often rely on an assumption of equilibrium (Farmer and Geanakoplos 2009), the results of ABM simulations can be either in or out of equilibrium. Importantly, the results of simulations can be interrogated to understand how the interactions of heterogeneous agents at the micro-level drive and give rise to the macro-level system dynamics. As such, ABMs have a much wider range of applicability than traditional approaches.

This breadth of applicability comes at a cost though; the necessary micro-economic data, over relatively short time periods, are often hard to obtain, the quantity of data is often difficult to manage, and the quality of the data itself can be heterogeneous. At the same time, the decision-making algorithms of the agents need to be well founded in micro-economic principles, as do the interactions between the agents that influence these decisions. While these factors make the task difficult, significant advances have been made recently in the collection, curation, and deployment of government data, as well as in the commercial availability of data collected by private industry. For example, many non-economic ABMs need to integrate disparate data sets and yet have had significant success in simulating complex social dynamics such as the collapse of societies (Axtell et al. 2002) and pandemic spread and intervention strategies across a country or the globe (Cliff et al. 2018; Zachreson et al. 2018).

In housing economics, there have also been recent successes, but there are still only a few models that have used high-resolution household level data to successfully model large sectors of the market. The ABM developed by Axtell et al. (Geanakoplos et al. 2012; Axtell et al. 2014; Goldstein et al. 2017) for Washington DC replicated the features of the rise and fall (bubble and crash) dynamics seen in the house price index for Washington DC during the 1997–2009 period, including the period of the global financial crisis. The Washington DC model incorporated a large amount of demographic, economic, and financial data, and detailed the decision-making behavior of household agents. As a result, it was able to provide a good understanding of housing market indicators, such as real estate sales, inventories, and market tightness, although it did not forecast the exact timing and magnitude
of the GFC bubble. The subsequent ABMs investigated various aspects of housing markets, such as the long-term macro-economic aspects of a repeated rise and fall dynamic (Kouwenberg and Zwinkels 2015; Baptista et al. 2016), households’ creditworthiness conditions (Erlingsson et al. 2014), income segregation (Pangallo et al. 2019), effects of loans and mortgage securitization (Lauretta 2018; Mazzocchetti et al. 2018), and general financial instability (Roberto et al. 2019).

In this paper, we use an ABM approach to model the Greater Sydney region at the individual ‘household accounts’ level. Our model follows the general framework developed in the seminal Washington DC (Geanakoplos et al. 2012; Axtell et al. 2014; Goldstein et al. 2017) and U.K. (Baptista et al. 2016) models. Unlike the works within the EURACE project (Cincotti et al. 2010; Erlingsson et al. 2014), we focus specifically on the housing market, modeling the housing transactions only. This allows us to isolate the details of non-linear housing price dynamics, revealing the importance of the coupling between herding and the collective propensity to borrow in forming the market sentiment. Furthermore, we do not investigate long-term rise and fall patterns (Ge 2017; Baptista et al. 2016; Kouwenberg and Zwinkels 2015); rather, we look at short-term dynamics, closely reproducing observed non-linearities. Furthermore, contrary to other models, our ABM simulates the decision-making dynamics of a large number of household agents (about 200 thousand). Being applied to a single metropolitan area with about 2 million households, this allows us to capture the heterogeneous nature across major variables of the real population structure taken from the Australian Census. Finally, the model is calibrated and tested on two separate historical periods. In particular, the calibration is performed on 2006–2009 and 2011–2014 periods, while testing/prediction is performed on 2016–2019 period. This allows us to reduce the number of free parameters in the model, making our ABM essentially single-parametric. The single adjustable parameter in the model controls the agents’ aptitude towards trend-following and represents a collective state variable of the market (Bouchaud 2013). As the degree of herding in the market may vary in time, the trend-following aptitude must therefore be adjusted correspondingly.

Model

Our ABM for the housing market of Greater Sydney consist of the decision-making algorithm of the household agents, together with its internal parameters representing typical household decisions, relevant for the Australian housing market. The model includes a set of environmental parameters, which represent the input from the real market. Changing the input allows us to simulate possible effects of various financial and economic policies over time.

The agents implement their decisions, acting in discrete time steps according to a certain algorithm. In particular, they interact with each other, following the same budget-balancing and investment rules, which model typical decisions of real households. Every agent possesses certain attributes (e.g., income, liquid wealth, residence), which affect their decisions and, in turn, are affected by these decisions. Furthermore, the agents interact with the environment (e.g., the bank) subject to certain
constraints, such as mortgage rate and financial prudence policies. Each simulation run results in a multivariate time-series of key market indicators, such as price index, proportion of investing households, foreign participation, etc. The output of the model is an aggregate result of the decisions of the interacting heterogeneous household agents. The households are heterogeneous in the sense of having different values of their attributes (wealth, income, etc.) and different dynamic trajectories.

The decision model of a household agent is composed of a deterministic component and a stochastic component. The deterministic component is reflected in the behavioral algorithm of an agent and in the values of environmental constraints. The stochastic component is reflected in the heterogeneity of agents’ decisions and attributes, resembling the actual Sydney housing market and typical household behavior. In particular, all agents follow identical decision rules (deterministic component), yet have different values of their attributes sampled from the specific distributions (stochastic component). The result of a single simulation is a particular evolution trajectory of the simulated world, which may be compared to the real world evolution. Yet, because of the presence of a stochastic component, we analyze the evolution of an ensemble of trajectories, which is a collection of the simulation outputs with the same values of the deterministic component.

The model uses a set of the external environmental parameters, the values of which represent the state of the real market at the beginning of the simulation period. They include the external financial constraints (Table 1) and statistical structure of the population (Table 2). The corresponding time evolution and the statistical distributions are shown in Figs. 5–9. Furthermore, the model is characterized by a set of internal algorithmic parameters (Table 3), which do not vary in time, and are independently calibrated.

The parameters reflecting the financial constraints may vary in time, but have the same values for all agents. In contrast, the parameters which reflect the agents’ individual properties are heterogeneous, i.e., different for each agent. These include properties like wealth and income, which are sampled from the observable statistical

| Table 1 | External parameters of ABM |
|---------|---------------------------|
| Name    | Symbol | Values  |
|         |        | 2006–2009 | 2011–2014 | 2016–2019 |
| Income tax brackets, $’000 | Φ_{T} | 6, 25, 75, 150 | 6, 37, 80, 180 | 18.2, 37, 87, 180 |
| Income tax rates, % | Φ_{T} | 15, 30, 40, 45 | 15, 30, 37, 45 | 19, 32.5, 37, 45 |
| House owning expenses, % | Φ_{H} | 4.2 | 4.2 | 4.2 |
| House purchase tax, % | – | 5 | 5 | 5 |
| Annual mortgage rate, % | Φ_{M} | 7.3–9.45 | 5.53–7.79 | 4.95–5.35 |
| Mortgage duration, years | – | 30 | 30 | 30 |
| Mortgage LVR mean, % | Φ_{LTV} | 72.5 | 67.5 | 60 |
| Mortgage LVR variance, % | – | 12.5 | 12.5 | 12.5 |
| Mortgage-income statistics | Φ_{b}, Φ_{I} | 689.53; 0.81 | 1072.1; 0.75 | 1141.7; 0.80 |

The parameters describing external economic and financial conditions of each period used in simulations. These percentages are converted to fractions when used in equations.
distributions (Table 2), as well as internal algorithmic parameters (Table 3), such as “fraction of income to spend on rental” or “bid price factor”, which are sampled from calibrated uniform distributions.

Finally, each of the simulated periods is characterized by a single feedback parameter which couples the external and internal aspects of the simulated market. The seminal paper by Bikhchandani et al. (1992) showed that the existence of a feedback can generate herding behavior even in models populated by rational agents.
In our model, the feedback parameter reflects the agents’ desire and capacity to follow the price trend; it will be referred to as the trend-following aptitude. Similarly to the financial constraints, this parameter has the same value for all agents. The value of the trend-following aptitude is calibrated, so that the price resulting from the model resembles the observable price dynamics, and thus, it is different across historical periods.

Every residential agent receives a monthly income, which is accumulated as wealth. Furthermore, it may possess a number of houses. One of these houses (if there are any) is the agent’s residence, and the other (if there are any) are the valence houses, used for investment. In particular, the valence houses are available to other agents without own houses for renting as residences. Renting continues indefinitely until the resident manages to purchase an own house. A house is owned by a single owner, either an agent or the developer, who creates new houses. Every house is characterized by a single attribute called quality, which is defined as the price of the house before the start of the simulation and is kept constant during the simulation. This attribute reflects an intrinsic value of the house, which is assumed to not deteriorate with time. A house may be transferred from the one agent (seller) to the other agent (buyer), which is compensated by the price being transferred from the buyer to the seller. This constitutes a deal which is a result of the market, and the deal price contributes to the output of the model. Every agent aims to own at least one house (to be used as a residence) while balancing its own budget, which essentially means attempting to buy a house whenever circumstances allow doing that.

Besides the developer, the model contains three other auxiliary agents, the overseas agent, the bank, and the government. The overseas agent is endowed with a certain capacity to buy and rent out valence houses, the specific number and total volume of which is approved by the regulator, and aims to fill that capacity as soon as possible and depending on market conditions, acting essentially as a buy-to-let investor. The bank agent can issue an unconstrained amount of lending to residential agents in the form of mortgages. The government applies taxes and determining the capacity of the overseas agent.

At every month t, the residential agents update their income I and wealth W according to basic income growth and budget accounting rules [see Eq. (1)]. Next, the agents participate in the market, which consists of several steps. First, every residential agent chooses its bid price \( P_b \), as the minimum of three budgetary constraints based on the agent’s capacity to repay the corresponding mortgage, namely, \( P_1 \), \( P_2 \) and \( P_3 \), defined by Eq. (3). In particular, \( P_1 \) is the price based on a self-assessment of the agent’s budget expectations, while \( P_2 \) and \( P_3 \) are the prices based, respectively, on the maximum loan-to-value and the maximum debt-to-income ratios allowed by the bank, either due to its internal policy or imposed by the regulator. If \( P_b / P_1 \) is larger than the expectation downshift (willingness to downgrade the pre-purchase expectation in house price/quality under financial prudence measures), the agent puts the bidding record on the market. This process captures the analysis of the agent’s affordability and negotiations with the bank. The overseas agent simply puts its bidding records on the market according to its capacity, as regulated by the government. Next, all agents go through their owned houses and with a certain probability put the listing record on the market.
with the list price defined by Eq. (4). The market is cleared with a one-step process based on bidding and offer price order. The owners of the listed houses, acting in the order of the decreasing list price, find the buyer with the highest bid price which is also higher than the list price. If a match is found, then the deal is cleared with a probability of 0.8, which reflects potential obstacles for the deal to proceed (e.g., geographical). This changes the ownership of the house and financial states of the buyer and seller. If no match is found, the listing record is transferred to the next month. Note that a deal is driven by selling agents: sellers scan the list of potential buyers, rather than buyers scan the list of potential sellers.

In the following equations, we use a simplified notation for ease of reading. The environmental parameters are denoted by the Greek letter $\Phi$ with corresponding subscripts and are listed in Table 1. They are observed in reality, set the same for all agents, but are different across the simulation periods. The internal parameters are denoted by the Latin letter $b$ with corresponding subscripts and listed in Table 3. They are the same across all simulated periods. The internal parameters also account for heterogeneity of the agents, which means that the actual value for a particular agent is sampled from a uniform distribution with a fixed mean and width. The other system variables are denoted by Latin capital letters, e.g., $Q$, $M$, etc. If a variable depends on time within a particular period, this is indicated explicitly by the argument $[t]$.

The income $I[t]$ and the wealth $W[t]$ are updated according to the following rules:

$$
I[t] = (1 + b_I)I[t-1] \\
W[t] = (1 - b_{CW})W[t-1] + (1 - b_{CI})(1 - \Phi_T)I[t] \\
- R_r - \sum_{i=1}^{H} (\Phi_H Q_i + M_i[t] - R_i).
$$

(1)

Here, $H$ is the number of the owned houses, while $i$ is the counter over these owned houses, $Q_i$ is the quality of the house, and $M_i$ is the monthly mortgage payment for the house. Furthermore, $R_i$ is the monthly rental payment (if applicable), which is subtracted from the wealth if the house is the residence $r$ and is added to the wealth if the house is an owned valence house $i$. Rent is fixed to its initial value and is calculated as

$$
R_h = \frac{1}{3} \Phi_R + \frac{1}{3} b_{RI} I[0] + \frac{1}{3} b_{RH} M_h[0],
$$

(2)

where $\Phi_R$ is a random value drawn from the rent bracket distribution, sourced from Census for each simulated period, $b_{RI}$ is the fraction of income spent on rental payments, and $b_{RH}$ is the fraction of mortgage payments compensated by rent (see Table 3).

The bid price is chosen as the minimum of three alternative candidates:
where $U_b$ is the urgency of the agent to buy a house, which is different from 1 when the agent has recently sold a house and has excess cash, and the term $\Phi_b(I[t])$ represents the collective propensity to borrow. As suggested by previous studies (Axtell et al. 2014; Goldstein et al. 2017), the expression for $P_1$ follows a basic accounting principle of anticipated costs, balancing the house owning expenses $\Phi_H$ and the cost of servicing the loan $\Phi_{LTV} \Phi_M[t]$, given the mean mortgage loan-to-value ratio $\Phi_{LTV}$ and the annual mortgage rate $\Phi_M[t]$, against the gains (the term $h \Delta_{HPI}[t]$). In contrast, $P_2$ and $P_3$ are motivated by loan policies of the bank which ensures the household’s capacity to pay the mortgage. In particular, they are set to reflect the threshold values of the loan-to-value and the debt-to-income ratios.

The list price is determined as

$$P_\uparrow[t] = \frac{b_\uparrow \bar{Q}_h(S[t])^{b_\uparrow} U_\uparrow[t]}{(1 + D[t])^{b_\uparrow}}.$$  

where $b_\uparrow$ is the listing premium. Furthermore $U_\uparrow$ is the urgency of the agent to sell a house, which is different from 1 either when the agent is financially stressed or when his valence house is not rented out. $S[t]$ is the market average of the sold-to-list price ratio, while $D[t]$ is the amount of months the house has been listed on the market. Finally, $\bar{Q}_h$ is the average quality of the ten most similar houses.

**Implementation**

**Simulation details**

In the model, we calculate the average monthly housing price of the simulated market. We next compute the 12-step moving average price, which is referred to as the yearly moving average and represents the resulting price. The range of 12 steps (corresponding to 12 months) is chosen to discard the effect of seasonal price variations.

Each simulation produces a particular trajectory of the price dynamics, which corresponds to the imposed market structure. An ensemble of 1000 trajectories is analyzed for each period to obtain the resulting price evolution. Each trajectory is characterized by a different random seed for the stochastic component. Each simulated household represents ten real households, resulting in more than 200 thousand households in the system. The model runs in time steps, which are equivalent to 1 month of real time each. Each simulation consists of the equilibration period and
the calendar period. The equilibration period is needed to accommodate biases of
the initial distribution of wealth and houses between the households. The calendar
period follows the real time with a specific starting date. In our model, we use an
equilibration period of 26 months and a calendar period of 30 months. A typical
simulation run corresponding to up to 60 months of the housing market dynamics
with approximately 200 thousand agents takes 15–25 s on a laptop with an i5-6300U
CPU (2.4 GHz, 2 cores), 7.6 Gb RAM, and Windows 10 Enterprise OS, as imple-
mented in a stand-alone C++ code, developed specifically for this model.

Data description

The model uses a number of data sources to initialize the agents’ behavior, which
are listed in Table 2. The data are available in an aggregate format, in term of distri-
butions or time-series, which are illustrated in the Appendix. The individual prop-
erties of the agents are sampled from the corresponding distributions.

The model uses a number of internal parameters, which reflect characteristics of
an individual agent and of the algorithm and are listed in Table 3. The values of
these are the same for all periods and therefore reflect the algorithm rather than the
actual state of the market. Yet, just like the algorithm is designed to mimic the typi-
cal households’ behavior, the values of the internal parameters are chosen to account
for the typical households’ decisions.

The model is calibrated against aggregate housing transactions data, synthesized
from anonymized individual property transaction records, approved and supplied
by Securities Industry Research Centre of Asia–Pacific (SIRCA) on behalf of Core-
Logic Inc.

Calibration

The model is calibrated by simulating two periods 2006–2009 and 2011–2014, cor-
responding to the Censuses held in Australia in 2006 and 2011. We use the resulting
parameters, as described above, to simulate the market from July 2016 to December
2018, i.e., over a period of 30 months. The starting date of the simulation is aligned
with the Australian Census held in 2016, which ensures the best representation of
the real population.

To calibrate the trend-following aptitude, we run simulations for different val-
ues of h. The median price of the ensemble of 64 trajectories is compared to the
observable price dynamics given by the SIRCA data on behalf of CoreLogic Inc.
The resulting value of h is chosen as the one which produced the best fit trajectory
by the least-squares method. The trajectories for different h and their distance to the
CoreLogic trajectory are shown in Fig. 11. In a parallel study, we have carried out a
sensitivity analysis of the model with respect to several key parameters, establishing
its robustness (Evans et al. 2021).

We use the variability of individual simulated trajectories within the ensemble to
evaluate the volatility of the actual price observed in the actual data for Greater Syd-
ney (Fig. 1). In particular, we expect them to correlate, hence allowing us to analyze
the actual price volatility by tracing the price evolution within the entire simulated ensemble.

To investigate high price variability in the period of 2016–2019, we have simulated a number of “alternative histories”, as defined by alternative sets of input data. Each alternative history is described by almost exactly the same data as the real data of the 2016–2019 period, except the values of one parameter. The alternative values for each of these parameters are taken from the 2011–2014 input data. Plugging the values of each of the alternative parameters into the 2016–2019 data we were able to isolate their effect on the price dynamics, in particular, on its ensemble variability.

To investigate the long-run dynamics that can be generated by the model, we have simulated a long-term evolution (20 years). The results are shown in Figs. 12–15. In particular, we observe that the dynamics generated by different values of the trend-following aptitude do not just relax in the long-run, but exhibit non-linearity. Specifically, the nature of the long-run behavior appears to be cyclical, to a greater extent for high values of the trend-following aptitude. Such behavior has also been a prominent feature in the dynamics produced by similar models (Geanakoplos et al. 2012; Axtell et al. 2014; Baptista et al. 2016). Additionally, in the long-run dynamics which start in 2011 (e.g., \( h = -0.2 \)), we observe emergence of bifurcations. These long-run dynamics develop beyond the horizon used in our study (30 months). In general, the value of trend-following aptitude would vary in time, making a substantial impact on the eventual market dynamics. For example, the long-run cycles observed for high trend-following aptitudes are not expected to continue ad infinitum, since a strong price correction would most certainly lead households to revise their trend-following behavior downwards, thus preventing further cycles. On the opposite side, when the trend-following aptitude is low, positive price fluctuations would lead households to revise this aptitude upwards, driven by the fear of missing out.

**Synthetic population**

Individual household and house characteristics are sourced from the actual distributions corresponding to a specific date range, listed in Table 2. House ownership and residence are distributed randomly between households, according to four categories: (1) owned outright; (2) owned with mortgage; (3) rented out; (4) vacant. Each household is assigned as a resident of one random house. The number of households is fewer than the number of houses, so some of the houses become automatically vacant. Random houses among the occupied one are assigned as owned outright, and their residents become their owners. Random houses among those occupied are assigned as owned with a mortgage, and their residents become their owners and receive random mortgage. The remaining houses are all rented out. Their owners are chosen randomly from the households who own houses outright; for each rented out house, these households receive a mortgage for a random fraction of the house value, assuming the remaining fraction has been paid off. This ensures that initially investors do not have mortgage debts on their residences.
Results

We present the results of an agent-based model which simulates the price dynamics of the Greater Sydney housing market. In particular, we address three interrelated aspects of the price dynamics in the corresponding sections below: the temporal evolution of the price (trajectory), the ensemble variability of the price, and the herding feedback parameter (trend-following aptitude).

A key feature capturing the heterogeneity of agents is the relationship between the household income and their collective propensity to borrow. Particularly, at the high end of the income distribution, this propensity varies substantially across the agents. We show that this relationship, when coupled with the trend-following mechanism, is essential to capture the large increase in variability of the market seen immediately prior to the turning point in 2018.

Price trajectory

The results for the periods of 2006–2009, 2011–2014, and 2016–2019 are shown in Fig. 2. Each simulated period is represented by ensemble trajectories (left) and the histogram (right) of the yearly moving average price. The corresponding values of the monthly average deal price and yearly moving average deal price from the SIRCA/CoreLogic data are shown for reference as well.

We see that the simulated price trajectories in the period of 2006–2009 exhibit a strong cyclical dynamic, showing a stable increase followed by a rapid change of trend and a stable decrease. The magnitude and the width of the cycle reproduce those observed in reality, with the simulated price trajectory being slightly ahead of the actual one. All simulated trajectories follow a similar rising-then-declining trend. The price volatility within a single trajectory as well as the variability between different trajectories is small. Still, each trajectory represents a separate market dynamic. This can be verified by the absence of correlations between the price at the beginning of the simulated period and the price at the end of the simulated period, as illustrated in Fig. 10 (left). For this particular period, 2006–2009, the simulated trajectories follow a similar profile within a narrow band (Fig. 2). The observed pattern of the price dynamics is endogenous, with no specific external force causing it (i.e., it is a consequence of a canonical supply–demand balance). The simulated ensemble contains several outlier trajectories along which the price significantly increases near the peak. As is evident from the histogram distribution and the average curve, these outliers comprise only a small proportion of the ensemble; yet, their existence indicates that the market was close to a cusp during 2007–2008.

The simulated price trajectories in the period of 2011–2014 exhibit low but steady growth. This is also similar to the actual price dynamics, except for a short dip during 2012. The ensemble variability is again low, while individual trajectories show little correlation with significant heterogeneity between the start and the end of the period (Fig. 10, middle).
Fig. 2 Agent-based model output. Market price produced by multiple simulations, for the period of 2006–2009 (top), the period of 2011–2014 (middle), and the period of 2016–2019 (bottom). For each period, the left figure shows 1000 simulated trajectories (thin solid colored lines), together with the median trajectory (thick yellow line) and the monthly averages of the actual sale prices (CoreLogic: black circles with a thin dashed line). The right figure shows the histogram distribution of the ensemble (color shade), together with the yearly moving average of sale prices (CoreLogic: dashed black line).
Price variability

In contrast to the two previous periods, the simulated price trajectories in the period of 2016–2019 exhibit high ensemble variability. This indicates that the market conditions facilitate a broad range of possible trajectory realizations and there is a high degree of uncertainty in the price dynamics. Yet, the ensemble average of the trajectories reproduces the actual dynamics well. In particular, it shows significant growth which eventually plateaus in mid-2017 and is followed by a slow decline until 2019. Furthermore, the rising-then-declining dynamics in the period of 2006–2009 and of 2016–2019 are similar, while the latter one shows much larger variability.

We have also found that there are two parameters which most affect the price variability: the mortgage rate and the heterogeneous relationship between mortgages and income, which reflects the collective propensity to borrow. This effect is only observed in combination with a high trend-following aptitude. Importantly, changing the trend-following aptitude alone does not reduce the ensemble variability either.

In particular, we examined a range of possible factors potentially contributing to variability, investigating “alternative” historical scenarios by changing one of the financial conditions (which are accounted by the external parameters) from the 2016–2019 values to 2011–2014 values (when the variability is low), while keeping all other parameters at their 2016–2019 values. We found that the majority of the external parameters do not affect the price ensemble variability for the 2016–2019 period. This is illustrated by the top-right panel of Fig. 3, where the altered parameter is the initial price level, and the ensemble variability is still high. Altering other parameters, such as population level, housing stock, distribution of wealth, income, mortgage, or overseas investment activity, similarly, does not affect much the price variability within the ensemble (although it does change the price trend).

In contrast, we found that using the 2011–2014 values of either the mortgage rate (which is higher during 2011–2014 than during 2016–2019, see Fig. 6) or the collective propensity to borrow (which is lower during 2011–2014 than during 2016–2019, see Fig. 9), in conjunction with a moderate trend-following aptitude, does reduce the price ensemble variability, as evidenced by the bottom panels of Fig. 3. Hence, we conclude that high ensemble variability is caused by one of the two combinations:

(i) high trend-following aptitude and low mortgage rate;
(ii) high trend-following aptitude and high collective propensity to borrow.

Trend-following aptitude

In addition to the environmental parameters the model uses a feedback parameter which reflects the agent’s desire to follow the price trend. This influences the agent’s bid price when they participate in the market. The price trend is represented by the annual change of the house price index, $\Delta_{HPI}$, which is positive if prices are rising
and negative if they are falling, while the price index itself is calculated by the BMN methodology (Bailey et al. 1963). The price trend contributes to the bid price decision, which imposes a feedback in the model and couples the fixed internal decision model with the dynamic external conditions. The bid price $P_b$ is modeled by Eq. (3), where the trend-following aptitude $h$ comes as $P_b = A/(B - h\Delta \text{HPI})$, with $A$ and $B$ being independent of $h$. The bid price follows a basic accounting principle of anticipated monthly costs (i.e., mortgage and taxes) and gains (i.e., anticipated growth in value of the house due to market growth). The latter is modulated by the parameter $h$, which shows how sensitive the agents’ desire to buy a house is to the overall price trend. If $h = 0$, then the agents are completely indifferent to the observable price dynamics, and the magnitude of $h$ quantifies the strength of the feedback.

The value of the trend-following aptitude is the same for all agents. One may draw an analogy with thermodynamics in line with social physics research (Bouchaud
For example, the trend-following aptitude may be seen as a collective state variable of the market. A higher magnitude of the aptitude would correspond to a more “heated” market, while a lower magnitude of the aptitude would correspond to a more “cooled” market.

One of the purposes of this work is to identify how the trend-following aptitude may be related to the actual market dynamics. To do this, we assume that the value of the aptitude is fixed during a single simulation period. Yet, we allow the aptitude to be different for different simulated periods. The actual value of the trend-following aptitude is calibrated to the actual price dynamics, minimizing the distance between the actual and simulated prices over each period.

The resulting values for each period are the following: \( h_{2006} = 0.45 \) for the period of 2006–2009, \( h_{2011} = -0.10 \) for the period of 2011–2014, and \( h_{2016} = 0.65 \) for the period of 2016–2019.

The aptitude value is quite high for the period of 2006–2009, which means that the agents tend to strongly follow the collective behavior. This agrees with the perception of the actual market at the time, given both the GFC shock and the post-GFC government stimulus initiatives, such as the First Home Owners Boost, which reignited the market (Randolph et al. 2013).

The magnitude of the aptitude is the lowest for the period of 2011–2014, having negative sign and moderate magnitude. This means that the simulated market is “cooled” and agents are not expecting the price to increase. Rather, they tend to ignore the price trend or even expect the price to reverse. The Sydney market was transitioning from a peak in 2011 to a dip in 2012, followed by a steady growth in the subsequent 5 years. A negative value of the obtained aptitude indicates the agents’ caution and skepticism towards trend-following. However, the model still reproduces the modest growth which was seen in the actual market. The other features of the model, reflecting fundamental rather than speculative aspects of the market, are sufficient to override the negative aptitude. This suggests that increasing price on the housing market in 2011–2014 was driven by financial factors rather than people’s collective behavior.

For the period of 2016–2019, the value of the aptitude is the highest, which indicates that the market is “super-heated”. This value, in combination with low interest rates and/or high collective propensity to borrow, is, as we explained above, the mechanism which generates the large ensemble variability of the market in the simulations, within a broader distribution exhibiting outlier trajectories. This reflects the large variability in the actual market.

**Discussion**

In this work, we have developed an agent-based model which simulates universal features of urban housing markets observed across the world.

Our empirical realization of the model is based on demographic data and market conditions for Greater Sydney over three different historical periods taken from the last 15 years. Using a decision-making algorithm for interactions between ca. 200 thousand heterogeneous agents, we reproduce the actual market dynamics for these
three periods. The first period coincides with the global financial crisis and a corresponding price increase and correction in the Sydney housing market. The second period covers a completely different historical experience in which prices initially fell slightly and then recovered moderately.

The third period covers the end of a period of rapid growth in the Sydney market followed by its subsequent decline. Crucially, the variability of the actual prices increased very markedly immediately prior to the turning point and the model replicates this behavior. We note that, with the exception of the trend-following parameter, the parameters used in the simulations of the third period are those obtained from the calibration using the first two periods. In other words, the model is capable of generating novel behavior not observed in the real world during the calibration periods. This novel behavior does concur with the actual market dynamics in the third period, given initial market and economic conditions.

The households in the model follow rules of behavior which are consistent with the concept of bounded rationality as developed by Simon (1955). In particular, they form backward-looking expectations about the future evolution of prices, which they then use to decide on their bid price using simple accounting rules. The agents can be thought of as following satisficing behavioral rules in the sense of Simon. We noted above, however, that the phenomenon of herding behavior by following sentiment is also consistent with individual rationality in the more classic economic sense of the term. The key insights of the model are obtained by combining such postulates of behavior with data-driven approaches. The large data sets which we access enable a very fine resolution of heterogeneous agents’ behavior to be included and calibrated in the model. Such an agent-based framework allows us to investigate in detail the effects of multi-agent micro-economic interactions resulting in emergent macro-economic dynamics (Assenza et al. 2015). These dynamics are not, in general, susceptible to solutions based on simple analytic techniques. Such canonical methods typically assume normal distributions around equilibrium outcomes as well as linearity of cause and effect (Rogers 2017). Agent-based models capture non-linear interactions more naturally by exploiting the fine-grained behavior calibrated by large data sets.

Agent-based models have already found considerable success in epidemiology (Zachreson et al. 2018; Germann et al. 2006), social sciences (Axtell et al. 2002; Bonabeau 2002), and ecology (Grimm et al. 2005; Filatova et al. 2013). In this paper, we provide further evidence for the applicability of ABMs for uncovering the mechanisms generating non-linear behavior in economics.

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**Author contributions** KG analyzed the source data, developed the software code, performed and analyzed the simulations, and prepared the manuscript (“Model”, “Implementation”, and “Results” sections,
Figures, and Tables); KG, MP, and MH developed the model; AC consulted on agent-based modeling; PO consulted on economic modeling; all authors contributed to “Introduction”, “Related works”, and “Discussion” sections of the manuscript.

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**Availability of data and materials** All data needed to evaluate the conclusions in the paper are present or referred to in the paper. The reference data for housing transactions are owned by CoreLogic, Inc. Additional information related to this paper may be requested from the authors.

**Declarations**

**Conflict of interest** The authors declare that they have no conflict of interests.

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