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 homeowners, young households and residents of lower price postcodes in particular, consistent with higher price growth affecting users behavior through wealth effects or the easing of collateral constraints. Our 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 implies that fluctuations in households' attention have procyclical effects on house price growth and generate spillovers within metropolitan areas.

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1 Introduction

Extensive evidence in financial markets indicates that fluctuations in investors' attention are related to market conditions and have real effects.[1] 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,[2] and one in which fluctuations in attention may play a key role for several reasons. First, home buyers are mostly retail investors with limited time to allocate to house search, and whose interest in housing is likely to fluctuate over time. Second, housing market conditions, and in particular price fluctuations, are salient for households, and may affect attention to the housing market through a multiplicity of channels.[3] 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. 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) and house characteristics. On the other hand, the amount of attention devoted to individual listings remains unchanged. We test several competing hypotheses for the mechanism linking local price fluctuations to attention and search behavior. We provide evidence consistent with wealth effects and the relaxation of collateral constraints playing a key role. The largest re-

[1] Fluctuations in attention have been shown to induce a delay in price responses to news and earning announcements, to generate temporary price pressure, volatility spillovers and return co-movements (see Hirshleifer, Lim, and Teoh, 2009, Da, Engelberg, and Gao, 2011, Andrei and Hasler, 2015, Huang, Huang, and Lin, 2019 and Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016).

[2] According to Zillow Research, the market value of the U.S. housing stock was close to $30 trillion in 2016. At the end of the same year, total U.S. stock market capitalization was close to $25 trillion.

[3] For instance, through wealth effects or the relaxation of collateral constraints (see Campbell and Cocco, 2007 and Landvoigt, 2017), through the formation of extrapolative beliefs (see Agarwal, Hu, and Huang, 2016 and Glaeser and Nathanson, 2017), or through behavioral channels (see Genesove and Mayer, 2001).

sponses of attention and search behavior are observed for users who are homeowners, live in postcodes with prices below the median within the metropolitan area, and are younger than 40 years old. The increase in attention driven by local house prices, and in particular its allocation towards 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 variation both in the time-series and the cross-section. Crucially, online activity is merged with information on user characteristics, such as postcode of residence, homeownership status and demographics. Along with information on user behavior, we also observe detailed information on listings, including house characteristics, listing prices and sale prices. We construct measures of attention at the level of individual users, 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 fluctuations in households' attention to the housing market coincide with changes in market conditions, which we measure using recent house price growth in the buyers' postcode of residence. We estimate the response of total attention, as well as of the intensive and an extensive margin of attention allocation. The intensive margin can be interpreted as the dimension in which the buyer allocates attention to each single property, evaluating the potential quality of the match with each specific house. The extensive margin determines the range of possible matches available to the buyer, delimiting the breadth of her search within the larger housing market.

We use panel regressions including a rich set of fixed-effects: time by metropolitan area[4]

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

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 6% 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 combination of listed homes locations and characteristics) visited. In response to higher price growth users appear to uniformly shift their searches towards more expensive postcodes, leaving the dispersion of prices considered largely unaffected. The relationship between price growth and the intensive margin, measured as 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 find that there is no statistically significant relationship between past price growth and concentration.

There are several mechanisms that can drive the response of user behavior to local price growth, and therefore generate heterogeneous effects across postcodes. First, higher prices increase homeowners' wealth and relax collateral constraints, potentially leading to higher demand for housing (see Stein, 1995). The increase in attention might be driven either by the decision to move, or the one to acquire a second house or an investment property. Second, both homeowners and renters might form extrapolative expectations on the general housing market based on recent price growth, and so feel compelled to purchase for "fear of missing out" (see Glaeser and Nathanson (2017)). Third, homeowners behavior might be motivated by behavioral channels, most importantly loss aversion (see Genesove and Mayer, 2001).

Exploiting information on user characteristics, we can disentangle the role of these different channels. 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. Moreover, we show that the effects in the data are driven by households living in postcodes with house prices below the median in the metropolitan area, and by young homeowners. This is consistent with wealth effects or collateral constraints driving the heterogeneous levels of attention across postcodes. Extrapolative expectations would affect both homeowners and (probably even more strongly) renters. Behavioral biases would be at work across both more and less expensive postcodes.

Our results also provide an insight in describing different patterns in housing demand within a metropolitan area, and suggest that price growth impacts demand and mobility more strongly in less expensive and lower quality areas.[5]

Attention and search behavior endogenously affect house prices. However, we believe that the results we are capturing in the data are causal. We study the response of users to price growth in the postcode where they are currently living, and we observe that in the data the vast majority of visited listings are located outside the postcode where a user lives. Moreover, the evidence on the economic mechanism raises the bar for endogeneity concerns, since endogenous effects should line up with the heterogeneity we document across postcodes and user characteristics. To further dispel endogeneity concerns, we develop an instrumental variable strategy, that exploits local land supply elasticity.[6] To this end, we use data on land utilization 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),[7] 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

[5] This is consistent with what shown in the context of the San Diego housing market by Landvoigt, Piazzesi, and Schneider (2015).

[6] Our approach is related to the one in Stroebel and Vavra (2019).

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

number of postcodes and segments visited.

Our findings imply that search breadth responds to local price growth. In recent work, Piazzesi, Schneider, and Stroebel (2019) show that the breadth of house searches determines 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 do not 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 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 in interpreting our results is that the match between listings and visitors might be driven by unobserved characteristics of the properties. To address this concern, we first rely on the methodology developed by Oster (2019), building on Altonji, Elder, and Taber (2005), which assesses the importance of omitted variable bias. For unobservables-induced bias to explain the effect on sale prices of experienced price growth, 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), which along with home location and sale timing already account for more than 80% of the variation in prices. To further address unobserved heterogeneity in the data, we also estimate a specification where we include among the controls the last listing price available for each house. This variable should incorporate all the information on house characteristics that are priced by the market, and should also attenuate our results, since it in part already reflects the price pressure generated by users that experienced higher price growth. Nonetheless, we still find a positive and statistically significant effect of experienced price growth on sale price.

These real effects on sale prices are substantial. When visitors 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 also provide direct 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 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.

Finally, we show that the effects are heterogeneous across postcodes and listings. In particular, the effects are stronger for listings that face less competition, which we measure as the number of listings with the same characteristics that are available online at the same time and located in the same postcode. In the bottom quartile of competition, the real effects on sale prices of a one standard deviation higher experienced price growth is greater than 3%.

We repeat the entire set of tests just described to detect the effects of higher experienced price growth and search breadth on time on the market. We find that higher price growth experienced by users predicts shorter time on the market. Even though the magnitude of the effect is quantitatively small, this finding is still relevant, since it is consistent with higher demand generating higher prices without increasing time on the market, but rather generating matches between buyers and sellers at a slightly faster pace.

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 represent a monetary cost –rather than just a cost in terms of effort– that an investor must incur 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,[8] a fact that can induce a delay in price responses (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, 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

[8] Corwin and Coughenour (2008) study the behavior of NYSE floor specialists, Della Vigna and Pollet (2009) compare 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.

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 behavior for market prices and liquidity, which only arise in search-and-matching models (e.g. Wheaton, 1990, Genesove and Han, 2012, Piazzesi and Schneider, 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.[9]

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. Our dataset has three key unique features that make it uniquely suited to analyze the relation between search behavior and housing market conditions.

[9]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 and disentangle the economic mechanism driving users' responses.

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.[10] This dataset covers the period from the 1st of January 2017 to the 30th of April 2019, for a total of approximately 3 millions 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, sex and whether she is searching for a property to occupy or for an investment property.

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.[11] Hobart (TAS) and Adelaide (SA) have experienced positive growth for the entire period covered

[10] 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.

[11] 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 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 with that of the Australian population. Figure 2 displays the postcodes where the users are located: each red dot represents a postcode for which we have at least one user. The majority of users are concentrated 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 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). 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.[12]

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

House prices fluctuate substantially over market cycles. It is then reasonable to expect that these fluctuations would translate into changes in attention to the housing market. There are several channels that can explain this relationship. First, for homeowners, positive growth generates wealth effects, relaxes borrowing constraints and can then compel households to look for new properties to occupy (see Stein (1995) and more recently Landvoigt (2017)) or to purchase as investments. Second, both owners and renters may be extrapolating from past price growth, and expect even higher future prices (see Case, Shiller, and Thomson (2015), Agarwal, Hu, and Huang (2016), Kaplan, Mitman, and Violante (2017) and Glaeser and Nathanson (2017)). Third, there might be behavioral mechanisms that make owners more likely to sell their house after price growth (see Genesove and Mayer, 2001), or more likely to pay attention.

[12]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 request.

However, assessing empirically the impact of market conditions on attention poses multiple empirical challenges. First, we need to construct measures of attention. In this section we describe in detail 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.

Second, we need to select a suitable right hand side variable. Estimates of the effect of price growth on attention at a high level of aggregation, such as a metropolitan area or state, are hard to interpret, since they are plagued by reverse causality and endogeneity: as online activity proxies for market demand, higher (lower) attention may drive prices up (down). Thus, we exploit information on the postcode where users are *currently living* and heterogeneity in *local* price growth.

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.[13] 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.

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

[13] 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.

individual financial securities rather than to the broader financial market.

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 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

[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 compute all distances $dist_{i,post,\tau}$. We then exclude postcodes for which the distance from the mean center 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.

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 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 $\mathbb{1}_{i,\ell \in (.),\tau}$ is a dummy equal to one for the first listing (ℓ) in a certain segment that is visited by user i in month t.

Panel A of Table 1 reports summary statistics of our measures of total attention and of the

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

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

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 90th 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

Our aim is now to assess the relationship between the overall level of attention to the housing market and local price growth. A key advantage of our data is that we can estimate the response of users behavior to price growth in the postcode where they are currently living. This reduces the endogeneity constraints that plague a regression of house price growth on house search behavior, since most searches take place outside of the postcode of residence. 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%. 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] which then control for common price movements in the area. To 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

[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.

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.

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 errors by postcode and year-month.[19]

4.3 Results

Estimates of the effect of price growth on the level of attention (β from equation 1) are reported in Table 2 and are positive and statistically significant across the board. We find that a 15% higher price growth (roughly equal to a one standard deviation increase in postcode-level price growth) corresponds to approximately a 6% 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.[20] 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

[19]When we double-cluster standard errors by user and year-month we obtain smaller estimates of standard errors and higher t-statistics.

[20]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, evidence of extrapolative beliefs in the housing market typically shows a relationship between price expectations and price growth experienced over a period of several years (see Case, Shiller, and Thomson, 2015 and Kaplan, Mitman, and Violante, 2017 among others).

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. However, while average attention per listing may remain unchanged, as overall attention increases, prospective buyers may be skewing attention allocation towards specific listings. To test this hypothesis, in panel (C) we set the dependent variable equal to the Herfindhal Index of time allocated to individual listings each 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 affecting the extensive margin: households may not only be exploring a larger number of listings, but extending the breadth of their house searches, both across postcodes and across market segments. 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 approximately a 6% larger number of postcodes explored. Panel (B) shows that it also leads to a 6% 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).

Is the expansion of search ranges just driven by the fact that, in response to higher local price growth, households expand the price range of their searches to include homes from more expensive areas? To answer this question we collect the median house price for all postcodes explored by users each month, and for each month and user we compute a measure of the range (standard deviation) of prices, and the quantiles of the price distribution. We then estimate the same specification as in equation (1), and report results in Table 5.

In Panel (A), we show that there is only a weak relationship between range of (median postcode) prices explored by users and higher experienced price growth, and this relationship is not statistically significant once metropolitan area by month fixed effects are included in the regression specification. Thus, the expansion in the number of explored postcodes is not driven just by the inclusion of pricier areas.

To gain a better understanding of user behavior, in Panels (B) through (E) we study how the entire distribution of prices responds to experienced price growth. In response to price growth, all (the 10th, the 25th, the 75th and the 90th) quantiles of the price distribution shift upwards. The magnitude of this effects is such that a one standard deviation higher price growth increases the quantiles of the distribution from 1.5% to 2.5%. Thus, all quantiles shift upwards in a similar way, so that the overall price range remains the same and users uniformly shift attention towards more expensive postcodes.

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 The Economic Mechanism

Multiple mechanisms can explain why prospective buyers may expand their home searches as prices rise in their postcode of residence.

First, 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). In particular, house price growth may also affect the demand for housing and increase the likelihood of homeowners engaging in house sales and purchases (see Stein, 1995 and Ortalo-Magne and Rady, 2006). These effects would be stronger for homeowners that have lower income, are less wealthy and are more financially constrained. They also would be stronger for homeowners that have intrinsically higher mobility, such as young households.

Second, renters could be motivated by the opposite effect. They may interpret local price growth as a signal that prices are growing everywhere, and they may decide to scout the market more carefully to find affordable homes. Moreover, both owners and renters might be motivated by extrapolative beliefs, and may want to secure a home before prices grow further.

Third, there can be behavioral effects, that may lead homeowners to be more likely to sell their home in response to price growth (such as loss aversion, see Genesove and Mayer (2001)).

Documenting in more detail the economic mechanism linking house price growth to user behavior provides further evidence of a causal relationship, since endogenous responses would need to match the specific channels documented in the data. To further reassure the reader of the causal nature of our findings, in the last part of this section we also use an instrumental variable approach that exploits constraints to local housing supply elasticity.

5.1 Heterogeneity: Homeowners and Renters

We first test whether the effects discussed in the previous section are driven by homeowners or renters. Our test exploits user-level information, since users in our dataset disclose whether they are currently homeowners. We can then estimate the regression specification:

$$\begin{aligned} log(1 + Meas_{i,t}) = \alpha_{post_{(i)}} + \alpha_{t,area} + \delta_{own}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,owner}\right) + \\ + \delta_{noown}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,noowner}\right) + \kappa \mathbb{1}_{i,owner} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $Meas_{i,t}$ is any of the measures of attention developed in section 4.1, either capturing the overall level of attention, the listing-level intensity of attention, or the extension of house searches. $\mathbb{1}_{i,owner}$ 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 measures the average difference in attention between owners and non-owners.

Our results are reported in Table 6. Estimates of κ are negative and statistically significant. As we may expect, 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) 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 are the measures of search breadth. We find again 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.

Thus, to provide further support to our findings on owners' as opposed to renters' behavior, we also exploit an alternative specification. We use information available form the 2016 Australian Census on the postcode-level homeownership rate. Our intuition is that users are more likely to be homeowners in areas where homeownership is higher. Our results are reported in Table A.2 in the Appendix. Consistent with our previous results, we find that the effects of price growth are stronger for households living in postcodes with higher homeownership rate.[21]

The results presented in this section are consistent with the hypothesis that the effect of price growth on user behavior operates through wealth effects or the relaxation of collateral constraints, while they reject the hypothesis that renters may respond to higher price growth by scouting the market more carefully, or that extrapolative beliefs drive the behavior of both homeowners and renters.

5.2 Heterogeneity: Housing Wealth, Age and Mobility

We can further exploit heterogeneity across users to explore the mechanism linking price growth and attention or search. While the evidence in the previous section is consistent with wealth effects or the relaxation of collateral constraints, homeowners' behavior might still be driven by other factors, for example behavioral biases such as loss aversion. However, in this section we show that homeowners more likely to belong to the lower half of the housing wealth distribution, and of younger age, are the most sensitive to price growth. This evidence on heterogeneity lines up with the prediction of the wealth effects or collateral constraints channels, while we would expect behavioral effects to be at work across the entire cross-section of postcodes.

Moreover, our evidence implies that the response to price growth is concentrated among households at the lower end of the house quality distribution. This can contribute to hetero-

[21] We estimate the following regression equation:

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

$Homeonwership2016_{post(i)}$ 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.

geneity in mobility and in the volatility of housing demand across neighborhoods of different quality within a metropolitan area, consistent with the results in Landvoigt, Piazzesi, and Schneider (2015) for San Diego.

First, if our results were driven by wealth effects or collateral constraints, we would expect them to be stronger for lower to middle income or wealth households, for which fluctuation in housing values are going to be more important. While we do not have information on individual income and wealth of our users, we can still explore this dimension of heterogeneity exploiting information at the postcode level. We can sort prospective buyers based on the median house price in their postcode of residence. It is reasonable to expect that homeowners in less expensive neighborhoods will likely be less wealthy, or more constrained.

For each postcode, we calculate the average house price over the period from January 2017 through April 2019.[22] Then, for each metropolitan area (defined along the same lines as in the previous sections) we calculate $\bar{p}^{med}_{area}$, which is the median house price across the postcodes within the area. We can then estimate:

$$log(1 + Meas_{i,t}) = \alpha_i + \alpha_{t,area} + \delta_{plow}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{\bar{p}_{post(i)} \leq \bar{p}^{med}_{i,area}}\right) + \\ + \delta_{phigh}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{\bar{p}_{post(i)} > \bar{p}^{med}_{i,area}}\right) + \epsilon_{i,t} \tag{3}$$

where $\mathbb{1}_{\bar{p}_{post(i)} \leq p^{med}_{i,area}}$ and $\mathbb{1}_{\bar{p}_{post(i)} > p^{med}_{i,area}}$ are indicator variables equal to one for homeowners living in postcodes with price less or equal, or above the median price in the metropolitan area. Thus, the coefficients δ_{plow} and δ_{phigh} measure the response of users behavior to experienced price growth in postcodes with prices less or equal, or above median. Estimates of the coefficients in equation (3) are reported in Table 7. Panel (A) focuses on overall attention level and the intensive margin. It appears clear that users living in lower price postcodes are driving the response of attention level to price growth in the data. In fact, estimates of δ_{plow} are always highly statistically significant, and 2 to 3 times larger than the point estimates in Table 2.

[22]We repeat the same exercise by calculating average price only over year 2017. Our results remain unchanged.

On the other hand, estimates of δ_{phigh} are not significant for all the measures of attention level. While there is also some evidence of an increase in attention on the intensive margin for users in lower price postcodes, this effect remains very weak. Panel (B) reports the results for the extensive margin, where we again find that estimates of δ_{plow} are highly statistically significant and up to 2 times as large as the estimates in Table 4. We obtain similar results on both attention level and the extensive margin when sorting postcodes on average income of the residents based on the 2016 Census, rather than the price level. The response of users behavior to price growth becomes weak an noisy in high income postcodes.

We can also show evidence that the stronger responses in the data are observed for the youngest homeowners. We observe some details on the demographic characteristics of users, including their age range: *18 to 25*, *25 to 34*, *35 to 49*, *50 to 64* and *65 or above*. We can then estimate a regression specification similar to equation (2), but where we include age range, and interact them with experienced price growth. Table 8 reports our estimates, both for the full sample of users and for the restricted sample of homeowners. In the regression specification we drop the youngest group of users (18 to 25), who are almost exclusively renters, and group together users with ages from 50 to 64 and 65 or above into a *50 or above* group. Panel (A) focuses on the level of attention and the intensive margin. Users in the *25 to 34* group, and to some extent users in the *50 or above* group, are more active than the intermediate group. The higher degree of activity of younger homeowners is consistent with them more actively considering to move rather than older groups. Moreover, the highest (and statistically significant) estimate of the interaction between experienced price growth and age dummy is again found for the *25 to 34* group. This implies that young homeowners are the ones most likely to increase attention in response to price growth in their postcode of residence.

Thus, it appears that the most sensitive users are homeowners, who live in postcodes with lower house prices and who are young. This evidence suggests that price growth may mainly affect homeowners who are considering to move, rather than owners that are looking for a second home or an invest house. In fact, homeowners in this second category would likely be wealthier (and therefore living in more expensive postcodes) and older. We can directly test our conjecture in the data. Users can provide information on the reason for looking for a new home: whether to purchase a new property to occupy, or to buy an investment property. Table 9 reports estimates from a regression specification similar to equation (2), but with dummies equal to one for users that are searching for a new house to occupy, or for an investment property. The coefficient for the interaction term between price growth and the dummy selecting users looking for a new house to occupy is highly statistically significant both when the dependent variable is one of the measures of the level of attention or a measure of search breadth. On the other hand, the coefficients for the interaction between the dummy selecting users looking for an investment property and price growth is not statistically significant, and point estimates are frequently close to zero.

5.3 Instrumenting Price Growth Using Land Supply Elasticity

The results in the previous sections already corroborate the causal interpretation of our findings, by providing an insight into the mechanism at work in the data. Nonetheless, 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.[23]

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

[23] 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).

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.

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. 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.[24] 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).[25] 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*.

The instrument in Saiz (2010) is constructed at the U.S. Census Metropolian area-level. Davidoff (2015) criticizes the validity of this instrument, arguing that physical supply con-

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

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

straints appear to be correlated to demand side factors across U.S. metropolitan areas. While this is a valid criticism, we believe it applies to a much lesser degree to the instrument we develop in this paper, which exploits local differences in supply elasticity within a metropolitan area. Han and Baum-Snow (2019) also show using U.S. data that local supply elasticities (at the census tract-level) affect the production of new housing and house prices.

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 and along the coast. 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 calculate land supply elasticity at the location of residence of each of the households in our dataset.[26]

Our measure of 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

[26] 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.

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[27] 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 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 10. 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 11. The first stage F-statistics are large across the board, consistent with the results in Table 10.

Panel (A) of Table 11 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

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

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[28] 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 this section we focus on the real effects of fluctuations in attention. Higher attention leads to 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

[28]See references to the related literature in section 2.

listings face more integrated demand within their metropolitan area. The fact that changes in home buyers search breadth are procyclical drives the extent to which positive and negative local shocks are spread and amplified within a metropolitan area.

6.1 Effects on Sale Prices

To measure the effects of home buyers attention on houses listed for sale, we track all users' visits to each listing in our dataset.[29] For each listing l, we can compute the average price growth in the postcode of residence for the users that visited the listing:

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

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.

As a next step, we estimate the relationship between price growth experienced by visitors and sale prices, using the following regression equation:

$$p_l^{sale} = a_{post(l)} + a_{t \times area} + \beta \Delta p_l^{visits} + \mathcal{B} X_l + e_l \tag{6}$$

where p_l^{sale} is the log of the sale price for listing l, $a_{post(l)}$ and $a_{t \times area}$ are fixed effects for the postcode where listing l is located and for the month of sale and area where the postcode is

[29] 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.

located.[30] The vector of controls X_l, 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 in equation 6 are reported in the first two columns of Table 12. 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 results just described 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 within the same postcode. These properties may be selling at higher prices only due to characteristics that are not spanned by the controls in our regressions.

We address this concern through two main empirical tests. First, we use a methodology introduced by Altonji, Elder, and Taber (2005) and then fully developed by Oster (2019), which assesses the importance of omitted variable bias.[31] Oster (2019) 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. 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

[30] 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 (for the median user the fraction is 95%).

[31] The methodology is used in many recent empirical studies in economics (see for example Allcot et al. (2019), Bertrand et al. (2019) and Tabellini (2019)), urban economics (see Clarke and Freedman (2019) and Albert and Viladecans-Marsal (2019)), and finance (see Heimer, Myrseth, and Schoenle (2019), Dougal et al. (2019) and Gao, Huang, and Goldstein (2019)).

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.[32] In our application, the "short" regression consists of equation 6 omitting the vector of property characteristics X_l, while the "long" regression consists of the full specification in equation 6. 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[33], our estimate of δ is approximately equal to 1. Thus, in order to entirely attribute our results to bias, 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 (2019) does not completely dispel concerns on unobservable characteristics, we believe it suggest that our results are robust to bias induced by unobservables.

As a second step, we collect information on the last listed price available for each home listing in our dataset. We then include the listed price as a further control in equation 6. The latest listing price of a home should be the most informative valuation posted by the seller, and should be based both on the characteristics that we observe in the data and on unobservables. Thus, differences in sale prices for houses that have the same final listed price should reflect the outcome of bargaining between buyers and sellers, and higher prices should signal higher bargaining power for the sellers, or competition among buyers. In column (3) of Table 12 we show that the estimate of the coefficient for Δp_l^{visits} is still positive and statistically

[32]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.

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

significant. The point estimate implies that a one standard deviation higher experienced price growth would translate into 0.5%-0.6% higher sale price, roughly equal to 4,400 Australian dollars for the average house price, or 3,000 U.S. dollars. We believe that this specification is overly conservative, since the higher bargaining power of sellers, or higher demand for listing, will already partially be reflected in the listing prices.[34] Thus, we believe that these estimate serve as a lower bound for the average real effect of users' experienced price growth on home listings, and that the actual effect should be in the range between 0.5%-0.6% and 1.5%-1.6%.

As a further step, we directly provide evidence that the effect of experienced price growth on sale prices operates through the change in attention and search breadth. We first calculate the extensive 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 $\overline{\Delta p}_i$. We then calculate $logSearch_l = log(1 + Search_l)$. We then estimate the following regression equation by 2SLS:

$$p_l^{sale} = a_{post(l)} + a_{t \times area} + \gamma log\widehat{Search}_l + \mathcal{B}X_l + e_l \tag{7}$$

where $log\widehat{Search}_l$ is the part of variation in the attention measure across listings that is explained by differences in experienced price growth.[35] Columns 4 to 12 of Table 12 report

[34]This is because sellers will update listing prices in response to demand, since listing prices affect the likelihood of a match between buyers and sellers (see for example Genesove and Han (2012)).

[35]First, we explore the relationship between price growth experienced in the postcode of residence and attention allocation for the users visiting each listings:

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

The coefficient λ 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 estimates of the coefficients in equation (7). Estimates of γ are positive and statistically significant, and quantitatively similar to the estimates of β from equation (6) in columns 1 and 3. 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 10 to 12). However, once results are scaled by standard deviation, the magnitudes are uniform across all measures, and consistent with the estimates in columns 1 to 3.

To further corroborate the causal interpretation of our findings, we can show that there is substantial heterogeneity in the magnitude of the effects on prices. It is reasonable to assume that attention and pressure on the demand side would have stronger effects on prices when sellers face less competition. To measure this, for each listing we count the number of properties listed over the same period of time and with the same charatertistics (number of bedrooms and type, intended as apartment or single family residence). We then average the number of "competitors" at the postcode level, and estimate the following regression equation:

$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \sum_{k=1}^{4} \beta_k \left(\Delta p_l^{visits} \times \mathbb{1}_{Qk,post(l)}\right) + \mathcal{B}X_l + e_l \tag{8}$$

where $I_{Qk,post(l)}$ is a dummy equal to one if the average number of competitors across listings in the postcode is in the kth quartile of the distribution within the metropolitan area. The first three columns of Table 13 report estimates of the coefficients of equation (8). We find that the real effect of price growth experienced by users on sale prices is twice as large in the bottom quartile of competition, and steadily decreasing moving to the higher quartiles. In the bottom quartile, a one standard deviation increase in experienced price growth translates into a 3% increase in the sale price, or a 1% increase after controlling for the last listing price of each property.

Along similar lines we expect experienced price growth to have stronger real effects in postcodes that attract visitors from postcodes where houses are substantially less expensive.

fluctuations. Coefficient estimates are reported in Table A.3.

In fact, owners trying to move up the housing ladder are the ones who may respond more strongly to the increase in wealth due to price growth, and compete more fiercely for new homes in relatively more expensive postcodes. To this end, we measure the gap between the median house price in the postcode where each listing is located, and the average of the median house prices across the postcodes where users visiting the listing reside. We then estimate a specification similar to equation (8). Estimates are reported in columns 4 to 6 of Table 13. Real effects are stronger in the top quartile of gap distribution, where a one standard deviation change in experienced price growth among visitors leads to a 3.75% to a 2.1% (when the last listing price is included in the specification) increase in the final sale price.

Summing up, our results are consistent with higher local price growth leading to broader searches and 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[36] and X_l is the vector of property characteristics described for equation 6.

Estimates are reported in the first three columns of Table 14. 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.

While the magnitude of these effects is relatively small, the evidence on time-on-market contributes is consistent with the idea that higher experienced price growth is indeed generating higher demand and price pressure. In fact, houses are selling at higher prices without staying longer on the market, but rather they are getting matched slightly faster.

We can link the effect of price growth to search breadth, using a 2SLS approach similar to the one detailed in equation 7, 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 columns 4 to 12 of Table 14. Consistent with results for prices in Table 12,

[36]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.

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.

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 listings translates into searches over a broader range of homes, both in terms of locations and characteristics.

The response to price growth in the data appears to be driven by users that are particularly exposed to wealth effects or collateral constraints. The largest responses are observed for homeowners, and, in particular, residents in postcodes with house prices below the median in the metropolitan area, and younger owners (with age below 40).

We argue that our findings can be interpreted as causal evidence of the effect of price growth on users' behavior. First, the vast majority of a user's 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 consistent with a clear economic mechanism, making it less likely to be endogenous. 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. We show that the effects on prices are stronger when listings face less competition from neighboring properties and when there is a large price gap between the postcode where a listing is located and the postcodes where prospective home buyers are currently living.

Taken together our results suggest that fluctuations in home buyers' search behavior can reduce market segmentation procylically over housing booms and busts, and in turn amplify fluctuations in house prices. Since we have shown that the sensitivity of attention to price growth is heterogeneous across households with difference characteristics, these effects may also contribute to heterogeneous price patterns within the same metropolitan area.

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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; $\alpha_{t,*}$ 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: Allocation of Attention: Price Ranges

	Panel A: Price Dispersion			
Δp_{2y}	0.143	0.037	0.219**	0.105
	(1.43)	(0.33)	(2.19)	(0.90)
$R^2_{adjusted}$	0.282	0.282	0.470	0.471
Nobs	45264	45262	43100	43098
	Panel B: 90th Percentile			
Δp_{2y}	0.057	0.071	0.160***	0.168***
	(1.05)	(1.26)	(3.30)	(3.11)
$R^2_{adjusted}$	0.461	0.461	0.691	0.691
Nobs	55105	55104	52814	52813
	Panel C: 75th Percentile			
Δp_{2y}	0.037	0.071	0.145***	0.156***
	(0.75)	(1.34)	(3.24)	(3.26)
$R^2_{adjusted}$	0.487	0.486	0.728	0.728
Nobs	55105	55104	52814	52813
	Panel D: 25th Percentile			
Δp_{2y}	-0.029	0.068	0.072*	0.121***
	(-0.55)	(1.24)	(1.84)	(2.82)
$R^2_{adjusted}$	0.434	0.434	0.708	0.709
Nobs	55105	55104	52814	52813
	Panel E: 10th Percentile			
Δp_{2y}	-0.037	0.069	0.049	0.100**
	(-0.69)	(1.24)	(1.15)	(2.27)
$R^2_{adjusted}$	0.374	0.374	0.652	0.653
Nobs	55105	55104	52814	52813
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:

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

where $Price\_Search_{i,t}$ is either equal to the standard deviation of the prices of postcodes visited by user i in month t (Panel A), the 90th, 75th, 25th and 10th Percentile of the distribution of prices (Panel B to Panel E); 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 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:

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

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: Attention across Postcodes: Price Levels

Panel A: Overall Attention and Intensive Margin

	Listings		*Visits*		*Minutes*		$\overline{Minutes}$	
$\Delta p \times \mathbb{1}_{\bar{p}_{post} \leq \bar{p}^{med}_{area}}$	0.820***	0.860***	0.917***	0.918***	1.181***	1.316***	0.241	0.327*
	(3.78)	(4.37)	(3.76)	(4.15)	(3.40)	(3.80)	(1.32)	(1.91)
$\Delta p \times \mathbb{1}_{\bar{p}_{post} > \bar{p}^{med}_{area}}$	0.068	-0.043	-0.015	-0.163	-0.110	-0.291	-0.158	-0.228
	(0.29)	(-0.19)	(-0.06)	(-0.63)	(-0.35)	(-0.92)	(-1.11)	(-1.35)
$R^2_{adjusted}$	0.130	0.474	0.139	0.509	0.100	0.393	0.095	0.337
Nobs	55119	52828	55119	52828	55119	52828	55119	52828

Panel B: Extensive Margin (Search Breadth)

	$NumPost$		$MeanDist$		$NumSeg(p, type, nb)$		$NumSeg(\mathbb{Q}, type, nb)$	
$\Delta p \times \mathbb{1}_{\bar{p}_{post} \leq \bar{p}^{med}_{area}}$	0.579***	0.732***	0.366*	0.425*	0.392***	0.428***	0.569***	0.665***
	(3.09)	(4.20)	(1.81)	(1.99)	(3.37)	(3.87)	(3.18)	(4.01)
$\Delta p \times \mathbb{1}_{\bar{p}_{post} > \bar{p}^{med}_{area}}$	0.076	0.022	0.082	-0.017	0.071	0.027	0.141	0.054
	(0.37)	(0.12)	(0.37)	(-0.08)	(0.60)	(0.23)	(0.72)	(0.29)
$R^2_{adjusted}$	0.157	0.515	0.120	0.377	0.118	0.456	0.154	0.518
Nobs	55128	52835	44893	42612	53657	51339	53657	51339
Postcode FE	Yes	No	Yes	No	Yes	No	Yes	No
ID FE	No	Yes	No	Yes	No	Yes	No	Yes

This table displays estimates from the following panel regression:

$$log(1 + Meas_{i,t}) = \alpha_* + \alpha_{t,area} + \delta_{plow}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{\bar{p}_{post(i)} \leq \bar{p}^{med}_{area}}\right) + \delta_{phigh}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{\bar{p}_{post(i)} > \bar{p}^{med}_{area}}\right) + \epsilon_{i,t}$$

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 a postcode or a user 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; $\mathbb{1}_{\bar{p}_{post(i)} \leq \bar{p}^{med}_{area}}$ is a dummy equal to one if the average postcode-level price for the postcode of residence of user i is below the median in the metropolitan area, while $\mathbb{1}_{\bar{p}_{post(i)} > \bar{p}^{med}_{area}}$ is a dummy equal to one for postcodes with average below the median. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 8: Attention and User Age

Panel A: Overall Attention and Intensive Margin

	$Listings$	$Listings$ Homeowners	$Visits$	$Visits$ Homeowners	$Minutes$	$Minutes$ Homeowners	$\overline{Minutes}$	$\overline{Minutes}$ Homeowners
$\Delta p \times \mathbb{1}_{age\ 25:34}$	0.458	1.001**	0.542	1.257**	0.545	1.840***	0.047	0.718**
	(1.57)	(2.30)	(1.55)	(2.67)	(1.27)	(3.08)	(0.24)	(2.30)
$\Delta p \times \mathbb{1}_{age\ 35:49}$	0.287	0.345	0.265	0.317	0.368	0.524	0.061	0.154
	(1.26)	(1.26)	(1.04)	(1.05)	(1.22)	(1.38)	(0.43)	(0.82)
$\Delta p \times \mathbb{1}_{age\geq 50}$	0.417**	0.421*	0.381*	0.363	0.517*	0.579	0.044	0.097
	(2.22)	(1.89)	(1.74)	(1.42)	(1.74)	(1.63)	(0.28)	(0.52)
$\mathbb{1}_{age\ 25:34}$	-0.108	0.155*	-0.087	0.240**	0.125	0.549***	0.238***	0.375***
	(-1.66)	(1.71)	(-1.15)	(2.29)	(1.37)	(4.36)	(5.69)	(6.86)
$\mathbb{1}_{age\geq 50}$	-0.162**	0.026	-0.104	0.137	0.313***	0.664***	0.486***	0.630***
	(-2.48)	(0.30)	(-1.36)	(1.34)	(3.48)	(5.51)	(11.93)	(11.49)
$R^2_{adjusted}$	0.135	0.169	0.144	0.178	0.105	0.127	0.116	0.121
Nobs	52372	34740	52372	34740	52372	34740	52372	34740

Panel B: Extensive Margin (Search Breadth)

	$NumPost$	$NumPost$ Homeowners	$MeanDist$	$MeanDist$ Homeowners	$NumSeg(p, type, nb)$	$NumSeg(p, type, nb)$ Homeowners	$NumSeg(\mathbb{Q}, type, nb)$	$NumSeg(\mathbb{Q}, type, nb)$ Homeowners
$\Delta p \times \mathbb{1}_{age\ 25:34}$	0.424*	0.730**	0.387	0.561	0.393	0.689*	0.146	0.315
	(1.71)	(2.07)	(1.37)	(1.12)	(1.63)	(2.02)	(0.89)	(1.19)
$\Delta p \times \mathbb{1}_{age\ 35:49}$	0.246	0.311	0.044	0.172	0.282	0.333	0.102	0.225
	(1.25)	(1.33)	(0.19)	(0.62)	(1.49)	(1.52)	(0.84)	(1.49)
$\Delta p \times \mathbb{1}_{age\geq 50}$	0.248	0.198	0.291	0.178	0.298*	0.268	0.274**	0.298**
	(1.38)	(0.94)	(1.51)	(0.79)	(1.86)	(1.45)	(2.78)	(2.55)
$\mathbb{1}_{age\ 25:34}$	-0.061	0.123*	0.077	0.156**	-0.068	0.111	-0.072**	0.039
	(-1.15)	(1.77)	(1.49)	(2.07)	(-1.37)	(1.67)	(-2.11)	(0.77)
$\mathbb{1}_{age\geq 50}$	-0.061	0.057	0.170***	0.230***	-0.054	0.063	-0.070**	0.028
	(-1.15)	(0.86)	(3.10)	(2.83)	(-1.09)	(1.00)	(-2.16)	(0.56)
$R^2_{adjusted}$	0.161	0.191	0.113	0.127	0.159	0.192	0.124	0.151
Nobs	52381	34747	47731	31419	51021	34066	51021	34066

This table displays estimates from the following panel regression:

$$log(1 + Meas_{i,t}) = \alpha_{post(i)} + \alpha_{t,area} + \delta_{age\ 25:34}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,age\ 25:34}\right) + \delta_{age\ 35:49}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,age\ 35:49}\right) + \delta_{age\geq 50}\left(\Delta p^{(h)}_{post_{(i)},t-1} \times \mathbb{1}_{i,age\geq 50}\right) + \kappa_{age\ 25:34}\mathbb{1}_{i,age\ 25:34} + \kappa_{i,age\geq 50}\mathbb{1}_{i,age\geq 50} + \epsilon_{i,t}$$

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; $\mathbb{1}_{i,age\ 25:34}$, $\mathbb{1}_{i,age\ 35:49}$ and $\mathbb{1}_{i,age\geq 50}$ are, respectively, dummies equal to one for users that have age between 25 and 34, 35 and 49, and 50 or more. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 9: Attention and Users' Intention

Panel A: Overall Attention and Intensive Margin

	$Listings$		$Visits$		$Minutes$		$\overline{Minutes}$	
		$Homeowners$		$Homeowners$		$Homeowners$		$Homeowners$
$\Delta p \times \mathbb{1}_{Invest}$	0.051	0.161	0.129	0.221	0.147	0.262	0.093	0.088
	(0.17)	(0.43)	(0.38)	(0.54)	(0.34)	(0.52)	(0.43)	(0.39)
$\Delta p \times \mathbb{1}_{Occupy}$	0.454**	0.562**	0.416*	0.517**	0.505*	0.827**	0.004	0.199
	(2.57)	(2.55)	(2.04)	(2.13)	(1.95)	(2.50)	(0.03)	(1.20)
$\mathbb{1}_{Invest}$	-0.185***	-0.131*	-0.276***	-0.227**	-0.353***	-0.315***	-0.147***	-0.164***
	(-3.39)	(-1.76)	(-4.47)	(-2.72)	(-4.57)	(-3.27)	(-3.41)	(-3.63)
$R^2_{adjusted}$	0.137	0.174	0.148	0.185	0.108	0.130	0.100	0.107
Nobs	52434	33612	52434	33612	52434	33612	52434	33612

Panel B: Extensive Margin (Search Breadth)

	$NumPost$		$MeanDist$		$NumSeg(p, type, nb)$		$NumSeg(\mathbb{Q}, type, nb)$	
		$Homeowners$		$Homeowners$		$Homeowners$		$Homeowners$
$\Delta p \times \mathbb{1}_{Invest}$	0.083	0.217	-0.061	0.090	0.082	0.188	0.022	0.114
	(0.33)	(0.69)	(-0.21)	(0.26)	(0.34)	(0.63)	(0.14)	(0.55)
$\Delta p \times \mathbb{1}_{Occupy}$	0.340**	0.309	0.263	0.178	0.369**	0.397**	0.239**	0.338***
	(2.26)	(1.70)	(1.51)	(0.79)	(2.59)	(2.36)	(2.56)	(2.94)
$\mathbb{1}_{Invest}$	-0.113**	-0.082	-0.021	-0.054	-0.083*	-0.042	0.014	0.038
	(-2.58)	(-1.47)	(-0.39)	(-0.81)	(-2.04)	(-0.77)	(0.46)	(0.95)
$R^2_{adjusted}$	0.165	0.197	0.112	0.131	0.161	0.198	0.123	0.155
Nobs	52443	33619	47849	30389	51035	32962	51035	32962

This table displays estimates from the following panel regression:

$$log(1 + Meas_{i,t}) = \alpha_{post(i)} + \alpha_{t,area} + \delta_{i:invest}\left(\Delta p_{post_{(i)},t-1} \times \mathbb{1}_{i:Invest}\right) + \delta_{i:Occupy}\left(\Delta p_{post_{(i)},t-1} \times \mathbb{1}_{i:Occupy}\right) + \gamma \mathbb{1}_{Invest} + \epsilon_{i,t}$$

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; $\mathbb{1}_{i,invest}$ and $\mathbb{1}_{i,Occupy}$ is a dummy equal to one if user i intends to purchase a property, respectively, to invest and to move.Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 10: 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 $post(i)$ 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 11: 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 5.3. 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 12: Real Effects on Sale Price

Δp_l^{visits}	0.205***	0.097***	0.034***									
	(7.01)	(5.62)	(3.61)									
$log\widehat{Num}Post$				0.227***	0.092***	0.033***						
				(4.76)	(4.38)	(2.99)						
$log\widehat{Num}Seg(p, type, nb)$							0.233***	0.093***	0.033***			
							(4.54)	(4.49)	(3.03)			
$log\widehat{Num}Seg(\mathbb{Q}, type, nb)$										0.615***	0.231***	0.083***
										(3.88)	(4.52)	(3.07)
$log(p_{list})$			0.719***			0.719***			0.719***			0.717***
			(17.71)			(17.75)			(17.71)			(17.61)
I_{unit}		-0.112***	-0.035***		-0.104***	-0.032***		-0.105***	-0.032***		-0.123***	-0.039***
		(-12.85)	(-5.39)		(-11.61)	(-5.13)		(-11.95)	(-5.22)		(-13.49)	(-5.62)
I_{1bed}		-0.275***	-0.078***		-0.279***	-0.079***		-0.276***	-0.078***		-0.275***	-0.078***
		(-20.43)	(-6.07)		(-20.11)	(-6.02)		(-19.87)	(-5.99)		(-19.79)	(-5.99)
I_{3beds}		0.102***	0.028***		0.106***	0.029***		0.106***	0.029***		0.112***	0.031***
		(28.69)	(5.60)		(28.90)	(5.69)		(28.59)	(5.68)		(25.65)	(5.67)
$I_{\geq 4beds}$		0.213***	0.059***		0.217***	0.060***		0.221***	0.062***		0.236***	0.067***
		(55.02)	(6.12)		(50.96)	(6.19)		(49.10)	(6.21)		(34.25)	(6.20)
I_{1bath}		-0.162***	-0.045***		-0.164***	-0.045***		-0.165***	-0.046***		-0.166***	-0.047***
		(-40.53)	(-6.97)		(-41.31)	(-6.89)		(-41.32)	(-6.89)		(-41.79)	(-6.96)
$I_{\geq 3baths}$		0.225***	0.060***		0.219***	0.058***		0.220***	0.058***		0.225***	0.061***
		(44.71)	(6.47)		(43.19)	(6.48)		(43.30)	(6.47)		(43.10)	(6.44)
I_{1park}		0.030***	0.009***		0.033***	0.010***		0.032***	0.010***		0.031***	0.009***
		(6.73)	(3.73)		(6.83)	(3.99)		(6.81)	(3.93)		(6.46)	(3.76)
I_{2park}		0.087***	0.026***		0.091***	0.028***		0.091***	0.028***		0.090***	0.028***
		(18.55)	(6.26)		(17.22)	(6.27)		(17.45)	(6.28)		(17.53)	(6.35)
I_{3park}		0.138***	0.040***		0.141***	0.041***		0.141***	0.041***		0.142***	0.042***
		(28.24)	(7.09)		(26.72)	(7.17)		(27.19)	(7.16)		(27.86)	(7.19)
$log(size)$		0.134***	0.037***		0.132***	0.037***		0.133***	0.037***		0.135***	0.038***
		(51.96)	(6.43)		(49.65)	(6.35)		(51.06)	(6.38)		(50.98)	(6.45)
$R^2_{adjusted}$	0.534	0.797	0.924	-	-	-	-	-	-	-	-	-
Nobs	394696	254450	254361	394696	254450	254361	394600	254400	254312	394600	254400	254312

This table displays estimates from the following regressions:

$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \beta\Delta p_l^{visits} + \mathcal{B}X_l + e_l \quad \textit{Columns 1 to 3}$$
$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \gamma log\widehat{Search}_l + \mathcal{B}X_l + v_l \quad \textit{Columns 4 to 12}$$

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; $log\widehat{Search}_l$ is the part of the variation in one the search measures across listings that is explained by experienced price growth. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 13: Real Effects on Sale Price: Heterogeneity

$\Delta p_l^{visits} \times \mathbb{1}_{Q1}^{liq}$	-0.033	0.197***	0.066***			
	(-0.88)	(9.68)	(4.96)			
$\Delta p_l^{visits} \times \mathbb{1}_{Q2}^{liq}$	0.204***	0.111***	0.042***			
	(5.71)	(5.75)	(4.14)			
$\Delta p_l^{visits} \times \mathbb{1}_{Q3}^{liq}$	0.336***	0.063***	0.025**			
	(10.06)	(2.95)	(2.35)			
$\Delta p_l^{visits} \times \mathbb{1}_{Q4}^{liq}$	0.386***	0.003	-0.000			
	(8.44)	(0.15)	(-0.05)			
$\Delta p_l^{visits} \times \mathbb{1}_{Q1}^{gap}$				0.143***	0.042*	0.003
				(3.29)	(1.90)	(0.41)
$\Delta p_l^{visits} \times \mathbb{1}_{Q2}^{gap}$				0.187***	0.082***	0.006
				(3.62)	(3.51)	(0.57)
$\Delta p_l^{visits} \times \mathbb{1}_{Q3}^{gap}$				0.210***	0.072***	0.034**
				(4.29)	(2.76)	(2.23)
$\Delta p_l^{visits} \times \mathbb{1}_{Q4}^{gap}$				0.284***	0.256***	0.141***
				(4.26)	(4.09)	(3.01)
$log(p_{list})$			0.718***			0.718***
			(17.67)			(17.68)
Additional Controls	No	Yes	Yes	No	Yes	Yes
List Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month× Area FE	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates from the following regressions:

$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \sum_{k=1}^{4} \beta_k \left(\Delta p_l^{visits} \times \mathbb{1}_{Qk,post(l)}^{liq}\right) + \mathcal{B}X_l + e_l \quad \textit{Columns } 1 \textit{ to } 3$$

$$p_l^{sale} = a_{post(l)} + a_{t\times area} + \sum_{k=1}^{4} \beta_k \left(\Delta p_l^{visits} \times \mathbb{1}_{Qk,post(l)}^{gap}\right) + \mathcal{B}X_l + e_l \quad \textit{Columns } 4 \textit{ to } 6$$

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; $\mathbb{1}_{Qk,post(l)}^{liq}$ and $\mathbb{1}_{Qk,post(l)}^{gap}$ are dummies equal to one if the postcode in which the listing is located is in the kth quartile of the distribution, respectively of the liquidity measure and of the gap between listing prices and the prices of the postcodes in which visitors live. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 14: Real Effects on Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Sale within 90 days											
Δp_l^{visits}	0.023*	0.039***	0.045***									
	(2.04)	(2.94)	(3.51)									
$log\widehat{Num}Post$				0.024*	0.036**	0.042**						
				(1.82)	(2.32)	(2.58)						
$log\widehat{Num}Seg(p, type, nb)$							0.025*	0.037**	0.042**			
							(1.81)	(2.29)	(2.57)			
$log\widehat{Num}Seg(\mathbb{Q}, type, nb)$										0.061*	0.088**	0.102**
										(1.79)	(2.32)	(2.61)
$log(p_{list})$			-0.139***			-0.139***			-0.140***			-0.142***
$R^2_{adjusted}$	0.081	0.103	0.113	-	-	-	-	-	-	-	-	-
Nobs	857470	557021	556842	857470	557021	556842	857115	556809	556633	857115	556809	556633
	Panel B: Time-On-market (log)											
Δp_l^{visits}	-0.050*	-0.079**	-0.092**									
	(-1.76)	(-2.31)	(-2.67)									
$log\widehat{Num}Post$				-0.053	-0.074*	-0.086*						
				(-1.51)	(-1.85)	(-2.04)						
$log\widehat{Num}Seg(p, type, nb)$							-0.054	-0.074*	-0.086*			
							(-1.51)	(-1.82)	(-2.03)			
$log\widehat{Num}Seg(\mathbb{Q}, type, nb)$										-0.134	-0.177*	-0.207**
										(-1.54)	(-1.86)	(-2.07)
$log(p_{list})$			0.302***			0.302***			0.304***			0.308***
$R^2_{adjusted}$	0.092	0.113	0.120	-	-	-	-	-	-	-	-	-
Nobs	851074	553042	552865	851074	553042	552865	850719	552830	552656	850719	552830	552656
Additional Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
List Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month× Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table displays estimates from the following panel regressions:

$$tom_{l,t} = a_{post(l)} + a_{t\times area} + \beta\Delta p_l^{visits} + \mathcal{B}X_l + e_l \quad \textit{Columns } 1 \textit{ to } 3$$

$$tom_{l,t} = a_{post(l)} + a_{t\times area} + \beta log\widehat{Search}_{l,t} + \mathcal{B}X_l + e_l \quad \textit{Columns } 4 \textit{ to } 12$$

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; $log\widehat{Search}_{l,t}$ is the part of the variation in one the attention measures across listings that is explained by experienced price growth. 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).

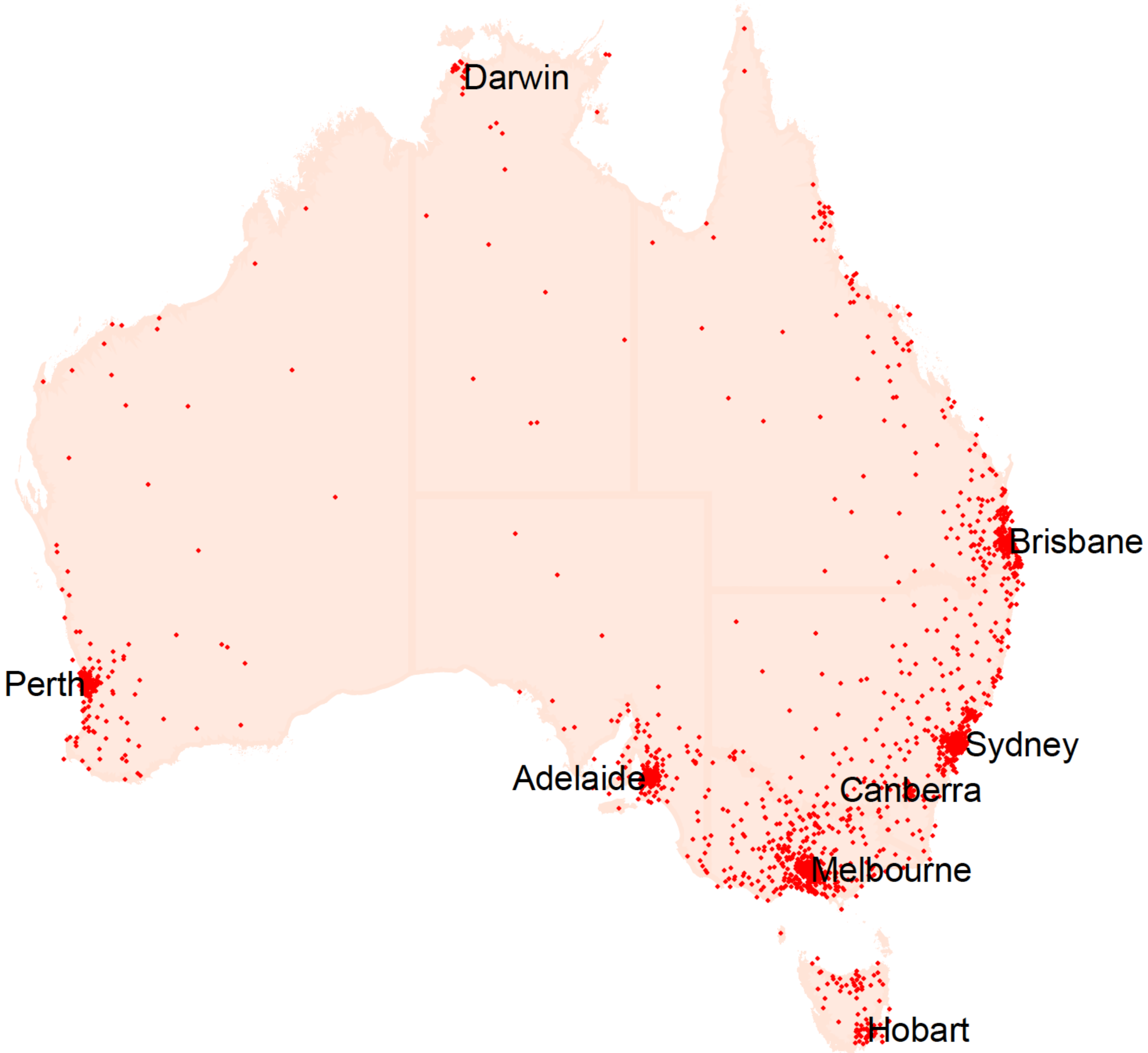


Figure 2: This figure displays the spatial distribution of the users in our sample. Each dot denotes a postcode which is the residence of at least one user.

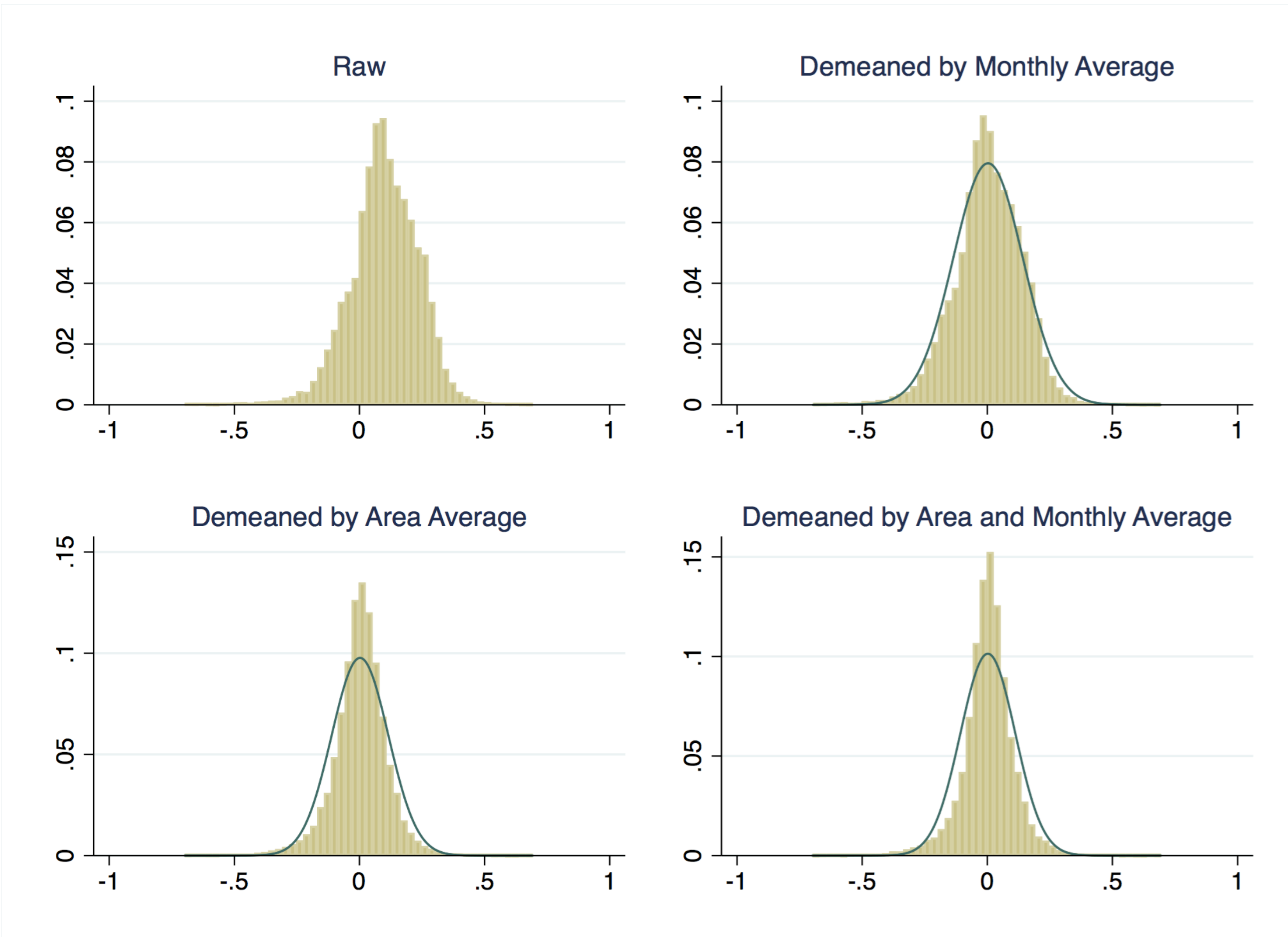


Figure 3: This figure displays the pooled distribution of the 2-year price growth for the postcodes in our sample. The top-left plot displays the distribution of the raw data. The remaining three plots display the distribution after we subtract the monthly (top-right plot), the area (bottom-left plot)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

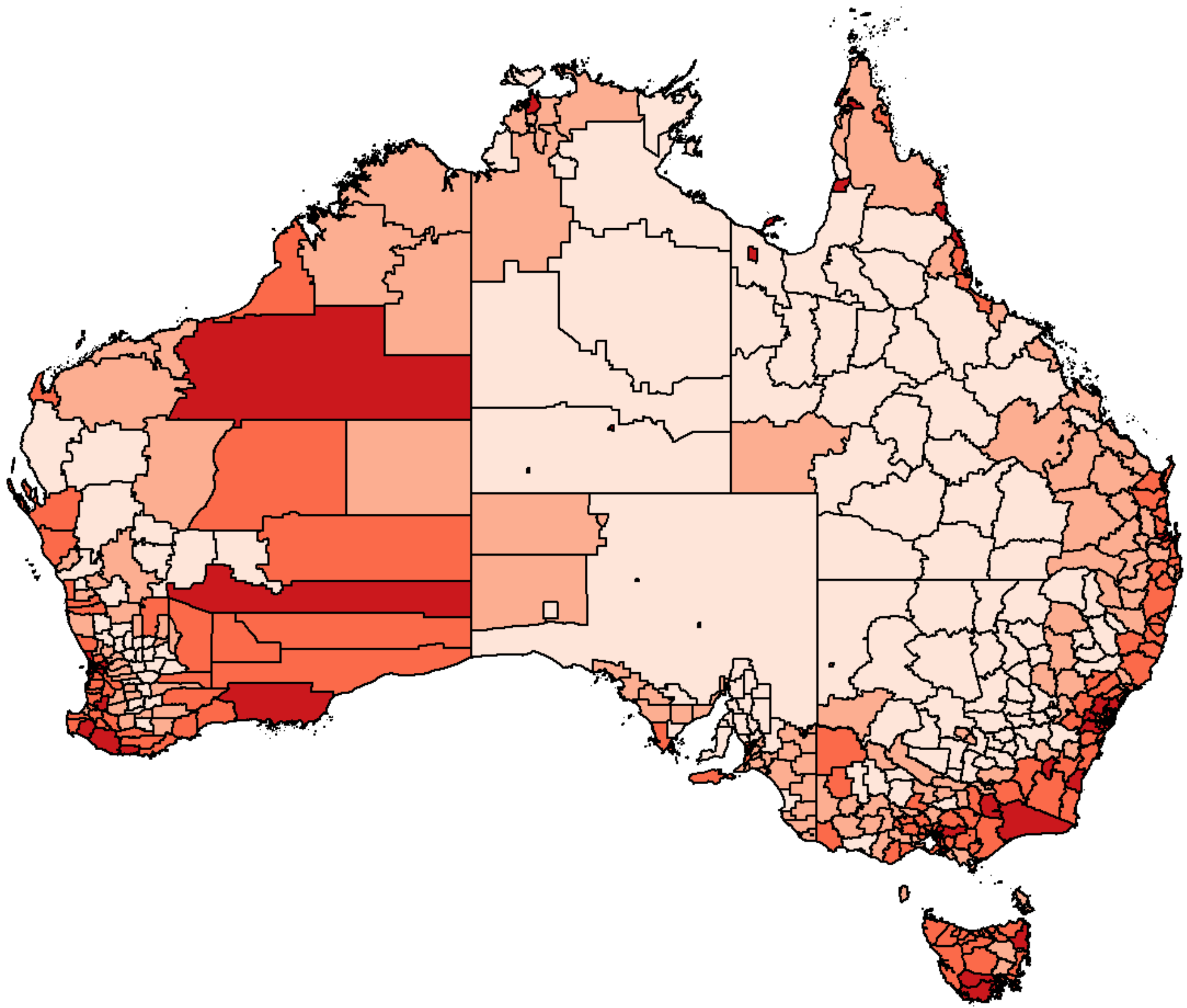


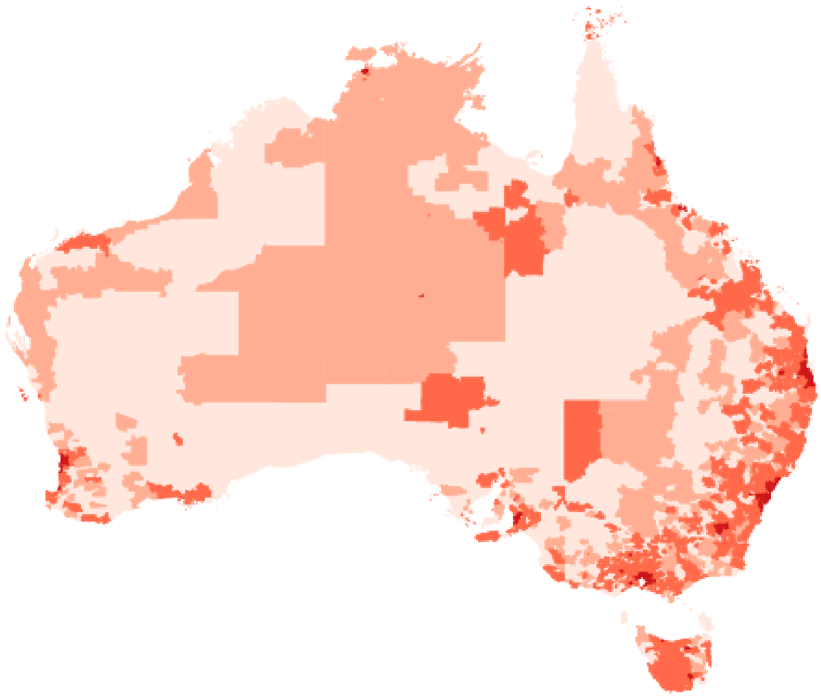
Figure 4: This figure provides a graphical representation of the land supply elasticity instrument introduced in Section 5.3. Each area corresponds to the land surface of a Local Government Area (LGA). Darker areas have a larger fraction of constrained land. The fraction of constrained land is above 73% in the areas with darkest color, while it is equal or smaller than 16% in the areas with lightest color.

Appendix

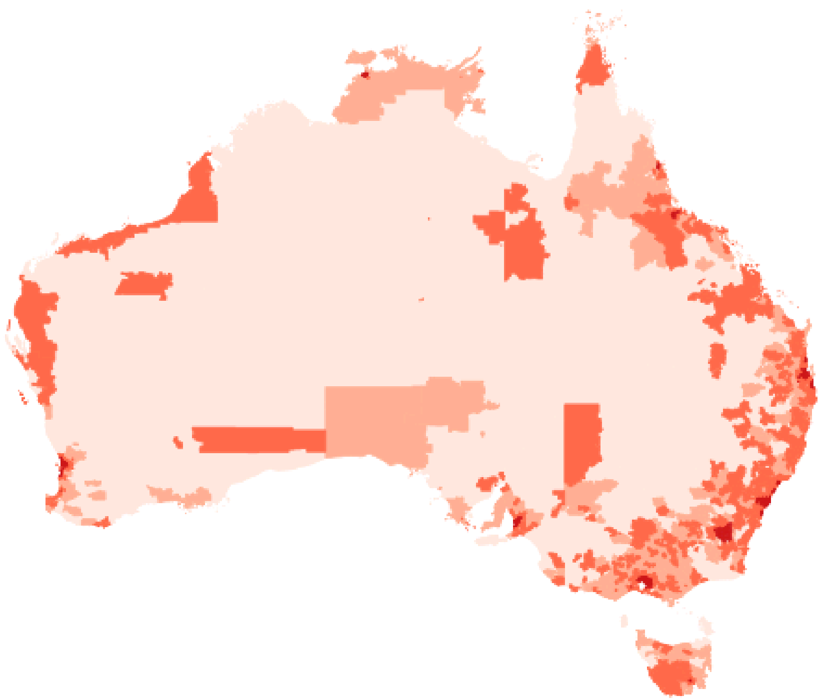
Table A.1: Summary Statistics

	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.

Table A.2: 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 A.3: 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.