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Local Experiences, Attention and Spillovers in the Housing Market

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Local Experiences, Attention and Spillovers in the Housing Market*

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Abstract

Recent local price growth explains differences in search behavior across prospective homebuyers. Those experiencing higher growth in their postcode of residence search more broadly across locations and house characteristics, without changing attention devoted to individual sales listings. Effects are stronger for homeowners, in particular those living in less wealthy areas and looking for a new primary residence. These findings are not consistent with local price growth influencing behavior through extrapolative expectations, and rather line up with the predictions of a collateral constraints channel. The expansion of search breadth leads to widespread spillovers onto house sales within a metropolitan area.

Keywords: Local Experiences, Search Behavior, Attention, Extrapolative Expectations, Collateral Constraints, House Prices

JEL Classification: D10, E32, G40, R31

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1 Introduction

Personal experiences shape households' behavior and explain differences in economic decisions (Nagel and Malmendier, 2011, 2016, D'Acunto et al., 2020 and Giglio et al., 2020). In the housing market, local price fluctuations impact households searching for a house by influencing views on future aggregate and local growth (see Armona, Fuster, and Zafar, 2019 and Kuchler and Zafar, 2019), and by impacting local homeowners' home equity, which in turn affects their ability and willingness to finance the purchase of a new house, in particular when facing collateral or liquidity constraints (Stein, 1995 and Fuster and Zafar, 2016). Then, experienced local price growth can determine substantial differences in attention allocation and effort during the house search process.[1] Since the housing market is highly segmented and illiquid, search behavior is a key determinant of the likelihood and quality of matches between buyers and sellers, and thus of house prices.[2] However, due to lack of data, little is known about this important aspect of homebuyers' behavior, and about how it is affected by local experiences.

In this paper, we exploit a unique dataset tracking online house search activity to study how attention allocation and search behavior of prospective homebuyers respond to local (postcode-level) price growth, through what channels experiences influence behavior, and the real effects on house sales prices. We find that buyers experiencing higher growth search more broadly across locations and house characteristics, and that this expansion of search breadth generates spillover effects onto house sales within a metropolitan area.

Our dataset contains information on the interactions of individual users, who self-identify as actively looking for a new house, with online listings from the largest Australian property website. Crucially, we observe users' current postcode of residence, their homeownership sta-

[1] Previous research has shown that in financial markets investors' attention fluctuates with experienced portfolio returns (Sicherman et al., 2016, Gargano and Rossi, 2018 and Olafsson and Pagel, 2019).

[2] Fluctuations in attention have been shown to affect prices of financial securities (see Hirshleifer, Lim, and Teoh, 2009 and Da, Engelberg, and Gao, 2011), generate volatility spillovers (Hasler and Ornthanalai, 2018) and stock returns co-movements (Huang, Huang, and Lin, 2019). In the housing market, Moller et al. (2021) construct a search index extracted from online search activity and test its ability to predict future price growth. The study of what triggers attention and its allocation has also been the focus of many theoretical contributions (Andrei and Hasler, 2015 and Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016).

tus, and whether they are looking for a new primary residence or an investment property, as well as detailed information on listings of properties for sale, including locations, dwellings characteristics, listing and sales prices.

We begin our analysis by exploring how prospective homebuyers respond to price growth in their postcode of residence. Households searching for a new house need to choose how to allocate their effort and attention across two dimensions: the breadth of the set of houses they want to explore, and the amount of information to gather on each individual listing. Piazzesi, Schneider, and Stroebel (2019) indeed show that homebuyers collect information only on subsegments of a local housing market.[3] The choice of the breadth of the set of houses considered (the "consideration set") presents a complex trade-off between the risk of excluding the actual optimal match from the set of considered alternatives, the cost of expanding the set, and the cost of increasing the time devoted to browsing each listing (see Caplin, 2016, and Caplin, Dean, and Leahy, 2019).

Figure 1 visually summarizes the relation between recent (over the past 2 years) postcode-level price growth and different dimensions of attention allocation in the search process of prospective homebuyers. Local price growth is positively correlated with the number of listings (top-left panel), postcodes (top-right panel) and market segments – defined through a combination of locations and property characteristics –(bottom-left panel) considered by homebuyers. On the other hand, there is only a weak (and *negative*) correlation with the amount of time allocated to browsing each listing (bottom-right panel). These patterns suggest that positive growth in the postcode of residence increases the perceived benefits of attention, and that expanding the consideration set (the breadth of searches) is perceived as more valuable than increasing the amount of attention allocated to individual listings.

[3]There is a rich theoretical literature on search and matching in housing (e.g. Wheaton, 1990, Genesove and Han, 2012 and Head, Huw, and Sun, 2014). However, none of these models tackles segmented search and the choice of the set of properties or submarkets on which a prospective homebuyer focuses her search activity. Piazzesi, Schneider, and Stroebel (2019) is the paper that gets closest to analyzing these issues by studying the general equilibrium implications of segmented search. However, the authors do not endogenize the choice of search breadth and do not explore how search breadth might be influenced by price experiences.

Panel regressions estimated at the user level, including both time by metropolitan area fixed effects, and postcode or even individual user fixed effects, provide results consistent with Figure 1. A one standard deviation (15%) higher experienced price growth over the previous 2 years leads to a 6% increase in the number of listings visited over the month. The effect is of similar magnitude for the number of postcodes and market segments explored. There is instead no significant effect on the amount of time spent browsing each individual listing. Higher experienced price growth is also associated with an upward shift of the distribution of browsed prices. The effects of experienced growth on the average and the tails of the distribution of prices among considered properties are of the same magnitude, so that the breadth of the range of considered prices remains unchanged.

While the panel regressions identify the effects of local price growth on behavior by controlling for metropolitan area-level price fluctuations and even individual user characteristics (through user fixed effects), there can still be concerns that postocode-level price growth might be correlated with factors influencing behavior through other mechanisms. Therefore, we expand our regression specifications to show that homebuyers who have just observed information on recent local price growth, by browsing listings of recently sold homes in their postcode, are more sensitive to local house price fluctuations. Moreover, among users living in the same postcode, those who have observed higher (lower) sales prices across the recently sold listings they browsed, have broader (narrower) search breadth or consideration sets. To further dispel the concern that the relationship between local price growth and the breadth of searches or consideration sets might be spurious or endogenous, we also develop an instrumental variable strategy that exploits local land supply elasticity.[4] Our instrumental variable (IV) estimates are larger than those from the OLS estimator: a 15% increase in postcode house prices over the previous 2 years leads to a 30% increase in the number of listings visited, and approximately a 25% increase in the number of postcodes and segments visited.

[4]Our measure is related to the one developed by Saiz (2010), but is constructed at a much narrower geographical level, for administrative units that are of comparable size to Public Use Microdata Areas in the United States.

In the second part of the paper, we shed light on the channels through which higher experienced price growth leads to the expansion of buyers' searches and consideration sets. The housing literature has highlighted how households are prone to over-extrapolating from recent price changes when forming beliefs about future, and even long term, price growth (see Case, Shiller, and Thomson, 2015, Armona, Fuster, and Zafar, 2019). This channel has clear predictions for the response of homeowners' search behavior. If homeowners infer from recent local growth higher future local price growth, in excess of the rest of the metro-area, they will then have an incentive to slow down or delay their house search. This is because moving typically involves selling the current house, and thus missing out on future local growth (see the evidence from the field-experiments developed by Bottan and Perez-Truglia, 2020). If instead local homeowners use postcode-specific growth to extrapolate future aggregate or metropolitan area-level growth (Kuchler and Zafar, 2019), they will have no reason to search either more or less intensively, since their house offers the best hedge against aggregate price fluctuations (Sinai and Souleles, 2005). On the other hand, local renters with extrapolative expectations about metro-area price growth will instead feel pressured by higher recent local growth to find a matching house quickly, since they are un-hedged. They will want to buy soon at current prices, before further growth takes place and ownership becomes less affordable (this is the so called "fear of missing out").

The implications of extrapolative beliefs for buyers' search behavior are rejected in the data. We find that postcode-level price growth has a statistically significant positive effect on the breadth of consideration sets for homeowners: point estimates are 50% larger than estimates based on the entire sample of users. Moreover, we do not find a statistically significant response for renters.

The stronger response of homeowners rather points at a role for collateral constraints. If homeowners use equity in their current house to finance their future house purchase, postcode-level growth increases their ability to finance new mortgage downpayments, and thus increases the ability to purchase a new home, and potentially the willingness to pay for new housing

(Fuster and Zafar, 2016, 2019). Moreover, if homeowners believe that postcode-level price growth is going to mean revert to (or even go below) metro-area price growth in the future, they will feel even more pressured to find their ideal match quickly, in order to take advantage of the high relative sales price for their current house. This provides an incentive to increase search effort and the breadth of searches. The collateral constraints mechanism also has clear empirical predictions. The effects of local price growth on homeowners' behavior shall be driven by households who are planning to sell their current home to finance a new purchase, by households who have lower wealth, and by households who are more likely to be moving up the housing ladder, and thus who are more likely to be affected by collateral constraints. All these predictions find support in the data.

First, the effect of recent price growth on search behavior is not statistically significant for homeowners who are looking for an investment house or a new secondary residence. Instead, they are highly significant, and twice stronger than the estimates based on the entire sample of users, when focusing on homeowners who are looking for a new house to occupy, and thus who are likely to be at the same time selling their primary residence. Second, the effects of local price growth are strong for homeowners living in "lower wealth" postcodes, with prices below the median of the metropolitan area, but absent for homeowners living in postcodes with house prices above the median in the metro-area. Finally, owners older than 65 are less responsive than younger owners. Expected retirement age is approximately 65 years old in Australia, and retirees are unlikely to be moving up the housing ladder, and usually have low leverage and high equity in their current home.

Interestingly, the response of homeowners to local prices is consistent with actual price dynamics. Local price growth in excess of the rest of the metropolitan area predicts lower growth in the following 1- and 2-year periods. Homeowners indeed have an incentive to quickly take advantage of higher relative sales prices induce by recent local price growth.

In the last part of the paper we test whether the expansion of consideration sets or search breadth driven by higher experienced price growth generates spillover effects onto house sales in

other parts of a metropolitan area. As search breadth expands, local housing markets become more integrated and listings are visited by a larger pool of potential buyers. This increases the likelihood of listings matching with the buyer with the highest valuation and, in turn, leads to higher sales prices. The housing literature typically studies spillovers induced by geographic proximity, for instance, between competing properties for sales that are located within a narrow distance radius.[5] The unique feature of spillover effects operating through the behavior of local homebuyers is that they can affect houses listed for sale across the entire metropolitan area. Our dataset can identify these effects, since we observe the postcodes from which searches originate and the ones to which they are directed.

Testing for spillovers by regressing sales prices on the growth experienced by the specific group of users visiting each individual listing could generate biased coefficients. Users who have experienced higher price growth in their home postcode may be systematically more likely to visit higher quality properties. These properties may then be selling at higher prices just due to characteristics that are not spanned by observable controls. To circumvent this issue, we construct experienced price growth for the sample of users that are *expected* to browse a listing based on its location. We do that by computing the average share of visits that listings in a certain suburb receive from different postcodes, over the full sample period covered by the data. Then, keeping shares fixed, we calculated the (weighted) mean experienced postcode-level price growth over time for this *expected* sample of visitors.

We use experienced price growth for the *expected* sample of visitors to predict the average search breadth of users visiting a listing, and estimate the ultimate effects on sales prices using 2SLS. We find that, after controlling for postcode and metro-area by year-month fixed effects, a one standard deviation higher experienced price growth for the *expected* sample of visitors predicts, through its effect on the breadth of searches, a 3% higher sales price, which amounts to roughly 22,500 Australian dollars, or approximately 16,000 U.S. dollars[6] for a listing with

[5] See for example Campbell, Giglio, and Pathak (2011) and Anenberg and Kung (2014). Bailey et al. (2018) also study spillovers that are unrelated to local proximity, but are instead driven by social network connections.

[6] Based on the average exchange rate over the period from January 2017 to May 2019.

average price in our sample. This result is unchanged when controlling for a wide range of listing characteristics (location, number of bedrooms, bathrooms, etc.), and is still significant even after controlling for the last available asking price for the listing. To further establish the robustness of our result, we use the methodology developed by Oster (2019) to assess the potential impact of bias induced by unobservable characteristics on our estimates, and find that, in order to wipe out our finding, the sensitivity of sales prices to unobservables would have to be more than 2.5 times as great as the sensitivity to the controls already included in the regressions. This is unlikely to be the case, since we control for the main explanatory variables for house prices (number of bedrooms, bathrooms, size and type of property), which along with dwelling location and metro-area by year-month fixed effects account for 80% of the variation in prices.

It is natural to expect that postcodes will not uniformly benefit from the expansion of search breadth, since some areas are persistently "popular", and are more typically included into the searches of many buyers. Consistent with this observation, we find that the expansion of search breadth has a stronger effect on listings located in areas that on average receive less attention and are less likely to be considered by prospective buyers. Sales prices in postcodes that are on average browsed by a one standard deviation lower number of users (normalized by the average number of newly posted listings) have an almost 17% larger sensitivity to changes in search behavior induced by experienced price growth.

The rest of the paper is organized as follows. Section 2 presents our dataset and the attention allocation and search behavior variables that we use in our analysis. Section 3 studies the response of buyers' search breadth and attention per listing to experienced price growth in their postcode of residence. Section 4 investigates the mechanism linking local experienced price growth to users' behavior. Section 5 analyzes the extent to which the response of search behavior to local price growth generates price spillovers in other parts of a metropolitan area. Section 6 concludes.

2 Online Real Estate Advertising Dataset

The proprietary dataset used in this study is made available to us by realestate.com.au (REA), which is Australia's largest property website and apps suite. According to Nielsen Digital Ratings – a leading provider of data on online consumers' activity – REA's website had 7 million visitors with 65.3 million total visits and 320 million total page impressions during March 2018.[7] There are three key features that make our dataset uniquely suited to studying the effects of local experienced price growth on homebuyers' search behavior.

First, the dataset contains detailed information on user activity over time and across listings, as well as detailed information on browsed listings. For a random sample of approximately 9,000 users, who self-identify as interested in purchasing a property,[8] we observe logins to the website, the listings they browse, how many times they visit each listing and the amount of time spent browsing each listing on a daily basis. This dataset covers the period from the 1st of January 2017 to the 30th of April 2019, for a total of approximately 3 million user-day-listing observations. Along with information on demand-side behavior, the property website also provides information on listings. For each listing we observe the listing date, the type of listing, and information on the associated property characteristics: 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. For listings associated with properties that are sold over the time period spanned by our study, the dataset provides the sale date and the sales price.

Second, we obtain information on user characteristics. We 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 a second house or an investment property.

[7] The main competitor, Domain Group, had instead about 3.3 million visitors and 32.5 million visits on November 2017, based on the same Nielsen Digital Ratings data.

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

Third, the dataset covers the entire Australia. This allows us to explore prospective home-buyers' behavior across a wide range of different local markets, and for different values of recent price growth within the same local market. As displayed in Figure A.1, the three most active cities, Sydney, Melbourne and Brisbane, have experienced high price growth over the four years prior to the start of our sample and have peaked, respectively, around July 2017, December 2017 and April 2018.[9] Hobart and Adelaide have experienced positive growth for the entire period covered in our sample, while Darwin and Perth – whose economies are tightly linked to the mining and commodities sectors – are at the opposite side of the spectrum in that they have experienced falling prices since 2014.

2.1 Measuring Attention Allocation from Online Activity

Households searching for a new house need to choose how to allocate their effort, and limited attention, across two main dimensions. First, they need to select the breadth of the set of houses to explore, i.e. their "consideration set". Second, they need to allocate attention to analyze each individual listing. Choices along these two dimensions present a trade-off between the risk of excluding the actual optimal match from the set of considered alternatives, and the attention costs of expanding the set and spending more time analyzing individual listings (see Caplin, 2016, and Caplin, Dean, and Leahy, 2019).

We measure the breadth of users' consideration sets by tracking the number of unique listings, the number of unique postcodes, and the number of "segments" browsed in a month. Our definition of segments is based on postcode, property type (house or apartment unit) and number of bedrooms, to reflect the fact that a broader search may not only touch more locations, but also houses within a wider set of characteristics. In order to construct segments we split all listings in groups based on postcode, and then divide the groups within each postcode into 8 subcategories: 1, 2, 3, and 4 or more bedrooms, separately for houses and apartment units.

[9] Since then, they have experienced decreasing prices until the end of our sample. While this is 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 at their peak in Sydney (Melbourne) (Brisbane).

We measure the number of segments visited by user i during the month t as:

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

where $\mathbb{1}_{i,\ell \in (.),\tau}$ is a dummy equal to one if user i in month t (in any day τ included in month t) visits at least one listing (ℓ) in a certain segment.

To instead track the effort and attention allocated to the analysis of individual listings, we calculate the number of minutes and the number of visits per listing in a month. To capture the extent to which attention is concentrated across listings browsed in a given month, we calculate the *Herfindahl index* based on time spent per listing.

Table 1 reports summary statistics. The table reports the mean, median, standard deviation and four percentiles (5th, 25th, 75th and 95th) of the average of each measure across users. The average user browses 42 listings, 9 postcodes and 14 segments in a month. There is substantial heterogeneity across users, as shown by the high cross-sectional standard deviations. The 95th percentile of users based on search activity browses on average 150 listings, 29 postcodes and 46 segments per month. Turning to the measures capturing the attention per listing, the average user tends to visit the listings in her consideration set 2.40 times in a month and spends about 4 minutes per listing. Finally, the Herfindahl index indicates that the average user allocates her time quite evenly across listings.

2.2 Representativeness and Comparison to the United States

Our dataset is representative of the overall population of listings and house searchers in Australia. First, the spatial distribution of users in the data closely matches the one of the Australian population. In Figure 2, the red dots display the centroids of postcodes for which at least one user is included in our data. The majority of users are located in two coastal regions (the south-east and east, and the south-west) and clusters corresponding to the eight

state capital cities[10] are clearly visible on the map. Figure A.2 (in the Appendix) compares the postcode-level density of the users in our sample (in Panel (a)) against population density estimates from the 2016 Australian Census (in Panel (b)). The correlation between the two at the postcode-level is approximately equal to 70%.

Second, while we do not have data on the demographic characteristics of the population of Australian homebuyers, cross-sectional summary statistics of users' characteristics (Panel A of Table A.1) closely match those provided by the American Association of Realtors during our sample period. Approximately 55% of users are female, 30% (32%) of users are between 35 and 49 (50 and 64) years old, and users younger than 35 represent 21% of the sample.

Third, the listings included in our dataset are representative of the total housing stock. Panel B of Table A.1 shows that 68% of listed dwellings 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 indicates that, when considering the entire Australian housing stock, 71% of dwellings are houses and 27% are apartment units. Also, the median number of bedrooms, bathrooms and parking spots in the Census are in line with the values we find in our dataset.

Finally, the listings browsed by the users in our data appear to be a representative sample of the entire set of listings available on the realestate.com.au website, and of Australian house sales listings in general. In panel (a) of Figure A.3 we compare the distributions of the characteristics of the subset of listings browsed by the users against the distributions of the full set of listings on the website, and find no significant differences. Moreover, Panel (b) shows that the average sales price across browsed listings in each postcode lines up with estimates of the average sales price across all registered transactions, available from Corelogic.

A last question concerns the extent to which the Australian market is comparable to other major housing markets in the word, such as the United States. There is large cross-country heterogeneity in the features of housing markets, such as homeownership rates, concentration

[10] Adelaide, Brisbane, Canberra, Darwin, Hobart, Melbourne, Perth and Sydney

of population along coastlines and within cities, and institutions. Nevertheless, the Australian housing market shares many commonalities with the United States market: homeownership rates are quite similar (68% vs 63%), as are the distributions of size and of other dwelling characteristics.

3 Local Price Growth, Attention and Search

Local price growth affects prospective homebuyers' beliefs and collateral constraints.[11] Armona, Fuster, and Zafar (2019) show that information on recent local (postcode-level) price changes affects views on future local price growth both at short and long horizons, while Kuchler and Zafar (2019) find that local price growth experienced by US households affects their views on future price growth at the national level. Moreover, local price growth has a direct effect on local homeowners' wealth and their ability to lever up, by increasing the price of their current house (see Stein, 1995 and Ortalo-Magne and Rady, 2006). Experimental evidence by Fuster and Zafar (2016) shows that households experiencing wealth shocks are more willing to purchase a new house and to make larger downpayments.

The existing body of evidence provides foundations for the study of the effects of local price growth on prospective homebuyers' attention allocation during house search. However, the theoretical predictions are not clear-cut. First, in the search process homebuyers are trading-off the cost and benefits of attention, both in terms of the effort that they allocate to collecting information on individual properties, and in choosing the breadth of the set of properties considered. Thus, it is not clear what aspects, if any, would be influenced by recently experienced local price growth. Second, beliefs about postcode-level price growth, beliefs about aggregate or city-level price growth, and collateral constraints have different effects on the incentive for prospective homebuyers to match with a new house quickly, and thus on the effort they allocate

[11] Other behavioral channels typically do not have clear predictions on the effects of recent local price growth on buyers' and sellers' actions. For instance, loss aversion (Genesove and Mayer, 2001) only has predictions on the effects of original house purchase prices on the current behavior of house sellers.

to house search.

This section focuses on the relationship between experienced price growth and the different dimensions of attention allocation and search behavior. The next section will exploit heterogeneity across households to better investigate the exact channel through which experienced growth affects behavior.

3.1 Effects of Postcode-Level Price Growth

Thanks to the high level of detail of our data, we are able to observe the postcode of residence of each prospective homebuyer. Figure 1 provides preliminary evidence of the relationship between recent local (postcode-level) price growth and homebuyers' behavior. On the x-axis, we report postcode-level price growth measured over the previous 2 years for each month in our sample. On the y-axis, we report different dimension of attention allocation, for the prospective homebuyers residing in the postcode and for the current month. Price growth is strongly correlated with the number of listings browsed in the month (top-left panel), and even more strongly with the number of postcodes (top-right panel), and market segments considered (bottom-left panel). On the other hand, there is only a weak and *negative* relationship between price growth and the amount of time allocated to browsing each individual listing.

The choice to focus our analysis on 2-year price growth is consistent with evidence showing that households' beliefs about future house price growth are highly sensitive to experienced growth over the previous 2 to 4 years, and rather insensitive to experienced price growth taking place further back in the past (see the analysis in Kuchler and Zafar, 2019). Results based on recent experienced price growth over 3- and 4-year horizons are similar to those for the 2-year horizon.

While highly suggestive, the patterns in Figure 1 might be in part explained by differences in aggregate price growth over time, or by persistent differences across locations. To isolate the

actual effect of postcode-level price growth, we estimate the following regression equation:

$$y_{i,t} = \beta \Delta p_{post(i),t-1} + \alpha_i + \alpha_{t \times area} + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is one of the measures described in section 2.1, capturing different aspects of search behavior and attention allocation for user i in month t, and $\Delta p_{post(i),t-1}$, is the 2-year price growth in the postcode where user i has her residence, lagged by one-month.[12] We choose to measure price growth with a one-month lag with respect the dependent variable, since households may not be aware of price levels in the current month.[13] To address the potential presence of confounding effects determined by metropolitan-area level or national trends, we include either year-month by area fixed effects, $\alpha_{t \times area}$, or year-month fixed effects, α_t.[14] To account for time-invariant factors at the postcode or user level, we include either postcode fixed effects, $\alpha_{post(i)}$, or individual user fixed effects, α_i. Figure 3 displays the pooled distribution of 2-years price growth for the postcodes in our sample. The top-left plot displays the distribution from the raw data, which has a mean of 9.6% and a standard deviation of 15%. In the remaining three plots we subtract the monthly (top-right plot), the area (bottom-left plot) and the monthly and area average growth (bottom-right plot). The distribution of demeaned price growth appears to be symmetrical, and even after removing area-wide fluctuations, there is still substantial heterogeneity in postcode-level growth. 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. If standard errors

[12]The dataset on postcode house price indexes at a monthly frequency is provided by Corelogic through the Securities Industry Research Center for Asia-Pacific (SIRCA). Corelogic 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 one for apartments.

[13]Our results are similar if we consider house price growth up to the current month, or if we choose a two-months lag.

[14]Areas are constructed 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 divide Australia into 16 areas.

are double-clustered by user and year-month, we obtain smaller standard errors estimates and higher t-statistics.

Table 2 displays estimates of the effect of price growth (the coefficient β in equation 1) on the breadth of consideration sets. Panel A (B) (C) reports estimates relative to the log of the number of listings (postcodes) (segments) browsed. The specifications in the first and second columns include postcode fixed effects, while the ones in the third and fourth columns include individual user fixed effects. The specifications in the first and third column include year-month fixed effects, while the specifications in the second and fourth column contain year-month by metropolitan area fixed effects. Thus, the fourth column presents results from the tightest specification, which coincides with equation 1. Panel regression estimates confirm the evidence presented in Figure 1, and are remarkably stable across specifications. A one-standard deviation higher price growth (i.e. 15%) over the previous two years coincides with approximately a 6% larger number of listings browsed. We find similar results when the dependent variable is the number of postcodes or the number of segments covered by house searches.

Table 3 has the same layout as Table 2, but focuses on the effects of experienced price growth on attention per listing. Panel A (B) displays results for the log of the number of minutes (visits) per listing over the month. Point estimates of these effects are economically small. One-standard deviation higher price growth increases (decreases) minutes (visits) per listing by 0.3%. Estimates are not statistically significant across all the different specifications presented in the Table. Even though average attention per listing remains unchanged, prospective buyers may still be skewing attention allocation towards specific listings in response to experienced price growth. To test this hypothesis, in panel (C) we set the dependent variable equal to the Herfindhal Index for the time allocated to individual listings over the 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 users experiencing higher price growth, if anything, allocate attention more uniformly across the listings they visit.

Given the evidence on the expansion of search breadth presented in Table 2, one may wonder

whether the finding might be driven by the fact that, in response to higher local price growth, users include a limited number of more expensive properties, or properties from more expensive areas, in their otherwise unchanged set of considered listings. We find that this is not the case. 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 our results in Table 4. In Panel (A), we show that the relationship between the breadth of the range of explored prices and experienced price growth is not statistically significant once metropolitan area by month fixed effects are included in the regression specification. In Panels (B) through (E) we show in more detail that there is no evidence of a stronger effect of higher experienced price growth on the right tail of the range of explored prices. Rather, a one standard deviation higher price growth uniformly shifts upwards (by approximately 1.5-2%) the 10th, the 25th, the 75th, and the 90th quantile of the distribution of explored prices. Therefore, while experienced growth in the postcode of residence does in general lead users to explore more expensive houses, the *breadth* of the range of explored prices remains the same.

The combined evidence from Tables 2, 3 and 4 paints the following picture. Higher experienced price growth affects the trade-off between the benefits and costs of attention, faced by prospective homebuyers during house search. Experienced growth increases the perceived benefits of attaining a match with the desired house, and of doing so quickly. Homebuyers then choose to expand attention on the dimension that has the highest impact on the likelihood of success of their search, and on matching speed. This is the breadth of the considerations sets, rather than the amount of attention allocated to individual listings.

3.2 Are Users Aware of Local Price Growth?

The users in our dataset can directly observe recent postcode-level price movements on the realestate.com.au website, in particular through the "research" section of the website. Unfor-

tunately, we cannot track visits to the research pages. However, we can still use individual users' online activity to establish a link between the information collected by each individual user and her response to recent local price growth.

The website includes a "sold" section, which contains information on expired listings of sold properties and the associated sales prices. We can then track whether and when a user visited listings located in her postcode of residence and reported in the "sold" section, thus observing the relative sales prices. Our intuition is that users who are browsing recently sold listings in their postcode are learning about recent transaction prices, and are more likely to be aware of recent postcode price growth. Based on this intuition, we focus on two testable hypotheses. First, users who have directly observed information on local sales should have a stronger response to recent local price fluctuations. Second, users' behavior should also respond to the specific prices that they observe. Users who have on average browsed, within their postcode of residence, listings with higher (lower) sales prices will likely perceive that local price growth has been higher (lower), and will adjust their behavior accordingly.

We test our first hypothesis using the specification in equation 1, augmented with an interaction term:

$$y_{i,t} = \beta_{info}\left(\Delta p_{post(i),t-1} \times I_{i,t}^{info}\right) + \beta \Delta p_{post(i),t-1} + \delta I_{i,t}^{info} + \alpha_i + \alpha_{t\times area} + u_{i,t} \tag{2}$$

where $I_{i,t}^{info}$ is a dummy equal to one if the user browsed during the month at least one property that sold in her postcode of residence over the last year. The other variables have the same interpretation as in equation 1. The coefficient β measures the response of buyers who have not browsed recently sold listings in their postcode of residence, while β_{info} measures the incremental response of buyers who have collected information on recent sales. Panel A of Table 5 shows that, for changes in prospective homebuyers' search breadth and breadth of consideration sets over time, estimates of β_{info} are positive and statistically significant, as predicted by our initial conjecture. In particular, the response to local price growth of users

who have recently browsed sold listings is twice as large: one standard deviation higher local price growth is associated with a 9%-10% increase in the number of postcodes and segments browsed during the month. When we instead focus (in Panel B) on the effects on attention per listing, estimates of the coefficient β_{info} are not statistically significant, and we again do not find any significant baseline relationship (coefficient β) between recent local price growth and minutes per listing, visits per listing or time allocation across listings over the month.

To test our second hypothesis, which states that average observed local sales prices should impact search behavior, we estimate the regression specification:

$$y_{i,t} = \gamma_{info}\left(\bar{p}_{i,t}^{info} \times I_{i,t}^{info}\right) + \beta\Delta p_{post(i),t-1} + \delta I_{i,t}^{info} + \alpha_i + \alpha_{t\times area} + v_{i,t} \tag{3}$$

where all variables have the same interpretation as in equation 2, with the exception of $\bar{p}_{i,t}^{info}$, which is the average sales price across recently sold (within the last year) listings browsed by user i in her postcode of residence during month t. The coefficient γ_{info} captures the effect of observed prices on the attention allocation variable $y_{i,t}$, on top of the effect of recent postcode-level price growth (measured by β). We find that when the attention allocation variable is one of the measures of the breadth of consideration sets, estimates of γ_{info} are statistically significant and positive, in line with our predictions. Point estimates of γ_{info} are virtually equal to zero and not statistically significant when the dependent variable is either minutes per listing, visits per listing or time allocation across listings over the month.

3.3 Instrumenting Price Growth with Land Supply Elasticity

A general concern when considering the effects of experienced price growth on behavior is that the search effort of local residents might influence local growth, thus generating reverse causality. However, the search behavior of local residents has limited effect on local prices, since the median (average) fraction of listings browsed by prospective buyers who reside in their postcode of current residence is only 7% (16%).

Nevertheless, to further dispel the concern that evidence on the effect of experienced price growth on attention allocation and consideration sets might be spurious or endogenous, we develop an empirical strategy that uses local land supply elasticity as an instrumental variable.[15] This instrument is well suited for our study. Our conjecture is that experienced price growth affects attention and search behavior by changing the perceived benefit from matching with a new house, and from achieving a match in a timely matter. However, this is more likely to be the case when price growth is driven by local excess demand and sticky supply, and thus is disconnected from changes in the underlying quality of local housing. If price growth is driven by improvements in local quality (for instance due to new amenities, better school quality, etc.), local users would trade this off against the benefits of moving, and may well feel an incentive to stay in their current neighborhood longer, and reduce attention and search effort.

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 provided by the Australian Department of Agriculture for fiscal year 2010-2011.[16] 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-sized cities, rural areas, and parts of large metropolitan areas. For each LGA we calculate the fraction of land for which housing supply is *constrained*. Since our measure is based on either topography or land use in 2011, it is plausibly not affected by the behavior of house prices over the period covered by our study, which extends from 2017 to 2019. By mapping each postcode to a corresponding LGA, we calculate land supply elasticity for the postcode of residence of each one of the users

[15] This approach is related to a broad literature that uses local differences in supply elasticity as an instrument for house price growth. 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), Chakraborty, Goldstein, and MacKinlay (2016), Chetty, Sandor, and Szeidl (2017), and Stroebel and Vavra (2019).

[16] ESRI files are at http://www.agriculture.gov.au/abares/aclump/land-use/data-download.

in our dataset.[17] 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 constraints 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.[18] Figure 4 provides a graphical depiction of the fraction of constrained land across Australia's LGAs, and shows how it changes substantially within Australian states, and even across close geographies and along the coasts.

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 metropolitan area in which the user lives. When prices are consistently rising in the broader metropolitan area, due to economic fundamentals, house prices in constrained LGAs should raise more than in the rest of the state. A limitation of our instrumental variable approach is that it relies on aggregate fluctuations in house price indexes. However, we are not exploiting the magnitude of price changes, but just 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. We estimate the following

[17] We identify the constrained areas using relatively broad criteria. 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 leading to constraints on housing supply: (1) the presence of water, in the form of internal basins, lakes, rivers, swamps and coastal waters, (2) the inclusion in a protected area or a natural conservation reserve, (3) the presence of intensive agricultural or industrial infrastructure, such as high-intensity plantations, mines, and industrial complexes, (4) the presence of high-density urban and residential development. Areas that do not fall in the above mentioned four categories are more likely to be readily available for real estate development, and are therefore *unconstrained*.

[18] Baum-Snow and Han (2019) show using U.S. data that local supply elasticities, at the census tract-level, indeed affect the production of new housing and house prices.

system of equations by two-stage-least-squares (2SLS):

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

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

where $\Lambda_{post_{(i)}}$ is the measure of house supply elasticity, and $\mathbb{1}_{\Delta p_{area_{(i)},t-1}>0}$ is a dummy equal to one if house price growth[19] over the last two years (up to month $t-1$) has been positive in the area where $post(i)$ (or user i) is located. $y_{i,t}$ is again one of the measures capturing either search breadth or listing-level attention for user i in month t. Estimates of the first stage regression (equation 4) are reported in Table A.2. 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 6. The first stage F-statistics are large across the board, consistent with the results in Table A.2.

Panel (A) of Table 6 reports 2SLS estimates of the effect of price growth on search breadth (breadth of consideration sets), while Panel (B) focuses on attention per listing. Estimates of the effect of price growth on the breadth of the set of houses considered are positive, statistically significant and 3 to 4 times larger than the OLS estimates reported in Table 2. A one-standard deviation higher experienced price growth leads to an increase in the number of visited listings in between 25% and 28%, and to an increase in the number of postcodes and segments visited above 20%. On the other hand, once we instrument price growth with supply elasticity, the effect of experienced price-growth on attention per listing appears to be negative across the board. The effect is not statistically significant for minutes per listing, but is significant for number of visits per listing and for the Herfindahl index measuring attention concentration across listings.

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

4 Economic Mechanism

In this section we exploit heterogeneity across prospective homebuyers to shed light on the mechanism that drives their response to experienced local price growth. Then, we assess the extent to which homebuyers' behavior reflects beliefs that are consistent with actual price dynamics in the data.

4.1 Extrapolative Expectations

Previous research has shown that households are prone to over-extrapolate from recent price changes when forming beliefs about future, and even long term, price growth (see Case, Shiller, and Thomson, 2015, Armona, Fuster, and Zafar, 2019). Over-extrapolation has clear predictions for the effects of recent local price growth on search behavior, in particular when studying separately the responses of homeowners and renters. If local households interpret recent postcode growth to be a signal of metro-area-level higher future growth (Kuchler and Zafar, 2019), homeowners looking for a new house would have no reason to search either more or less intensively. Their house offers the best hedge against metro-area wide price fluctuations (Sinai and Souleles, 2005). Local renters would instead feel pressure to find a matching house quickly in response to higher growth, since they are un-hedged against price movements, and would rather secure a house before prices in their metropolitan area grow further (so called "fear of missing out").

On the other hand, if local homeowners extrapolate future *local* postcode price growth, in excess of the rest of the metro-area, from past recent local postcode growth, they will have an incentive to slow their search activity in response to higher growth. This is because higher future local growth will increase homeowners' wealth and further relax their collateral constraints, *relative to other residents in the metro-area.* Moving typically involves selling the current house, and thus missing out on future local growth. Renters would instead have no incentive to search more or less, since they have the option to move in different parts of the city

or metro-area that are not influenced by local growth in their current postcode of residence.

We estimate the response to local price growth of homeowners and renters[20] using the following regression equation:

$$y_{i,t} = \delta_{own}\left(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,owner}\right) + \delta_{noown}\left(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,noowner}\right) + \\ + \kappa \mathbb{1}_{i,owner} + \alpha_{post(i)} + \alpha_{t\times area} + \epsilon_{i,t} \tag{6}$$

where $y_{i,t}$ is one of the measures of the breadth of consideration sets or of listing-level attention developed in section 2.1, and $\mathbb{1}_{i,owner}$ ($\mathbb{1}_{i,noowner}$) is a dummy equal to one if user i is a homeowner (renter). Thus, δ_{own} and δ_{noown} capture the response of search behavior to local price growth for users who are homeowners and renters, respectively. Panel A of Table 7 reports coefficient estimates and shows that postcode-level price growth has a positive and statistically significant effect on the number of listings, the number of postcodes and the number of segments explored by homeowners (δ_{own}). 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. On the contrary, the estimates of the effect for renters (δ_{noown}) are positive but not statistically significant.

Thus, the data reject the predictions of extrapolative expectations. If homeowners and renters extrapolate metro-area level growth from experienced local price appreciation, then δ_{own} should be indistinguishable from zero, and δ_{noown} should be positive and statistically significant. If homeowners and renters extrapolate excess postcode-level price growth from recent appreciation, then δ_{own} should be negative.

We again find little evidence of a response of attention per listing to recent price growth for both homeowners and renters, with the exception of the effects of price growth on the Herfindahl index for homeowners, which is negative and weakly significant (see Panel A of Table A.4 in the Internet Appendix).

[20] Homeowners and renters represent 65.11% and 34.89% of the users in our sample.

A potential concern when interpreting the estimates of the coefficients in equation 6 is that the distribution of users in the dataset might be correlated with experienced local price growth. For instance, users who are homeowners might be systematically more frequent in postcodes that have experienced higher growth. We show in Table A.3 in the Internet Appendix that this is not the case, and local price growth is not associated with users characteristics, or with the number of users active in the postcode.

4.2 Collateral Constraints and Mean Reverting Beliefs

Higher postcode-level growth is going to be associated with a higher sales price and higher home equity for the houses of local homeowners who are planning to move. This is particularly relevant for homeowners facing collateral or liquidity constraints, since they will likely have to roll-over their home equity into the downpayment for a new property. Thus, constrained homeowners searching for a new property may want to take advantage of higher local prices, and of their resulting stronger purchasing power, by searching more extensively and matching quickly with a new home. Even more so if they believe that postcode-level price growth is going to mean revert to (or fall below) metro-area price growth in the near future, thus reducing their purchasing power relative to other buyers.

We conduct three tests to assess whether the combination of collateral constraints and mean reverting beliefs can explain the behavior of users in the data. First, we compare homeowners living in postcodes with high property values against homeowners living in postcodes with low property values. The intuition is that homeowners in poorer postcodes are both more likely to rely on their current home equity to finance the purchase of a new house, and more likely to be eager to move up the housing ladder. For each postcode, we calculate the average house price over the period from January 2017 through April 2019.[21] Then, for each metropolitan area we calculate $\bar{p}^{med}_{area}$, which is the median house price across the postcodes within the area,

[21] We repeat the same exercise by calculating average price based on year 2017 only. Results remain unchanged. We also obtain similar results when sorting postcodes on the average income of residents according to the 2016 Census.

and estimate:

$$y_{i,t} = \delta_{plow}\left(\Delta p_{post(i),t-1} \times \mathbb{1}_{\bar{p}_{post(i)} \leq \bar{p}^{med}_{i,area}}\right) + \\ + \delta_{phigh}\left(\Delta p_{post(i),t-1} \times \mathbb{1}_{\bar{p}_{post(i)} > \bar{p}^{med}_{i,area}}\right) + \alpha_{post(i)} + \alpha_{t \times area} + \epsilon_{i,t} \tag{7}$$

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 users living in postcodes with price less or equal, and above the median price in the metropolitan area. Thus, the coefficients δ_{plow} and δ_{phigh} measure the response of homeowners to experienced price growth in postcodes with prices less or equal, and above median. Estimates of the coefficients in equation 7 are reported in Panel B of Table 7. We find that, in postcodes with prices below the median, one standard deviation higher experienced price growth translates into more than a 14% increase in the number of browsed listings, and a 10%-11% increase in the number of postcodes and segments browsed. This is roughly twice the magnitude of the effects for the entire sample of users, as reported in Table 2. The effect of experienced growth in postcodes above the median is not statistically significant, and point estimates of δ_{phigh} are close to zero and economically negligible.

In our second test, we compare homeowners who are looking for a new primary residence, against homeowners who are looking for a secondary residence or an investment property.[22] The intuition is that owners looking for a secondary residence or an investment property are likely less dependent on the current home equity in their primary residence to finance their new purchase, and are also likely not planning to sell their primary residence. We estimate equation:

$$y_{i,t} = \delta_{Occupy}\Big(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,Occupy}\Big) + \delta_{Invest}\Big(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,Invest}\Big) \\ + \kappa \mathbb{1}_{i,Invest} + \alpha_{post(i)} + \alpha_{t \times area} + \epsilon_{i,t} \tag{8}$$

[22] Owners looking for a new primary residence and investors represent 78.02% and 21.98% of homeowners.

where $\mathbb{1}_{i,Occupy}$ ($\mathbb{1}_{i,Invest}$) is a dummy equal to one for owners looking for a new owner-occupied (secondary or investment) property. Panel C of Table 7 shows that investors are unaffected by recent price growth, and that the entire effect in the data is driven by homeowners interested in moving to a new primary (owner-occupied) residence.

For our third and final test, we compare homeowners with age greater or equal than 65 against younger owners. We choose this particular age cutoff since it coincides with the average retirement age in Australia.[23] Retirees looking for a new home are more likely to be moving down the housing ladder. Moreover, they are likely to have substantial equity in their current property, since they will have paid back a large fraction, if not the entirety, of their mortgage. Thus, they are more likely to be able to finance the purchase of a new property independently of the fluctuations in their current home equity. If local price fluctuations affect local homeowners' behavior through collateral constraints, we would expect older owners to be less sensitive to local price fluctuations compared to younger ones. We test this conjecture with the regression equation:

$$\begin{aligned} y_{i,t} = {} & \delta_{Age<65}\Big(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,Age<65}\Big) + \delta_{Age\geq 65}\Big(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,Age\geq 65}\Big) \\ & + \kappa \mathbb{1}_{i,Age\geq 65} + \alpha_{post(i)} + \alpha_{t\times area} + \epsilon_{i,t} \end{aligned} \tag{9}$$

where $\mathbb{1}_{i,Age<65}$ ($\mathbb{1}_{i,Age\geq 65}$) is a dummy equal to one for owners younger than 65 (of age 65 and older). Panel D of Table 7 shows that, consistent with our conjecture, older owners' behavior is unaffected by price growth, while younger owners expand search breadth in response to local price fluctuations.[24]

When we estimate equations 7, 8 and 9 setting the dependent variable equal to one of the measures of attention allocation at the listing level, we find weak effects across users with

[23] See the statistics reported by the Australian Census at https://www.abs.gov.au/statistics/labour/employment-and-unemployment/retirement-and-retirement-intentions-australia/latest-release.

[24] Table A.3 in the Internet Appendix shows that the number of homeowners looking for a new owner-occupied property and the number of users younger than 65 in a certain postcode are not associated with postcode-level price growth.

different characteristics, with the exception of the effect of experienced price growth on the Herfindahl index of time spent per listing, which is negative and statistically significant for homeowners living in postcodes with prices below median (see Table A.4).

4.3 Homebuyers Behavior and Price Growth Dynamics

The results in the previous section confirm the predictions of the collateral constraint channel, and of the conjecture that homeowners believe current postcode appreciation in excess of the rest of the metro-area to be mean reverting. Are these beliefs consistent with actual postcode-level price dynamics? To answer this question, in each postcode for which we have access to at least 5 years of data, we estimate at monthly frequency:

$$\widetilde{\Delta p^h}_{j,t} = \rho_{j,0} + \rho_{j,1}\widetilde{\Delta p^h}_{j,t-h} + e^h_{j,t} \tag{10}$$

where $\widetilde{\Delta p^h}_{j,t}$ is price growth for postcode j in excess of the average within the metro-area, and is calculated as $\widetilde{\Delta p^h}_{j,t} = \Delta p^h_{j,t} - \Delta p^h_{area,t}$, with $\Delta p^h_{j,t} = p_{j,t+h} - p_{j,t}$ and $\Delta p^h_{area,t}$ equal to the average price growth over horizon h across postcodes in the same metropolitan area as j. The coefficient $\rho_{j,1}$ captures the persistence of "excess" price growth over horizon h for postcode j. Note our focus on local price growth in excess of the average within the metro-area. This variation is the focus of our study across all the regression specifications in the previous sections, and the most relevant for homeowners who need to sell their property in order to finance the purchase of another house within the same metro-area.

Figure 5 reports the distribution of point estimates of $\rho_{j,1}$ across postcodes, for price growth over horizons (h) of 1 year and 2 years. For both horizons the average point estimate is negative (equal to -0.20 and -0.25). Roughly 75% of postcodes have a negative estimates, while almost all the postcodes with positive estimates have coefficients below 0.5, which are consistent with quick mean-reversion in price growth.

Thus, empirical evidence suggests that postcode-level price growth in excess of the rest of

the metropolitan area is not persistent. Rather, for the majority of postcodes, larger excess-growth over the last two years predicts larger negative growth in the following two years. Homebuyers' response to recent excess local price growth appears then to reflect correct beliefs about postcode-level price dynamics.

5 Real Effects: Spillovers Induced by Search Behavior

In this section we test whether the expansion of search breadth driven by higher experienced price growth has real effects. In particular, we focus on spillover effects onto house sales. Note that empirical work in the housing literature typically studies spillovers induced by geographic proximity. However, the spillover effects operating through the behavior of local homebuyers affect houses listed for sale across an entire metropolitan area. The unique level of detail of our data allows us to identify these effects, since we observe the postcodes from which searches originate and the ones to which they are directed.

As search ranges expand, local housing markets become more integrated and listings are visited by a larger pool of potential buyers. This effect increases the likelihood of listings matching with the buyer with the highest valuation and, in turn, leads to higher sales prices. Piazzesi, Schneider, and Stroebel (2019) show that buyers who search broadly play a key role in sustaining housing demand, for example by absorbing postcode-level excess housing supply, while theoretical models by Novy-Marx (2009) and Ngai and Tenreyro (2014) have highlighted how search frictions can amplify price fluctuations, due to the effect that price fluctuations may have on the willingness to transact on the part of both buyers and sellers, and to the concurring feedback effects.

We first show that the magnitude of spillovers is economically significant. We then turn to cross-sectional differences across postcodes. We expect postcodes to benefit differently from the expansion of searches. In particular, the expansion of search breadth should have stronger effects on listings located in areas that persistently receive less attention, and are in general

less likely to fall into the searches of prospective buyers. This conjecture is confirmed in the data.

5.1 Effects on Sales Prices

Constructing a test for spillover effects poses important identification challenges. Users who have experienced higher price growth in their home postcode may be systematically more likely to visit higher quality properties. Then, these properties might be selling at higher prices only due to characteristics that are not spanned by the controls available in our dataset. Therefore, regressing listings sales prices on the growth experienced by the specific group of users visiting each listing could generate biased estimates.

To address this issue, rather than relying on the growth experienced by the users who *visit* a certain listing, we construct a measure of experienced growth for the sample of users that are *expected to visit* a listing, based on the suburb in which it is located.[25] We proceed in three steps. First, for each suburb browsed by our users, we calculate the fraction of visits coming from each postcode, excluding the one in which the suburb is located, over the entire sample period (from 2017 to 2019). This produces a $1 \times N_s$ vector of weights $\mathbf{w_s}$ for each suburb s, with N_s equal to the number of postcodes from which prospective homebuyers have been browsing the listings in the suburb. These weights identify the average composition, across postcodes, of users who explored suburb s. For our second step, we can use the weights to calculate, in each month, postcode-level price growth experienced by the average sample of users exploring the suburb. In formulas, we calculate: $\Delta p_{s,t-1} = \mathbf{w_s \Delta p_{t-1}}$, where $\mathbf{\Delta p_{t-1}}$ is a $N_s \times 1$ vector containing 2-years price growth (lagged by one month) in each of the N_s postcodes. Finally, as a last step, we assign to each listing l listed in month t the corresponding experienced price growth, and call it $\Delta p_l = \Delta p_{s(l),t-1}$, where $s(l)$ is the suburb in which listing l is located. We

[25] This is similar to constructing a Bartik-style instrument (Bartik, 1991), an approach widely used in the economics and finance literature.

can then estimate the effect of experienced homebuyers' price growth on listing sales prices:

$$p_l^{sale} = \beta \Delta p_l + \mathcal{B} X_l + a_{post(l)} + a_{t \times area} + u_l \tag{11}$$

where the vector of controls X_l, contains the log of the listed dwelling 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, $a_{post(l)}$ is a fixed effect for the postcode in which the listing is located and $a_{t \times area}$ is a year-month (of sale) by metropolitan area fixed effect.

Estimates from a parsimonious specification of equation 11, omitting the vector of controls X_l, as well as estimates from the full specification, are reported in the first two columns of Table 8. We find that a one standard deviation higher experienced price growth Δp_l (approximately equal to 8%) translates into approximately 3% higher sales prices, both when we do and do not control for property characteristics. Since the average home in our sample has a sales price of approximately 750,000 Australian dollars (562,000 U.S. dollars, based on the average exchange rate over the period from January 2017 to May 2019), this effect amounts to roughly 22,500 Australian dollars, or approximately 16,000 U.S. dollars.

Thus, spillover effects of local price growth operating through the behavior of local prospective homebuyers are substantial. In order to provide evidence that the effect of experienced price growth on sales prices is indeed channeled through the expansion of the breadth of consideration sets, we perform a second test. First, at the listing level, we calculate the log of the average breadth of searches across the users that visited the listing while posted online.[26] Since this measure is affected by the potential non-randomness of the match between prospective homebuyers and listings, we instrument it with Δp_l, and then use 2SLS to estimate the effect

[26] In formulas, for each of the measures capturing the breadth of consideration sets, we calculate:

$$Breadth_l = \frac{\sum_{k=1}^{N_l} Breadth_k}{N_l}$$

where N_l is the total number of visits the l listing receives before sale, and $Breadth_k$ is the breadth of the consideration set of the user involved in visit k, in the month in which the visit is conducted. We then calculate $logBreadth_l = log(1 + Breadth_l)$.

of instrumented search behavior of visitors on sales prices. Thus, we estimate equations:

$$logBreadth_l = \lambda \Delta p_l + \mathcal{B}X_l + a_{post(l)} + a_{t \times area} + v_l \tag{12}$$

$$p_l^{sale} = \gamma log\widehat{Breadth}_l + \mathcal{B}X_l + a_{post(l)} + a_{t \times area} + e_l \tag{13}$$

where $logBreadth_l$ is the log of average search breadth, or breadth of consideration sets (measured either as number of listings visited, number of postcodes or number of segments) across all users that visited the listing before sale, $log\widehat{Breadth}_l$ is the fitted value of log average search breadth based on equation 12 , while all other variables have the same interpretation as in equation 11.

Columns 3 to 8 of Table 8 report our estimates from the second stage regression (equation 13), while estimates for the first stage regression (equation 12) are reported in Table A.5. Estimates of the loading λ of experienced price growth on search behavior in the first stage are approximately equal to one for all $logBreadth$ measures, and estimates of the marginal effect on prices (γ) are in line with the ones from equation 11. Thus, the 2SLS estimates provide the same point estimate of the marginal effect of homebuyers' experienced price growth on listings sales prices as the ones from equation 11. One standard deviation higher experienced price growth predicts 3% higher sales prices.

5.2 Effects in Low-Attention Postcodes

We now show that the effects of the expansion of search breadth are more strongly felt by listings located in postcodes that persistently receive less attention. To this end, we construct three measures of the attention received by different postcodes: the average number of monthly visits, Vis_p, the average number of listings browsed, $List_p$, and the average number of separate users visiting listings on a monthly basis, $Users_p$. Since postcodes with a higher number of properties for sale might mechanically attract more attention, we normalize these measures by the average number of new monthly listings in each postcode to obtain $Att(Vis_p)$, $Att(List_p)$,

and $Att(Users_p)$.[27] The lower is the value of these ratios, the lower is, over the full sample, the attention that the postcode receives from the users in our dataset. We then estimate an augmented version of equation 13 which includes an interaction term:

$$p_l^{sale} = \theta \left(log\widehat{Breadth}_l \times Att(Meas)_{p(l)} \right) + \gamma log\widehat{Breadth}_l + \mathcal{B}X_l + \alpha_{post(l)} + \alpha_{t \times area} + e_l \quad (14)$$

where $Att(Meas)_{p(l)}$ is one of the measures of attention to postcode $p(l)$, in which listing l is located. The main coefficient of interest is then θ, which captures the interaction between the attention level for the postcode, and the expansion of search breath driven by local price growth (the instrumented value of log average search breadth per listing, $log\widehat{Breadth}_l$).Since we are focusing on attention per postcode, the variable $log\widehat{Breadth}_l$ is set equal to the instrumented log average number of postcodes visited by the users browsing listing l. Our conjecture is that estimates of θ shall be negative.

We report our estimates in Table 9. The first three columns report results for a specification of equation 14 in which we remove postcode fixed effects, and include the variable $Att(Meas)_{p(l)}$ as a control. Each column uses one of the three different measures of $Att(Meas)_{p(l)}$. We find consistent results across all measures: receiving higher attention is associated with higher prices in the postcode, while the coefficient θ for the interaction term is negative. Thus, the increase in consideration sets induced by higher experienced growth has a stronger impact on listings located in areas that on average receive less attention. In the last three columns the specification includes postcode fixed effects, which absorb the variables $Att(Meas)_{p(l)}$. We find that our results are largely unchanged. While the estimate of θ for the variable $Att(Vis)_{p(l)}$ is negative but not statistically significantly, the estimates for $Att(List)_{post(l)}$ and $Att(Users)_{post(l)}$ are both negative and highly statistically significant. Listings in postcodes that have one standard deviation (measured either with $Att(List)_{post(l)}$ and $Att(Users)_{post(l)}$) lower attention, have a 17% larger sensitivity to changes in search behavior induced by experienced price growth.

[27] We average over the full sample in order to smooth the effect of seasonality in both attention and the supply of new listings.

5.3 Robustness to Unobservable Characteristics

While we construct the variable Δp_l using an approach that addresses the endogeneity of the match between each individual listings and its visitors, there might still be concerns that Δp_l could be correlated with unobservable listing characteristics. To further address these concerns, we conduct three empirical tests.

First, we augment the set of controls in equations 11, 12 and 13 by including the last listing price available for each listing. This variable should incorporate all information on house characteristics which is priced by the seller, including information related to characteristics that are unobservable in our dataset. Moreover, the inclusion of the last listing price should attenuate our results. If sellers become aware that a broader set of interested buyers is considering their home, they will set higher listing prices, or they will be less likely to drop listing prices while the house sits on the market. Table A.5 shows specifications of the first stage regression in the 2SLS estimates (equation 12) both including and excluding the last listing price as a control. The inclusion of the additional variable has little impact on estimates of the effect of experienced price growth on search behavior. Table A.6 reports estimates from the regression equation in which we directly project sales prices on homebuyers' experienced price growth (equation 11), as well as from the second stage of the 2SLS estimator (13). The inclusion of the listing price affects point estimates of the impact of experienced growth, and of instrumented search behavior, on sales prices. However, the coefficients remain positive, and both statistically and economically significant. One standard deviation higher experienced price growth, either directly or though instrumented search behavior, leads to 1% higher sales prices.

As a second approach to assessing the robustness of our results to unobservables, we use the methodology introduced by Altonji, Elder, and Taber (2005) and Oster (2019). This approach allows us to establish the magnitude of the impact of omitted variables bias on our estimates.[28] Oster (2019) shows that the bias induced by unobservables is proportional to three factors.

[28]The methodology is used in several recent empirical studies in finance (see Heimer, Myrseth, and Schoenle, 2019, Dougal et al., 2019, Gao and Huang, 2020).

First, 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. Second, the ratio of the difference between the maximum feasible R-square for the regression and the estimated R-square in the long regression, over the difference between the R-squares in the long and short regression. Third, the ratio of the sensitivity of the outcome to unobservable characteristics over the sensitivity to observable characteristics, called δ.[29] In our settings, the "short" regression consists of equation 11 omitting the vector of property characteristics X_l, while the "long" regression consists of the full specification in equation 11. 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 estate markets,[30] our estimate of δ is 2.68. Thus, in order to entirely attribute our results to bias, sales prices should be more than 2.5 times as sensitive 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, dwelling type (single family residence or apartment), number of parking slots and size. This is unlikely.

For our third test, we exploit heterogeneity in the magnitude of the effects of experienced price growth across listings. If the measure of price growth experienced by the expected sample of visitors for each listings is capturing a demand-side effect, rather than listing characteristics, then the impact of experienced price growth should be stronger when sellers face less competition, and have stronger bargaining power over buyers. To test this prediction in the data, for each listing we count the number of properties listed over the same period of time, with the same number of bedrooms and of the same type (apartment unit or single-family residence). We then average the number of "competitors" at the postcode level, and estimate the following

[29] More formally,

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

β^* is an unbiased estimator of the population value of β, β° and R° are the coefficient estimate and R-square from the short regression, and $\hat{\beta}$ and $\hat{R}$ are the estimate and R-square from the long regression. R_{max} is the maximum feasible R-square for the regression. This exact relationship holds under restrictive assumptions, but Oster (2019) shows that it can be generalized. We use her framework and code for our calculations.

[30] See for example Peng (2015), Sagi (2015) and Giacoletti (2019).

regression equation:

$$p_l^{sale} = \sum_{k=1}^{4} \beta_k \left(\Delta p_l \times \mathbb{1}_{Qk,post(l)} \right) + \mathcal{B} X_l + a_{post(l)} + a_{t \times area} + u_l \tag{15}$$

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 two columns of Table A.7 report estimates of the coefficients of equation (15) for the different quartiles of competition. We find that the real effect of experienced price growth on sales prices in the lowest quartile of competition is almost twice as large as the estimate based on the entire sample of listings, reported in Table 8. The magnitude of the effect then monotonically decreases as we move to the higher quartiles of competition. This result is robust to the inclusion of the last available listing price as a control variable.

The findings in the previous sections also suggest that experienced price growth should have stronger real effects in postcodes that persistently attract visitors from locations in which houses are substantially less expensive. This is because prospective homebuyers' behavior is driven by the effect of prices on collateral constraints (see Section 4), and because prospective homebuyers who experienced higher price growth do indeed "shift" their searches towards postcodes with higher prices (see Table 4). We measure the gap between the median house price in the postcode in which each listing is located and the average of the median house prices across the postcodes where users visiting the listing have their residence. We then estimate equation 15 with interactions between experienced price growth and dummies for the different quartiles of the price gap distribution. Estimates are reported in the third and fourth column of Table A.7, both not including and including the last listing price as a control. The effects on sales prices are indeed strongest in the highest quartile of the price gap distribution.

6 Concluding Remarks

We show that differences in local experienced price growth explain differences in attention allocation in the house search process, and generate spillovers on house sales prices within a metropolitan area. Since the housing market is highly segmented and illiquid, search behavior is a key determinant of the likelihood of matches between buyers and sellers, and thus of house sales prices. While previous work has documented how local experienced price growth affects house price expectations and local homeowners' collateral constraints, there is virtually no empirical evidence on the effects on search behavior for prospective homebuyers. We provide a novel contribution taking advantage of a unique dataset tracking prospective homebuyers' activity on a major property website.

Higher recent postcode-level price growth increases the set of properties included in house searches, and the number of locations and segments (combinations of locations and property characteristics) browsed, but has no effect on the attention allocated to exploring individual listings. Exploiting heterogeneity across users, we test the competing implications of different channels that may explain the link between experienced price growth and behavior: extrapolative expectations and collateral constraints. We do not find support for the predictions of extrapolative beliefs, and instead find that evidence in the data lines up with the predictions of collateral constraints, and also suggests that households have mean reverting expectations for local price movements. Interestingly, households' behavior is consistent with price dynamics, since local (postcode-level) price growth in excess of average metro-area growth is mean reverting, and high past excess local price growth predicts local growth below the metro-area average in the future.

In the last part of the paper we provide evidence that the expansion of search breadth induced by local price fluctuations generates spillovers onto properties for sale across a metropolitan area. As search ranges expand, listings are visited by a larger pool of potential buyers. This increases the likelihood of matching with the buyer with the highest valuation and leads

to higher sales prices. These effects are stronger for postcodes that receive on average less attention.

Taken together, our results document how differences in local price experiences explain differences in behavior across households searching for a house, and the related real effects on prices. Since most real asset markets are search markets, our findings may apply to a broader set of asset classes, potentially explaining differences in search behavior and effects on prices more extensively in the economy.

Moreover, our results present a channel through which local house price growth may spread to the rest of a metropolitan area, with amplifying effects. Since the response of individuals depends on their characteristics, and the propagation of spillover effects depends on the network of searches, our results shed light on an important mechanism that contributes to heterogeneous price patterns and feedback effects within the same metropolitan area.

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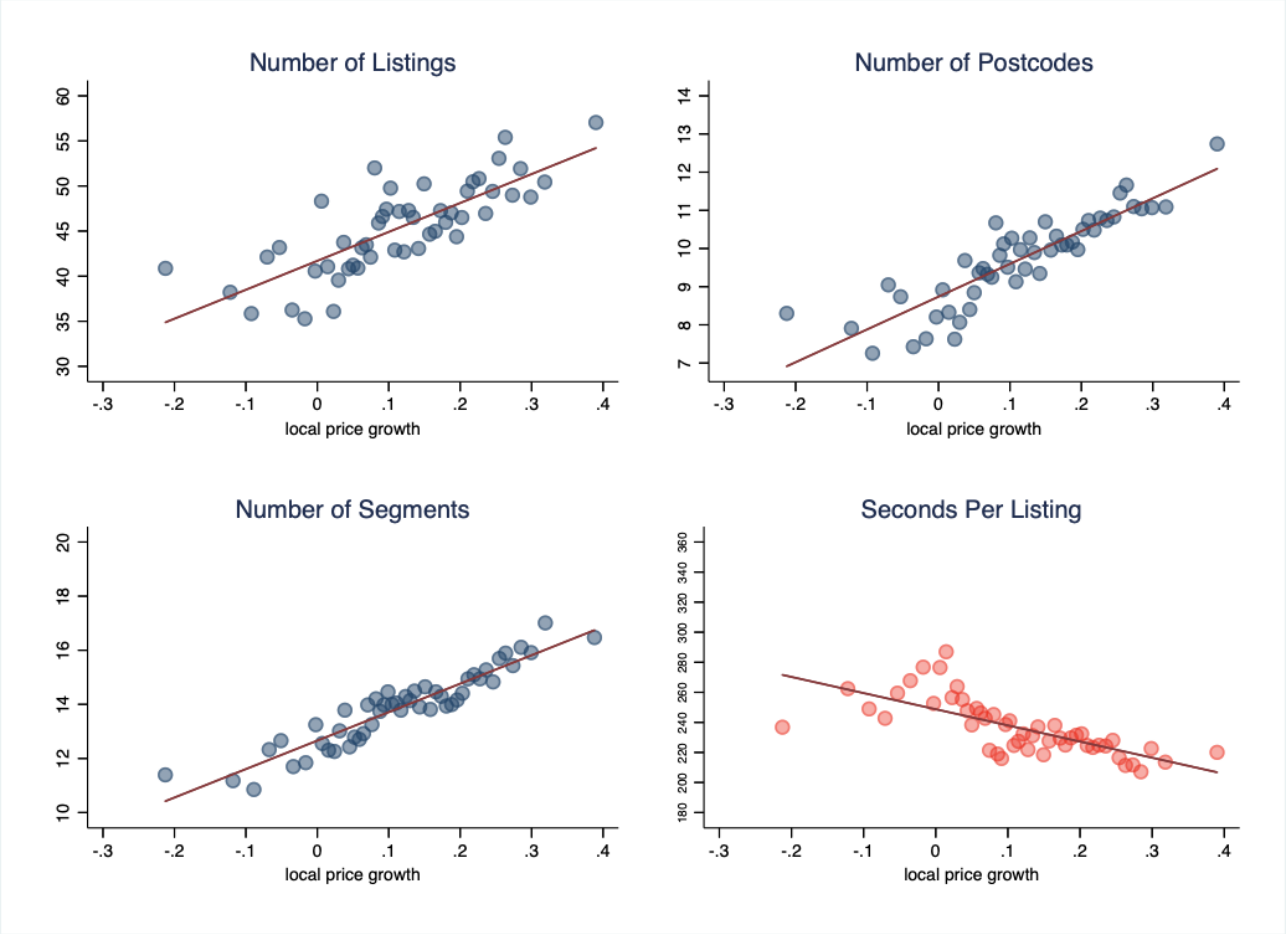


Figure 1: **Search Breadth, Attention Allocation and Local Price Growth.** This Figure displays binned scatter plots showing the relationship between users' monthly search behavior (y-axis) and 2-year price growth in their postcode of residence (x-axis). The y-axis displays either the number of listings browsed (top-left panel), the number of postcodes (top-right panel), the number of market segments (bottom-left panel), or the average number of seconds spent browsing each listing (bottom-right panel). See Section 2.1 for a detailed description of how these different measures are constructed.

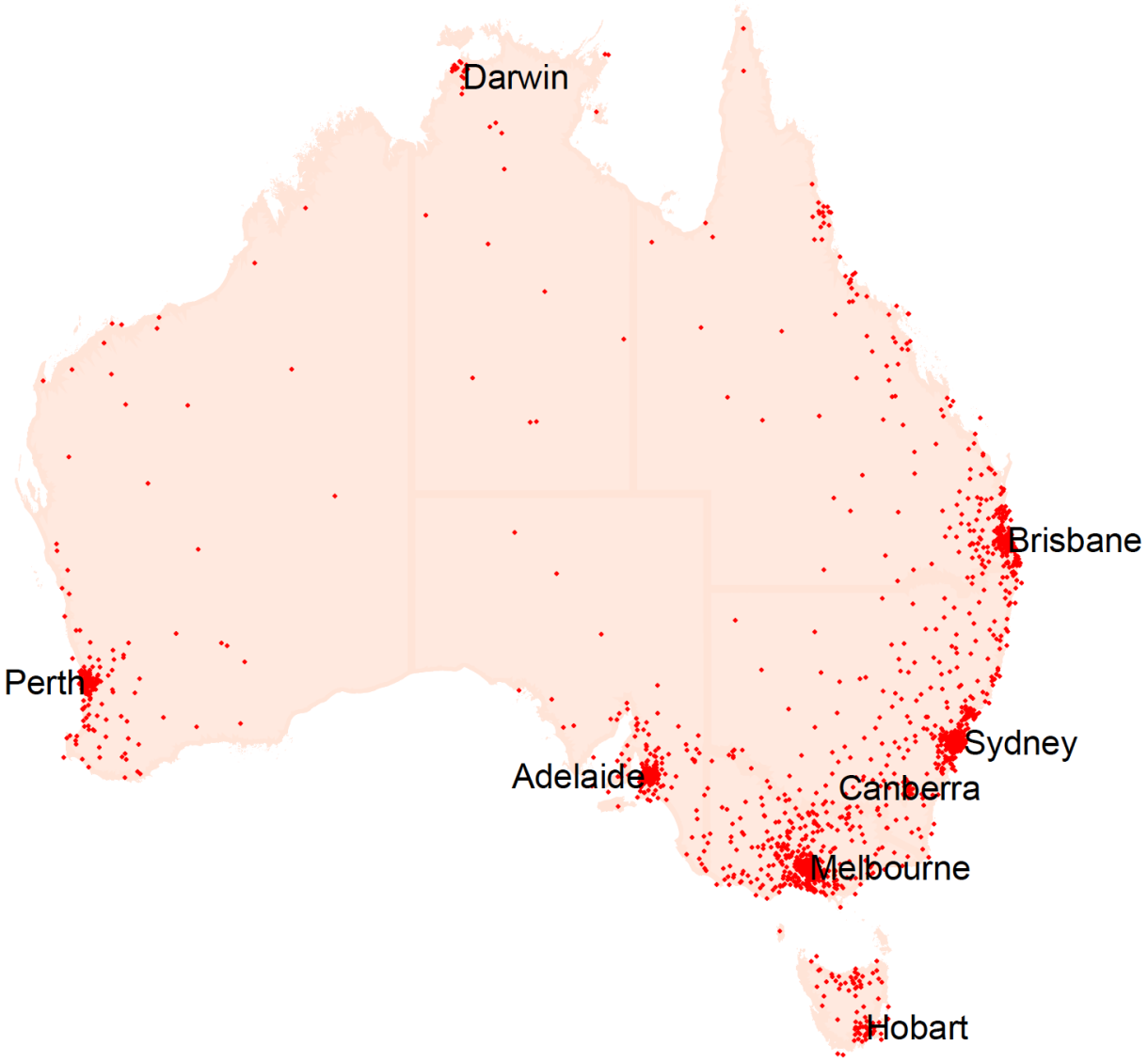


Figure 2: **Spatial Distribution of Users.** This Figure displays the spatial distribution of the users in our sample. Each dot denotes the centroid of a postcode where at least one user has her residence. The names of the state capital cities are also highlighted on the map: Adelaide (South Australia), Brisbane (Queensland), Canberra (Australian Capital Territory), Darwin (Northern Territories), Hobart (Tasmania), Melbourne (Victoria), Perth (Western Australia), and Sydney (New South Wales).

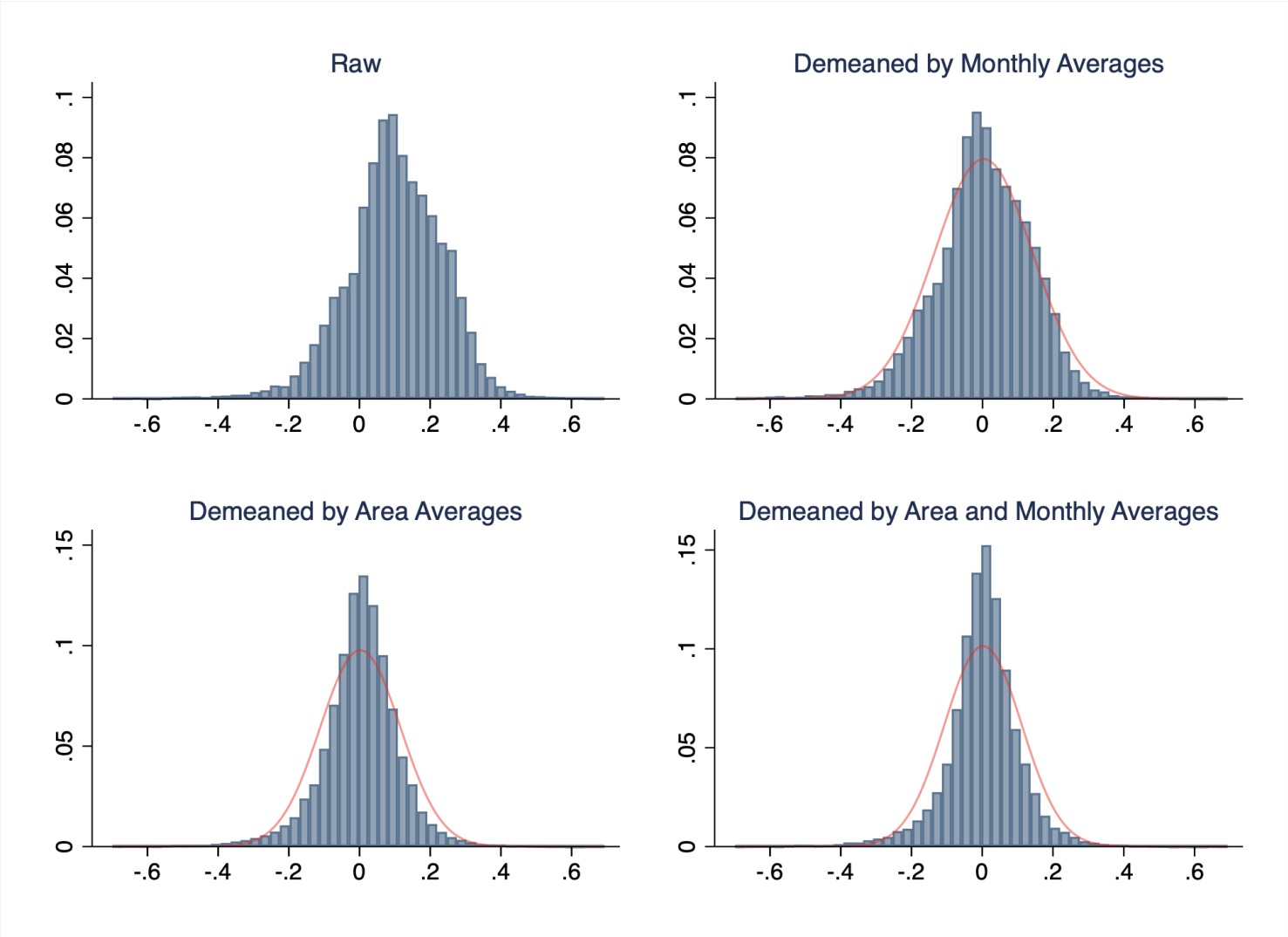


Figure 3: **Distribution of Postcode-Level Price Growth.** This Figure displays histograms of the pooled distribution of 2-year postcode-level price growth. The top-left plot displays raw growth rates. The remaining three plots display growth rates demeaned by monthly averages (top-right plot), metropolitan area averages (bottom-left plot) and month by metropolitan area averages (bottom-right plot).

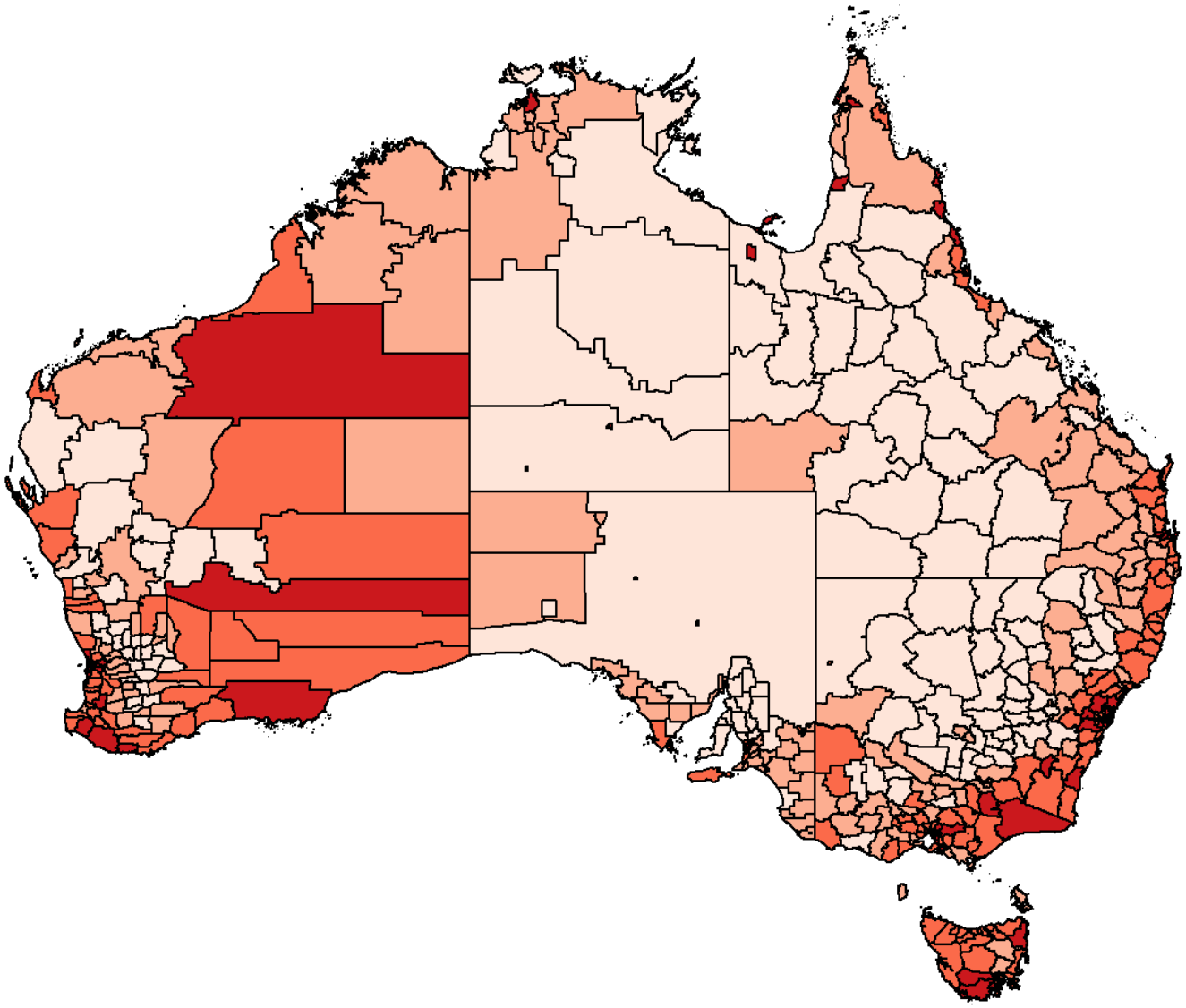


Figure 4: **Land Supply Elasticity.** This Figure provides a graphical representation of the land supply elasticity instrument described in Section 3.3. Each area corresponds to the land surface of a Local Government Area (LGA). Darker areas have a larger fraction of constrained land. The fraction of constrained land is above 73% in the areas with the darkest shade, while it is equal or smaller than 16% in the areas with the lightest shade.

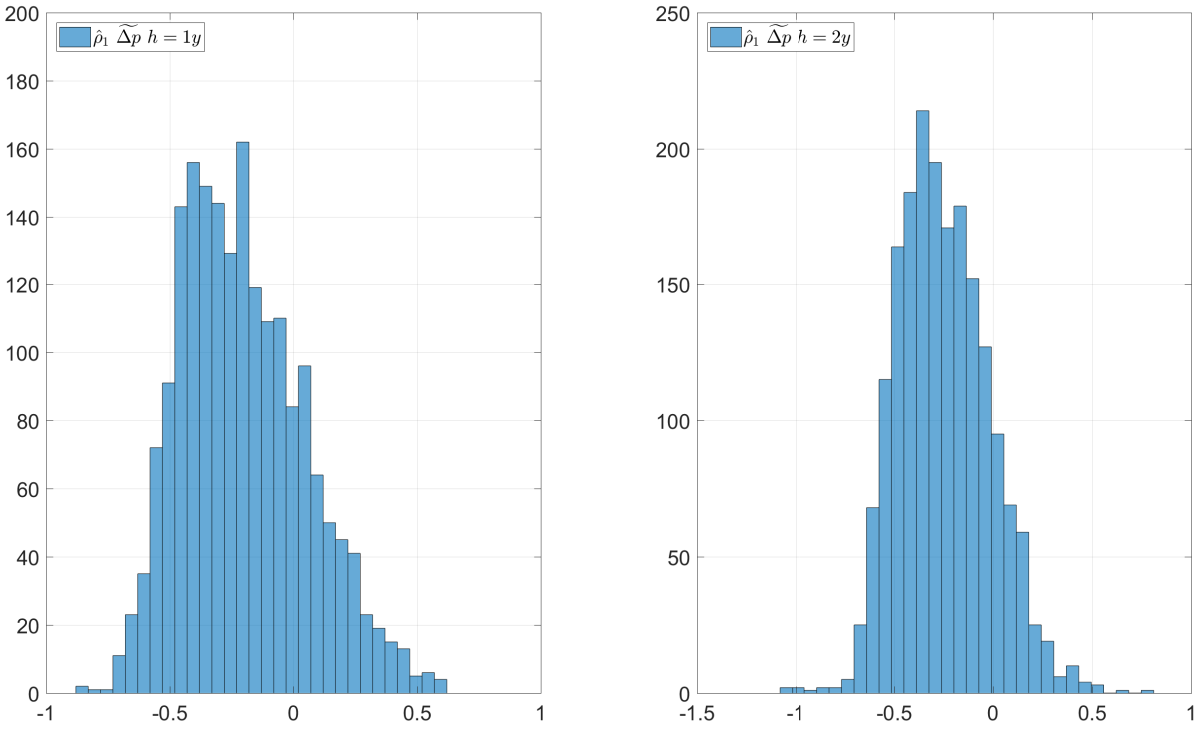


Figure 5: **Persistence of "Excess" Postcode-Level Growth Rates.** This Figure shows estimates of the persistence of postcode-level price growth in excess of metro-area average price growth (ρ_1 in Equation 10), over horizons of 1 year (left plot) and 2 years (right plot).

Table 1: **Summary Statistics**

	Panel A: Breadth of Consideration Sets						
	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
Listings	42.23	21.37	63.55	3.00	9.00	49.07	150.77
Postcodes	8.69	5.00	11.65	1.00	2.38	10.27	28.71
Segments	13.55	7.41	18.37	1.00	3.54	16.00	46.57

	Panel B: Listing-Level Attention						
	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
Visits	2.40	2.19	0.80	2.00	2.02	2.50	3.46
Minutes	3.93	2.93	5.11	0.81	1.83	4.66	9.85
Herfindahl	0.30	0.25	0.23	0.05	0.13	0.42	0.78

This Table presents cross-sectional summary statistics relative to breadth of consideration sets (Panel A) and attention per listing (Panel B). We first compute the average across monthly observations for each user, and then report the mean, median, standard deviation and percentiles (5th, 25th, 75th and 95th) of the resulting cross-sectional distributions. *Listings*, is the number of unique listings browsed, *Postcodes* is the number of unique postcodes in which the user visited at least one listing, *Segments* is the number of segments in which the user visited at least one listing (See section 2.1 for more details on how segments are constructed). *Visits* denotes the number of visits per listing, *Minutes* denotes the number of minutes per listing, and *Herfindahl*, is the Herfindahl index based on time spent across listings.

Table 2: **Allocation of Attention: Breadth of Consideration Sets**

	Panel A: Number of Listings			
Δp	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: Number of Postcodes			
Δp	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 C: Number of Segments			
Δp	0.399***	0.316**	0.357**	0.323**
	(3.14)	(2.33)	(2.68)	(2.35)
$R^2_{adjusted}$	0.155	0.154	0.517	0.518
Nobs	53764	53763	51442	51441
Postcode FE	Yes	Yes	No	No
User FE	No	No	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Year-Month× Area FE	No	Yes	No	Yes

This Table reports coefficient estimates and associated t-statistics (in parentheses) for the following panel regression:

$$y_{i,t} = \beta \Delta p_{post(i),t-1} + \alpha_* + \alpha_{t,*} + \epsilon_{i,t}$$

where $y_{i,t}$ is either equal to the log number of listings (Panel A), the log number of postcodes (Panel B), or the log number of segments (Panels C) browsed by user i in month t; α_* is either a postcode fixed effect or an individual user fixed effect; $\alpha_{t,*}$ is either a year-month or a year-month by area fixed effect; $\Delta p_{post(i),t-1}$ is the one-month lagged 2-year price growth in the postcode where user i has her residence. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 3: **Allocation of Attention: Listing-Level**

	Panel A: Minutes per Listing ($\overline{Minutes}$)			
Δp	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	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	-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
User FE	No	No	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Year-Month× Area FE	No	Yes	No	Yes

This Table reports coefficient estimates and associated t-statistics (in parentheses) for the following panel regression:

$$y_{i,t} = \beta \Delta p_{post(i),t-1} + \alpha_* + \alpha_{t,*} + \epsilon_{i,t}$$

where $y_{i,t}$ is either equal to the log number of minutes per listing (Panel A), the log number of visits per listing (Panel B) or the Herfindahl index based on minutes spent per listing (Panel C) for user i in month t; α_* is either a postcode fixed effect or an individual user fixed effect; $\alpha_{t,*}$ is either a year-month or a year-month by area fixed effect; $\Delta p_{post(i),t-1}$ is the one-month lagged 2-year price growth in the postcode where user i has her residence. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 4: **Allocation of Attention: Price Ranges**

	Panel A: Price Dispersion			
Δp	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	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	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	-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	-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
User FE	No	No	Yes	Yes
Year-Month FE	Yes	No	Yes	No
Year-Month× Area FE	No	Yes	No	Yes

This Table reports coefficient estimates and associated t-statistics (in parentheses) for the following panel regression:

$$y_{i,t} = \beta \Delta p_{post(i),t-1} + \alpha_* + \alpha_{t,*} + \epsilon_{i,t}$$

where $y_{i,t}$ is either equal to the standard deviation of log median prices across postcodes visited by user i in month t (Panel A), or the 90th, 75th, 25th and 10th percentile of the distribution of log prices (Panel B to Panel E); α_* is either a postcode fixed effect or an individual user fixed effect; $\alpha_{t,*}$ is either a year-month or a year-month by area fixed effect; $\Delta p_{post(i),t-1}$ is the one-month lagged 2-year price growth in the postcode where user i has her residence. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 5: **Allocation of Attention and Local Sales Information**

	Panel A: Breadth of Consideration Set					
	Listings	*Postcodes*	*Segments*	*Listings*	*Postcodes*	*Segments*
$\Delta p \times I^{info}$	0.191	0.332***	0.303**			
	(1.27)	(2.90)	(2.79)			
$\bar{p} \times I^{info}$				0.018***	0.016***	0.015***
				(2.84)	(3.39)	(3.54)
Δp	0.360**	0.320**	0.303**	0.380**	0.353**	0.334**
	(2.25)	(2.24)	(2.22)	(2.38)	(2.49)	(2.48)
I^{info}	0.577***	0.289***	0.318***	0.367***	0.120*	0.163***
	(22.37)	(12.96)	(16.04)	(4.37)	(1.87)	(2.83)
$R^2_{adjusted}$	0.410	0.521	0.528	0.491	0.521	0.528
Nobs	52935	52942	51441	52935	52942	51441
	Panel B: Listing-Level Attention					
	$\overline{Minutes}$	$\overline{Visits}$	*Herfindahl*	$\overline{Minutes}$	$\overline{Visits}$	*Herfindahl*
$\Delta p \times I^{info}$	-0.109	-0.007	0.001			
	(-1.34)	(-0.28)	(0.04)			
$\bar{p} \times I^{info}$				0.001	-0.000	-0.001
				(0.41)	(-0.25)	(-1.20)
Δp	0.036	-0.032	-0.050.	0.025	-0.033	-0.050
	(0.29)	(-0.95)	(-1.42)	(0.20)	(-0.98)	(-1.42)
I^{info}	0.086***	0.015***	-0.094***	0.053	0.018	-0.080***
	(6.01)	(3.06)	(-17.98)	(1.14)	(1.13)	(-6.65)
$R^2_{adjusted}$	0.338	0.465	0.273	0.338	0.465	0.273
Nobs	52935	52942	52935	52935	52942	52935

This Table reports coefficient estimates and associated t-statistics (in parentheses) for the following panel regressions:

$$y_{i,t} = \beta_{info}\left(\Delta p_{post(i),t-1} \times I^{info}_{i,t}\right) + \beta \Delta p_{post(i),t-1} + \delta I^{info}_{i,t} + \alpha_i + \alpha_{t\times area} + u_{i,t}$$
$$y_{i,t} = \gamma_{info}\left(\bar{p}^{info}_{i,t} \times I^{info}_{i,t}\right) + \beta \Delta p_{post(i),t-1} + \delta I^{info}_{i,t} + \alpha_i + \alpha_{t\times area} + v_{i,t}$$

where $y_{i,t}$ is either the log number of listings, the log number of postcodes, or the log number of segments visited (Panel A) or the log of the average time per listing, the log of the average number of visits, or the Herfindahl index of time concentration across listings (Panel B) for user i in month t; α_i is an individual user fixed effect; $\alpha_{area\times t}$ is an area by year-month fixed effect; $\Delta p_{post(i),t-1}$ is the one-month lagged 2-year price growth in the postcode where user i has her residence, $I^{info}_{i,t}$ is a dummy variable equal to 1 if user i browses in month t at least one recently sold listing located in the postcode where she lives and $\bar{p}^{info}$ is the log of the average sales prices across the sold listings browsed in the postcode where the user lives. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 6: **2SLS Estimates with Supply Elasticity Instrument**

	Panel A: Breadth of Consideration Set					
	Listings		*Postcodes*		*Segments*	
Δp	1.581***	1.911***	1.453***	1.457***	1.247***	1.429***
	(3.95)	(4.02)	(4.30)	(4.04)	(3.73)	(4.10)
F_{robust} (1st Stage)	46.05	42.88	46.05	42.88	44.07	41.53
Nobs	55241	52943	55241	52943	53764	51442
	Panel B: Listing-Level Attention					
	$\overline{Minutes}$		$\overline{Visits}$		$Herfindahl$	
Δp	-0.023	-0.171	-0.238**	-0.205*	-0.195**	-0.189
	(-0.07)	(-0.40)	(-2.35)	(-1.91)	(-2.39)	(-1.68)
F_{robust} (1st Stage)	46.05	42.88	46.05	42.88	46.05	42.88
Nobs	55241	52943	55241	52943	55241	52943
Postcode FE	Yes	No	Yes	No	Yes	No
User FE	No	Yes	No	Yes	No	Yes
Year-Month	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports coefficient estimates and associated t-statistics (in parentheses) for the following panel regression:

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

where $y_{i,t}$ is either the log number of listings, the log number of postcodes, or the log number of segments visited (Panel A) or the log of the average time per listing, the log of the average number of visits, or the Herfindahl index of time concentration across listings (Panel B) 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 the one-month lagged 2-year price growth in the postcode where user i has her residence, instrumented with local land supply elasticity, as explained in section 3.3. 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 7: **Breadth of Consideration Sets and Users' Characteristics**

	Panel A: Homeownership		
	Listings	*Postcodes*	*Segments*
$\Delta p \times \mathbb{1}_{own}$	0.505**	0.319*	0.379**
	(2.77)	(2.02)	(2.55)
$\Delta p \times \mathbb{1}_{no\ own}$	0.201	0.242	0.211
	(0.96)	(1.34)	(1.24)
$\mathbb{1}_{no\ own}$	0.263***	0.193***	0.172***
	(6.50)	(5.71)	(5.46)
$R^2_{adjusted}$	0.134	0.161	0.157
$Nobs$	55231	55240	53763

	Panel B: Price Levels (Homeowners)		
	Listings	*Postcodes*	*Segments*
$\Delta p \times \mathbb{1}_{\bar{p}_{post} \leq \bar{p}^{med}_{area}}$	0.956***	0.656***	0.644***
	(3.53)	(2.90)	(2.98)
$\Delta p \times \mathbb{1}_{\bar{p}_{post} > \bar{p}^{med}_{area}}$	0.069	-0.030	0.096
	(0.25)	(-0.71)	(0.40)
$R^2_{adjusted}$	0.167	0.188	0.189
$Nobs$	35927	35934	35232

	Panel C: Owner Occupied (Homeowners)		
	Listings	*Postcodes*	*Segments*
$\Delta p \times \mathbb{1}_{Occupy}$	0.562**	0.309	0.397**
	(2.55)	(1.70)	(2.36)
$\Delta p \times \mathbb{1}_{Invest}$	0.161	0.217	0.188
	(0.43)	(0.69)	(0.63)
$\mathbb{1}_{Invest}$	-0.131*	-0.082	-0.042
	(-1.76)	(-1.47)	(-0.77)
$R^2_{adjusted}$	0.174	0.197	0.198
$Nobs$	33612	33619	32962

	Panel D: Age (Homeowners)		
	Listings	*Postcodes*	*Segments*
$\Delta p \times \mathbb{1}_{Age<65}$	0.503**	0.370*	0.409**
	(2.31)	(2.01)	(2.40)
$\Delta p \times \mathbb{1}_{Age\geq 65}$	0.199	-0.023	0.084
	(0.46)	(-0.06)	(0.24)
$\mathbb{1}_{Age\geq 65}$	-0.199**	-0.133*	-0.116*
	(-2.18)	(-1.74)	(-1.74)
$R^2_{adjusted}$	0.173	0.197	0.198
$Nobs$	32756	32763	32118

This Table reports coefficient estimates and associated t-statistics for the following panel regression:

$$y_{i,t} = \delta_{char}\left(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,char}\right) + \delta_{notchar}\left(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,notchar}\right) + \kappa \mathbb{1}_{i,notchar} + \alpha_{post(i)} + \alpha_{t\times area} + \epsilon_{i,t}$$

where $y_{i,t}$ is either the log number of listings, the log number of postcodes, or the log number of segments visited by user i in month t; $\alpha_{post(i)}$ is a postcode fixed effect; $\alpha_{area\times t}$ is an area by year-month fixed effect; $\Delta p_{post(i),t-1}$ is the one-month lagged 2-year price growth in the postcode where user i has her residence, $\mathbb{1}_{i,char}$ is a dummy equal to one if the user is a homeowner (Panel A), lives in a postcode with average house price below the median across postcodes in the metropolitan area (Panel B), is looking for a house to occupy as a primary residence (Panel C), or is younger than 65 (Panel D) and $\mathbb{1}_{i,notchar}$ is a dummy equal to one for users with the complementary characteristic (renters, living in postcodes with prices above median, looking for investment properties or second homes, with age greater or equal than 65). In panels B to D the sample is restricted to homeowners only. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 8: **Real Effects on Sales Prices**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δp_l	0.393***	0.359***						
	(3.98)	(5.43)						
$log\widehat{Listings}$			0.316***	0.278***				
			(3.22)	(3.93)				
$log\widehat{Postcodes}$					0.413***	0.369***		
					(3.07)	(3.72)		
$log\widehat{Segments}$							0.397***	0.345***
							(3.07)	(3.82)
I_{unit}		-0.112***		-0.063***		-0.080***		-0.087***
		(-12.70)		(-3.64)		(-5.48)		(-6.65)
I_{1bed}		-0.279***		-0.276***		-0.292***		-0.278***
		(-19.36)		(-15.57)		(-15.37)		(-15.37)
I_{3beds}		0.100***		0.092***		0.118***		0.116***
		(29.23)		(17.45)		(18.25)		(18.81)
$I_{\geq 4beds}$		0.212***		0.198***		0.227***		0.240***
		(55.88)		(26.52)		(31.53)		(26.27)
I_{1bath}		-0.159***		-0.160***		-0.163***		-0.167***
		(-38.23)		(-35.08)		(-32.27)		(-31.07)
$I_{\geq 3baths}$		0.221***		0.211***		0.196***		0.202***
		(45.15)		(33.42)		(22.27)		(26.39)
I_{1park}		0.031***		0.037***		0.044***		0.041***
		(6.99)		(6.14)		(6.58)		(6.59)
I_{2park}		0.088***		0.091***		0.106***		0.104***
		(18.38)		(15.13)		(13.88)		(14.70)
I_{3park}		0.137***		0.141***		0.149***		0.149***
		(27.23)		(24.49)		(21.24)		(22.53)
$log(size)$		0.136***		0.140***		0.126***		0.131***
		(50.72)		(44.65)		(31.96)		(40.82)
$R^2_{adjusted}$	0.534	0.796	-	-	-	-	-	-
$Nobs$	378318	244440	378318	244440	378318	244440	378229	244392

This Table reports coefficient estimates and associated t-statistics (in parentheses) for the following panel regressions:

$$p_l^{sale} = \beta \Delta p_l + \mathcal{B} X_l + \alpha_{post(l)} + \alpha_{t \times area} + u_l \quad \textit{Columns 1 to 2}$$
$$p_l^{sale} = \gamma \widehat{y}_l + \mathcal{B} X_l + \alpha_{post(l)} + \alpha_{t \times area} + e_l \quad \textit{Columns 3 to 8}$$

where p_l^{sale} is the log of the sales price for listing l; Δp_l is the price growth experienced by users expected to visit listing l; $\widehat{y}_l$ is the part of the log average number of browsed listings, the log average number of browsed postcodes, the log average number of browsed segments, across users who visited listing l, which is explained by experienced price growth; X_l is a vector of property characteristics; $\alpha_{post(l)}$ 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. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table 9: **Real Effects on Sales Prices and Postcode-Level Attention**

	(1)	(2)	(3)	(4)	(5)	(6)
$log\widehat{Postcodes}$	1.565***	2.037***	1.596***	0.292***	0.531***	0.356***
	(9.82)	(9.95)	(10.84)	(4.39)	(5.26)	(6.19)
$log\widehat{Postcodes} \times Att(Visits)$	-0.079***			-0.003		
	(-6.37)			(-0.61)		
$Att(Visits)$	0.285***					
	(7.26)					
$log\widehat{Postcodes} \times Att(Listings)$		-0.470***			-0.127***	
		(-6.79)			(-3.52)	
$Att(Listings)$		1.678***				
		(7.88)				
$log\widehat{Postcodes} \times Att(Users)$			-0.471***			-0.093***
			(-9.09)			(-4.57)
$Att(Users)$			1.618***			
			(9.72)			
I_{unit}	0.022	0.041**	0.041**	-0.097***	-0.097***	-0.097***
	(1.37)	(2.47)	(2.66)	(-10.49)	(-10.58)	(-10.51)
I_{1bed}	-0.310***	-0.315***	-0.325***	-0.297***	-0.296***	-0.294***
	(-15.62)	(-15.03)	(-15.97)	(-20.59)	(-20.52)	(-20.40)
I_{3beds}	0.137***	0.146***	0.147***	0.117***	0.115***	0.115***
	(11.85)	(11.73)	(11.86)	(26.11)	(25.68)	(25.53)
$I_{\geq 4beds}$	0.256***	0.271***	0.265***	0.229***	0.227***	0.227***
	(20.72)	(20.87)	(20.49)	(49.01)	(48.31)	(48.26)
I_{1bath}	-0.248***	-0.264***	-0.272***	-0.163***	-0.163***	-0.164***
	(-28.69)	(-28.51)	(-30.20)	(-38.08)	(-37.96)	(-38.21)
$I_{\geq 3baths}$	0.285***	0.280***	0.294***	0.198***	0.200***	0.199***
	(18.99)	(17.97)	(18.32)	(31.86)	(31.98)	(31.70)
I_{1park}	0.080***	0.088***	0.096***	0.053***	0.052***	0.051***
	(4.88)	(4.90)	(5.72)	(8.75)	(8.44)	(8.18)
I_{2park}	0.161***	0.171***	0.182***	0.115***	0.113***	0.112***
	(8.72)	(8.52)	(9.56)	(16.71)	(16.36)	(15.99)
I_{3park}	0.182***	0.180***	0.184***	0.159***	0.157***	0.156***
	(10.87)	(9.93)	(10.66)	(24.81)	(24.46)	(23.85)
$log(size)$	0.001	-0.003	-0.012	0.123***	0.124***	0.125***
	(0.17)	(-0.30)	(-1.42)	(33.86)	(34.06)	(33.68)
$R^2_{adjusted}$	0.553	0.529	0.518	0.795	0.795	0.795
$Nobs$	243181	243181	243181	243124	243124	243124

This Table reports coefficient estimates and associated t-statistics (in parentheses) for the following panel regressions:

$$p_l^{sale} = \theta\left(\widehat{y}_l \times Att(Meas)_{post(l)}\right) + \gamma\widehat{y}_l + \mathcal{B}X_l + \kappa Att(Meas)_{post(l)} + \alpha_{t\times area} + \epsilon_l \qquad Columns\ 1\ to\ 3$$

$$p_l^{sale} = \theta\left(\widehat{y}_l \times Att(Meas)_{post(l)}\right) + \gamma\widehat{y}_l + \mathcal{B}X_l + \alpha_{post(l)} + \alpha_{t\times area} + e_l \qquad Columns\ 4\ to\ 6$$

where p_l^{sale} is the log of the sales price for listing l; $\widehat{y}_l$ is the part of the log average number of browsed postcodes, across users who visited listing l, which is explained by experienced price growth (calculated as described in Section 5.1); X_l is a vector of property characteristics; $\alpha_{post(l)}$ 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. $Att(Meas)_{post(l)}$ is overall attention to the postcode where listing l is located, measured as the sample average of the monthly number of visits, the number of listings visited, and the number of users visiting listings, over the monthly average of the number of new listings from the postcode published on realestate.com.au. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Internet Appendix to

Local Experiences, Attention and Spillovers in the Housing Market

Table A.1: **Summary Statistics**

	Panel A: Demographic Characteristics						
	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
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: 65 or older	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						
	Mean	Median	St.Dev.	pc5	pc25	pc75	pc95
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 the users in our dataset (Panel A), and of the characteristics of listings visited by the users over the period from January 2017 through April 2019 (Panel B).

Table A.2: **Supply Elasticity: First Stage IV**

	(1)	(2)
$\mathbb{1}_{\Delta p_{area(i),t-1}>0} \times \Lambda_{post(i)}$	0.090***	0.090***
	(34.68)	(6.55)
Postcode FE	Yes	Yes
Year-Month FE	Yes	Yes
Clustering	None	$post, year-month$
$R^2_{adjusted}$	0.859	0.859
Nobs	52943	52943

This Table displays estimates from the following panel regression:

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

where $\Delta p_{post(i),t-1}$ is one-month lagged 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 described in Section 3.3. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table A.3: **Composition of Users**

	Number of Users			
	All	Homeowner	Owner Occupied (Homeowner)	Younger than 65 (Homeowner)
Δp	0.0590	0.0892	0.0521	0.0714
	(1.17)	(1.43)	(0.85)	(1.11)
$R^2_{adjusted}$	0.656	0.634	0.630	0.620
Nobs	23348	23348	23348	23348

This Table reports coefficient estimates and associated t-statistics (in parentheses) for the following panel regression:

$$ln(1 + y_{j,t}) = \beta \Delta p_{j,t-1} + \alpha_j + \alpha_{t \times area} + \epsilon_{j,t}$$

where $y_{i,t}$ is either the number of users (first column), the number of homeowners (second column), the number of homeowners looking for a house to occupy as a primary residence (third column), the number of homeowners younger than 65 (fourth column) residing in postcode j and browsing listings in month t; α_i is a postcode fixed-effect; $\alpha_{area \times t}$ is an area by year-month fixed effect; $\Delta p_{j,t-1}$ is the one-month lagged 2-year house price growth in postcode j. Standard errors are double-clustered by postcode and time. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table A.4: **Attention Allocation and Users' Characteristics**

Panel A: Homeownership

	$\overline{Minutes}$	$\overline{Visits}$	$Herfindahl$
$\Delta p \times \mathbb{1}_{own}$	0.105	0.038	-0.067*
	(0.85)	(1.03)	(-1.73)
$\Delta p \times \mathbb{1}_{no\ own}$	-0.134	-0.080	-0.021
	(-0.86)	(-1.61)	(-0.51)
$\mathbb{1}_{no\ own}$	0.012	0.048***	-0.032***
	(0.35)	(4.55)	(-4.58)
$R^2_{adjusted}$	0.095	0.156	0.065
$Nobs$	55231	55231	55231

Panel B: Price Levels (Homeowners)

	$\overline{Minutes}$	$\overline{Visits}$	$Herfindahl$
$\Delta p \times \mathbb{1}_{\bar{p}_{post} \leq \bar{p}^{med}_{area}}$	0.337	0.038	-0.118**
	(1.54)	(0.65)	(-2.27)
$\Delta p \times \mathbb{1}_{\bar{p}_{post} > \bar{p}^{med}_{area}}$	-0.007	-0.056	-0.002
	(-0.04)	(-1.39)	(-0.03)
$R^2_{adjusted}$	0.103	0.156	0.083
$Nobs$	35927	35927	35927

Panel C: Owner Occupied (Homeowners)

	$\overline{Minutes}$	$\overline{Visits}$	$Herfindahl$
$\Delta p \times \mathbb{1}_{Occupy}$	0.199	-0.038	-0.074
	(1.20)	(-0.98)	(-1.60)
$\Delta p \times \mathbb{1}_{Invest}$	0.088	0.045	0.031
	(0.39)	(0.87)	(0.42)
$\mathbb{1}_{Invest}$	-0.164***	-0.064***	0.021
	(-3.63)	(-5.94)	(1.61)
$R^2_{adjusted}$	0.107	0.169	0.086
$Nobs$	33612	33612	33612

Panel D: Age (Homeowners)

	$\overline{Minutes}$	$\overline{Visits}$	$Herfindahl$
$\Delta p \times \mathbb{1}_{Age<65}$	-0.014	0.198	-0.043
	(-0.39)	(1.28)	(-0.95)
$\Delta p \times \mathbb{1}_{Age\geq 65}$	-0.129	-0.011	-0.047
	(-1.65)	(-0.03)	(-0.57)
$\mathbb{1}_{Age\geq 65}$	0.054***	0.377***	0.031*
	(3.70)	(7.12)	(2.04)
$R^2_{adjusted}$	0.168	0.113	0.085
$Nobs$	32756	32756	32756

This Table displays estimates from the following panel regression:

$$y_{i,t} = \delta_{char}\left(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,char}\right) + \delta_{notchar}\left(\Delta p_{post(i),t-1} \times \mathbb{1}_{i,notchar}\right) + \kappa \mathbb{1}_{i,notchar} + \alpha_{post(i)} + \alpha_{t,area} + \epsilon_{i,t}$$

where $y_{i,t}$ is either the log average time per listing, the log average number of visits per listing, or the Herfindahl index for time allocation across listings for user i in month t; $\alpha_{post(i)}$ is a postcode fixed effect; $\alpha_{area,t}$ is a area by year-month fixed effect; $\Delta p_{post(i),t-1}$ is the one-month lagged house price growth in the postcode where user i is currently living computed over the previous two years, $\mathbb{1}_{i,char}$ is a dummy equal to one if the user is a homeowner (Panel A), lives in a postcode with average house price below the median across postcodes in the metropolitan area (Panel B), is looking for a house to occupy as a primary residence (Panel C) or is younger than 65 (Panel D) and $\mathbb{1}_{i,notchar}$ is a dummy equal to one for uses with the complementary characteristic (renters, living in postcodes with prices above median, looking for an investment property or a second home, with age greater or equal than 65). In panels B to D the sample is restricted to homeowners only. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table A.5: **Listing-Level Effect of Price Growth on Search Breadth**

	$Listings_l$		$NumPost_l$		$NumSeg_l$	
Δp_l	1.346***	1.334***	1.011***	1.010***	1.077***	1.072***
	(5.51)	(5.49)	(5.05)	(5.04)	(5.18)	(5.16)
p_l^{list}		0.035***		-0.008		0.009
		(3.49)		(-0.74)		(0.85)
I_{unit}	-0.173***	-0.169***	-0.082***	-0.082***	-0.070***	-0.069***
	(-7.96)	(-7.67)	(-4.39)	(-4.37)	(-3.97)	(-3.86)
I_{1bed}	-0.015	-0.006	0.034	0.031	-0.004	-0.003
	(-0.48)	(-0.19)	(1.27)	(1.17)	(-0.16)	(-0.09)
I_{3beds}	0.032**	0.028**	-0.045***	-0.044***	-0.045***	-0.046***
	(2.64)	(2.31)	(-4.28)	(-4.09)	(-4.33)	(-4.32)
$I_{\geq 4beds}$	0.052***	0.044***	-0.038***	-0.036***	-0.079***	-0.081***
	(3.23)	(2.77)	(-3.02)	(-2.87)	(-6.17)	(-6.32)
I_{1bath}	0.004	0.010	0.012	0.011	0.023***	0.025***
	(0.46)	(1.12)	(1.48)	(1.40)	(2.78)	(3.11)
I_{3beds}	0.034***	0.026***	0.065***	0.067***	0.052***	0.050***
	(3.74)	(2.75)	(7.78)	(7.34)	(6.38)	(5.63)
I_{1park}	-0.022*	-0.024*	-0.038***	-0.038***	-0.032***	-0.033***
	(-1.83)	(-1.93)	(-3.95)	(-3.88)	(-3.27)	(-3.27)
$I_{2park}2$	-0.016	-0.019*	-0.051***	-0.050***	-0.048***	-0.049***
	(-1.44)	(-1.72)	(-5.29)	(-5.17)	(-5.13)	(-5.19)
I_{3park}	-0.016	-0.022*	-0.034***	-0.033***	-0.036***	-0.038***
	(-1.40)	(-1.80)	(-3.50)	(-3.39)	(-3.68)	(-3.81)
$log(size)$	-0.013***	-0.018***	0.027***	0.028***	0.015***	0.014***
	(-3.55)	(-4.98)	(6.37)	(6.80)	(3.77)	(3.56)
$R^2_{adjusted}$	0.147	0.147	0.171	0.171	0.175	0.175
$Nobs$	250832	250735	250832	250735	250781	250685

This Table displays estimates from the following regression:

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

where y_l is either the log average number of browsed listings, the log average number of browsed postcodes, or the log average number of browsed segments across users who visited listing l; Δp_l is price growth experienced by users expected to visit listing l; p_l^{list} is the log of the last asking listed price available for each listing, X_l is a vector of property characteristics; $\alpha_{post(l)}$ 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. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table A.6: **Real Effects on Sales Prices**

	(1)	(2)	(3)	(4)
Δp_l	0.135***			
	(3.38)			
$log\widehat{Listings}$		0.105**		
		(2.70)		
$log\widehat{NumPost}$			0.139**	
			(2.63)	
$log\widehat{NumSeg}$				0.131**
				(2.66)
p_l^{list}	0.711***	0.707***	0.712***	0.710***
	(16.56)	(16.20)	(16.71)	(16.47)
I_{unit}	-0.035***	-0.017**	-0.023***	-0.026***
	(-5.31)	(-2.40)	(-3.55)	(-4.14)
I_{1bed}	-0.082***	-0.082***	-0.086***	-0.082***
	(-5.94)	(-5.65)	(-5.46)	(-5.57)
I_{3beds}	0.028***	0.025***	0.034***	0.034***
	(5.53)	(5.46)	(5.16)	(5.12)
$I_{\geq 4beds}$	0.060***	0.055***	0.065***	0.071***
	(6.00)	(6.31)	(5.90)	(5.62)
I_{1bath}	-0.045***	-0.046***	-0.047***	-0.048***
	(-6.94)	(-6.69)	(-6.50)	(-6.35)
$I_{\geq 3baths}$	0.061***	0.058***	0.052***	0.054***
	(6.36)	(6.43)	(6.67)	(6.56)
I_{1park}	0.010***	0.012***	0.015***	0.014***
	(3.80)	(3.71)	(3.81)	(3.79)
I_{2park}	0.027***	0.029***	0.034***	0.033***
	(6.17)	(5.82)	(5.28)	(5.41)
I_{3park}	0.041***	0.043***	0.045***	0.045***
	(7.03)	(6.74)	(6.50)	(6.47)
$log(size)$	0.039***	0.041***	0.035***	0.038***
	(6.18)	(5.96)	(6.19)	(6.16)
$R^2_{adjusted}$	0.922	0.716	0.687	0.698
$Nobs$	244353	244353	244353	244306

This Table displays estimates from the following regressions:

$$p_l^{sale} = \beta \Delta p_l + \delta p_l^{list} + \mathcal{B} X_l + \alpha_{post(l)} + \alpha_{t \times area} + u_l \quad Column\ 1$$
$$p_l^{sale} = \gamma \widehat{y}_l + \delta p_l^{list} + \mathcal{B} X_l + \alpha_{post(l)} + \alpha_{t \times area} + e_l \quad Columns\ 2\ to\ 4$$

where p_l^{sale} is the log of the sales price for listing l; Δp_l is price growth experienced by users expected to visit listing l; p_l^{list} is the log of the last asking listed price available for each listing; X_l is a vector of property characteristics; $\alpha_{post(l)}$ 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; $\widehat{y}_l$ is the part of the log average number browsed of listings, the log average number of browsed postcodes, the log average number of browsed segments, across users who visited listing l, which is explained by experienced price growth. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

Table A.7: **Real Effects on Sales Prices: Heterogeneity**

	p_l^{sale}	p_l^{sale}	p_l^{sale}	p_l^{sale}
$\Delta p_l \times \mathbb{1}_{Q1}^{comp}$	0.515***	0.185***		
	(7.79)	(4.55)		
$\Delta p_l \times \mathbb{1}_{Q2}^{comp}$	0.381***	0.143***		
	(5.75)	(3.55)		
$\Delta p_l \times \mathbb{1}_{Q3}^{comp}$	0.318***	0.124***		
	(4.61)	(2.99)		
$\Delta p_l \times \mathbb{1}_{Q4}^{comp}$	0.244***	0.093**		
	(3.49)	(2.34)		
$\Delta p_l \times \mathbb{1}_{Q1}^{gap}$			0.371***	0.062
			(2.99)	(1.15)
$\Delta p_l \times \mathbb{1}_{Q2}^{gap}$			0.179	0.016
			(1.51)	(0.35)
$\Delta p_l \times \mathbb{1}_{Q3}^{gap}$			0.403***	0.158***
			(4.84)	(2.79)
$\Delta p_l \times \mathbb{1}_{Q4}^{gap}$			0.510***	0.331***
			(4.55)	(3.43)
p_l^{list}		0.710***		0.711***
		(16.52)		(16.53)
$R^2_{adjusted}$	0.795	0.921	0.795	0.921
$Nobs$	243124	243037	243124	243037

This Table displays estimates from the following regressions:

$$p_l^{sale} = \sum_{k=1}^{4} \beta_k \left(\Delta p_l \times \mathbb{1}_{Qk,post(l)}\right) + \delta p_l^{list} + \mathcal{B} X_l + \alpha_{post(l)} + \alpha_{t\times area} + u_l$$

where p_l^{sale} is the log of the sales price for listing l; Δp_l is price growth experienced by users expected to visit listing l; $\mathbb{1}_{Qk,post(l)}$ is a dummy equal to one if the postcode in which the listing is located is in the kth quartile of the distribution of either the measure of competition, or of the measure of price gap discussed in Section 5.3; p_l^{list} is the log of the latest asking listed price available for each listing; X_l is a vector of property characteristics; $\alpha_{post(l)}$ 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. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level.

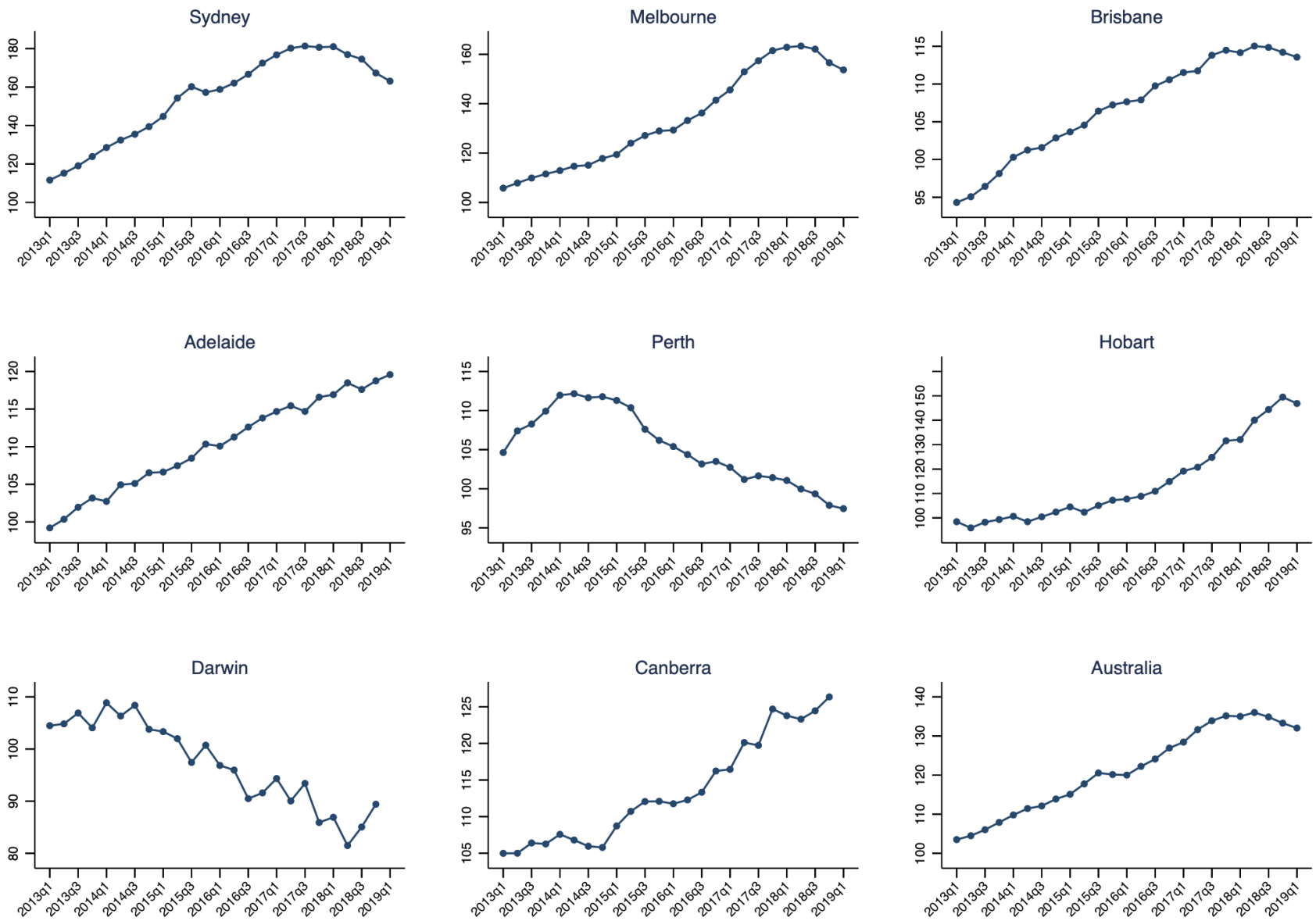
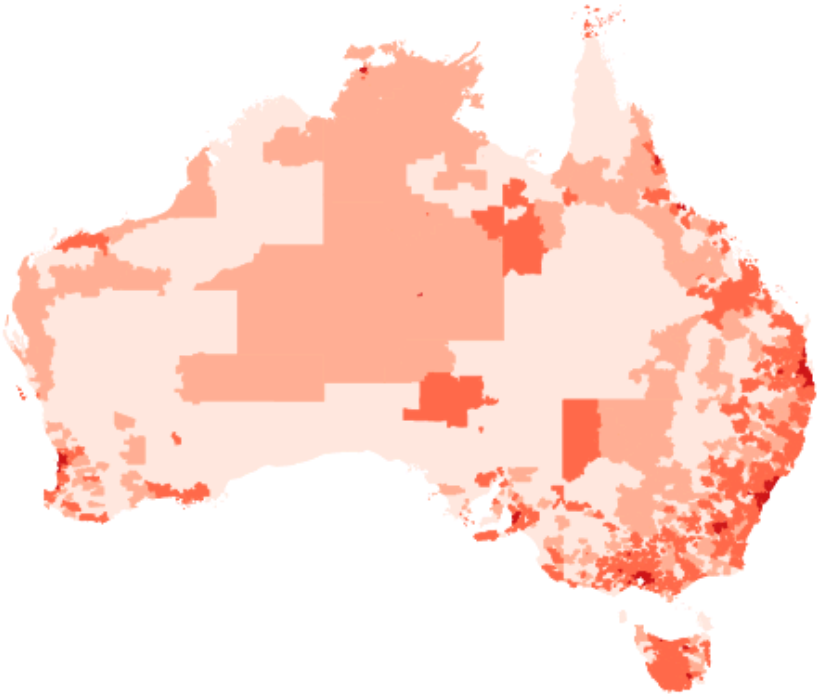
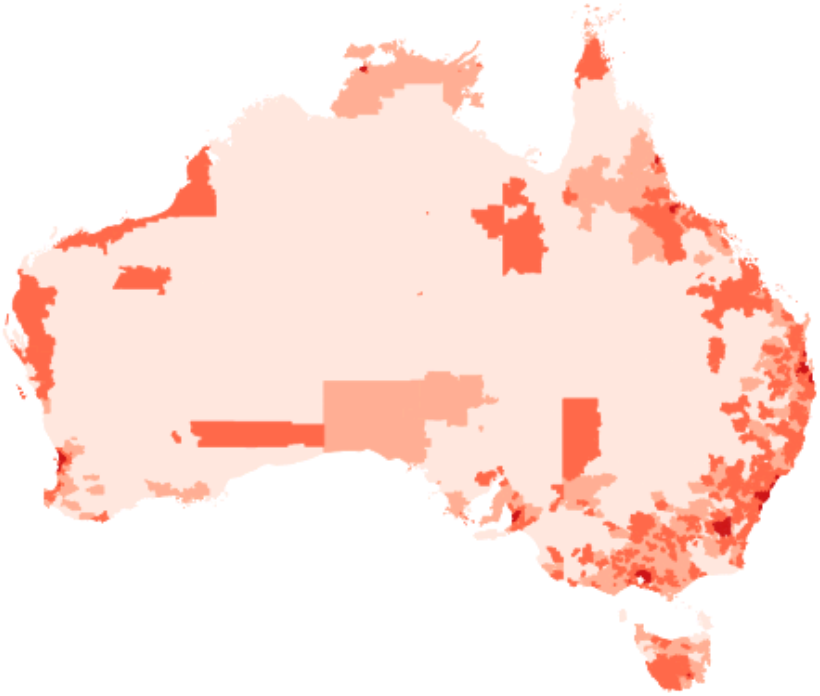


Figure A.1: **House Prices in Australian State Capital Cities.** This Figure displays the quarterly Corelogic repeat sales price index for the eight state capital cities (Sydney, Melbourne, Brisbane, Adelaide, Perth, Hobart, Darwin and Canberra) and for Australia (bottom-right plot).

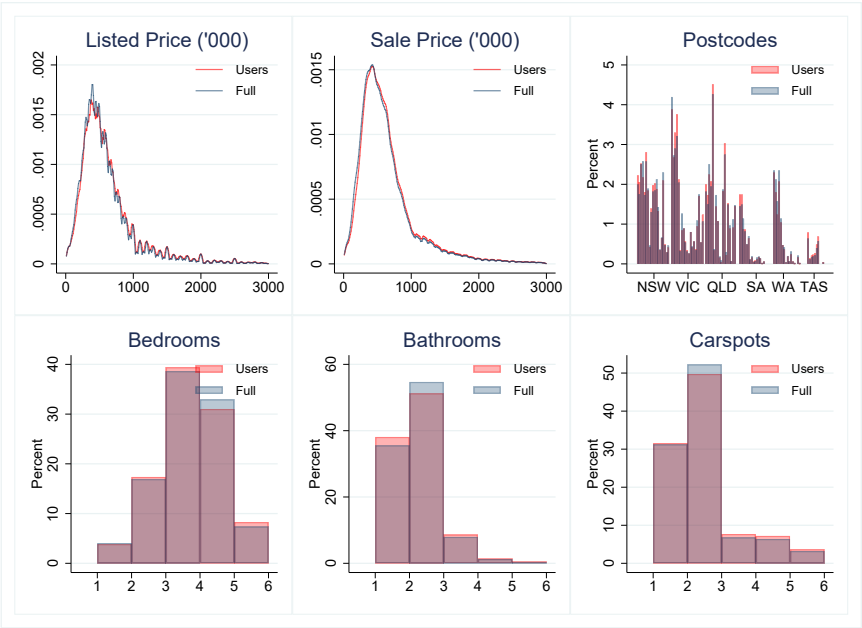


(a) Population Density: Our sample

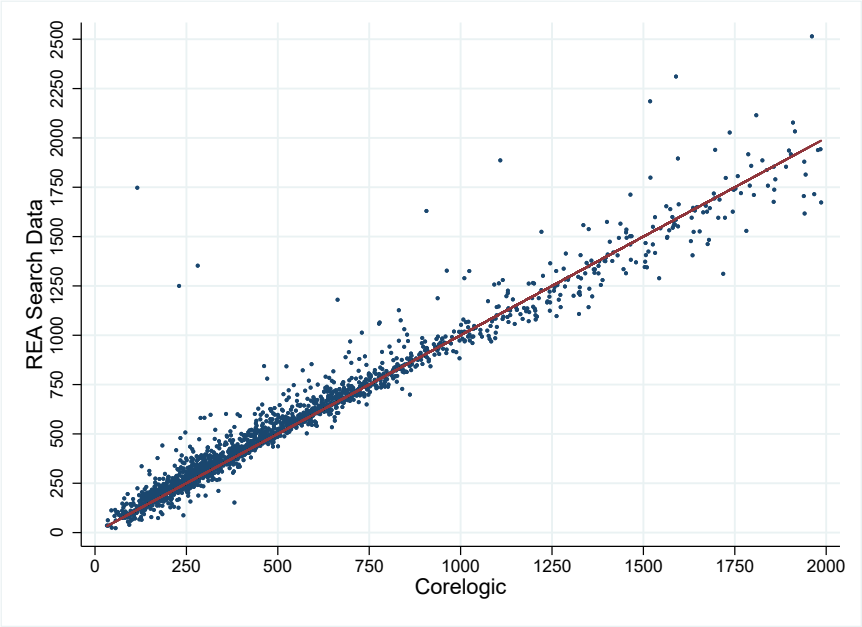


(b) Population Density: 2016 Census

Figure A.2: **Density of REA Users Compared to Australian Population.** This figure displays a heatmap of the density, at the postcode level, of users in our data (Panel a) and of the Australian population according to the 2016 Census (Panel b). Postcodes with higher density are denoted by darker shades of color.



(a) Characteristics: Browsed Listings and All REA Listings



(b) Postcode Sales Prices (AUD 1,000): Browsed Listings and Corelogic

Figure A.3: **Characteristics of Browsed Listings Compared to All Listings and Transactions.** The top panel of the Figure displays a comparison between the characteristics of the sample of listings browsed by the users in our dataset and the entire population of dwellings listed on realestate.com.au (REA) over the same time span (January 2017 to April 2019). The bottom panel compares the average sales price per postcode for listings browsed by the users against the average sales price based on Corelogic postcode indexes over the same time span (January 2017 to April 2019).

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