Attention and Housing Search: Evidence from Online Listings*

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Abstract

We study fluctuations in households' attention to the housing market and their effects on home sales. Exploiting a unique dataset that tracks user activity on a major property website, we show that buyers' attention positively responds to price growth in their postcode of residence. The increase in attention does not translate into higher effort allocated to inspecting individual listings, but in more extensive searches, covering a broader range of locations and property characteristics. These effects are mainly driven by the response of homeowners, and results are stronger when postcode price growth is instrumented using a measure of local supply-elasticity. More extensive searches reduce segmentation on the demand side of the market, leading to higher prices and lower time on the market for homes listed for sale. This is consistent with fluctuations in households' attention having procyclical effects on house price growth and generating spillovers within metropolitan areas.

Keywords: Attention, House Search, Homeownership, Segmentation, House Prices
JEL Classification: D10, E32, G40, R31

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1 Introduction

Extensive evidence in financial markets indicates that fluctuations in investors' attention do have real effects[1] and are linked to market conditions.[2] However, little is known about investors' attention in real asset markets, and in particular in housing, despite it being one of the main asset classes in the economy,[3] and one in which fluctuations in attention play a key role for several reasons. First, home buyers are mostly retail investors whose interest in housing is likely to fluctuate with changes in their personal wealth and in general market conditions. Second, choosing how to allocate attention to house search is a complex problem. It involves an intensive margin (i.e. the amount of information collected on individual homes) and an extensive margin (i.e. the breadth of searches). Third, by changing the degree of scrutiny of individual home listings and the breadth of searches, fluctuations in attention affect the likelihood of matches between buyers and sellers, and thus house prices and market liquidity.

In this paper, we exploit a unique dataset tracking the behavior of users on a large property website to show that buyers' attention to the housing market increases in response to price fluctuations in their postcode of residence. Most importantly, we show that the increase in attention is not symmetric across the intensive and the extensive margin. The amount of attention devoted to individual listings remains unchanged. When households increase attention, they appear to act on the extensive margin, by visiting a larger number of home listings within their metropolitan area, and searching over a broader set of homes, in terms of locations (postcodes), house characteristics, and prices.

The increase in attention driven by local house prices, and in particular its allocation to-

[1] Fluctuations in attention have been shown to induce a delay in price response to news and earning announcements (Hirshleifer, Lim, and Teoh, 2009, Della Vigna and Pollet, 2009 and Loh, 2010) to generate temporary price pressure (Barber and Odean, 2007 and Da, Engelberg, and Gao, 2011), volatility spillovers (Hasler and Ornthanalai, 2018) and return co-movements (Huang, Huang, and Lin, 2019 and Drake et al., 2019).

[2] See Yuan (2015) and Sicherman et al. (2016) for empirical evidence and Andrei and Hasler (2015) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) for a theoretical background.

[3] According to a report published by Zillow, the market value of the U.S. housing stock was estimated to be close to $30 trillion in 2016. At the end of the same year, total U.S. stock market capitalization was close to $25 trillion.

wards the expansion of search ranges, impacts house sales in the broader metropolitan area. Higher attention decreases market segmentation, since individual listings become integrated into broader searches. This in turn leads to higher sale prices and lower time on the market.

Our dataset tracks the interactions of individual users with online listings, across the entirety of Australia and over a period – January 1, 2017 to 30 April, 2019 – characterized by large price variations both in the time-series and the cross-section. Crucially, user behavior is merged with information on users characteristics, such as postcode of residence, homeownership status and demographics. We construct measures of attention based on the number of listings visited, the number of visits and the time spent browsing listings on the website. Similarly, we use information on the geographical dispersion of listings visited by the individual users, as well as differences in listing characteristics, to construct measures of search breadth.

Our first focus is to establish that there are fluctuations in households' attention to the housing market, and that these fluctuations coincide with changes in market conditions. To this end, we study the response of buyers' attention to local housing market conditions, which we measure using recent house price growth in the buyers' postcode of residence. We estimate buyers' response using regressions of measures of total attention, and then of the intensive and the extensive margin, on price growth. The regressions include a rich set of fixed-effects: time by metropolitan area[4] fixed effects, which control for common housing market fluctuations, as well as postcode and even individual user fixed effects, which control for heterogeneity across, respectively, locations and users. A 15% larger increase in postcode house prices over the previous two years (roughly equal to a one-standard deviation increase) leads to close to a 5% increase in our proxies for the level of attention: number of listings visited, the number of visits to listings and the time spent on the website. We find effects of similar magnitude when the dependent variable is one of the measures of search breadth, equal to either the number of postcodes, the breadth of the area, or the number of market segments (defined based on a

[4]We construct these areas by splitting each Australian state into the metropolitan area of its capital city and the rest of the state.

combination of listed homes locations and characteristics) visited. However, the relationship between price growth and *the average number of visits and minutes spent per listing* is not statistically significant. Even when we measure the *concentration* of attention across listings using the *Herfindahl Index* of time spent per listing, we again find that there is no statistically significant relationship between past price growth and concentration, and the point estimates of the coefficients are actually negative.

There is a clear parallel between the insights on attention allocation along the intensive and extensive margin described in this paper and previous work that focused on the trade-off between allocating attention to individual financial securities rather than to the broader financial market (see Peng and Xiong, 2006, Mondria, 2010 and Van Nieuwerburgh and Veldkamp, 2010). The implications of the distinction between intensive and extensive margin are uniquely important for housing search. Home buyers are not deciding portfolio composition across multiple assets, but they are typically focusing on purchasing an individual asset, in a market that is highly segmented and while facing asymmetric information with respect to sellers. The intensive margin can be interpreted as the dimension in which the buyer evaluates the potential quality of the match with a specific house, and establishes whether to move further, for example by visiting the property. The extensive margin determines the range of possible matches available to the buyer, delimiting her search within the broader housing market.

An immediate concern with interpreting our empirical results is that attention endogenously affects house prices. However, it is uncommon for households to move within postcode, and in our data the vast majority of visited listings are located outside the postcode where a user lives. Moreover, to further argue for a causal relationship between price growth and attention, we develop two alternative empirical strategies.[5]

First, we rely on the intuition that homeownership is a natural channel through which a causal relationship between local price growth and attention would operate. Higher prices

[5]Our approach here is related to the one in Stroebel and Vavra (2019), who study the effects of house prices on retail prices and markups.

increase the likelihood of homeowners engaging in house sales and purchases, either because higher prices increase homeowners' wealth and relax collateral constraints (see Stein, 1995), or because of behavioral mechanisms, for example linked to loss aversion (see Genesove and Mayer, 2001). In our dataset, we find that buyers' response to price fluctuations is stronger in postcodes with higher homeownership rates. Across postcodes, a 10% higher homeownership rate is associated with a one-third larger effect of price growth on overall attention (number of listings visited) and on the extensive margin (search breadth). Moreover, exploiting information on the homeownership status of individual users, we find that when the sample is restricted to homeowners, point estimates of the sensitivity of the number of listings visited to local price growth are 50% larger than estimates based on the entire sample of users, which includes renters. Consistent with our previous results, we find that the homeownership rate of the postcode has no effects on the intensive margin (attention per listing), and even when restricting the sample to homeowners, we don't find effects of price growth on the intensive margin.

Second, we develop an instrumental variable strategy, that exploits local land supply elasticity. To this end, we use data on land utilization and characteristics available from the Australian Department of Agriculture, to construct a measure based on physical constraints to land development – similar to the one introduced by Saiz (2010) – at the level of local government areas (LGA),[6] which are administrative areas corresponding to medium size cities, rural areas, and parts of large metropolitan areas. Our instrumental variable (IV) estimates of the response of buyers attention to house price growth are larger than the ones from the OLS estimator: a 15% increase in postcode house prices over the previous two years leads to up to a 30% increase in the number of listings visited, and up to a 23% increase in the number of postcodes and segments visited.

Our findings imply that search breadth responds to local price growth. In previous work, Piazzesi, Schneider, and Stroebel (2019) show that the breadth of house searches determines

[6]LGAs are the third tier of local government aggregates in Australia, and are roughly equivalent to Public Use Microdata Areas in the United States.

how local shocks to housing supply and demand can spread to the broader market. Thus, the fact that changes in home buyers' search breadth are procyclical, strengthens the extent to which positive and negative local shocks are spread and amplified within a metropolitan area. We provide empirical evidence that this effect materially impacts houses listed for sale. In a broader sense, this can be interpreted as evidence showing how search frictions in the housing market can amplify price fluctuations, consistent with the implications of the models developed by Novy-Marx, 2009 and Ngai and Tenreyro, 2014. However, our reduced form study does not directly test these models, and we don't provide direct evidence of feedback effects between buyers and sellers. Rather, we show that a channel through which buyers procyclical behavior impacts home sales is the increase in search breadth, a mechanism which is absent from previous models studying amplification.

In the data, we first show that, for listings visited by users who have on average experienced higher price growth at their residence, the average breadth of users searches is higher, while, quite interestingly, the time devoted to individual visits is shorter. Thus, higher price growth experienced by visitors of a specific listing implies better integration with the rest of the housing market, and lower scrutiny. We then document that listings visited by users who experienced higher price growth have higher sale prices, even after controlling for the characteristics of the underlying properties, their location and time of sale. An important issue with our results is that the match between listings and visitors might be driven by unobserved characteristics of the properties. To address this concern, we rely on the methodology developed by Oster (2016), building on Altonji, Elder, and Taber (2005), which assesses the importance of omitted variable bias. To explain the effect of price growth experienced by house searchers at their residence on sale prices, the sensitivity of sale prices to the remaining unobservables would have to be as large as the sensitivity to the controls for house characteristics already included in the regressions. This is unlikely, since we include some of the main explanatory variables for house prices (number of bedrooms, bathrooms, size and type of property). These controls, together with home location and sale timing already account for more than 80% of the variation in prices.

Finally, we provide evidence that the attention allocation channel is a driver of the effect of experienced price growth on sale prices. We estimate at the listing level the fitted value of average search breadth that is explained by average experienced price growth across users. We then use this value to predict sale prices, after including our usual set of controls. We find that price sensitivity to fitted search breadth gives use point estimates for the effect of a one standard deviation increase in price growth that are similar to the ones from the specification where we directly regress sale prices on users' experienced price growth. While these estimates need to be interpreted carefully, their magnitude is still substantial. When users experience one standard deviation higher price growth over the previous two years in their postcodes of residence, the sale price is approximately 1.5% higher. For the average home in our dataset, this effect is equivalent to a price difference of 12,000 Australian dollars, or approximately 8,200 U.S. dollars. We conduct a similar analysis for time on the market and find that higher price growth experienced by users predicts shorter time on the market, even though the magnitude of the effect is quantitatively small. Also this effect appears to be associated with the higher search breadth of users.

The rest of the paper is organized as follows. Section 2 summarizes our contributions to several strands of the finance and economics literature. Section 3 describes our dataset and addresses concerns about the representativeness of our sample. Section 4 illustrates how households' attention to the housing market responds to local house price fluctuations. Section 5 investigates the mechanism linking price growth to users behavior, and addresses endogeneity concerns. Section 6 assesses the real effects of households' attention on sale prices and time on the market. Section 7 contains our concluding remarks.

2 Related Literature

We contribute to the literature on attention. Humans are limited in their ability to process information and to perform multiple tasks simultaneously (see Kahneman, 1973 and Mangun, 2012). Paying attention can also represents a cost that an investor must incur, not just in effort but monetarily, to gain information (see Abel, Eberly, and Panageas, 2007 and Abel, Eberly, and Panageas, 2013). Consistent with these facts, extensive evidence indicates that agents display limited attention even when exposed to new relevant information,[7] which can induce a delay in price response (see Huberman and Regev, 2001 and Hirshleifer, Lim, and Teoh, 2009). Fluctuations in attention can also generate temporary price pressure (Barber and Odean, 2007 and Da, Engelberg, and Gao, 2011), volatility spillovers (Hasler and Ornthanalai, 2018) and stock return co-movements (Huang, Huang, and Lin, 2019 and Drake et al., 2019). Understanding what triggers attention and how it varies over different market conditions has, therefore, been the focus of many empirical (Yuan, 2015, Sicherman et al., 2016, Gargano and Rossi, 2018 and Olafsson and Pagel, 2019) and theoretical (Andrei and Hasler, 2015 and Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016) papers. Our contribution is to study the implications of limited attention for housing search, and the related effects on house prices and liquidity.

We also contribute to the literature on search behavior in housing markets. Due to the difficulty of measuring search activity, most of the literature in this area is either theoretical (see Han and Strange, 2015 for a literature review) or based on survey data. Motivated by one-sided search models, Anglin (1997), Elder, Zumpano, and Baryla (1999) use survey data to study the cross-section of home buyers search duration. However, these models are silent on the implications of search behaviour for market prices and liquidity, which only arise in search-and-matching models (e.g. Wheaton, 1990, Genesove and Han, 2012, Piazzesi and Schneider,

[7] Corwin and Coughenour (2008) study the behavior of NYSE floor specialists, Della Vigna and Pollet (2009) compares investors' response to earnings announcements on Friday, when investor inattention is more likely, to the response on other weekday, Loh (2010) shows that low-attention stocks react less to stock recommendations than high-attention stocks. Finally, Gabaix et al. (2006) provide experimental evidence.

2009 and Head, Huw, and Sun, 2014). In this respect, our work is closer to the models of Novy-Marx (2009) and Ngai and Tenreyro (2014) where search frictions can amplify price fluctuations. Piazzesi, Schneider, and Stroebel (2019), uses data on households' email alerts set on trulia.com to explore home-buyers' search ranges and the relationship between housing inventory and search ranges at various levels of geographic aggregation. Our novel contribution is twofold. We study how buyers' attention and search effort respond to market fluctuations, and whether buyers' behavior amplifies or dampens these fluctuations. Moreover, we believe that our dataset delivers a unique and extensive perspective on online house search behavior.[8]

3 Online Real Estate Advertising Dataset

The key dataset in our study is made available by realestate.com.au (REA), Australia's largest property website and apps suite. Based on Nielsen Digital Ratings – a leading provider of data on online consumers' activity – REA website had an audience of 7 million visitors with 65.3 million total visits and 320 million total page impressions on March 2018. This dataset has three key unique features that make it uniquely suited to analyze the relation between search behavior and housing market conditions.

First, the dataset contains detailed information about user activity over time and across space, as well as detailed information on home listings. For a random sample of approximately 9,000 users (anonymized by means of an alphanumeric *User_ID*), who self-identify as interested in purchasing a property, we observe logins to the website, which listings (identified by an alphanumeric *Listing_ID*) they browse, how many times they visit each listing and the total number of seconds spent across visits on a daily basis.[9] This dataset covers the period from the 1st of January 2017 to the 30th of April 2019, for a total of approximately 3 millions

[8] First, we observe search activity, consisting of the listings browsed by each user at each point in time, as well as the time allocated to each listing; second, the dataset covers a large cross-section of cities with different characteristics; third, we observe important user characteristics which help us to establish causality.

[9] We verify the accuracy of users self-identification by computing the total time spent on listings in the "for sale" section of the portal: the average (median) user spends 95% (100%) of her time browsing properties for sale.

user-day-listing observations. Along with information on demand-side behavior, the property website also provides information on listings. For each *Listing_ID* we observe information about the listing, i.e. listing date and type of listing (whether for sale or rent), and the associated property: type of property (whether house/townhouse, unit, land or other), postcode, asking price, number of bedrooms, number of bathrooms, number of parking spots and size. Finally, for listings associated with properties that are sold over the time period spanned by our study, the dataset provides the sale date and the sale price.

Second, we are provided with information on user characteristics, which we exploit in our analysis to show how attention, along different margins, responds to local price fluctuations. We can observe the postcode where the user is currently living, whether she owns a property, her age and sex.

Third, the data cover *all* regional markets in Australia. As displayed in Figure 1, the three most active markets, Sydney (NSW), Melbourne (VIC) and Brisbane (QLD) have experienced high price growth over the four years prior to the start of our sample (approximately 70% in Sydney, 40% in Melbourne and 20% in Brisbane) and have peaked around July 2017, December 2017 and April 2018 respectively. Since then, they have experienced negative growth in prices.[10] Hobart (TAS) and Adelaide (SA) have experienced positive growth for the entire period covered in our sample while Darwin and Perth – whose economies are tightly linked to the mining and commodity sectors – are at the opposite side of the spectrum in that they have experienced price downturns since 2014.

While internet is the most used tool in modern house search, it is important to address concerns regarding the representativeness of our sample along several dimensions. First, we compare the spatial distribution of users in our sample with that of the Australian population. Figure 2 displays the postcodes where the users in our sample are located: each red dot represents a postcode for which we have at least one user. The majority of users are concentrated

[10] While being the biggest downturn in many years, it is closer to a "soft landing" than to a "crash" with prices being 10% (9%) (0.5%) lower than their peaks in Sydney (Melbourne) (Brisbane).

in two widely separated coastal regions: the south-east and east, and the south-west. The population of users within these regions is concentrated in urban centers, particularly the eight capital cities (Adelaide, Brisbane, Canberra, Darwin, Hobart, Melbourne and Sydney). Figure A.1 compares the population density, at the postcode level, of our sample (in Panel (a)) with the one from the 2016 Australian Census (in Panel (b)). The correlation between the two is approximately 70%, from which we conclude that the spatial distribution of users in our sample closely matches the one of the Australian population. This is particularly important given that we use price shocks at the postcode level as our key explanatory variable throughout the paper.

Panel A of Table A.1 displays cross-sectional summary statistics of the demographic characteristics of the users. Approximately 55% of users are female, while in terms of age, 30% (32%) of users are between 35 and 49 (50 and 64) and users younger than 34 only represent 21% of the sample. While we do not have data on the demographic characteristics of the population of Australian home buyers, these values closely match those provided by the American Association of Realtors during our sample period. Moreover, given that REA Group is the largest property website in Australia, our sample likely offers the best representation of the overall population of online home searchers.

Another concern is that the properties listed on the REA website might not be representative of the total supply (since some properties might not be listed online because are negotiated and sold prior to going on the market). Panel B of Table A.1 displays summary statistics of the listings in our sample. First, in terms of dwelling type, 68% are either houses or townhouses while 25% are apartment units. The average (median) dwelling has 2.85 (3) bedrooms, 1.64 (2) bathrooms and 1.68 (2) parking spots. The 2016 Australian census of population and housing indicates that 71% of dwellings are houses and 27% are apartment units. Also the median number of bedrooms, bathrooms and parking spots in our dataset are perfectly in line with the values from the census.[11]

[11] We also compare the characteristics of the dwellings browsed by the users in our sample with the full population listed on the REA website and find no significant difference between the two. These results are available upon requests.

A final concern relates to the external validity of our findings. Unfortunately, housing markets are more heterogenous than financial markets in that there is a large cross-country dispersion in key features such as composition of inventory, home-ownership rates, concentration of population along coastlines and/or cities, and financing sources. Nevertheless, the Australian housing market shares many commonalities with the US market: homeownership rates are quite similar (68% vs 63%) as well as the composition of inventory both in terms of dwelling types and size.

4 Local Prices, Attention and Search

In this section we study fluctuations in households' attention to the housing market induced by local house price fluctuations. We first describe how we exploit our data to measure attention from online activity, and in particular how we disentangle the intensive –attention per listing– and the extensive –breadth of searches– margin of attention. We then focus on the empirical results showing that households' attention increases in response to price growth. However, we find it is not attention per listing that increases, but rather the extension or breadth of house searches.

4.1 Measuring Attention from Online Activity

Since browsing is a multidimensional and complex set of actions, and we are interested in disentangling different aspects of attention to the housing market, we construct multiple measures.[12] First, to capture the overall level of attention for each user, we track the number of listings browsed each month ($Listings$). We then also compute the total number of visits to listings in the month ($Visits$), and the total number of minutes spent browsing listing-related information ($Minutes$) during the month.

[12]Similar measures are constructed by Sicherman et al. (2016) and Gargano and Rossi (2018), who use online browsing data in their analysis of the effects of limited attention on financial portfolio decisions.

When searching for a home, a buyer needs to allocate attention across two margins. She needs to decide how much attention is devoted to individual listings (the intensive margin) and the breadth of house searches, which determines the number of houses included in her search (the extensive margin). This trade-off is related to the one found in many models (e.g. Peng and Xiong, 2006, Mondria, 2010, Van Nieuwerburgh and Veldkamp, 2010 and Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016) that focus on the problem of allocating attention to individual financial securities rather than to the broader financial market.[13]

The richness of our data allows us to shed light on the different margins of attention. We assess the intensive margin of attention by calculating the number of minutes and visits per listing and the *Herfindahl Index*, which measures the concentration of time allocation across listings. To capture the extensive margin of attention, we first measure the geographic extension of searches. We start by tracking the number of postcodes for which the user visited at least one listing. In formulas, this is equal to:

$$NumPost_{i,t} = \sum_{\tau \in t} \mathbb{1}_{i,post,\tau}$$

where $\mathbb{1}_{i,\ell,\tau}$ is an indicator variable equal to 1 if the postcode *post* is visited for the first time in month t by user i. We then try to directly measure the geographic area covered by the users' searches. To this end we use the *mean distance* across explored listings, calculated using the centroids of the postcodes visited by each user. For each user, we can calculate the *mean center* based on the postcodes visited in a certain month, with coordinates $\overline{lat}_{i,t}$ and $\overline{lon}_{i,t}$, which are the average latitude and longitude of the explored postcodes. The mean distance

[13]The key focus in Peng and Xiong (2006) and Mondria (2010) is the trade-off between allocating attention to individual financial securities rather than to the wider market. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) develop a model where the state of the business cycle predicts the choice between aggregate or idiosyncratic sources of information. Finally, Van Nieuwerburgh and Veldkamp (2010) propose a model in which, depending on their preferences, agents behave as "specialized learners" who concentrate their attention on a subset of the assets or "generalized learners" who focus their attention more evenly across the assets in their information set.

across postcodes visited by user i in month t is then computed as:

$$MeanDist_{i,t} = \sum_{\tau \in t} \mathbb{1}_{i,post,\tau} \frac{dist_{i,post,\tau}}{NumPost_{i,t}}$$

where $dist_{i,post,\tau}$ is the distance between the centroid of postcode *post* and the mean center for user i and month t.[14]

While the two measures just discussed focus on the extent to which search covers different postcodes and areas, there is still substantial heterogeneity even among houses belonging to the same postcode. Thus, a broader search may not only touch more locations, but also houses with a wider set of characteristics, such as the number of bedrooms or the type of property (house or apartment). To provide a more general measurement of the extension of searches, we split listings across different *segments*, defined jointly based on location and house characteristics, and we track the number of segments explored by each user. We first define segments based on postcode, property type (house or apartment unit) and number of bedrooms. In other words, we first split all listings based on postcode, and then divide the listings within each postcode into 8 subcategories: 1, 2, 3 and 4 or more bedroom, separately for houses and apartment units. We also consider an alternative definition of segments, which exploits the cross-sectional distribution of prices.[15] In particular, we allocate postcodes to 6 groups based on price quintiles ($\mathbb{Q}$) within each "area". We construct areas by splitting each state into the metropolitan area of its capital and the rest of the state. There are 6 states in Australia (New South Wales, Queensland, South Australia, Tasmania, Victoria and Western Australia). In our analysis, we also treat as states the Australian Capital Territory of Canberra and the Northern Territory.[16] In total, there are 16 areas. The price quintiles are based on average house prices in each

[14] Mean distance is highly sensitive to outliers. In order to address this problem, we first estimate the mean center based on all postcodes visited, and computed all distances $dist_{i,post,\tau}$. We then exclude postcodes for which the distance from the mean distance is greater than 150 miles, and we repeat our calculations from the beginning on the remaining set of postcodes, by re-estimating the mean center and then the mean distance.

[15] Landvoigt, Piazzesi, and Schneider (2015) argue that the ranking of prices across postcodes can be used as reasonable proxy for the ranking of neighborhood quality within a metropolitan area.

[16] Juridically, they function essentially as states. Each has self-government, through its legislative assembly but the assembly's legislation can be federally overridden.

postcode, calculated over the entire period from January 2017 through April 2019. Within each group of postcodes we identify 8 segments, based on number of bedrooms and property types (house or apartment units). In formulas, we measure the number of segments visited according to the two different definitions as:

$$NumSeg(post, type, nbed)_{i,t} = \sum_{\tau \in t} \mathbb{1}_{i,\ell \in (post,type,nbed),\tau}$$

$$NumSeg(\mathbb{Q}, type, nbed)_{i,t} = \sum_{\tau \in t} \mathbb{1}_{i,\ell \in (\mathbb{Q},type,nbed),\tau}$$

where $\mathbb{1}_{i,\ell \in (post,type,nbed),\tau}$ is a dummy equal to one for the first listing (ℓ) in a certain segment, based on our first definition, that is visited by user i in month t, and $\mathbb{1}_{i,\ell \in (\mathbb{Q},type,nbed)}$ has an analogous interpretation for the second definition of segments.

Panel A of Table 1 reports summary statistics of our measures of total attention and of the intensive margin. We first compute the average across monthly observations relative to each *User_ID*, and then report the mean, median, standard deviation and four percentiles (5th, 25th, 75th and 95th) of the resulting cross-section. The average user browses quite a high number of listings: 42 per months, on average. The distribution also has a high standard deviation (63.55) driven by the long-tail of most active users. On average, users conduct 67 visits to listings per months. The standard deviation of the distribution of visits is almost double the one relative to the number of listings (125). Finally, in terms of number of minutes spent on the website, we find that the average user spends about 2 hours per month, with the most active (i.e. the 95th percentile) spending up to 7.4 hours per month.

Panel B of Table 1 reports summary statistics relating to the extensive margin measures. The average *User_ID* looks at 8.69 different postcodes per month, on average. However, this distribution displays a high degree of variation. While users in the bottom 5th percentile only look at one postcode per month, users in the top 9th percentile look at 28 postcodes.The average distance covered in a month, is on average equal to 7.5 miles. Based on the first (finer) definition of segments, users on average explore in a single month between 13 and 14 segments. Based on the second (coarser) definition, users on average explore 6.5 segments.

4.2 Local Price Growth and Attention

The literature on limited attention in financial markets has shown that investors attention fluctuates over time and that these fluctuations are associated with market conditions. Along the same lines, the first step of our analysis is to establish how attention to the housing market responds to house price growth. However, the sign of the effect of price growth on attention at a high level of aggregation, such as a metropolitan area or state, is hard to interpret, since its estimate is plagued by reverse causality and endogeneity: as online activity proxies for market demand, higher (lower) attention may drive prices up (down). In this study, we exploit a key feature of our dataset, which is that website users provide information on the postcode where they are *currently living*. On average, only 16% of the listings browsed by users that reside in a certain postcode are within that same postcode. This value is in large part driven by outliers, since the median fraction of listings browsed in the home postcode is only 7%. Thus, households mostly browse listings outside their home postcode, and the response of household's attention to the evolution of house prices in the postcode where they are living is less susceptible to endogeneity concerns rather than the response to more aggregate movements in house prices.

As a first step, our aim is to assess the relationship between the overall level of attention to the housing market and local price growth. Even the existence of this basic relationship is not obvious. If households were unaware of price fluctuations, or their attention was overwhelmingly driven by idiosyncratic factors (for example, life events like marriage and inheritance), then local price growth would not affect attention. We estimate the following regression equation:

$$log(1 + Attention_{i,t}) = \alpha_i + \alpha_{t,area} + \beta \Delta p^{(h)}_{post_{(i)},t-1} + \epsilon_{i,t} \quad (1)$$

where $Attention_{i,t}$ is either equal to the number of listings visited by user i in month t

($Listings_{i,t}$), the total number of visits to listings ($Visits_{i,t}$) or the total minutes spent visiting listings ($Minutes_{i,t}$). Since our focus is the effect of local price growth on households' attention, we include in the regression specification year-month by "area" fixed effects, $\alpha_{t,area}$.[17] These fixed effects control for common price movements in the area. To then account for heterogeneity at the postcode or user level, we include either postcode fixed effects, $\alpha_{post_{(i)}}$, or individual user fixed effects, α_i. The remaining variation in the data consists of postcode-specific or user-specific variation over time. We relate this variation to local price growth using the variable $\Delta p^{(h)}_{post_{(i)},t-1}$, the house price growth in the postcode $post_{(i)}$ where user i is currently living, computed over a backward-looking horizon of h months, over the period from $t-1-h$ through $t-1$.[18]

We choose to measure price growth with a one-month lag with respect to attention (the dependent variable) since households may not be aware of price levels in the current month, and may have access to information only up to the previous month. Our results are similar if we consider house price growth up to the current month, or if we choose a two- or three-months lag. We calculate price growth over a 2-year horizon ($h = 24$ months). Results for a 3- and 4-years horizons are similar to the those for 2-years. Figure 3 displays the pooled distribution of 2-year price growth for the postcodes in our sample. The top-left plot displays the distribution of the raw data which has an average of 9.6% and a standard deviation of 15%. In the remaining three plots we subtract the monthly (top-right plot), the area (bottom-left plot) and the monthly and area average (bottom-right plot). The distribution of demeaned price growth appears to be symmetric.

[17] As mentioned in section 4.1, areas are constructed by the authors by splitting each state into the metropolitan area of its capital and the rest of the state. There are 6 states in Australia (New South Wales, Queensland, South Australia, Tasmania, Victoria and Western Australia). In our analysis, we also treat the Australian Capital Territory of Canberra and the Northern Territory as states. In total, we splits Australia into 16 areas.

[18] Data on postcode house price indexes at a monthly frequency is provided by the Securities Industry Research Center for Asia-Pacific (SIRCA). SIRCA provides separate house price indexes for single family residences (houses) and condo or apartments (units). To construct the postcode-level indexes, we calculate the fraction of households living in houses and apartment buildings using data from the 2011 Australian Census. We set the postcode index equal to the index for houses, unless the majority of households in the postcode lives in apartments or condos. In the latter case we set the index equal to the index for units.

For what concerns standard errors clustering, since price growth is measured at the postcode level, it induces correlation across individuals living in the same postcode. Thus, we choose to double-cluster standard error by postcode and year-month.

Estimates of the effect of price growth on attention (β from equation 1) are reported in Table 2. Past price growth is positively correlated with individual users' attention in that the estimates of β are statistically significant across the board. We find that a 15% higher price growth corresponds to up to a 5% larger number of listings surfed. Point estimates of this effect are similar across the three measures, even though not always significant when the dependent variable is total amount of time spent browsing listings.[19] Finally, while the inclusion of individual fixed effects increase the adjusted R-square of the regressions, it does not greatly impact coefficient estimates.

This first results show that past price growth leads to higher attention. Our main focus is now to disentangle how higher attention translates into changes along the intensive and extensive margin. First, we focus on the intensive margin, and test whether past price growth leads to higher attention and more intense information acquisition at the level of individual listings. We then estimate different specifications of equation 1, where the *Attention* variable is now specifically a measure of the intensive margin: either visits per listing ($\overline{Visits}$) or minutes per listing ($\overline{Minutes}$). Results are reported in Panels (A) and (B) of Table 3. Point estimates of the effect of price growth on these measures are quantitatively small, and not statistically significant. While average attention per listing may remain unchanged, may be the case, as overall attention increases, prospective buyers may be skewing attention allocation towards specific listings included in their search. To test this hypothesis, in panel (C) we set the dependent variable equal to the Herfindhal Index of time allocated to individual listings each

[19]Estimates of β for a 1-year horizon do have the same sign, but are smaller and not statistically significant. The fact that our results are stronger when considering price growth over longer horizons is not surprising. First, growth over multiple years might be more likely to be salient for households, and especially homeowners. Second, there is evidence in the literature showing that households tend to form expectations on the future evolution of house prices by extrapolating price growth that they experienced over the previous few years (see Case, Shiller, and Thomson, 2015 and Kaplan, Mitman, and Violante, 2017 among others).

month. We again find that the effects of price growth on the dependent variable are not statistically significant. Moreover, point estimates are negative, suggesting that households experiencing higher price growth, if anything, allocate attention more uniformly across the listings they visit.

Thus, while households are exploring a larger number of listings, the amount of attention allocated to the individual listings remains unchanged. This suggests that the increase in attention is operating along the extensive margin. In fact, households are not only exploring a larger number of listings, but are also extending the breadth of their house searches, both across postcodes and across market segments, as defined in section 4.1. Panel (A) of Table 4 shows that higher price growth leads households to explore listings in a larger number of postcodes. The magnitude of the effects is similar to the one on the different measures of total attention level, reported in Table 2. Higher price growth of 15% over the previous two years coincides with a 5% larger number of postcodes explored. Panel (B) shows that it also leads to a 5% broader geographic area covered by the buyer (measured using the $MeanDist$ variable). The effects are also strong and statistically significant when the dependent variable is the (log of) the number of housing segments covered by house searches, both when when segments are measured by postcode and characteristics (Panel (C) of Table 4), and when segments are measure by price quintiles and characteristics (Panel (D) of Table 4).

The fact that higher attention mainly impacts the extensive margin, and translates into more extensive and comprehensive searches, has potentially amplifying effects on housing market fluctuations. The broader is buyers' exploration of the market, the lower is segmentation and the higher the likelihood of home listings matching with buyers. Moreover, this creates potential spillover effects of local price growth to other parts of the housing market. The implications for home sale prices and market liquidity will be the focus of section 6.

5 Economic Mechanism: Homeownership and Instrumental Variable Estimates

While the link between local (postcode-level) house price growth and attention to the housing market is not as plagued by endogeneity as the link between general market trends and attention, there can still be some concerns. We address these concerns in two steps. First, we dig deeper into the mechanism linking house prices and users behavior, and show that our results are driven by homeowners, who are most immediately affected by local price growth. Second, we construct a measure of constraints to local housing supply, that we use to instrument house price growth.

5.1 Local Price Growth and Homeowners' Attention

A key channel through which price growth affects household behavior is homeownership. There is an extensive literature studying the effects of house prices on homeowners' wealth and collateral constraints, and documenting empirically the implications for homeowners' consumption (see for example Campbell and Cocco (2007), Gan (2010), Mian, Rao, and Sufi (2013) and more recently Stroebel and Vavra, 2019). House price growth also increases the likelihood of homeowners to engage in house sales and purchases, either because it increases homeowners' wealth and relaxes collateral constraints (see Stein, 1995), or for behavioral reasons, for example linked to loss aversion (see Genesove and Mayer, 2001). In this section, we use two different empirical strategies to show that price growth impacts more strongly attention and search breadth of homeowners.

First, we exploit information available form the 2016 Australian Census, to construct the postcode-level homeownership rate: users are more likely to be homeowners in areas where homeownership is higher. We then estimate the following regression equation:

$$\begin{aligned} log(1 + Meas_{i,t}) = \alpha_i + \alpha_{t,area} + \beta\Delta p^{(h)}_{post_{(i)},t-1} + \\ + \gamma\left(\Delta p^{(h)}_{post_{(i)},t-1} \times Homeonwership2016_{post_{(i)}}\right) + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $Meas_{i,t}$ is any of the measures of attention from section 4.1, either capturing the overall level of attention, the listing-level intensity of attention, or the extension of house searches. $Homeonwership2016_{post(i)}$ is the homeownership rate in postcode $post_{(i)}$ in 2016, in percentage terms ($1 = 1\%$). In the estimation, the homeownership rate is measured as the difference between the average homeownership rate across Australian postcodes and the rate in postcode $post(i)$. Thus, when $Homeonwership2016_{post_{(i)}}$ is equal to 0, the homeownership rate in postcode $post(i)$ is equal to the national average. The key coefficient of interest in this specification is γ, which captures the effect of the interaction term between past price growth and the homeownership rate.

We report our results in Table 5. We do indeed find that the effects of price growth are stronger for households living in postcodes with higher homeownership rate. When the dependent variable is one of the measures of total attention – in Panel (A)–, estimates of γ are statistically significant and large. Given the same historical price growth over the previous two years, 10% higher homeownership rate in the postcode leads to a 0.16 (34%) larger effect of experienced price growth on the number of listings visited and a 0.20 (44%) and 0.18 (32%) larger effect on the number of visits and on the total time spent browsing listings. Moreover, controlling for the interaction with the local homeownership rate increases the magnitude and statistical significance of the estimates of the effect of price growth on attention (coefficient β). Consistent with the results in the previous section, we find no effect on the average amount of time devoted to each listing ($\overline{Minutes}$). On the other hand, we find evidence that postcodes with higher homeownership rate see larger increases in attention specifically on the extensive margin. Estimates in Panel (B) of the Table suggest that 10% higher homeownership rate in the postcode leads to a 0.14 (32%) larger effect of price growth on the number of postcodes visited. We obtain similar estimates when the dependent variable is the number of segments defined based on postcode, number of bedrooms and property type. Estimates of γ are not statistically significant for the extension of the geographic area covered by searches (the standard distance deviation of explored postcodes) and for the definition of segments based on price quintiles within metropolitan area.

Our second test exploits user-level information, since users in our dataset disclose whether they are currently homeowners. We can then estimate the regression specification:

$$\begin{aligned} log(1+Meas_{i,t}) = \alpha_{post_{(i)}} + \alpha_t + \delta_{own}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,owner}\right) + \\ + \delta_{noown}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,noowner}\right) + \kappa \mathbb{1}_{i,owner} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $\mathbb{1}_{i,owner}$ is a dummy equal to one if user i is a homeowner, and $\mathbb{1}_{i,noowner}$ is a dummy equal to one if the user is not a homeowner. Thus, δ_{own} captures the response of attention to house price growth for users who are homeowners, and δ_{noown} captures the same response for users who do not own a house. The coefficient κ captures the average difference in attention between owners and non-owners.

The results of this second test are reported in Table 6. First, it is important to note that estimates of κ are negative and statistically significant. On average, people who already own a home devote less time to house search than households who bear the cost of renting. However, homeowners respond more strongly to local price growth. Panel (A) of the Table shows that homeowners' overall attention level responds strongly to price growth. Estimates of the coefficient δ_{own} are 20% to 50% larger than the estimates of β from equation 1 reported in Table 2. The opposite is true for non-homeowners, for which point estimates of δ_{noown} are substantially smaller than the corresponding estimates of β, and not statistically significant. On the other hand, it is also important to note that the effects on the average time allocated to each listing remain not statistically significant for both homeowners and non-homeowners.

In Panel (B) the dependent variables of the different regressions are the measures of search extension. Similarly to our prior comments for the measures of the overall attention level, we find that homeowners are more responsive than non-homeowners, for which the effect of past price growth on the extensive margin of attention is not significant. Point estimates of δ_{own} are larger than the corresponding estimates of β reported in Table 4, even though the difference is not as stark as for the measures in Panel (A).

Overall, it appears that in the data the behavior of homeowners drives the relationship between price growth and attention, and between price growth and the extensive margin of attention. This is consistent with our conjectured mechanism, and supports the notion that our findings are indeed capturing a causal relationship.

5.2 Instrumenting Price Growth Using Land Supply Elasticity

To further address the potential endogeneity of the relationship between price growth and attention, we develop an empirical strategy that uses local land supply elasticity as an instrumental variable. This approach is related to a broad literature that uses cross-MSA differences in supply elasticity within the U.S. as an instrument for house price growth.[20]

This instrument is particularly well suited for our study. In postcodes where local house price fluctuations are just driven by changes in local housing quality (like new amenities, better quality of local schools, etc.), homeowners (who, as shown in the previous section, play a key role in driving our results) will feel less compelled to adjust their housing consumption and move, since higher prices also correspond to higher quality of the asset, and higher implicit dividends. On the other hand, when price appreciation is driven by local excess demand and sticky supply, price growth is more likely to be disconnected from changes in underlying quality, and households will be more likely to move in response to rising prices.

[20] Gyourko, Saiz, and Summers (2008) develop a measure based on local regulations and zoning, while Saiz (2010) develops a measure based on satellite-generated data on terrain elevation and the presence of water bodies. Both measures have been widely used as instruments for house price growth, see for example, Mian, Rao, and Sufi (2013), Chetty, Sandor, and Szeidl (2017), and Stroebel and Vavra (2019).

To measure local supply (in)elasticity, we take inspiration from the work of Saiz (2010), and construct a measure based on physical constraints that make land unavailable for real estate development. To this end, we use data on land use and characteristics provided by the Australian Department of Agriculture in the national scale map for fiscal year 2010-2011.[21] The data integrate information from several sources to provide an accurate assessment of land characteristics at the level of half-kilometer land squares.

We merge the dataset with shapefiles for the jurisdictions of Australian Local Government Areas (LGAs), which are administrative areas corresponding to medium size cities, rural areas, and parts of large metropolitan areas (the state capital cities).[22] For each LGA we calculate the fraction of land for which housing supply is *constrained*. We take a broad approach in defining the constrained area. Any area that in 2010-2011 was not available for development for topographic reasons, or that would have required significant demolition of local infrastructure to become available, is considered constrained. In practice, we identify four land features that are consistent with the existence of constraints to housing supply. The first one, is the presence of water, in the form of internal basins, lakes, rivers, swamps and coastal waters. The second, is the inclusion in a protected area or a natural conservation reserve. The third, is the presence of intensive agricultural or industrial infrastructure, such as high intensity plantations, mines and industrial complexes. The last one is the presence of high density urban and residential development. Areas that do not fall in the mentioned four categories are more likely to be readily available for real estate development, and therefore can be considered as *unconstrained*.

Figure 4 provides a graphical depiction of the fraction of constrained land across Australia's LGAs, which we use as our proxy for supply (in)elasticity. The Figure shows how elasticity is lowest (the fraction of constrained land is highest) in the area of Sydney, and in general on the south-western and south-eastern coasts of the continent. However, the fraction of constrained land changes substantially within Australian states, and even across relatively close geographies.

[21] The data are available as ESRI raster files at http://www.agriculture.gov.au/abares/aclump/land-use/data-download.

[22] Shapefiles are available from the 2016 Australian Census at https://datapacks.censusdata.abs.gov.au/datapacks/.

Since our measure is based on either topography or land-use in 2011, we argue that our measure of supply elasticity is plausibly exogenous to the behavior of house prices over the period covered by our study, which consists of the years from 2017 to 2019. By mapping each postcode into a corresponding LGA, we find land supply elasticity at the location of residence of each of the households in our dataset.[23]

Our measure of land supply elasticity only varies in the cross-section, since it is observed at a specific point in time (2010-2011). To construct an instrument that allows for time variation, we interact supply elasticity with a dummy equal to one if house price growth over the last two years has been positive in the "area" –areas are defined as explained in section 4.1– where the household lives (this is similar to what done by Stroebel and Vavra (2019)). The intuition is that when prices have been consistently rising in the broader metropolitan area, ideally due to economic fundamentals, house prices in constrained LGAs should raise more than in the rest of the state. We estimate the following system of equations by two-stage-least-squares (2SLS):

$$\Delta p_{post_{(i)},t} = \alpha_{post_{(i)}} + \alpha_t + \psi \left(\mathbb{1}_{\Delta p_{area_{(i)}},t>0} \times \Lambda_{post_{(i)}} \right) + \eta_{post_{(i)},t} \tag{4}$$

$$log(1 + Meas_{i,t}) = \alpha_i + \alpha_t + \beta \widehat{\Delta p}_{post(i),t-1} + \epsilon_{i,t} \tag{5}$$

Where $\Lambda_{post_{(i)}}$ is the measure of house supply elasticity, and $\mathbb{1}_{\Delta p_{area_{(i)}},t>0}$ is a dummy equal to one if house price growth[24] over the last two years has been positive in the area where $post(i)$ (or user i) is located. $Meas_{i,t}$ is again any of the attention measures, either capturing the total level of attention by user i at time t, or the intensive or extensive margin.

A limitation of our instrumental variable approach is that it relies on aggregate fluctuations in house price indexes. However, we are not relying on the magnitude of price changes, but just on their sign, and the entire cross-sectional variation in the instrument is driven by the

[23] There is no perfect overlap between LGAs and postcodes, since some postcodes are split across multiple LGAs. We solve this issues by allocating the fraction of postcode belonging to each LGA, using crosswalk files made available by the Australian Bureau of Statistics at https://www.abs.gov.au/census.

[24] For simplicity, we consider price growth for houses, since within all areas apartment buildings are home to less than 50% of households.

land use-based measure of supply elasticity, which, as argued above, is plausibly exogenous. Estimates of the first stage regression (equation 4) are reported in Table 7. The instrument is relevant, and predicts postcode-level price fluctuations with a positive sign, as expected. The 2SLS estimates of equation 5 are reported in Table 8. The first stage F-statistics are large across the board, consistent with the results in Table 7.

Panel (A) of Table 8 reports 2SLS estimates of the effect of price growth on attention level and on the intensive margin (measured as the average number of minutes per listing). Estimates of the effect of price growth on the overall attention level (β from equation 5) are positive, statistically significant and 3 to 4 times larger than the OLS estimates reported in Table 2. Once we instrument price growth with supply elasticity, 15% higher price growth leads to approximately a 30% increase in attention, measured either as the number of listings browsed, the number of visits to listings, or the time spent browsing. Consistent with our previous findings, the 2SLS estimates of the effect of price growth on the average time spent browsing each listing are not statistically significant. The point estimate of the effect is actually *negative*. This again confirms that users do not appear to allocate higher attention to the analysis of individual listings. Panel (B) shows –again, consistent with our previous findings – that the main effect is on the extension of house searches. We find that the 2SLS estimates of the effect of price growth on the extension of searches are positive and statistically significant, and substantially larger than the OLS estimates in Table 4. A user experiencing 15% higher price growth over the previous two years increases the number of postcodes visited, the geographic area covered by her searches and the number of segments visited by approximately 25%. The increase in the number of segments browsed is only 8% when the segments are defined based on price quintiles within area and house characteristics. All these effects are highly statistically significant, with t-statistics larger than 3.5 and standard errors double clustered by postcode and time (month).

6 Effects on House Sales

There is a broad literature studying search in the housing market[25] and its implications for house prices and time on the market, mostly focusing on models with random matching between sellers and buyers. Piazzesi, Schneider, and Stroebel (2019) show that housing search is segmented, with buyers searching both broadly and narrowly in the market, and that the breadth of buyers searches affects how local shocks to housing supply and demand can spread to the broader market.

We have documented in the previous sections that households' – and in particular, homeowners' – attention to the housing market increases with local price growth. In particular, higher attention results in the expansion of the range of homes searched by individual buyers, both across locations and property characteristics. As search ranges expand, home searchers connect to a larger number of listings and listings face more integrated demand within their metropolitan area. The fact that changes in home buyers search breadth are procyclical amplifies the extent to which positive and negative local shocks are spread and amplified within a metropolitan area. This section exploits our micro-data to provide evidence of this channel, and to document the existence and magnitude of effects on home sales, both in terms of sale prices and time on the market.

6.1 Effects on Sale Prices

To measure the effects of home buyers attention and on houses listed for sale, we track all users' visits to each listing in our dataset.[26] For each listing l, we can compute the average price growth in the postcode of residence for the users that visited the listing:

$$\Delta p_l^{visits} = \frac{\sum_{i=1}^{N_l} \overline{\Delta p}_i}{N_l}$$

[25]See section 2.

[26]The size of our sample is limited, but, as shown in section 3, the sample is representative of Australia's population. Thus, when studying effects on sale prices and liquidity, we interpret the behavior of our users as a proxy for the more general patterns in buyers behavior across postcodes and listings.

where N_l denotes the number of users visiting listing l and $\overline{\Delta p}_i$ is the average price growth experienced by user i across all visits to listing l (i.e. $\frac{\sum_{t\in T_{i,l}} \Delta p_{i,t-1}}{|T_{i,l}|}$ where $T_{i,l}$ is the set of months when user i has visited listing l and $|T_{i,l}|$ is the number of months).

We base our calculations only on visits by users that reside outside of the postcode where listing l is located. Moreover, since we established in section 5 that our results on the response of users' attention to local price growth are mainly driven by the behavior of homeowners, we also base our calculations only on visits by users who are homeowners.

We then calculate the extensive and intensive margin of attention for the users who visited a specific listing. Consistent with the previous sections, we use measures of search breadth to assess the extensive margin: the number of postcodes visited, and the number of segments visited based on the two definitions in section 4.1. In formulas, we calculate:

$$Search_l = \frac{\sum_{i=1}^{N_l} Search_i}{N_l}$$

where $Search_i$ is defined along the same lines as $\overline{\Delta p}_i$. To capture the intensive margin, we consider the average time spent on the listing. In formulas:

$$\overline{Minutes}_l = \frac{\sum_{i=1}^{N_l} \overline{Minutes}_i}{N_l}$$

We generically refer to $Search_l$ and $\overline{Minutes}_l$ as $Meas_l$, since they are measures of the different margins of attention. We then calculate $logMeas_l = log(1 + Meas_l)$, for both the measures of the extensive and intensive margin. First, we explore the relationship between price growth experienced in the postcode of residence and attention allocation for the users visiting each listings:

$$logMeas_l = a_{post(l)} + a_{t\times area} + \lambda \Delta p_l^{visits} + \mathcal{B} X_l + v_l \quad (6)$$

where $a_{post(l)}$ and $a_{t\times subd(l)}$ are fixed effects for the postcode where listing l is located and for the month of sale and area where the postcode is located. Thus, the coefficient β measures the effect on time on the market that is specifically driven by the "abnormal" price growth experienced by the visitors of each specific listing, and not by postcode characteristics, or general market fluctuations. Almost all of the listings visited by the users belong to the same metropolitan area of their postcode of residence, so that our results capture within area spillovers.[27] We also include a vector of controls X_l, which contains the log of house size, a dummy equal to one if the property is an apartment unit, as well as dummies for number of bedrooms, bathrooms and parking slots.

Estimates of the coefficients from regression equation 6 are reported in Table 9. Consistent with the results in the previous sections of the paper, when the dependent variable is one of the measures of search breadth, we find that estimates of λ are positive and statistically significant. Higher price growth increases attention on the extensive margin, so that users that experienced higher price growth also explore the housing market more broadly, and visiting a larger number of postcodes and segments. Thus, listings that are visited by users that experienced higher price growth have more "integrated" demand, and attract attention more extensively within the metropolitan area.

When the dependent variable in equation 6 is the average number of minutes per visit, the sign of λ is negative. Listings that are visited by users that experienced higher price growth see these users spend on average a *shorter* amount of time per visit. This is consistent with the estimates based on the supply elasticity instrument in Table 8, which found a negative (but not statistically significant) relationship between price growth and attention on the intensive margin. Summing up, when users experienced higher price growth, listings are better integrated within the rest of the local market, but the attention devoted to each individual visit is lower.

The evidence collected so far provides some foundations for a mechanism through which higher price growth may have real effects on house sales. This channel would operate through attention allocation at the level of individual listings. As a next step, we estimate the relationship between price growth experienced by visitors and sale prices, using the following regression

[27] For the median user the fraction is 95%.

equation:

$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \beta\Delta p_l^{visits} + \mathcal{B}X_l + e_l \tag{7}$$

where p_l^{sale} is the log of the sale price for listing l. Estimates of the coefficients in equation 7 are reported in the first two columns of Table 10. Even after controlling for property characteristics, estimates of the coefficient β are positive and statistically significant. A one standard deviation higher price growth experienced by visitors is associated with 1.5-1.6% higher sale prices. Since the average home in our sample has a sale price of approximately 750,000 Australian dollars (510,000 U.S. dollars), this effect amounts to roughly 12,000 Australian dollars, or slightly less than 8,200 U.S. dollars.

Taken at face value, the figures above suggest that spillover effects of local price growth on homes listed for sale are substantial. However, a concern with our estimates is that the match between visitors and listings is not random. In particular, households who have experienced higher price growth in their home postcode may be systematically more likely to visit higher quality properties. These properties may be selling at higher prices only due to some their characteristics that are not spanned by the controls in our regressions.

We try to address this concern using a methodology introduced by Altonji, Elder, and Taber (2005) and then fully developed by Oster (2016), which assesses the importance of omitted variable bias. Oster (2016) shows that coefficient changes due to the inclusion of broader sets of controls are informative only if selection on observables is informative about selection on unobservables and that researchers should take into account both changes in coefficients and R-squares. Loosely speaking, the bias induced by unobservables is proportional to three factors. The first one is the change in coefficient estimates when comparing a "short" regression, with only a limited set of controls, and a "long" regression with all available controls. The second one is the ratio of the difference between the maximum feasible R-square for the regression and the estimated R-square in the long regression, over the difference between the R-squares in the long and short regression. The third one is the ratio of the sensitivity of the outcome to unobservable characteristics over the sensitivity to observable characteristics δ.[28] In our application, the "short" regression consists of equation 7 omitting the vector of property characteristics X_l, while the "long" regression consists of the full specification in equation 7. Even under the assumption that the maximum feasible R-square for the regression is 1, which is unlikely given existing evidence on idiosyncratic price dispersion in real asset markets[29], our estimate of δ is approximately equal to 1. This suggests that in order to invalidate our results, sale prices should have the same sensitivity to omitted variables as to the controls already included in X_l, which are some of the main drivers of differences in house prices, including number of bedrooms, bathrooms, parking slots and size. This is unlikely. Thus, while the analysis based on Oster (2016) does not completely dispel concerns on unobservable characteristics, we believe it suggest that our results are robust to bias induced by unobservables.

Even when interpreting our results as evidence of the effect of users' experienced price growth on home sales, we still must acknowledge that there are several channels through which this effect may operate. Is there a way to link the impact of local price growth on users' attention to the ultimate effect on sale prices, bringing together the evidence based on estimates of equations 6 and 7? We do this in a suggestive way, by estimating the following regression equation by 2SLS:

$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \gamma \widehat{logMeas}_l + \mathcal{B}X_l + e_l \tag{8}$$

where $\widehat{logMeas}_l$ is the part of variation in the attention measure across listings that is explained by differences in experienced price growth. This coincides with the "predicted" measure based on regression equation 6. Columns 3 to 10 of Table 10 report estimates of the coefficients in equation 8. Columns 3 to 8 focus on the effects of experienced price growth channeled

[28]More formally,

$$\beta^* - \hat{\beta} \approx \delta \left(\hat{\beta} - \beta^\circ\right) \frac{R_{max} - \hat{R}}{\hat{R} - R^\circ}$$

Where β^* is an unbiased estimator of the population value of β, β° and R° are the regression coefficient and the R-square estimates from the regression that only includes the treatment and $\hat{\beta}$ and the R-square is $\hat{R}$ are the coefficient and the R-square estimates from the regression that includes the treatment and the observable controls. R_{max} is the maximum feasible R-square for the regression.

[29]See for example Peng (2015), Sagi (2015) and Giacoletti (2017).

through the extensive margin of attention. Estimates of γ are positive and statistically significant, and quantitatively similar to the estimates of β from equation 7 in columns 1 and 2. Magnitudes are larger for the case in which search breadth is measured using the number of segments based on price quintiles, house type and number of bedrooms (columns 7 and 8). However, once results are scaled by standard deviation, the magnitudes are uniform across all measures, and consistent with the estimates in columns 1 and 2.

Columns 9 and 10 show the effects of experienced price growth channeled through the intensive margin, measured as the average number of minutes per visit. In this case, the sign of γ is negative and statistically significant. This is in line with the results from Table 9: Higher price growth reduces attention on the intensive margin. This effect is correlated with sale prices, so that lower attention on the intensive margin is associated with higher sale prices. This might appear surprising at first. However, predictions on the sign of the effect of attention devoted to individual listings onto prices are ambiguous. In particular, higher scrutiny can translate into lower or slower engagement with sellers if it reveals negative information.

In interpreting our results, we focus on the evidence on the extensive margin. These are consistent with higher local price growth leading to broader searches ad higher integration of demand for individual listings, which then in turn induces real effects on house sales. Our findings suggest that buyers' procyclical behavior contributes to spreading local price growth and amplifying house price fluctuations. This mechanism is related to previous theoretical work that has shown how buyers' and sellers' search behavior may amplify fundamental shocks. Novy-Marx, 2009 shows that a shock to the supply of buyers can increase market tightness directly and indirectly, by increasing the number of house sales and reducing for-sale inventory. Ngai and Tenreyro, 2014 construct a model where higher thickness (more sellers and buyers) raises prices and transaction volume, by improving the quality of matches. Our reduced form setup cannot directly speak to these models, but pins down a specific channel through which buyers procyclical behavior impacts home sales –the increase in search breadth–, which is absent from either model.

6.2 Effects on Time on the Market

Our analysis has so far focused on the effects on house prices. However, the housing market is illiquid, and homes for sale remain listed for a relevant amount of time before sale. Does higher local price growth also affect time on the market through buyers search behavior? To answer this question, we first estimate the regression equation:

$$tom_{l,t} = a_{post(l)} + a_{t\times area} + \beta\Delta p^{visits}_{l,t} + \mathcal{B}X_l + e_{l,t} \tag{9}$$

where $tom_{l,t}$ is either the probability of the home listed for sale reporting a sale in the following 90 days (which is roughly the median time on the market in the data), or the log of the remaining days the house spent on the market after month t, before being sold. $\Delta p^{visits}_{l,t}$ is average price growth experienced over the previous two years by users who visited listing l in month t[30] and X_l is the vector of property characteristics described for equation 7.

Estimates are reported in Table 11. An increase in price growth experienced by visitors is associated with higher probability of observing a sale in the following 90 days, and reduces the remaining time spent on the market. In the specification including postcode fixed effects and controls for listing characteristics, a one standard deviation higher price growth is associated (in relative terms) to a 2% increase in the probability of the listing selling within the following 90 days and a 1.2% shorter time on the market. We again face the concern that users that experience higher price growth in their postcode of residence may systematically match with higher quality listings, which are more likely to sell quickly. To address this concern, we exploit the panel structure of our dataset, and estimate a specification of equation 9 with listing fixed effects. This approach involves a trade-off between the ability to address bias

[30] This is calculated as:

$$\Delta p^{visits}_{l,t} = \frac{\sum_{i\in N_{t,l}} \Delta p_{i,t}}{|N_{l,t}|}$$

where i is an individual visit, $N_{t,l}$ is the set of visits to listing l in month t, $|N_{l,t}|$ is the total number of visits to listing l in month t, and $\Delta p_{i,t}$ is price growth over the previous two years in the postcode of residence of users matching with listing l in visit i.

due to unobservables and lower statistical power, since while it controls for listing specific heterogeneity, it also severely limits the variation in the data that identifies the coefficient β. This variation is reduced to changes in the experienced price growth of visitors for *for the same listing over time*. Table 11 shows that the effect of price growth on the probability of a house selling in less than 90 days are still statistically significant, even though the magnitude of the point estimates is smaller. When the dependent variable is time on the market, the estimate has a negative sign, but is noisy and not statistically significant.

We can link the effect of price growth to the extensive and intensive attention margin channels, using a 2SLS approach similar to the one detailed by equations 8 and 6, but in which the dependent variable in the second stage equation is a measure of time on the market. Estimates of the coefficients in the second stage regressions are reported in Table 12. Consistent with results for prices in Table 10, we find that listings that, as a result of higher price growth in the postcodes of residence, are visited by users with broader search ranges, have a higher probability of selling in the following 90 days, and shorter remaining time on the market. At the same time, variation in attention on the intensive margin (time allocated to each visit) that is associated with price growth in the postcodes of residence is related to time on the market with a positive sign, leading to a lower probability of selling within 90 days and longer time on the market. However, these estimates are not statistically significant.

7 Concluding Remarks

We study fluctuations in investors' attention to the housing market and their effects on home sales, using a unique dataset tracking users activity on a large property website.

Users living in postcodes that have experienced higher price growth over the previous two years devote a higher amount of time to house search, visit home listings more frequently, and browse a larger number of listings. However, this increase in attention impacts the extensive, rather than the intensive margin. The amount of time and the number of visits devoted to each individual listing remain unchanged. Rather, the increase in the number of browsed listing translates into searches on a broader range of homes, both in terms of locations and characteristics.

We provide several arguments that support a causal interpretation of our findings. First, the vast majority of house searches involve listings that are located outside the postcode of residence, and our estimates are based on regression specifications that include metropolitan area by time fixed effects, as well as postcode and even user fixed effects, so that price variation impacting the response of users is only based on postcode-specific fluctuations taking place over time. Second, the response of attention on the extensive margin appears to be driven by homeowners, who are more directly affected by movements in house prices. Third, we construct an empirical strategy that exploits local supply elasticity as an instrumental variable, and we find that instrumented estimates of the response of attention and search extension to house prices are larger than OLS estimates.

In the last part of the paper we provide evidence that changes in attention allocation and search behavior induced by local price fluctuations have real effects on houses for sale, leading to higher sale prices and (to a lesser extent) shorter time on the market. These results suggest that fluctuations in attention and effort devoted to house search, and in particular fluctuations in search breadth over time, might be of key importance also at an aggregate level. In particular, since search breadth responds to local price growth, we believe that our study provides evidence that home buyers' search behavior is likely to amplify housing market fluctuations, changing market segmentation procylically over housing booms and busts.

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Table 1: Summary Statistics

	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
	Panel A: Attention						
Listings	42.23	21.37	63.55	3.00	9.00	49.07	150.77
Visits	67.31	26.50	125.47	3.00	10.00	72.00	264.25
Minutes	122.21	55.85	212.33	4.55	22.95	134.65	448.74
Herfindahl	0.30	0.25	0.23	0.05	0.13	0.42	0.78
	Panel B: Search Breadth						
Postcodes	8.69	5.00	11.65	1.00	2.38	10.27	28.71
Distance	7.46	4.56	8.14	0.00	1.76	10.39	24.84
Segments(Post,Type,Nbed)	13.55	7.41	18.37	1.00	3.54	16.00	46.57
Segments($\mathbb{Q}$,Type,Nbed)	6.46	5.29	4.45	1.00	3.00	8.67	15.31

This table presents cross-sectional summary statistics relative to total attention and its allocation across listings (Panel A), as well as the extensive margin of attention, or search breadth (Panel B). We first compute the average across the monthly observations relative to each user, and then report the mean, median, standard deviation and four percentiles (5th, 25th, 75th and 95th) of the resulting cross-section. $Listings$, is the total number of unique listings browsed, $Visits$ denotes the total number of visits aggregated across listings, $Minutes$ denotes the total number of minutes aggregated across listings, $Herfindahl$, is the Herfindahl Index, based on time spent across listings, $Postcodes$ denotes the number of postcodes where the user visited at least one listing, $Distance$ is the average distance from the centroid of the postcodes visited by the user. Finally, $Segments(Post, Type, Nbed)$ and $Segments(\mathbb{Q}, Type, Nbed)$ denote the number of segments where the user visited at least one listing. See section 4.1 for more details on how segments are constructed.

Table 2: Attention Level and Local Price Growth

	Panel A: Listings (*Listings*)			
Δp_{2y}	0.447***	0.386**	0.394**	0.365**
	(2.80)	(2.39)	(2.34)	(2.21)
$R^2_{adjusted}$	0.130	0.130	0.473	0.474
Nobs	55241	55231	52943	52935
	Panel B: Visits (*Visits*)			
Δp_{2y}	0.452**	0.380*	0.370*	0.324*
	(2.59)	(2.04)	(2.01)	(1.73)
$R^2_{adjusted}$	0.140	0.139	0.508	0.508
Nobs	55241	55231	52943	52935
	Panel C: Minutes (*Minutes*)			
Δp_{2y}	0.549**	0.439*	0.453*	0.436
	(2.61)	(1.82)	(1.90)	(1.69)
$R^2_{adjusted}$	0.100	0.100	0.393	0.393
Nobs	55241	55231	52943	52935
Postcode FE	Yes	Yes	No	No
ID FE	No	No	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Year-Month× Area FE	No	Yes	No	Yes

This table displays estimates from the following panel regression:

$$log(1 + Attention_{i,t}) = \alpha_* + \alpha_{t,*} + \beta\Delta p_{post_{(i)},t-1} + \epsilon_{i,t}$$

where $Attention_{i,t}$ is the attention to the website by user i in month t and is either equal to the number of unique listings browsed (Panel A), number of visits (Panel B) or number of minutes (Panel C); α_* is either a postcode fixed effect or an individual user fixed effect; $\alpha_{t,*}$ is a year-month, or year-month by area fixed effect; $\Delta p_{post_{(i)},t-1}$ is the lagged house price growth in the postcode where user i is currently living, computed over the previous two years. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 3: Allocation of Attention: the Intensive Margin

	Panel A: Minutes per Listing ($\overline{Minutes}$)			
Δp_{2y}	0.061	0.012	0.025	0.024
	(0.57)	(0.11)	(0.22)	(0.19)
$R^2_{adjusted}$	0.096	0.095	0.338	0.338
Nobs	55241	55231	52943	52935
	Panel B: Visits per Listing ($\overline{Visits}$)			
Δp_{2y}	0.003	-0.008	-0.016	-0.033
	(0.10)	(-0.23)	(-0.55)	(-0.99)
$R^2_{adjusted}$	0.152	0.153	0.463	0.465
Nobs	55241	55231	52943	52935
	Panel C: Herfindahl of Minutes per Listing			
Δp_{2y}	-0.050	-0.049	-0.038	-0.048
	(-1.62)	(-1.44)	(-1.07)	(-1.31)
$R^2_{adjusted}$	0.064	0.063	0.264	0.265
Nobs	55241	55231	52943	52935
Postcode FE	Yes	Yes	No	No
ID FE	No	No	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Year-Month× Area FE	No	Yes	No	Yes

This table displays estimates from the following panel regression:

$$log(1 + IntAttention_{i,t}) = \alpha_* + \alpha_{t,*} + \beta\Delta p_{post_{(i)},t-1} + \epsilon_{i,t}$$

where $IntAttention_{i,t}$ is one of the measures of the intensive margin of attention for user i in month t and is either equal to the number of minutes per listings browsed (Panel A), number of visits per listing (Panel B) or the Herfindahl Index based on time spent on listings (Panel C); α_* is either a postcode fixed effect or an individual user fixed effect; $\alpha_{t,*}$ is a year-month, or year-month by area fixed effect; $\Delta p_{post_{(i)},t-1}$ is the lagged house price growth in the postcode where user i is currently living, computed over the previous two years. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 4: Allocation of Attention: the Extensive Margin (Search Extension/Breadth)

	Panel A: Number of Postcodes ($NumPost$)			
Δp_{2y}	0.421***	0.288*	0.404***	0.345**
	(3.16)	(2.00)	(3.01)	(2.39)
$R^2_{adjusted}$	0.158	0.157	0.514	0.514
Nobs	55241	55231	52943	52935
	Panel B: Geographic Area ($MeanDist$)			
Δp_{2y}	0.338**	0.207	0.337**	0.348**
	(2.37)	(1.25)	(2.32)	(2.09)
$R^2_{adjusted}$	0.120	0.120	0.375	0.376
Nobs	45028	45016	42746	42734
	Panel C: Number of Segments ($NumSeg$) (Postcode, Type, NBedrooms)			
Δp_{2y}	0.400***	0.314**	0.355**	0.320**
	(3.16)	(2.32)	(2.65)	(2.32)
$R^2_{adjusted}$	0.155	0.154	0.518	0.518
Nobs	53773	53763	51449	51440
	Panel D: Number of Segments ($NumSeg$) (Price Quantile, Type, NBedrooms)			
Δp_{2y}	0.225***	0.204**	0.206**	0.203**
	(2.97)	(2.36)	(2.50)	(2.23)
$R^2_{adjusted}$	0.118	0.119	0.456	0.457
Nobs	53773	53763	51449	51440
Postcode FE	Yes	Yes	No	No
ID FE	No	No	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Year-Month× Area FE	No	Yes	No	Yes

This table displays estimates from the following panel regression:

$$log(1 + Search_{i,t}) = \alpha_* + \alpha_{t,*} + \beta \Delta p_{post_{(i)},t-1} + \epsilon_{i,t}$$

where $Search_{i,t}$ is one of the search breadth measure for user i in month t and it is either equal to the number of postcodes browsed (Panel A), the mean distance across the postcode centroids (Panel B), or either one of the measures of the number of segments browsed (Panels C and D); α_* is either a postcode fixed effect or an individual user fixed effect; α_t is a year-month fixed effect; $\alpha_{t,*}$ is a year-month, or year-month by area fixed effect; $\Delta p_{post_{(i)},t-1}$ is the lagged house price growth in the postcode where user i is currently living, computed over the previous two years. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 5: Attention and Local Homeownership Rate

Panel A: Overall Attention and Intensive Margin

	Listings		*Visits*		*Minutes*		$\overline{Minutes}$	
Δp	0.491***	0.473**	0.518**	0.458**	0.570**	0.559*	0.020	0.028
	(2.89)	(2.66)	(2.64)	(2.30)	(2.25)	(2.05)	(0.16)	(0.22)
$\Delta p \times Own$	0.014*	0.016**	0.018**	0.020**	0.017	0.018*	0.001	0.001
	(1.78)	(2.34)	(2.11)	(2.53)	(1.61)	(1.72)	(0.19)	(0.13)
$R^2_{adjusted}$	0.130	0.474	0.139	0.509	0.100	0.393	0.095	0.338
Nobs	55231	52935	55231	52935	55231	52935	55231	52935

Panel B: Extensive Margin (Search Breadth)

	$NumPost$		$MeanDist$		$NumSeg(p, type, nb)$		$NumSeg(\mathbb{Q}, type, nb)$	
Δp	0.366**	0.443***	0.189	0.350**	0.375**	0.405***	0.222**	0.229**
	(2.45)	(2.95)	(1.06)	(2.10)	(2.73)	(2.87)	(2.53)	(2.47)
$\Delta p \times Own$	0.010	0.014**	-0.002	0.000	0.008	0.013*	0.003	0.004
	(1.55)	(2.21)	(-0.39)	(0.03)	(1.23)	(2.03)	(0.61)	(1.01)
$R^2_{adjusted}$	0.157	0.514	0.109	0.360	0.154	0.518	0.119	0.456
Nobs	55240	52942	50376	48114	53762	51439	53762	51439
Postcode FE	Yes	No	Yes	No	Yes	No	Yes	No
ID FE	No	Yes	No	Yes	No	Yes	No	Yes
Year-Month× Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates from the following panel regression:

$$log(1 + Meas_{i,t}) = \alpha_* + \alpha_{t,area} + \beta \Delta p_{post_{(i)},t-1} + \gamma \left(\Delta p_{post_{(i)},t-1} \times Homeonwership2016_{post_{(i)}} \right) + \epsilon_{i,t}$$

where $Meas_{i,t}$ is either one of the total attention and intensive margin (Panel A) or search breadth (Panel B) measures for user i in month t; α_* is either an user or postcode fixed effect; $\alpha_{t,area}$ is a year-month by area fixed effect; $\Delta p_{post_{(i)},t-1}$ is the lagged house price growth in the postcode where user i is currently living, computed over the previous two years; $Homeonwership2016_{post_{(i)}}$ is the homeownership rate in postcode $post(i)$ in 2016. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 6: Attention and Users' Homeownership Status

Panel A: Overall Attention and Intensive Margin

	$Listings$	$Visits$	$Minutes$	$\overline{Minutes}$
$\Delta p \times \mathbb{1}_{own}$	0.505**	0.568**	0.666**	0.105
	(2.78)	(2.73)	(2.50)	(0.85)
$\Delta p \times \mathbb{1}_{noown}$	0.201	0.085	0.082	-0.134
	(0.96)	(0.35)	(0.27)	(-0.86)
$\mathbb{1}_{own}$	-0.263***	-0.336***	-0.301***	-0.012
	(-6.52)	(-7.27)	(-5.32)	(-0.35)
$R^2_{adjusted}$	0.134	0.145	0.102	0.095
Nobs	55231	55231	55231	55231

Panel B: Extensive Margin (Search Breadth)

	$NumPost$	$MeanDist$	$NumSeg$ $(p, type, nb)$	$NumSeg$ $(\mathbb{Q}, type, nb)$
$\Delta p \times \mathbb{1}_{own}$	0.319*	0.185	0.260**	0.379**
	(2.02)	(1.06)	(2.69)	(2.56)
$\Delta p \times \mathbb{1}_{noown}$	0.242	0.243	0.110	0.213
	(1.34)	(1.16)	(1.03)	(1.26)
$\mathbb{1}_{own}$	-0.193***	-0.048	-0.094***	-0.172***
	(-5.73)	(-1.41)	(-4.55)	(-5.48)
$R^2_{adjusted}$	0.161	0.109	0.121	0.157
Nobs	55240	50376	53762	53762

This table displays estimates from the following panel regression:

$$log(1 + Meas_{i,t}) = \alpha_{post_{(i)}} + \alpha_{t,area} + \delta_{own}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,owner}\right) + \delta_{noown}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,noowner}\right) + \kappa \mathbb{1}_{i,owner} + \epsilon_{i,t}$$

where $Meas_{i,t}$ is either one of the total attention and intensive margin (Panel A) or search breadth (Panel B) measures for user i in month t; $\alpha_{post_{(i)}}$ is a postcode fixed-effect ; $\alpha_{t,area}$ is a year-month by area fixed effect; $\Delta p_{post_{(i)},t-1}$ is the lagged house price growth in the postcode where user i is currently living, computed over the previous two years; $\mathbb{1}_{i,owner}$ is a dummy equal to one if user i is a homeowner, and $\mathbb{1}_{i,noowner}$ is a dummy equal to one is the user is not a homeowner. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 7: Supply Elasticity: First Stage IV

	Dep. Variable: Δp	
$I_{\Delta p_{subd,ym}>0} \times \Lambda_{post}$	0.090^{***}	0.090^{***}
	(34.68)	(6.55)
Postcode FE	Yes	Yes
Year-Month FE	Yes	Yes
Clustering	None	Post,YM
$R^2_{adjusted}$	0.859	0.859
Nobs	52943	52943

This table displays estimates from the following panel regression:

$$\Delta p_{post_{(i)},t} = \alpha_{post_{(i)}} + \alpha_t + \psi \left(\mathbb{1}_{\Delta p_{area_{(i)},t}>0} \times \Lambda_{post_{(i)}} \right) + \eta_{post_{(i)},t}$$

where $\Delta p_{post_{(i)},t}$ is house price growth in the postcode where user i is currently living, computed over the previous two years; $\alpha_{post_{(i)}}$ is a postcode fixed-effect ; α_t is a year-month fixed effect; $\mathbb{1}_{\Delta p_{area_{(i)},t}>0}$ is a dummy equal to one if house price growth over the last two years has been positive in the area where $post(i)$ (and therefore user i) is located; $\Lambda_{post_{(i)}}$ is the measure of house supply elasticity. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 8: Attention and Price Growth: 2SLS Estimates with Supply Elasticity Instrument

	Panel A: Overall Attention and Intensive Margin							
	$Listings$		$Visits$		$Minutes$		$\overline{Minutes}$	
Δp	1.581***	1.911***	1.293***	1.670***	1.669***	1.841**	-0.023	-0.171
	(3.95)	(4.02)	(2.83)	(2.98)	(2.79)	(2.26)	(-0.07)	(-0.40)
F_{robust} (1st Stage)	46.053	42.881	46.053	42.881	46.053	42.881	46.053	42.881
N	55241	52943	55241	52943	55241	52943	55241	52943
	Panel B: Extensive Margin (Search Breadth)							
	$NumPost$		$MeanDist$		$NumSeg(p, type, nb)$		$NumSeg(\mathbb{Q}, type, nb)$	
Δp	1.453***	1.457***	2.011***	1.680***	1.286***	1.462***	0.400*	0.553**
	(4.30)	(4.04)	(4.62)	(3.69)	(3.78)	(4.10)	(1.96)	(2.16)
F_{robust} (1st Stage)	46.053	42.881	46.484	45.534	44.469	41.906	44.469	41.906
N	55241	52943	45028	42746	53773	51449	53773	51449
Postcode FE	Yes	No	Yes	No	Yes	No	Yes	No
ID FE	No	Yes	No	Yes	No	Yes	No	Yes
Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates from the following panel regression:

$$log(1 + Meas_{i,t}) = \alpha_* + \alpha_t + \beta\widehat{\Delta p}_{post(i),t-1} + \epsilon_{i,t}$$

where $Meas_{i,t}$ is either one of the total attention and intensive margin (Panel A) or search breadth (Panel B) measures for user i in month t; α_* is either a postcode fixed effect or an individual user fixed effect; α_t is a year-month fixed effect; $\widehat{\Delta p}_{post(i),t-1}$ is house price growth computed over the previous two years instrumented with local land supply elasticity, as explained in section 5.2. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level. F_{robust} is a heteroskedasticity robust variant of the F-statistic for the first-stage regression, which is calculated according the methodology developed by Kleibergen and Paap (2006).

Table 9: Effect of Price Growth on Attention at the Listing Level

	$NumPost$		$NumSeg(p, type, nb)$		$NumSeg(\mathbb{Q}, type, nb)$		$\overline{Minutes}$	
Δp_l^{visits}	0.896***	1.036***	0.876***	1.035***	0.334***	0.417***	-0.251***	-0.350***
	(7.84)	(7.76)	(7.37)	(7.81)	(6.00)	(7.36)	(-3.11)	(-3.74)
I_{unit}		-0.082***		-0.069***		0.050***		0.059**
		(-4.53)		(-4.04)		(5.56)		(2.13)
I_{1bed}		0.037		0.000		-0.003		-0.017
		(1.49)		(0.01)		(-0.28)		(-0.41)
I_{3beds}		-0.046***		-0.045***		-0.042***		0.011
		(-4.51)		(-4.50)		(-9.73)		(0.79)
$I_{\geq 4beds}$		-0.041***		-0.082***		-0.099***		0.036**
		(-3.41)		(-6.60)		(-15.57)		(2.31)
I_{1bath}		0.018**		0.029***		0.019***		-0.093***
		(2.25)		(3.64)		(5.37)		(-9.70)
$I_{\geq 3baths}$		0.066***		0.054***		-0.003		0.068***
		(7.81)		(6.58)		(-0.60)		(6.21)
I_{1park}		-0.032***		-0.026***		-0.003		-0.011
		(-3.39)		(-2.73)		(-0.63)		(-0.78)
I_{2park}		-0.047***		-0.045***		-0.013***		-0.007
		(-5.02)		(-4.93)		(-2.82)		(-0.59)
I_{3park}		-0.030***		-0.033***		-0.015**		0.047***
		(-2.93)		(-3.26)		(-2.67)		(4.15)
$log(size)$		0.027***		0.015***		-0.006***		0.078***
		(6.35)		(3.83)		(-3.36)		(12.50)
$R^2_{adjusted}$	0.158	0.176	0.158	0.179	0.130	0.157	0.073	0.084
Nobs	404178	260346	404078	260293	404078	260293	402494	259334

This table displays estimates from the following regressions:

$$logMeas_l = a_{post(l)} + a_{t \times area} + \lambda \Delta p_l^{visits} + \mathcal{B} X_l + v_l$$

where $logMeas_l$ is the log of (one plus) one of the measure of the extensive or intensive margin of attention; $\alpha_{post(l)}$ is a postcode fixed effect for the postcode where listing l is located; $\alpha_{t \times area}$ is a year-month by area (where listing l is located) fixed effect; X_l is a vector of characteristics of the home in listing l; Δp_l^{visits} is the average price growth experienced by users that visited listing l before sale. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 10: Real Effects on Sale Price

Δp_l^{visits}	0.205***	0.097***								
	(7.06)	(5.62)								
$log\widehat{NumPost}$			0.227***	0.092***						
			(4.76)	(4.38)						
$log\widehat{NumSeg}(p, type, nb)$					0.233***	0.093***				
					(4.54)	(4.49)				
$log\widehat{NumSeg}(\mathbb{Q}, type, nb)$							0.615***	0.231***		
							(3.88)	(4.52)		
$log\widehat{\overline{Minutes}}$									-0.796***	-0.270***
									(-2.91)	(-3.11)
I_{unit}		-0.112***		-0.104***		-0.105***		-0.123***		-0.095***
		(-12.85)		(-11.61)		(-11.95)		(-13.49)		(-7.19)
I_{1bed}		-0.275***		-0.279***		-0.276***		-0.275***		-0.279***
		(-20.43)		(-20.11)		(-19.87)		(-19.79)		(-16.83)
I_{3beds}		0.102***		0.106***		0.106***		0.112***		0.105***
		(28.69)		(28.90)		(28.59)		(25.65)		(21.42)
$I_{\geq 4beds}$		0.213***		0.217***		0.221***		0.236***		0.223***
		(55.02)		(50.96)		(49.10)		(34.25)		(33.40)
I_{1bath}		-0.162***		-0.164***		-0.165***		-0.166***		-0.187***
		(-40.53)		(-41.31)		(-41.32)		(-41.79)		(-20.38)
$I_{\geq 3baths}$		0.225***		0.219***		0.220***		0.225***		0.243***
		(44.71)		(43.19)		(43.30)		(43.10)		(29.01)
I_{1park}		0.030***		0.033***		0.032***		0.031***		0.027***
		(6.73)		(6.83)		(6.81)		(6.46)		(5.01)
I_{2park}		0.087***		0.091***		0.091***		0.090***		0.086***
		(18.55)		(17.22)		(17.45)		(17.53)		(14.42)
I_{3park}		0.138***		0.141***		0.141***		0.142***		0.152***
		(28.24)		(26.72)		(27.19)		(27.86)		(18.15)
$log(size)$		0.134***		0.132***		0.133***		0.135***		0.155***
		(51.95)		(49.65)		(51.06)		(50.98)		(19.96)
$R^2_{adjusted}$	0.534	0.797	-	-	-	-	-	-	-	-
Nobs	394696	254450	394696	254450	394600	254400	394600	254400	393057	253460

This table displays estimates from the following regressions:

$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \beta\Delta p_l^{visits} + \mathcal{B}X_l + e_l \quad Columns\ 1\ and\ 2$$
$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \gamma log\widehat{Meas}_l + \mathcal{B}X_l + v_l \quad Columns\ 3\ to\ 10$$

where p_l^{sale} is the log of the sale price for listing l; $\alpha_{post(l)}$ is a postcode fixed effect for the postcode where listing l is located; $\alpha_{t\times area}$ is a year-month by area (where listing l is located) fixed effect; X_l is a vector of characteristics of the home in listing l; Δp_l^{visits} is the average price growth experienced by users that visited listing l before sale; $log\widehat{Meas}_l$ is the part of the variation in one the attention measures across listings that is explained by experienced price growth (the fitted value from equation 6). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 11: Real Effects on Liquidity

	Sale Within 90 days			Time-On-market (log)		
Δp_l^{visits}	0.025**	0.041***	0.026***	-0.050*	-0.079**	-0.020
	(2.44)	(3.05)	(3.16)	(-1.80)	(-2.31)	(-0.98)
I_{unit}		-0.090***			0.183***	
		(-14.83)			(12.50)	
I_{1bed}		-0.084***			0.206***	
		(-9.32)			(9.74)	
I_{3beds}		0.007*			-0.012	
		(2.02)			(-1.57)	
$I_{\geq 4beds}$		-0.023***			0.069***	
		(-5.61)			(7.96)	
I_{1bath}		0.041***			-0.103***	
		(15.47)			(-17.22)	
$I_{\geq 3baths}$		-0.093***			0.205***	
		(-29.85)			(31.25)	
I_{1park}		0.033***			-0.077***	
		(8.05)			(-8.80)	
I_{2parks}		0.033***			-0.074***	
		(7.61)			(-8.00)	
I_{3parks}		0.022***			-0.048***	
		(4.96)			(-5.10)	
$log(size)$		-0.020***			0.045***	
		(-16.13)			(15.67)	
$R^2_{adjusted}$	0.084	0.108	0.529	0.092	0.113	0.456
N	857470	557021	488071	851074	553042	483068
Postcode FE	Yes	Yes	No	Yes	Yes	No
Listing FE	No	No	Yes	No	No	Yes
Year-Month× Area FE	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates from the following panel regressions:

$$tom_{l,t} = a_{post(l)} + a_{t\times area} + \beta\Delta p_{l,t}^{visits} + \mathcal{B}X_l + e_{l,t}$$
$$tom_{l,t} = a_l + a_{t\times area} + \beta\Delta p_{l,t}^{visits} + e_{l,t}$$

where $tom_{l,t}$ is a measure of time on the market; $\alpha_{post(l)}$ is a postcode fixed effect for the postcode where listing l is located; α_l is a listing fixed effect; $\alpha_{t\times area}$ is a year-month by area (where listing l is located) fixed effect; X_l is a vector of characteristics of the home in listing l; $\Delta p_{l,t}^{visits}$ is the average price growth experienced by users that visit listing l in month t. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 12: Real Effects on Liquidity

	Panel A: Sale within 90 days							
$log\widehat{NumPost}$	0.027*	0.038**						
	(2.04)	(2.38)						
$log\widehat{NumSeg}(p, type, nb)$			0.028*	0.038**				
			(2.02)	(2.35)				
$log\widehat{NumSeg}(\mathbb{Q}, type, nb)$					0.069*	0.092**		
					(2.01)	(2.38)		
$log\overline{\widehat{Minutes}}$							-0.248	-0.281
							(-0.68)	(-0.90)
N	857470	557021	857115	556809	857115	556809	852218	553737
	Panel B: Time-On-market (log)							
$log\widehat{NumPost}$	-0.099*	-0.096*						
	(-1.95)	(-1.96)						
$log\widehat{NumSeg}(p, type, nb)$			-0.101*	-0.096*				
			(-1.93)	(-1.95)				
$log\widehat{NumSeg}(\mathbb{Q}, type, nb)$					-0.250*	-0.232*		
					(-2.05)	(-2.06)		
$log\overline{\widehat{Minutes}}$							0.804	0.564
							(0.80)	(1.13)
N	525944	346670	525755	346557	525755	346557	523106	344842
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes
List Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month× Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates from the following panel regressions:

$$tom_{l,t} = a_{post(l)} + a_{t\times area} + \beta log\widehat{Meas}_{l,t} + \mathcal{B}X_l + e_l$$

where $tom_{l,t}$ is a measure of time on the market; $\alpha_{post(l)}$ is a postcode fixed effect for the postcode where listing l is located; $\alpha_{t\times area}$ is a year-month by area (where listing l is located) fixed effect; X_l is a vector of characteristics of the home in listing l; $log\widehat{Meas}_{l,t}$ is the part of the variation in one the attention measures across listings that is explained by experienced price growth (the fitted value from equation 6). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Figure 1: This figure displays the quarterly Corelogic repeat sales price Index for the eight state capital cities (Sydney, Melbourne, Brisbane, Adelaide, Perth, Hobart, Darwin and Canberra) and Australia (bottom-right plot).

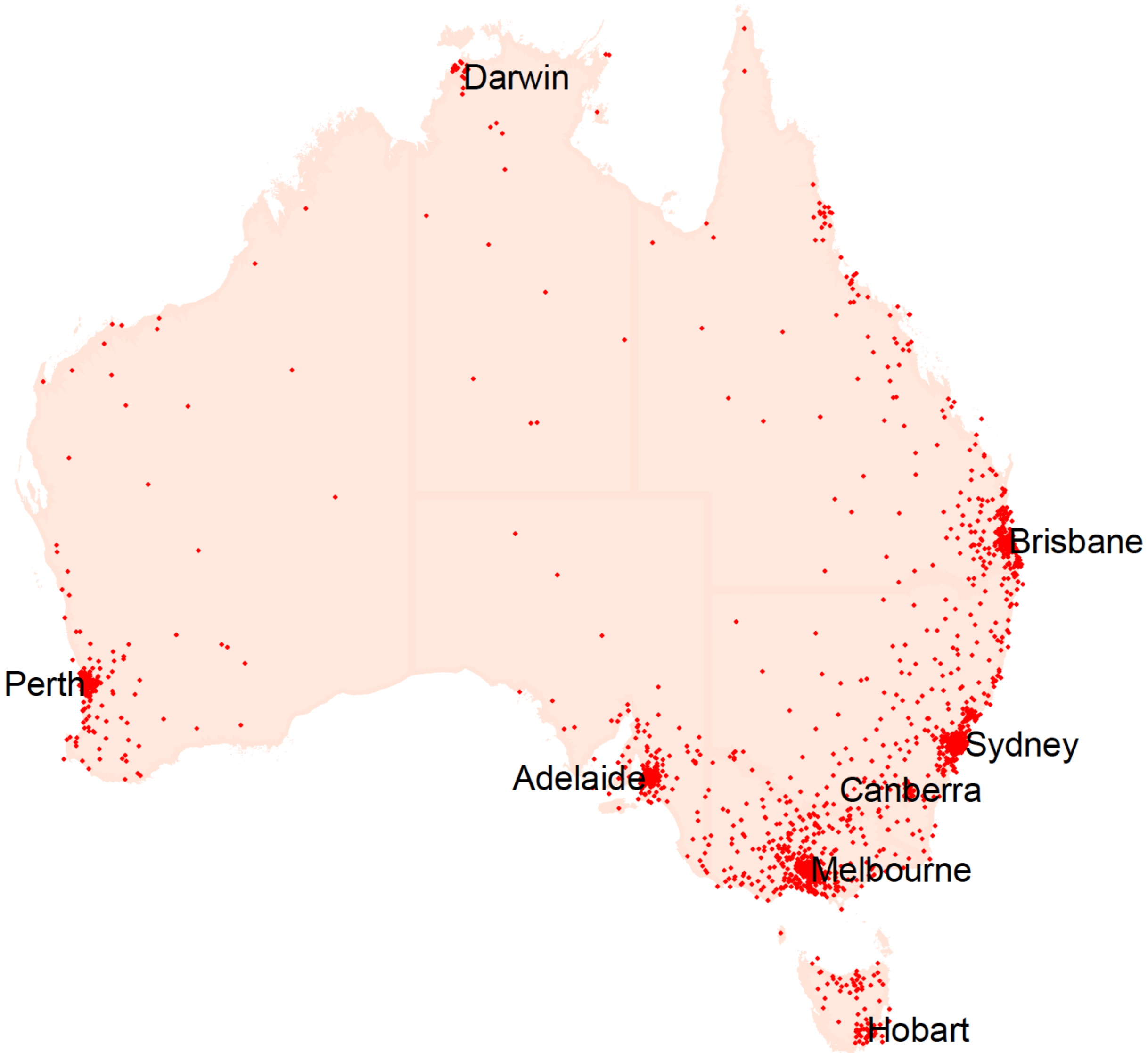


Figure 2: This figure displays the spatial distribution of the users in our sample. Each dot denotes a postcode which is the residence of at least one user.

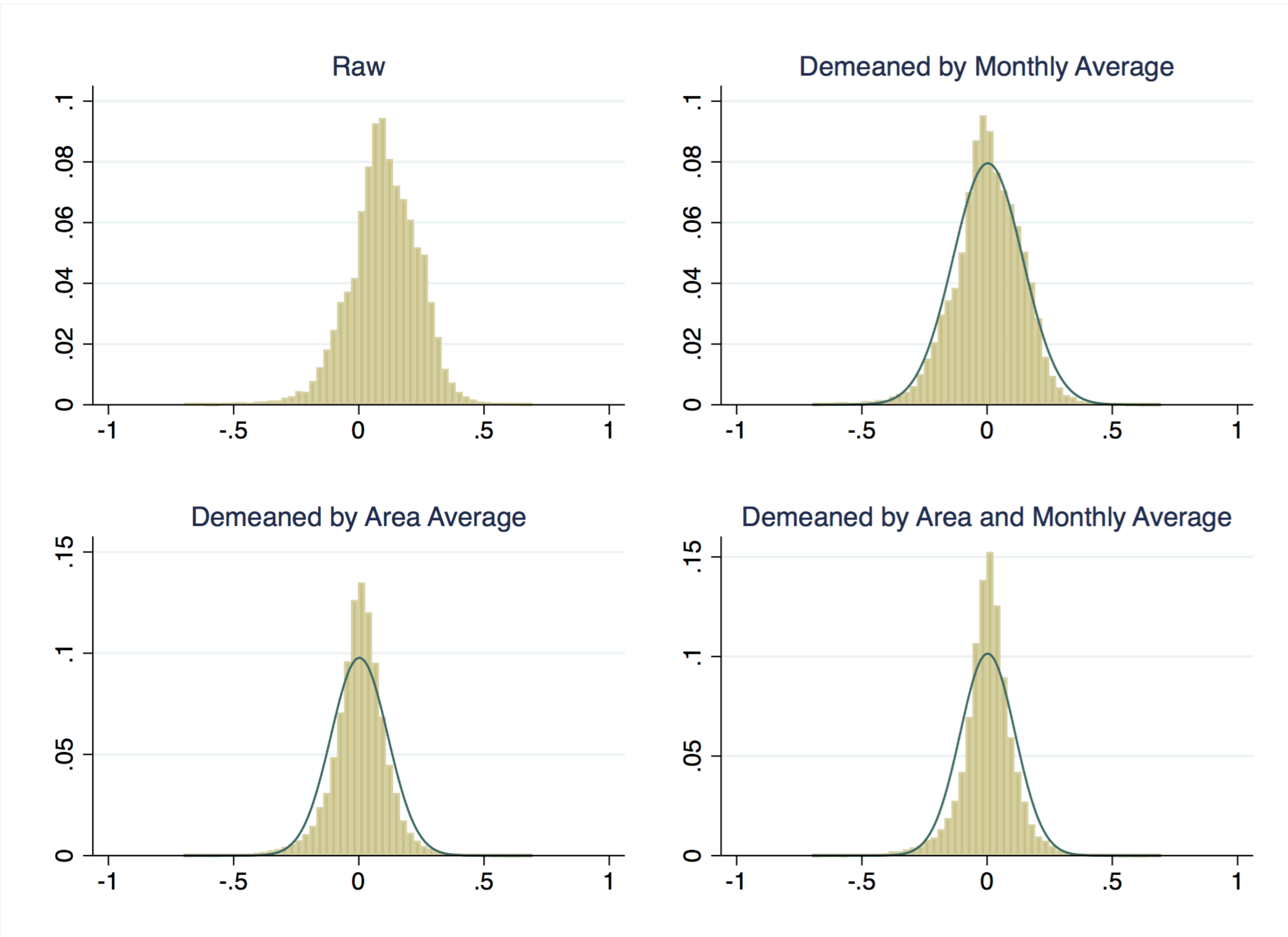


Figure 3: This figure displays the pooled distribution of the 2-year price growth for the postcodes in our sample. The top-left plot displays the distribution of the raw data. The remaining three plots display the distribution after we subtract the monthly (top-right plot), the area (bottom-left plot) and the monthly and area average (bottom-right plot).

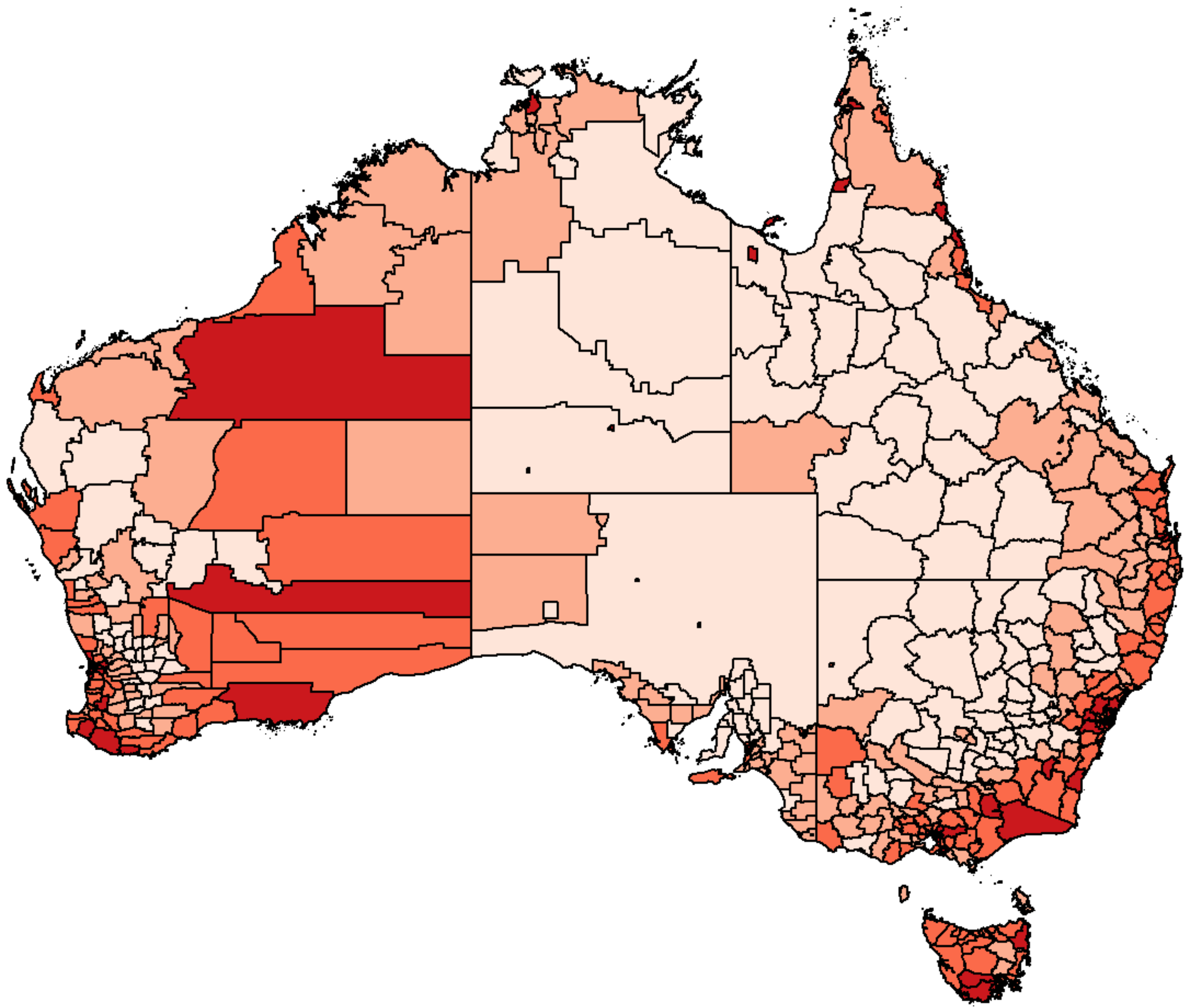


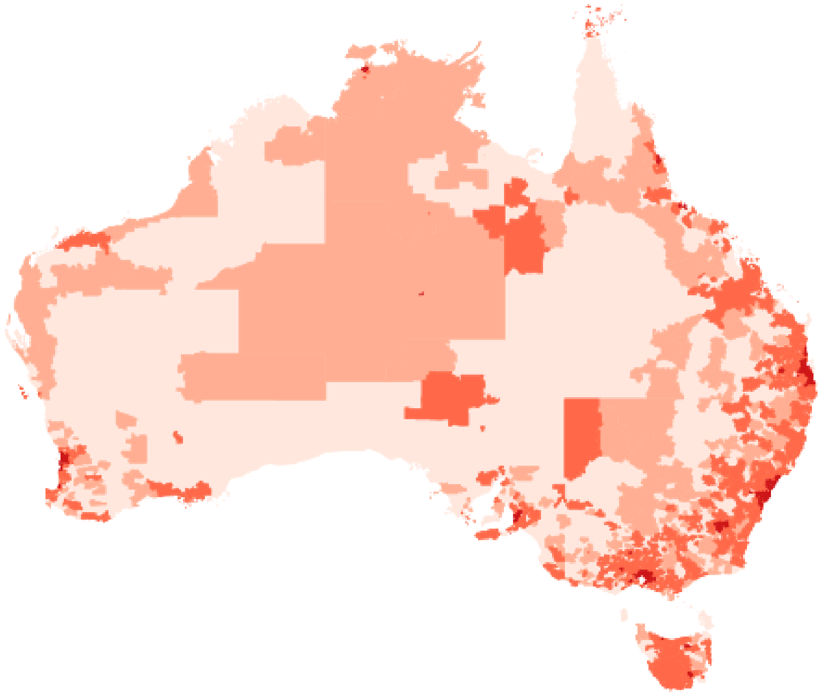
Figure 4: This figure provides a graphical representation of the land supply elasticity instrument introduced in Section 5.2. Each area corresponds to the land surface of a Local Government Area (LGA). Darker areas have a larger fraction of constrained land. The fraction of constrained land is above 73% in the areas with darkest color, while it is equal or smaller than 16% in the areas with lightest color.

Appendix

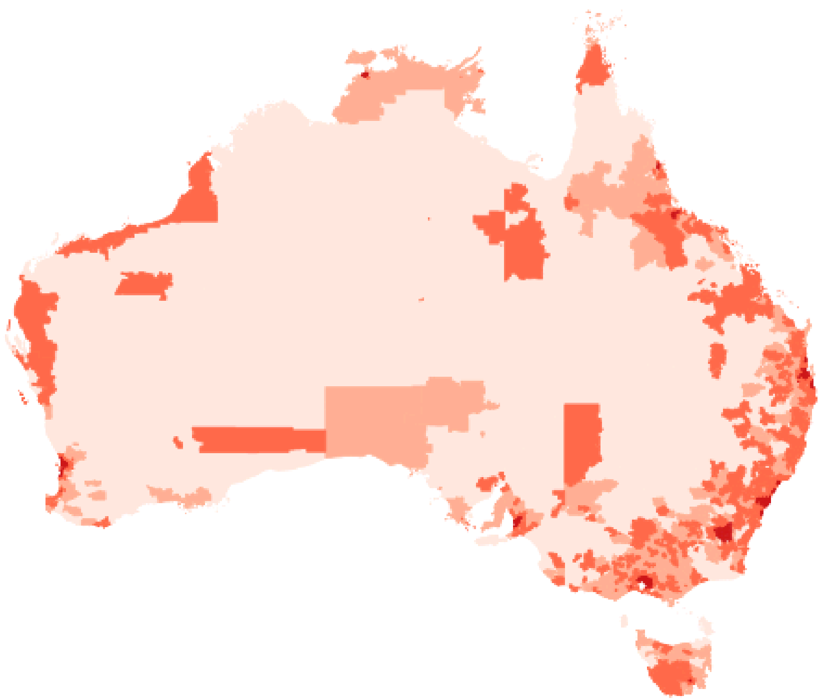
Table A.1: Summary Statistics

	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
	Panel A: Demographic Characteristics						
Dummy Age: 18 to 24	0.06	0.00	0.24	0.00	0.00	0.00	1.00
Dummy Age: 25 to 34	0.15	0.00	0.35	0.00	0.00	0.00	1.00
Dummy Age: 35 to 49	0.30	0.00	0.46	0.00	0.00	1.00	1.00
Dummy Age: 50 to 64	0.32	0.00	0.47	0.00	0.00	1.00	1.00
Dummy Age: over 65	0.13	0.00	0.33	0.00	0.00	0.00	1.00
Female	0.55	1.00	0.50	0.00	0.00	1.00	1.00
	Panel B: Listings						
Dummy Type: House	0.62	1.00	0.48	0.00	0.00	1.00	1.00
Dummy Type: Townhouse	0.06	0.00	0.23	0.00	0.00	0.00	1.00
Dummy Type: Unit	0.25	0.00	0.43	0.00	0.00	0.00	1.00
Dummy Type: Land	0.05	0.00	0.21	0.00	0.00	0.00	0.00
Dummy Type: Other	0.02	0.00	0.15	0.00	0.00	0.00	0.00
Number of Bathrooms	1.64	2.00	0.74	1.00	1.00	2.00	3.00
Number of Bedrooms	2.85	3.00	1.29	0.00	2.00	4.00	5.00
Number of Parking spots	1.68	2.00	1.38	0.00	1.00	2.00	4.00

This table presents summary statistics of the demographic characteristics of users in the dataset (Panel A), and of the characteristics of listings visited by the users over the period from January 2017 through April 2019 (Panel B).



(a) Population Density: Our sample



(b) Population Density: 2016 Census

Figure A.1: This figure displays the density, at the postcode level, of users in our data (Panel a) and Australian population density, at the postcode level, according to the 2016 Census (Panel b). Postcodes with higher density are denoted by darker color.