How Do Homes Transfer Across The Income Distribution? The Role of Supply Constraints*

James Hansen[a], Alicia N. Rambaldi[b]

[a] *The University of Melbourne, 111 Barry Street, Melbourne, 3010, Victoria, Australia*
[b] *The University of Queensland, St. Lucia, Brisbane, 4072, Queensland, Australia*

Abstract

We study how homes transfer across the income distribution. Positing a DMP model, homes can be resold down or up depending on home quality and land values. Constraining new supply raises land values, trade-reservation values, and increases the odds that homes filter up. Using transaction data from Australia, we estimate substantial dispersion in filtering from sellers to buyers within and across locations, with over one half of all homes transferring up to a buyer with higher income than the seller. Causal estimates of the effects of planning refusal suggest supply constraints can explain the upward filtering of homes.

Keywords: Filtering, Housing Search, Supply Constraints, Household Income

JEL Codes: R21, R31, R38

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1. Introduction

The transfer of homes down the income distribution is thought to be a crucial source of housing for the poor. Also known as filtering, theoretical models posit that as homes depreciate over time, they provide lower quality housing services, decrease in price, and are transferred to households with lower income (Muth 1973, Sweeney 1974, Braid 1984). Recent estimates confirm that homes filter down the income distribution on average (Rosenthal, 2014). However, there is substantial spatial variation in mean filter rates: in some cities, homes transfer *up* the income distribution (Liu, McManus, and Yannopoulos, 2021).

Central to the viability of filtering is that new homes are built to replace low-quality homes, and that new homes are also resold down the income distribution. This mechanism is crucial if developers do not build homes at all quality levels, especially low-quality homes. Notwithstanding the importance of new supply for filtering's viability, there is little, if any, direct evidence on how supply constraints on the building of new homes might affect it.[1]

This paper closes this gap. Our contribution is to show when regulatory supply constraints are likely to impede filtering in a standard search model of housing, and to quantify the size of this effect. We do this in three ways: first, we use a Diamond-Mortensen-Pissarides (DMP) model for existing home trade to show that supply constraints alter the willingness of buyers and sellers to transact, and thus the rate that existing homes (hereafter homes) filter across the income distribution from sellers to buyers. Second, we construct a novel unit record dataset matching seller and buyer income to home sales, at the transaction level, to establish new facts on the distribution of buyer income relative to seller income and to estimate marginal filter rates from sellers to buyers as homes age. Third, we exploit the heterogenous responses of local planning authorities (councils) to a statewide planning reform to identify the casual effect of a change in regulatory constraints on seller to buyer filtering.

Previous theory posits that as homes depreciate, they should filter down the income distribution, transferring to households with lower income than that of the previous occu-

[1]See also Molloy (2020).

pants (Sweeney, 1974, Ohls, 1975, Braid, 1984, Bond and Coulson, 1989, Arnott and Braid, 1997). Using either an assignment or commodity-hierarchy approach, these models capture the frictionless impacts of filtering. However, they do not consider how search frictions or constraints on new supply might matter.

Search frictions are essential for understanding a range of housing market facts including: (i) that homes take time to sell (Wheaton, 1990); (ii) there is a strong negative correlation between time on market and price (Genesove and Han, 2012); (iii) there is significant dispersion in home prices (Rekkas et al., 2025); and (iv) that market dynamics are affected by buyers and sellers willingness to transact (see e.g., Ngai and Sheedy 2024, Gabrovski and Ortego-Marti 2019, Guren 2018, Han and Strange 2015, Ngai and Tenreyro 2014 among others). In our application, search is crucial for explaining the dispersion observed in incomes and filter rates when buyers and sellers trade.

We study how regulatory supply constraints (hereafter supply constraints) affect filtering within a DMP model of existing home trade. We assume that: (i) utility derived from housing services depends on home quality and homeowner income (Määttänen and Terviö, 2014, Rosenthal, 2014, Braid, 1984, Rosen, 1979); (ii) search frictions constrain opportunities to trade (Head et al. 2014, Genesove and Han 2012, Novy-Marx 2009); (iii) new and existing homes are imperfect substitutes (Gabrovski and Ortego-Marti, 2025); and (iv) developers build new homes subject to regulatory approval (Glaeser and Gyourko, 2018).

The model's core insight is that tightening supply constraints – an increase in the refusal rate for new development – raises land values, the outside option value of selling to a developer, and seller reservation values when meeting a buyer. By reducing the supply of new homes, the measure of high-income buyers searching for an existing home and their willingness to pay for those homes increase. Raising both buyer and seller reservation values, older homes are then more likely to transfer up the income distribution to buyers with higher income than sellers in locations where new supply is constrained. These results are not obtained in a Walrasian equilibrium. In the Walrasian case, homes always filter down the income distribution in expectation, even when the supply of new homes is constrained.

Our econometric framework aligns with the model. The outcome variable is log-buyer less log-seller income (relative income) and the covariate of interest is home age – the number of years since the home was first built. The estimate of how an additional home-year – a marginal decline in quality – affects relative income is known as the *marginal filter rate*. We use this measure to infer whether older homes are more likely to transfer down or up the income distribution.

Our data are from the State of Victoria, which covers approximately one-quarter of the Australian housing market. That data are unique in that: (i) they allow us to match buyer and seller income from tax filings at the individual level to housing transactions in the same calendar year that each home was sold; (ii) they provide a measure of supply constraints that directly corresponds to our model-theoretic measure; (iii) we can infer exogenous variation in the refusal rate; and (iv) that the topography of the cities within Victoria is quite smooth allowing for precise identification of regulatory supply constraints as opposed to other natural barriers that might otherwise impede the building of new homes.

To measure relative income we use the log of total income of all buyers listed on the exchange of property title less the log of total income of all sellers listed. Income includes all labour and capital income earned. To measure the refusal rate, we use the average share of all residential planning applications made in the local area that are refused.[2] Local planning areas are also known as councils, and there are 79 such councils that span Victoria. Importantly, there is considerable heterogeneity in the rates at which councials approve new residential development, a key bottleneck in the supply of new homes.

The data allow us to establish new facts about the incomes of buyers and sellers. First, we find remarkable spatial heterogeneity in relative income across council areas. Estimates of mean relative income range from -5.7 log points (-5.9%) in the lowest decile to $+36.8$ log

[2]This measure of supply constraints aligns with the DMP model and is often used in models of constraints on urban growth (e.g. Duranton and Puga (2023) and Ortalo-Magné and Prat (2014)).

points (+44.5%) in the highest decile across councils. Estimates of the variation in relative income *within* council areas are not dissimilar. Second, in addition to substantial dispersion in relative income, mean relative income taken across all transactions in Victoria is *positive*, statistically significant and large at +16.2 log points (+17.6%). This estimate implies that buyers have *higher* income on average than sellers. We find that relative income is positively correlated with measures of local supply constraints and that this positive correlation is not an artefact of differences in the age of buyers and sellers, investor purchases, or downsizing sales, as well as a wide range of specification checks considered below.

Third, controlling for measures of home and neighbourhood quality – property type, land or internal area, the number of bedrooms, home age and postcode fixed effects – we estimate a *positive* and statistically significant mean for the marginal filter rate from sellers to buyers as homes age: +0.3 log points per additional home year for houses and +0.4 log points for apartments, with the average house (apartment) traded just under 40 (30) years old. That is, older homes are more likely to transfer *up* the income distribution.[3] We find reduced-form evidence that marginal filter rates are higher in locations where new supply is more constrained – a one standard deviation increase in the planning refusal rate increases the marginal filter rate by about +0.1% per home year.

Nevertheless, marginal filter rates measured across locations that differ in their supply restrictiveness are unlikely to provide an accurate estimate of the marginal effects of supply constraints on filtering. The concern here is that council areas with high demand for new homes are also likely to be those where refusal rates are high due to opposition to new development from local residents. Moreover, the distributions of buyer income, seller income and council refusal rates are jointly determined.[4] To address these concerns, we exploit a

[3]These estimates exceed the mean estimates of filtering using repeat-buyer income, at -0.4% to -0.5% per home year on average across US cities (Rosenthal, 2014), but do accord with estimates for larger more supply constrained cities (Liu et al., 2021).

[4]This can occur, for example, due to local agglomeration benefits and congestion costs (Duranton and Puga, 2023), local amenities (Ortalo-Magné and Rady, 2008), or the age and tenure of local residents that

change in local planning laws that applied to all Victorian councils in the middle of our sample. The reform, known as *VicSmart*, applied to a subset of straight-forward planning applications. It removed the discretion of councils to refuse these applications and required a much faster decision time for their assessment – at most 10 business days.[5] As well as requiring expedited assessment and a loss of council discretion, the reform also protected *VicSmart* eligible applications from the lodgement of appeals.[6]

Implemented in September 2014, councils had strong incentives to respond heterogenously to the VicSmart reform. More restrictive councils could continue to restrict new development by refusing a greater share of planning applications that were not eligible for consideration under VicSmart. Less restrictive councils had no similar incentive. As discussed below, we see clear evidence of this in the data – overall refusal rates rose sharply in the same quarter that the VicSmart reforms took effect and remained higher thereafter consistent with a substitution in how councils continued to restrict new development.

We construct instruments using the change in the mean council refusal rate, and separately the change in council planning decision times, taken before and after VicSmart. As an additional robustness check, we also use a third instrument derived from a separate data source, historical national voting shares (Hilber and Vermeulen, 2015). Instrumenting for local planning refusal entirely explains the upward filtering mean. Estimates of the marginal filter rate for houses fall from +0.3% to zero, or negative but insignificant estimates. These estimates imply that reducing the refusal rate by one standard deviation in all Victorian councils would lower the mean difference in log-buyer and log-seller income from +16.8% to +4.6%; removing supply constraints altogether predicts that homes would, on average, transfer down the income distribution from sellers to buyers.

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determine voting incentives in favour or against new supply, which are jointly determined with income (Ortalo-Magné and Prat, 2014).

[5]The average decision time in our sample across all applications is about 110 days.

[6]Appeals can delay or overturn a council's approval for new development. They can involve lengthy and costly administrative delays as they are referred to a statewide tribunal that ultimately decides the outcome.

Policymakers are also interested in whether marginal filter rates vary over the relative income distribution: indeed, non-linearity is also predicted by the DMP model. To accommodate this, we extend our baseline IV estimates using the quantile-IV estimator of Chetverikov, Larsen, and Palmer (2016) that allows marginal filter rates to vary by relative income quantile. At low quantiles (0.15 and 0.30), the marginal filter rate from seller to buyers is about −2.0% per home year when excluding the effects of local planning refusal. In the absence of supply constraints, homes filter quickly down the income distribution precisely as previous theory and the DMP-model suggests. However, at high quantiles (0.75 and 0.90), the marginal filter rate rises and is essentially zero.

Estimating the effects of local planning refusal on the marginal filter rate across quantiles provides an almost mirror image. At low relative-income quantiles, the marginal effects of supply constraints on filtering from sellers to buyers are positive and significant (a one standard deviation increase in local planning refusal increases the marginal filter rate by about +0.1% per home year), but these estimates dissipate to zero at high relative-income quantiles. Thus, we find considerable heterogeneity in marginal filter rates over the relative income distribution and across locations. Interestingly, the marginal effects of supply constraints are highest in areas with *low* relative income. This is notwithstanding the fact that supply constraints themselves are typically most binding in high-income urban areas.

We next discuss related literature. Section 2 posits a DMP model of seller-to-buyer filtering with supply constraints. Section 3 discusses an empirical framework for estimation, and Section 4 data and identification. Section 5 reports our empirical findings and robustness. Final conclusions are then drawn.

Related literature. This paper contributes to a growing theoretical and empirical literature on the importance of filtering for housing supply. Previous theoretical models study an equilibrium where homes filter down the income distribution as they age, and assume frictionless trade in housing. Examples include Sweeney (1974), Ohls (1975), Braid (1984), Bond and Coulson (1989), and Arnott and Braid (1997). However, this literature does not consider the role of search in filtering or the effects of regulatory supply constraints as we do here.

We also connect to recent advances in measuring filtering using the incomes of buyers only. The seminal work is Rosenthal (2014), who measures filtering directly by observing changes in log-buyer income over time for the same home using data from the American Housing Survey.[7] While Rosenthal's paper provides a crucial step forward in the estimation of marginal filter rates, we cannot use this approach on our sample as it is likely that homes only resold within a short time window are likely to be a very select sub-sample of homes.[8] By using differences in buyer and seller income, we offer an alternative where estimates that use repeat-income-buyer estimation might be severely biased or even infeasible.[9]

Finally, our paper also adds to the broader literature that examines new supply and household income. The most closely related papers include Nathanson (2025) who studies the effects of low and high-quality new construction on prices and filtering (trickle-down); Favilukis, Mabille, and Van Nieuwerburgh (2023) who study the implications of regulatory constraints on welfare in a spatial model with income risk; Mast (2023), the quantitative effects of moving chains; Molloy, Nathanson, and Paciorek (2022), the effects of supply constraints on rental prices, housing structure and lot size; Diamond and McQuade (2019), the spillovers of building new multi-family housing financed by the Low Income Housing Tax Credit; Hilber and Vermeulen (2015) the effects of supply constraints on prices, and Paciorek

[7]This framework has subsequently been employed by Liu et al. (2021) and Spader (2025), who extend the geographic and temporal coverage of Rosenthal's estimates to understand how filtering rates might have changed across time and space in the US

[8]There are multiple biases including homes that are more likely to renovated and resold (flippers) or homes where sellers have faced large negative shocks to either match quality or income.

[9]See, for example, Nowak and Smith (2020) for estimates of bias due to unobserved or imperfectly recorded renovation activity when measuring home prices. One advantage of our approach is that it does not require the assumptions of time invariant-home attributes, or implicit prices of those attributes. See Appendix A.1 for further detail.

(2013) on price volatility. To our knowledge, we are the first quantify the impact of spatial variation in local supply constraints, specifically local planning refusal, on filtering.

2. A DMP Model of Seller to Buyer Filtering

We posit a simple DMP model of home search with filtering. There are three types of private agents: buyers, sellers and developers. We assume that buyers and sellers independently draw their log-income from the same continuous distribution, F. Buyers have unit home demand and search either for a new high-quality home or an existing home of lower quality. Buyers direct their search conditional on their income, purchasing a new home if their income is sufficiently high, or searching for an existing home otherwise.

Existing homes are supplied by sellers. A subset of them each have a single home to sell with idiosyncratic quality, q_s, that is positive and drawn from a continuous distribution. Sellers and buyers can meet bilaterally, but only with some positive probability determined by a matching function. Conditional on meeting, the seller and the buyer only trade if their joint surplus is positive.

The remaining subset of sellers draw a home with zero quality. Zero-quality homes are sold to a competitive market of developers. Developers purchase these homes, demolish them, and then build a new home at unique quality level q^{new}, which is higher than any existing home quality offered by a seller. However, the construction of a new home requires approval. We assume a council randomly decides whether to approve or refuse each application to build a new home. In effect, the aggregate supply of new homes is determined by the council.[10]

Sellers: We assume a continuum of sellers with measure $\mathcal{S}$, where each seller draws a home quality (q_s) from a continuous distribution $G_{\underline{q},\overline{q}}$ with positive supports $[\underline{q}, \overline{q}]$, and their log-income ($y$) independently from distribution F. With probability $1-\delta$ the home quality is retained and the seller searches to find a buyer. Paying the search cost, c^S, a buyer arrives at rate λ^S, but trade is consummated only if the joint trade surplus is positive, otherwise

[10] Associated proofs are in Appendix C. Extensions of the model are discussed in Appendix E.

the seller remains on the market. For simplicity, we assume that the seller extracts the full surplus from trade.

With probability δ the home quality depreciates to zero. In this case, a developer arrives at rate $\lambda^{\dagger}$ and the seller sells their home at a positive price Z – the value of the lot less demolition costs (hereafter the value of land). The expected value of selling an existing home with quality q_s, given the quality-adjusted price for new homes, P, $V^S(q_s, P)$, is:

$$rV^S(q_s, P) = \underbrace{(1-\delta)}_{\substack{\text{Prob. search}\\ \text{for buyer}}} \left(\underbrace{\lambda^S \int_{x_l}^{x_u} \Pi^S(x; q_s, P) dF(x)}_{E[\text{Surplus}|\text{Trade with a buyer}]} - \underbrace{c^S}_{\text{Search cost}} \right) + \underbrace{\delta \lambda^{\dagger} \widetilde{Z}(q_s, P)}_{\substack{\Pr(\text{Sell developer}) \times \\ E[\text{Surplus}|\text{Sell developer}]}} \quad (1)$$

where $\Pi^S(x; q_s, P) \equiv V^H(q_s, x) - V^B - V^S(q_s, P)$ is the surplus obtained by a seller when trading a home of quality q_s to a buyer with log-income x and given quality-adjusted new home price $P \equiv \frac{P^{new}}{(q^{new})^{\varepsilon_q}}$, P^{new} is the market-clearing price for new homes, q^{new} is new home quality, ε_q is a demand elasticity for home quality defined below, $\widetilde{Z}(q_s, P) \equiv Z - V^S(q_s, P)$ is the surplus obtained when selling to a developer, and r is the discount rate. The thresholds governing trade in the existing home market are defined by the lower log-income threshold $x_l \equiv x_l(q_s, P)$, required to generate a positive surplus from trade, and the upper log-income threshold $x_u \equiv x_u(P)$ denoting the highest log-income of any buyer searching the existing home market. These thresholds are determined endogenously in equilibrium and are derived below.

Buyers: We assume a continuum of buyers with measure $\mathcal{B}$, who each demand a single home and draw their log-income (x) independently from F. The utility derived from acquiring a home is a function of the quality of the home (q_s) and the buyer's income (e^x) with the value of housing services provided when purchasing an existing home with quality q_s given by $V^H(q_s, x) \equiv (q_s)^{\varepsilon_q} (e^x)^{\varepsilon_x}$, and where ε_q and ε_x are positive demand elasticities over home quality and income.[11]

Buyers direct their search conditional on their income. If a buyer's income is sufficiently high, they visit the new home market and purchase a new home from a developer at quality q^{new}. In equilibrium, it will always be optimal for a buyer to purchase a new home if their income is sufficiently high.

Buyers purchase a new home whenever: $V^H(q^{new}, x) - V^B \geq P^{new} \Rightarrow x \geq x_u$ where V^B is the value of remaining a buyer, and $x_u = \varepsilon_x^{-1} \log\left(P + \frac{V^B}{(q^{new})^{\varepsilon_q}}\right)$ is the threshold for log-buyer income that generates a positive surplus when purchasing a new home. If a buyer's log-income is not sufficient to generate a positive surplus when purchasing a new home (is below x_u), they search for an existing home. Then they make contact with a seller at rate λ^B, but only trade when the joint trade surplus is positive: $V^H(q_s, x) - V^B \geq V^S(q_s, P) \Rightarrow x \geq x_l$ where $x_l = \varepsilon_x^{-1} \log\left(\frac{V^S(q_s,P)+V^B}{(q_s)^{\varepsilon_q}}\right)$ is the minimum log-buyer income required for a positive trade surplus of an existing home with quality q_s. The expected value of searching as a buyer, $V^B \equiv V^B(q^{new}, P^{new})$, is:

$$rV^B = \lambda^{new} \int_{x_u}^{\infty} \Pi^B(x; q^{new}, P^{new}) dF(x) - (1 - F(x_u))c^B(B^{new}) \tag{2}$$

where $\Pi^B(x; q^{new}, P^{new}) \equiv V^H(q^{new}, x) - P^{new} - V^B$ is the surplus from buying a new home, $c^B(B^{new})$ is the cost of search for a new home and λ^{new} the arrival rate for finding a new home. Similar to Gabrovski and Ortego-Marti (2019), we assume that new home buyer search costs are increasing and convex in the measure of buyers searching the new home market, $B^{new} \equiv (1 - F(x_u))\mathcal{B}$.[12]

Home Quality: Existing homes with positive quality can be sold to buyers, while those that depreciate to zero quality are sold to developers. The distribution of home quality for

[11]See, for example, Määttänen and Terviö (2014), Rosenthal (2014), Braid (1984), Rosen (1979).

[12]The interpretation of this assumption is that an increase in the measure of new home buyers increases the cost of search for those buyers. For example, increasing costs in arranging display home viewings, negotiating construction plans, designing modifications, commencing the build and so forth.

all homes is $\mathcal{G}_Q(q_s) = \delta\mathcal{S} \cdot \mathbb{1}_{[0,q)}(q_s) + \Big(\delta\mathcal{S} + (1-\delta\mathcal{S})G_{\underline{q},\overline{q}}(q_s)\Big) \cdot \mathbb{1}_{[\underline{q},\overline{q}]}(q_s) + \mathbb{1}_{(\overline{q},\infty)}(q_s)$. This distribution has a discrete jump at quality 0, consistent with measure $\delta\mathcal{S}$ of existing homes being to sold to developers. Conditional on a seller drawing a positive home quality, existing home quality offered by sellers to buyers has continuous distribution $G_{\underline{q},\overline{q}}$ on $[\underline{q},\overline{q}]$. New homes are built at a unique quality level, $q^{new} \geq \overline{q}$.

Existing and New Home Matching: For buyers and sellers of existing homes, we assume that search frictions constrain opportunities to trade. Buyers and sellers meet through a constant-returns-to-scale matching function $\mathcal{M}(F(x_u)\mathcal{B},\mathcal{S})$, and thus the contact rates for buyers (λ^B) and sellers (λ^S) are determined via the matching function with: $\mathcal{M}(F(x_u)\mathcal{B},\mathcal{S}) = \lambda^B F(x_u)\mathcal{B} = \lambda^S\mathcal{S}$. For homes requiring demolition and the new homes subsequently built on them, we assume that the contact rates for sellers and buyers approach one ($\lambda^\dagger \to 1^-$ and $\lambda^{new} \to 1^-$), although our results can be generalised to accommodate lower contact rates.

Market Clearing for New Homes: New home supply is determined by a local planning authority who controls the intensity of land use (subdivisions) at rate d, and the probability that an application to build a new home is approved, $1-\tau$, where τ is the probability of refusal. The measure of homes ready for demolition and requiring planning approval is $\delta\mathcal{S}$. We assume that the unimproved value of land, Z, and thus the quality-adjusted new home price, P, adjust to clear the market for new homes:

$$\underbrace{(1-\tau)}_{\text{Approval rate}} \times \underbrace{(1+d)}_{\text{Subdivisions}} \times \underbrace{\delta\mathcal{S}}_{\text{New home applications}} = \underbrace{\mathcal{B}\int_{x_u(P)}^{\infty} dF(x)}_{\text{New homes purchased}} \tag{3}$$

where developers supply new homes competitively at price P^{new} equal to the marginal cost of building a new home: $P^{new} = mc(q^{new}) + Z$. The marginal cost of producing a new home includes the cost of purchasing one unit of land (a lot at price Z), and the cost of building of the new home structure. The latter is governed by the marginal cost function $mc(.)$, which is strictly increasing in new home quality and convex.

Equilibrium: We study an equilibrium where free buyer entry implies that the expected value of searching as a buyer, V^B, is small (approaches zero) and where the measure of existing home buyers $F(x_u)\mathcal{B}$ increases when the quality adjusted-new home price increases. The equilibrium is characterised by:

i. Distributions of seller values, $V^S(q_s, P)$, and ownership values, $V^H(q_s, x)$, for $q_s \in [\underline{q}, \overline{q}]$, and measure of buyers $\mathcal{B}$ that satisfy Equations (1) and (2), the definition of the value of home ownership, and where free buyer entry implies that the expected value of buyer search is zero;

ii. A quality-adjusted new home price (P) and unimproved land value (Z) that clear the market for new homes given competitive new home supply (Equation 3) and the marginal cost of building a new home; and

iii. A joint distribution of log-seller income (y), existing home quality (q_s), and log-buyer income (x) conditional on trade, $\mathcal{J}_{Y,Q,X|X\in\mathcal{X},Q\in[\underline{q},\overline{q}]}(y, q_s, x)$ with $\mathcal{X} \equiv (x_l, x_u)$.

The equilibrium is solved taking as given: the log-income distribution from which buyers and sellers draw their income (F), the unique quality of new homes built by developers (q^{new}), the distribution of home quality ($\mathcal{G}_Q$), the probability a home depreciates to zero-quality and requires demolition (δ), buyer and seller arrival rates (λ^B and λ^S) given seller measure $\mathcal{S}$, and local planning authority choices for the subdivision rate (d) and the probability of refusal (τ). We assume that F is Gaussian, which provides a good approximation of the empirical data as we show below.

Model insights: Define $\underline{x}_l \equiv x_l(\overline{q}, P)$ and $\overline{x}_l \equiv x_l(\underline{q}, P)$ as the minimum thresholds on log-buyer income required for a positive trade surplus where $\overline{q}$ and $\underline{q}$ denote the maximum and minimum existing home qualities on offer by any seller. Proposition 2.1 first establishes the existence and uniqueness of the equilibrium when the expected gain from selling to a developer exceeds the expected seller cost of searching for a buyer.[13]

[13]Proposition 2.1(i) shows that an equilibrium exists if the log quality-adjusted seller value lies within

Proposition 2.1. ***Existence and Uniqueness***

Let $\mathcal{V}(x_l, q_s) \equiv \varepsilon_x^{-1} \log \frac{V^S(q_s,P)}{q_s^{\varepsilon_q}}$ *be the log quality-adjusted value of a seller with home quality* q_s*,* $F_{x_l,x_u}(r,s) \equiv \frac{F(r)-F(x_l(s))}{F(x_u)-F(x_l(s))}$ *denote the conditional distribution of log-buyer income, and assume* $\delta Z > (1-\delta)c^S$*. For a given local planning rejection rate,* τ*, and quality-adjusted price of new homes,* P*:*

(i) At least one equilibrium exists if for all $q_s \in [\underline{q}, \overline{q}],$*,* $\mathcal{V}(x_l, q_s) \in [\underline{x}_l, \overline{x}_l]$ *with* $\overline{x}_l < x_u$*;*

(ii) It is unique if there exists $k \in (0,1)$*, such that* $\left|\frac{\partial \mathcal{V}(x_l,q_s)}{\partial x_l}\right| \leq k$ *for all* $q_s \in \left(\underline{q}, \overline{q}\right)$*;*

(iii) The joint distribution of log-seller income, home quality and log-buyer income is:

$$\mathcal{J}_{Y,Q,X}(y, q_s, x) = \int_{-\infty}^{y} \int_{\underline{q}}^{q_s} \int_{x_l}^{x} dF_{x_l,x_u}(r,s) dG_{\underline{q},\overline{q}}(s) dF(t)$$

Proposition 2.2 shows how expected relative income is affected by a change in the quality of the home offered by a seller, and the refusal rate. If the value of unimproved land is high – the expected return from selling a home of zero quality to a developer exceeds the expected cost of search for a seller ($\delta Z > (1-\delta)c^S$) – then a marginal decline in the home quality offered by a seller *increases* expected relative income. Thus, we should see an *increase* in the expected difference between log-buyer and log-seller income for that home, and a *positive* expected marginal filter rate. Conversely, in areas where land values are low relative to the cost of seller search, $\delta Z < (1-\delta)c^S$, the marginal filter rate is negative and the home filters down in expectation.

Proposition 2.2. ***The Marginal Effects of Home Quality and Planning Refusal***

Define expected relative income given home quality q_s *as* $\mathbb{E}[\mathcal{R}|Q = q_s]$*. (i) If the value of*

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the support defined by the minimum log-buyer income threshold for trade – that is, trade is always possible but not guaranteed for each home quality offered by a seller; 2.1(ii) shows that the equilibrium is unique if the elasticity of the quality-adjusted seller value with respect to their own reservation value (also quality-adjusted) is less than one. The joint distribution of log-buyer income, log-seller income and home quality conditional on trade is shown in 2.1(iii).

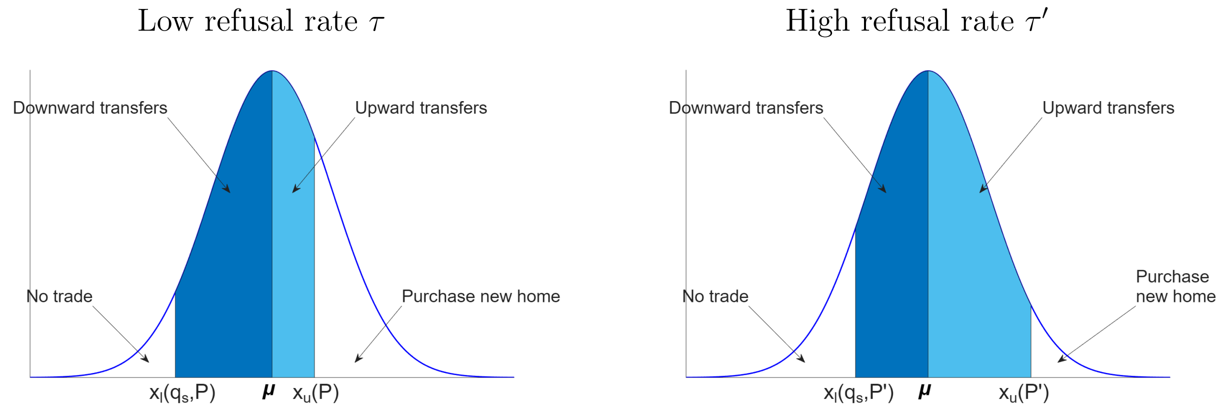
unimproved land is high relative to the expected cost of seller search, expected relative income is decreasing in home quality: $\frac{\partial \mathbb{E}[\mathcal{R}|Q=q_s]}{\partial q_s} < 0$ *and is increasing otherwise; (ii) Expected relative income is increasing in the planning refusal rate:* $\frac{\partial \mathbb{E}[\mathcal{R}|Q=q_s]}{\partial \tau} > 0$.

The possibility that homes can filter up the income distribution in expectation as they age in locations where land values are high is a direct implication of search. With search frictions and complementarity between home quality and income, a decrease in the quality of an existing home implies the seller reservation value falls more slowly than the value of the decline in quality to any potential buyer. Thus, the log quality-adjusted seller reservation values rises and the area of positive joint trade surplus contracts. This means that a decline in quality *reduces* the pool of potential buyers with low income who can trade with the seller, and so the home is now more likely to filter up in expectation.

Proposition 2.2(ii) shows how a higher planning refusal rate increases expected relative income. Higher planning refusal raises the value of land, increases the quality-adjusted price for new homes, and thus displaces marginal high-income buyers who can no longer afford them. These buyers now search for an existing home and, since they are more likely to trade when meeting a seller, this raises expected buyer income conditional on trade and the mean income difference observed between buyers and sellers. Both the increase in the measure of high-income buyers searching for an existing home and the consequent increase in the seller reservation value contribute to higher expected relative income. This intuition is also shown in Figure 1, where in the left-panel supply constraints are relaxed and the home is expected to transfer down in expectation. But in the right-panel, in a location with tight constraints, both the higher seller reservation value and the increase in buyer willingness to pay for an existing home imply the home is expected to transfer up in expectation.

Proposition 2.3(i) shows the expected direction that an existing home transfers at a given home quality q_s and expected relative income when integrating over the quality distribution for all existing homes offered by sellers (2.3(ii)). For a given home quality q_s, what matters is the equilibrium thresholds for trade. When $f(x_u) > f(x_l(q_s))$, the measure of high-income

Figure 1: Log-buyer income and Supply Constraints



Note: The left-panel shows the areas of downward filtering (dark shaded), upward filtering (light shaded), no trade, and for purchasing a new home when supply constraints are relaxed. The home filters downwards in expectation as the mass in the downward filtering area (the integral from the minimum log-buyer income threshold to mean log-seller income, μ) exceeds that in the upward filtering area (the integral from μ to the maximum log-buyer income threshold). The right-panel shows the same information, but in a location with tight supply constraints.

buyers who purchase new homes (and thus do not search for an existing home) exceeds the measure of low-income buyers searching for an existing home, but who cannot afford a home of quality q_s. This, in turn, implies that the measure of buyers with higher income than the expected income of the seller, and who would trade for an existing home of quality q_s, is smaller than the measure of buyers with relatively lower income and who are also able to trade. Thus, the home is expected to transfer down the income distribution. The converse applies when $f(x_u) < f(x_l(q_s))$, with the home expected to transfer up the income distribution then.

Proposition 2.3(ii) shows whether that homes transfer up on down the income distribution on average depends on how these effects integrate over the existing home quality distribution. When there is a large mass of existing homes offered at high qualities relative to low qualities, homes transfer down on average. However, if there is a large mass of existing homes with low quality relative to those with high quality, then homes will transfer up the income distribution on average as buyers with higher incomes trade for them. These results show that the quality distribution of existing homes is crucial for understanding the mean direction that homes transfer from sellers to buyers.

Proposition 2.3. ***The Direction that Homes Transfer from Sellers to Buyers:*** *For a given local planning refusal rate, τ, and quality-adjusted price of new homes, P:*

(i) An existing home with quality $q_s \in (\underline{q}, \overline{q})$ will transfer down the income distribution in expectation, $\mathbb{E}[\mathcal{R}|Q = q_s] < 0$, when $f(x_u) > f(x_l(q_s))$ and transfers upwards otherwise;

(ii) Mean relative income is negative, $\mathbb{E}[\mathcal{R}] = \int_{\underline{q}}^{\overline{q}} \mathbb{E}[\mathcal{R}|Q = q_s] \, dG_{\underline{q},\overline{q}}(q_s) < 0$, when $\int_{\underline{q}}^{\overline{q}} \frac{f(x_u)-f(x_l(q_s))}{F(x_u)-F(x_l(q_s))} dG_{\underline{q},\overline{q}}(q_s) > 0$ and is positive otherwise.

Proposition 2.4 shows how supply constraints affect expected relative income as the planning refusal rate approaches one (no new homes are approved), and separately how an increase in planning refusal affects the average filter rate from sellers to buyers, $\mathcal{F} \equiv -\int_{\underline{q}}^{\overline{q}} \frac{\partial \mathbb{E}[\mathcal{R}|Q=q_s]}{\partial q_s} dG_{\underline{q},\overline{q}}(q_s)$, hereafter the mean marginal filter rate (MFR). In the limit that no new homes are approved, the mean log-income difference between buyers and sellers conditional on trade must be positive. With few homes being added to supply, new homes are expensive and more buyers with high incomes demand existing homes and are more likely to trade for them.

However, the effects of supply constraints on relative income as homes age are less clear. The right hand side of Proposition 2.4(ii) is always positive. Thus, if the marginal effects on planning refusal at the lower and upper thresholds for trade were always equal, then a tightening of constraints in already supplied constrained locations would unambiguously imply an increase in the mean marginal filter rate.[14] However, because the effects of tightening supply constraints on the trade thresholds are in general unequal, and depend on the quality of home on offer by a seller, it is possible that filter rates at some quality levels increase in response to an increase in planning refusal but fall at other quality levels. Thus, whether planning refusal has a positive or negative effect on the MFR is ultimately an empirical question that we will return to below.

[14]See Corollary Appendix C.1. This follows from the assumption that the log-income distribution F is log-concave.

Proposition 2.4. ***The Effects of Supply Constraints on Filtering***

(i) In the limit that no new homes are approved, existing homes must transfer up the income distribution: $\lim_{\tau\to1^-}\mathbb{E}\left[\mathcal{R}\right]>0$.

(ii) When new homes are approved, $\tau\in(0,1)$*, an increase in the refusal rate increases the mean MFR (*$\frac{\partial\mathcal{F}}{\partial\tau}>0$*) if and only if:*

$$\int_{\underline{q}}^{\overline{q}}\left(M_{x_lx_l}\frac{\partial x_l}{\partial\tau}+M_{x_lx_u}\frac{\partial x_u}{\partial\tau}\right)\frac{\partial x_l}{\partial q_s}dG_{\underline{q},\overline{q}}\left(q_s\right)<-\int_{\underline{q}}^{\overline{q}}M_{x_l}\frac{\partial^2x_l}{\partial q_s\partial\tau}dG_{\underline{q},\overline{q}}\left(q_s\right)$$

where M is the expected value of log-buyer income conditional on trade, and M subscripts denote first and second partial derivatives with respect to the equilibrium trade thresholds.

Proposition 2.5 shows how the marginal filter rate at all existing home qualities is affected by a change in the mean income of all buyers and sellers on the existing home market, μ, holding fixed the price of new homes.[15] When μ increases and the value of unimproved land is high relative to the expected search cost paid by sellers, this *slows* the rate at which homes filter up the income distribution as they become older. The intuition here is that with an increase in the income of both buyers and sellers, and holding fixed the thresholds for trade, the probability that a seller meets a buyer with income below the lower income threshold for trade falls and so this threshold becomes less likely to constrain trade. Thus, when home quality changes and the lower income threshold for trade changes, the consequent effect on expected relative income is smaller.

Proposition 2.5. ***The Effects of Higher Income on the MFR:*** *Let the marginal filter rate of a home of quality q_s be given by* $\mathcal{F}_{q_s}\equiv-\frac{\partial\mathbb{E}[\mathcal{R}|Q=q_s]}{\partial q_s}$*. For a given quality-adjusted new home price, P, an increase in income dampens marginal filter rates. That is,* $\frac{\partial\mathcal{F}_{q_s}}{\partial\mu}\leq0$ *for all* $q_s\in\left(\underline{q},\overline{q}\right)$ *when* $\delta Z>\left(1-\delta\right)c^s$.

[15]Here we assume that the rate of sub-divisions, d, adjusts endogenously to accommodate the increase in new home demand.

It is crucial to note the differences in outcomes between the equilibrium with search and that of a Walrasian equilibrium as shown in Proposition 2.6. Since all buyers can meet all sellers in a Walrasian equilibrium, prices are determined by a first-order condition associated with buyers selecting their home quality optimally to maximise their surplus from trade. This implies a one-to-one mapping from home quality to price, and thus there is no dispersion in the income of buyers trading for a given home quality q_s.

Proposition 2.6 also shows that the Walrasian equilibrium mapping from the quality of the home traded to log-buyer income is perfectly assortative – the equilibrium ranking of home quality and log-buyer income is positive and perfectly correlated. This implies that expected relative income must decrease when home quality falls. Thus, in a Walrasian equilbrium homes can only filter downwards in expectation, even in the presence of supply constraints.

Proposition 2.6. ***Comparison to a Walrasian Equilibrium without Search***[16]***:***

Let $\widetilde{q}_s \equiv q_s^{\varepsilon_q}$ denote normalised home quality and $\widetilde{G}$ denote its corresponding CDF. In a Walrasian equilibrium where all agents trade, the equilibrium price function is:

$$p\left(\widetilde{q}_s\right) = P^{new} - \int_{\widetilde{q}_s}^{\bar{\bar{q}}} \exp\left[\varepsilon_x x(r)\right] dr$$

The equilibrium mapping from home quality to log-buyer income is perfectly assortative:

$$x\left(\widetilde{q}_s\right) = F^{-1}\left(F\left(\underline{x}_l\right) + \widetilde{G}\left(\widetilde{q}_s\right)\left[F\left(x_u\right) - F\left(\underline{x}_l\right)\right]\right)$$

and expected relative income is increasing in home quality: $\frac{\partial E[\mathcal{R}|Q=q_s]}{\partial q_s} > 0$.

These results show that search frictions have important consequences for predictions regarding the distribution of relative income and the direction that homes filter. In the Walrasian equilibrium, relative incomes are less dispersed as there is no dispersion in either price

[16] See Appendix D.

or buyer income, conditional on home quality. This is not so in the equilibrium with search, where there is both price and income dispersion for homes sold at the same quality. The Walrasian equilibrium also matches predictions from assignment and commodity hierarchy models. Homes that decline in quality should always filter down in expectation. With search frictions, however, this is not necessarily the case. The fact that not all buyers can meet all sellers implies that buyers are willing to trade over a range of home qualities, there is dispersion in prices, and it is possible that homes filter upwards as they age.

The DMP model has several testable implications. First, it predicts that homes can filter up or down the income distribution in different locations. The mean marginal filter rate depends on the distribution of home quality, the mean and dispersion of the joint distribution of buyer and seller income, and the rate at which applications to build new homes are refused. Second, it predicts that in areas where refusal rates are higher, we should observe higher odds of existing homes transferring up the income distribution to buyers with higher incomes on average than sellers. Conversely, in areas where supply constraints are relaxed, we should see that downward transfers more likely. Third, if supply constraints are tight and the value of land is high (homes are expected to filter upwards as they age), we should observe that homes filter upwards more slowly in areas where both buyer and seller incomes are high. We now discuss an estimation framework for quantifying these effects.

3. Estimation of Seller to Buyer Filtering

We use an estimation approach that aligns with the model and that directly maps to existing estimates of repeat-buyer filtering (Rosenthal, 2014). We assume that buyer and seller income each have a common and an idiosyncratic component: $Y_{it}^{j} = e^{\gamma_{it}^{j}}\mathcal{Y}\left(\mathbf{H}_{it};\boldsymbol{\omega}_t\right)$ for $j \in \{b, s\}$ where Y_{it}^{b} (Y_{it}^{s}) is the buyer (seller) income for home i at time t, $\mathcal{Y}\left(\mathbf{H}_{it};\boldsymbol{\omega}_t\right)$ is a common unknown function of a vector of home and neighborhood attributes, $\mathbf{H}_{it}$, and their associated implicit prices, vector $\boldsymbol{\omega}_t$, and where γ_{it}^{b} and γ_{it}^{s} are scalars that denote the idiosyncratic components of log-income.[17] Relative income ($\mathcal{R}_{it} \equiv \log \frac{Y_{it}^b}{Y_{it}^s}$), is then:

$$\mathcal{R}_{it} = \gamma_t^b - \gamma_t^s + \vartheta_{it} \tag{4}$$

where ϑ_{it} is a home-specific residual. Equation (4) provides a simple regression for estimating expected relative income conditional on trade, $\gamma_t^b - \gamma_t^s$.

Several points are worth noting. First, the usual approach to estimate repeat-buyer income filtering takes the difference in log-income between buyers of the same home over time (Rosenthal, 2014, Liu et al., 2021). That is, estimating $\gamma_t^b - \gamma_{t'}^b$, where $t > t'$. This approach maintains that all home attributes and their implicit prices are constant regardless of the time elapsed between re-sales – for all homes sold in periods t' and t, $\mathbf{H}_{it'} = \mathbf{H}_{it}$ and $\boldsymbol{\omega}_{t'} = \boldsymbol{\omega}_t$ for all i, and any $t > t'$. These are strong assumptions that can be difficult to verify in practice given that the duration between re-sales of the same home can vary from a few years to several decades, that homes may be renovated during this period, and that the implicit prices of home or neighbourhood attributes can change. Measuring relative income using the difference in log-buyer and log-seller income at the point that a home is sold does not require these assumptions and estimates with cross-sectional data only remain feasible.

Nevertheless, an important concern is that buyers and sellers may not necessarily share the same income function $\mathcal{Y}$. For example, the income distribution of buyers moving into an area may differ systematically from that of sellers who are moving out. To accommodate this, the income process Y_{it}^j can be generalised by allowing for buyer-specific and seller-specific income functions, $\mathcal{Y}^b$ and $\mathcal{Y}^s$, so that to a first-order approximation:

$$\mathcal{R}_{it} = \gamma + \sum_{j \in J} \beta_j h_{ijt} + \eta_{it} \tag{5}$$

[17] To link this to the search-theoretic model, one can think of $\mu = \log \mathcal{Y}(\mathbf{H}_{it}; \boldsymbol{\omega}_t)$ as the mean of F and γ_{it}^b and γ_{it}^s as demeaned realisations of log-buyer and log-seller income conditional on trade.

where we now include home attributes, h_{ijt}, as additional covariates and η_{it} is the regression error. The attribute coefficients – $\beta_j \equiv \overline{\mathcal{Y}}^b_{h_j}/\overline{\mathcal{Y}}^b - \overline{\mathcal{Y}}^s_{h_j}/\overline{\mathcal{Y}}^s$ for each $j \in J$ where J is the set of included home attributes – measure the marginal effect of each attribute on relative income and γ is now a reduced-form constant.[18]

Home attributes can include covariates that control for the location, size and type of home sold, permitting direct estimates of how filtering from sellers to buyers varies across these attributes. Importantly, with data on home age (years since first built), the estimated coefficient on home age ($\widehat{\beta}_{age}$) provides an estimate of how expected relative income varies in response to a marginal decline in home quality – the mean marginal filter rate or MFR. The model counterpart to this estimate is the (negative) derivative of expected relative income with respect to home quality when integrated over the home quality distribution offered by sellers: $\mathcal{F} = -\int_{\underline{q}}^{\overline{q}} \frac{\partial \mathbb{E}[\mathcal{R}|Q=q_s]}{\partial q_s} dG_{\underline{q},\overline{q}}(q_s)$.

It is worth emphasising that home age (hereafter age) is measured as the number of years from the sale of the home to when it was first built, and is not based on the time elapsed since the home was previously sold. The latter is the reference measure of age in repeat-buyer income estimates of filtering, which will yield the same filtering gradient under certain conditions but not in general. We discuss the mapping from repeat-buyer income estimates of filtering to our estimates of seller to buyer filtering in Appendix A.1.

Supply Constraints: Equation (5) does not separately identify the effects of supply constraints. Motivated by the intuition from the search-theoretic model, we posit that a higher refusal rate perturbs the rate at which homes filter across the income distribution as they age:

[18]Note that $\overline{\mathcal{Y}^b}$ and $\overline{\mathcal{Y}^s}$ are the mean common components of buyer and seller income (i.e. the point around which the approximation is taken) and $\overline{\mathcal{Y}}^b_{h_j}$ and $\overline{\mathcal{Y}}^s_{h_j}$ are the first partial derivatives with respect to the j^{th} home attribute evaluated at each mean. If buyers and sellers share the same income function, the specification reduces to Equation (4).

$$\mathcal{R}_{it} = \gamma + \sum_{j \in J \backslash age} \beta_j h_{ijt} + \beta_{age} age_{it} + \beta_{age,\tau} \left(age_{it} \times \tau_g \right) + \zeta_{it} \tag{6}$$

where we now distinguish between the set of home attributes excluding age ($J \backslash age$), age itself (age_{it}), and the interaction between age and the refusal rate in the local planning area in which the home is located ($age_{it} \times \tau_g$) (τ_g measures the refusal rate in local planning area g).[19] The only difference between Equations (5) and (6) is the inclusion of the interaction effect between the refusal rate and age. Its coefficient estimate, $\widehat{\beta}_{age,\tau}$, provides an estimate of the marginal effect of an increase in the refusal rate on the estimated mean MFR, and thus represents the empirical measure of $\frac{\partial \mathcal{F}}{\partial \tau}$.

To study how filtering from sellers to buyers might vary over the distribution of relative income, we consider two further specifications. The first uses the quantile regression analogue for Equation (5), where the u^{th} conditional quantile of relative income is modelled as:

$$\mathcal{R}_{it} \mid \mathbf{h}_t' \left(u \right) = \gamma \left(u \right) + \sum_{j \in J} \beta_j \left(u \right) h_{ijt} + \epsilon_{it} \left(u \right) \tag{7}$$

for $u \in \mathcal{U}$ and where $\mathcal{R}_{it} \mid \mathbf{h}_t' \left(u \right)$ denotes the u^{th} conditional quantile of relative income and $\mathbf{h}_t'$ denotes the vector of included home attributes. $\gamma \left(u \right)$ is now a quantile-specific constant, $\beta_j \left(u \right)$ is the quantile-specific home attribute coefficient for each $j \in J$, and $\epsilon_{it} \left(u \right)$ is the quantile-specific residual. Equation (7) can be viewed as a set of local approximations, evaluated at each quantile of the relative income distribution and allows for potential non-linearity in the marginal filter rate as implied by the DMP model.

A second specification, Equations (8)–(9),[20] modifies Equation (7) to allow for potentially heterogeneous effects of the refusal rate on filtering from sellers to buyers over the relative income distribution. Allowing for attribute coefficients that can also vary across local planning

[19] ζ_{it} is the residual of the regression with the supply constraints interaction.

[20] The quantile regression analogue of Equation (6).

areas, we estimate an IV-quantile model within the class proposed by Chetverikov, Larsen, and Palmer (2016), where we instrument for the local refusal rate and the u^{th} conditional-quantile is now:

$$\mathcal{R}_{it} \mid \mathbf{h}_t'(u), \tau_g = \gamma_g(u) + \beta_{g,age}(u) \times age_{it} + \sum_{j \in J \setminus age} \beta_{g,j}(u) h_{ijt} + \nu_{it}(u) \tag{8}$$

$$\beta_{g,age}(u) = \beta_{age}(u) + \beta_{age,\tau_g}(u) \times \tau_g + \varepsilon_g(u) \tag{9}$$

for each quantile $u \in \mathcal{U}$ and local planning area $g = 1, \ldots G$. The marginal filter rate by local planning area and quantile, $\beta_{g,age}(u)$, consists of a quantile-specific filter rate common to all local planning areas, $\beta_{age}(u)$, the local marginal effect of each local planning area's refusal rate, $\beta_{age,\tau_g}(u) \times \tau_g$, and an unobserved local area fixed effect, $\varepsilon_g(u)$, that affects filtering but that does not depend on local planning refusal.

4. Data and Identification

Our transactions data are drawn from a census of all home sales in the state of Victoria, Australia, between 2011 and 2016. These data are matched to buyer and seller income data sourced from annual tax filings using the name and address of each individual recorded on each side of a sale (transfer of residential property title). This matching is carried out by the national statistical office and the unique matching rate is 68%, which is comparable to international studies that use a similar approach.[21]

Income is measured as total annual before-tax income filed with the national tax office at the midpoint of the calendar year in which the transaction took place, and includes all

[21] The matching is undertaken by the Australian Bureau of Statistics (ABS) in consultation with the authors. Bayer et al. (2016) achieve a unique match rate of about 55% when matching housing transactions with mortgage data for the San Francisco Bay Area. The higher matching rate in Victoria likely reflects the use of state and federal administrative databases when matching (Appendix F).

income earned from labour and capital.[22] The analysis is restricted to transactions with up to two buyers and two sellers (the vast majority of transactions) and only include transactions where buyer and seller income are positive. We exclude atypical homes: the bottom 1% and top 1% of transactions by price and very small or very large homes as measured by lot size (for houses) or internal area (for apartments), see Appendix A.2. The final sample year, 2016, includes the age of each home sold – measured as the number of years since the home was first built – providing our main estimation sample when estimating the mean filtering rate (MFR) and the marginal effects of supply constraints on the MFR.

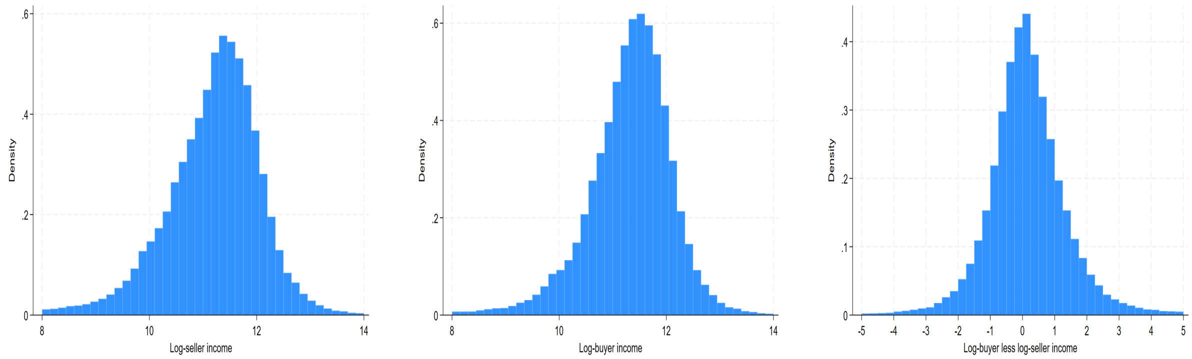
Consistent with the planning refusal probability used in the search-theoretic model, we use the share of residential planning applications refused in each local planning area in Victoria from 2007–2016 to measure local supply constraints. Planning decisions in each local planning area are made by a local government, also known as a council, and residential planning applications refer to a range of residential development activities including: applications to build new houses; build new apartments; sub-divisions; demolitions; the development of new and vacant land; land clearing; vegetation removal; and major extensions of existing home structures. There are 79 councils in Victoria that assess all residential planning applications in their local area. We measure the refusal rate by council and exclude applications that lapsed, are withdrawn, or where no final determination was made (see Appendix A.3).[23]

Documenting new facts: Figure 2 shows the log-income distributions for buyers and sellers over the full sample from 2011–2016, as well as the distribution of log-buyer income less log-seller income (relative income). There is considerable dispersion in relative income, with 54.05% of homes sold transferring up the income distribution to buyers with higher

[22]Tax returns are filed at the individual level in Australia each financial year ending 30 June. For each transaction we sum the individual incomes of all buyers, and separately the individual incomes of all sellers, to measure buyer income and seller income.

[23]Below and in the Appendix, we show that our results are not sensitive to using either narrower or broader measures of planning refusal.

Figure 2: Log income distributions: buyers and sellers (2011-2016)



Note: Histograms are reported for log-buyer income, log-seller income and relative income (log-buyer less log-seller income) for all transactions in Victoria from 2011 to 2016 based on over 218,000 housing transactions. The log-buyer income and log-seller income histograms are truncated at 8 and 14. The relative income histogram is truncated at -5 and 5.

income than sellers, and 45.95% transferring down to buyers with lower income.[24] The mean for relative income is +16 log points. Figure 3 shows the spatial distribution of mean relative income by council area. There is significant variation in relative income across council areas, but there is also evidence of clustering with high relative income more common in urban councils within cities such as Melbourne (right panel, Figure 3), and lower relative income more common in peri-urban and rural council areas.

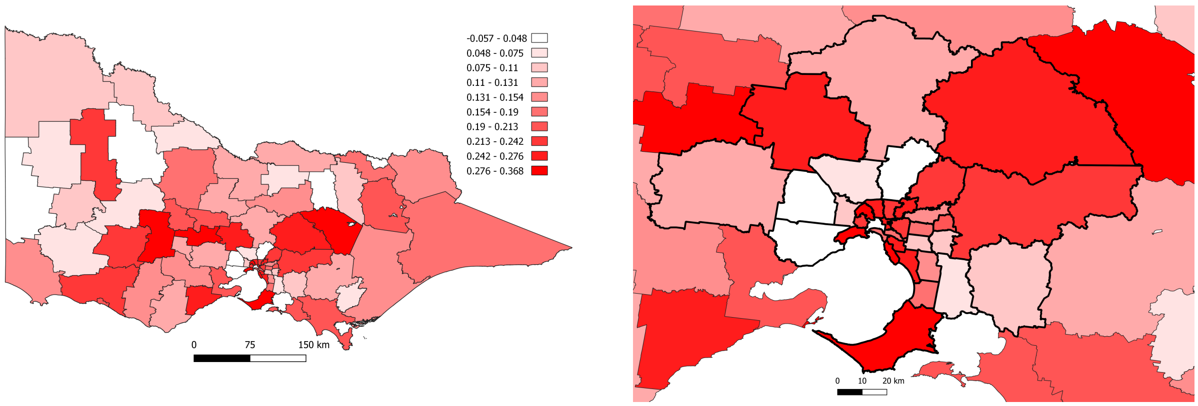
Figure 4 (left-panel) shows mean relative income when calculated using neighbourhood-level refusal rate quintiles, where neighbourhoods are smaller geographic areas than councils and represent communities that interact together socially and economically.[25] Neighbourhoods with a higher refusal rate have higher relative income, increasing from +12 log points in neighbourhoods in the lowest refusal rate quintile to +17 log points in the highest quintile.

A natural conjecture is that the positive mean for relative income is explained solely by differences in the ages of buyers and sellers, who may be at different stages of their lifecycle. Figure 4 (right-panel) shows that this is not the case. Estimating mean relative income

[24] This result is not specific to Victoria. Spader (2025) also finds almost half of all homes transfer up the income distribution when using data from the American Housing Survey.

[25] Neighbourhoods are measured using the Statistical Area 2 (SA2) definition from the national statistical office. There are approximately 450 neighbourhoods in Victoria that are covered by the 79 councils.

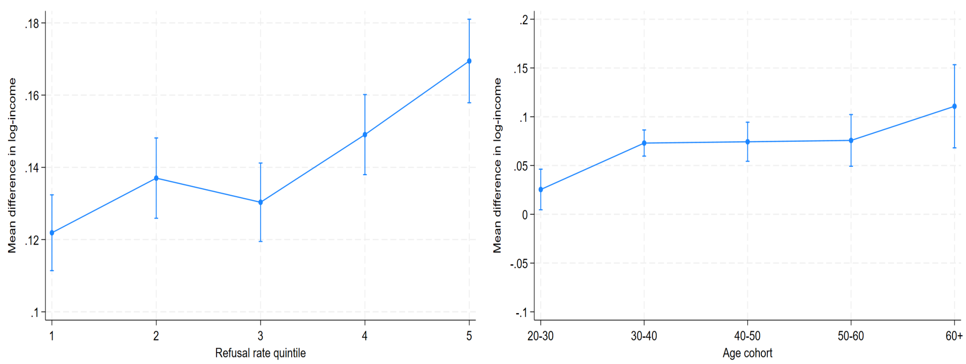
Figure 3: Relative Income by Local Government (Council) Area: 2011-2016



Note: Council areas within Victoria shaded by their relative income decile for 2011-2016. *Left-panel*: reports relative income deciles across councils for Victoria; *Right-panel*: Zooms to Greater Melbourne councils – enclosed with a bold outline.

restricting to transactions where the mean buyer and mean seller age are within the same 10-year age cohort, positive and statistically significant differences in relative income remain.

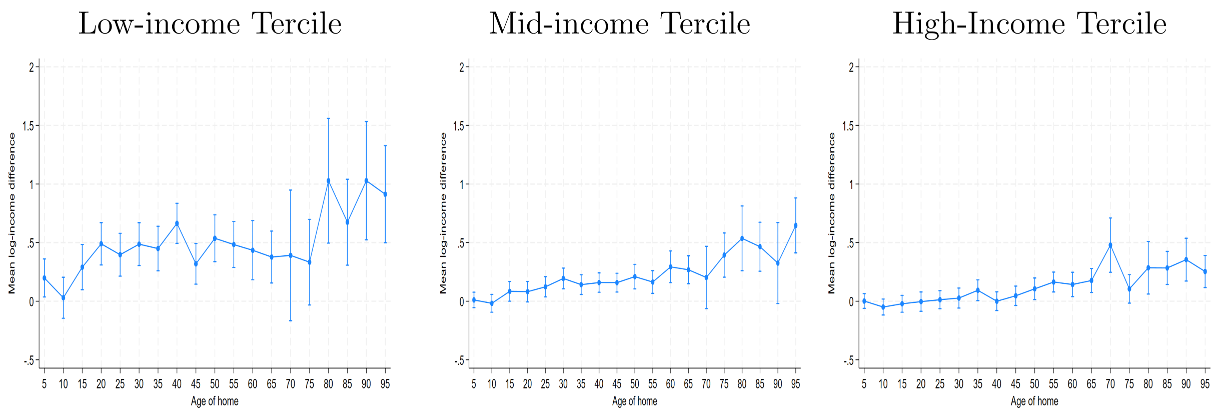
Figure 4: Relative Income by Neighbourhood Refusal Rate Quintile and by Buyer-Seller Age Cohort



Note: The left-panel measures the mean difference in log-buyer and log-seller income by neighbourhood refusal rate quintile from 2011–2016 with 95% confidence intervals reported using robust standard errors. The right-panel measures the mean difference in log-buyer and log-seller income for buyers and sellers in the same ten-year age-cohort. 95% confidence bands are reported using robust standard errors.

Figure 5 shows estimates of the seller-to-buyer filtering gradient (the change in the relative income) as homes age by income tercile, where income terciles are defined using the total income of all parties to a transaction. The estimates show a positive gradient with relative income increasing sharply as homes age in the lowest income tercile. For example, relative to a home that is less than 5-years old, a home that is 51-55 years old on average transfers to a buyer with income approximately 50 log points (+65%) higher than that of the seller. In the middle (2nd) and high (3rd) income terciles the gradient is not as steep, but remains positive and signficiant: relative to a home that is less than 5-years old, a home that is 51-55 years old transfers on average to a buyer with income approximately 20 log points higher than than that of the seller in the middle income tercile, and approximately 12.5 log points higher in the highest income tercile. Thus, we do observe that homes filter upwards more slowly as they age in higher income terciles consistent with the predictions of the search model.

Figure 5: Filtering by Home Age and Income Tercile: 2016



Note: The above figures report estimates of mean filtering rates by home age at different income terciles. For each tercile, we estimate: $\log \frac{Y^b_{it}}{Y^s_{it}} = \gamma + \beta^5_{age} \times d^{age,5}_{it} + \cdots + \beta^{95}_{age} \times d^{age,95}_{it} + \upsilon_{it}$ where $d^{age,n}_{it}$ is a dummy equal to 1 if home i sold at time t is $n+1$ to $n+5$ years old and zero otherwise. Robust standard errors are reported in parenthesis and all estimates are relative to homes that are 5-years old or less.

Table 1 reports descriptive statistics for our estimation sample with complete information on all home attributes (home type, size, number of bedrooms and home age). The mean house (apartment) age is 39 years (27 years) and the mean number of bedrooms is just over 3 (2). Mean lot size for houses and internal area for apartments are 650 sq. metres (777 sq. yards) and 95 sq. metres (114 sq. yards). The mean log-income for buyers is 11.31, which is +15.5 log points higher than sellers, and there is considerable dispersion in both log-buyer and log-seller income with a standard deviation of 0.90 and 1.04 log points.

Table 2 reports alternative measures of local planning refusal and decision times by application type. In our benchmark estimates, we use a measure of planning refusal that

Table 1: Descriptive Statistics

Data	(1) Mean	(2) S.D.	(3) P5	(4) P95
Planning applications (Unbalanced panel, 2007-2016)[a]				
Total No. applications = 186,042, Total No. Councils = 79				
Ref. Rate	0.031	0.023	0.000	0.080
Δ Ref. rate	-0.004	0.026	-0.036	0.030
Δ Dec. time	-23.99	24.58	-77.14	11.12
2001 Electoral data (Total votes matched to council areas = 2,675,481)[b]				
Total No. polling booths = 5,761, Total No. Councils = 79				
TPP	0.53	0.13	0.26	0.75

2016 Matched transactions with home age[c]	**Detached homes** Mean	S.D.	**Apartments** Mean	S.D.
Home age	39.15	30.37	27.24	22.52
Bedrooms	3.15	0.64	2.27	0.70
Log size	6.48	0.63	4.55	0.37
Log-buyer income	11.31	0.90	11.24	0.89
Log-seller income	11.16	1.04	11.19	1.05
Log price	13.17	0.55	13.11	0.48

Notes: [a] *Ref. rate* is the mean refusal rate from 2007 to 2016. Δ *Ref. rate* and Δ *Dec. time* are calculated as the change in the mean refusal rate and decision time by council before and after *VicSmart*. [b] *TPP* is the two-party-preferred percentage vote share measured by council for the 2001 national election to the Liberal-National Coalition. [c] Based on 22,237 (7,402) matched house (apartment) sales for 2016 with data on home age (*Home age*). *Log size* is the natural log of the lot size (internal area) for a house (apartment) measured in square metres. *Bedrooms* is the number of bedrooms. *Log price* is the natural log of the transaction price.

excludes applications that lapsed, where withdrawn, or did not have a final determination, and that treats notices of decision as approved applications. This measure implies that about 7% of new construction applications were refused outright (column 1), with a higher refusal rate for applications to build multiple dwellings (10%) than for the construction of a single dwelling (3%). Alternatively, treating applications that lapsed, were withdrawn, or without a final determination, as a form of implicit or tacit refusal, the tacit refusal rate on new construction rises to approximately 14% (column 2). Treating notices of decision as non-approved applications – since these decisions do not immediately confer a planning permit[26] – about a quarter of applications for new construction are either tacitly refused or

[26] A notice of decision is a notification by council that intends to approve the application subject to condi-

receive a notice of decision, with the tacit + notice refusal rate for multiple new dwellings rising to almost one third (column 3).

We use the refusal rate in column 1 throughout our analysis below, but similar estimates are obtained when using either of the broader measures of planning refusal (column 2 or column 3), as shown in Appendix A.3. Figure 6a shows the spatial distribution of the refusal rate in column 1 (hereafter the refusal rate) across Victorian councils (left-panel) and when zooming in to Greater Melbourne (right-panel). There is considerable spatial heterogeneity with refusal rates higher in urban councils and in councils with higher relative income.

Table 2: Local Planning Refusal and Decision Times by Application Type

	(1) Refusal rate (%)	(2) Tacit refsual rate (%)	(3) Tacit + notice rate (%)	(4) Decision time (days)
New construction	7.05	13.90	25.94	154.17
Single dwelling	3.08	9.17	16.46	118.04
Multiple dwellings	9.95	17.31	32.74	180.68
All applications	4.13	10.23	17.79	113.10

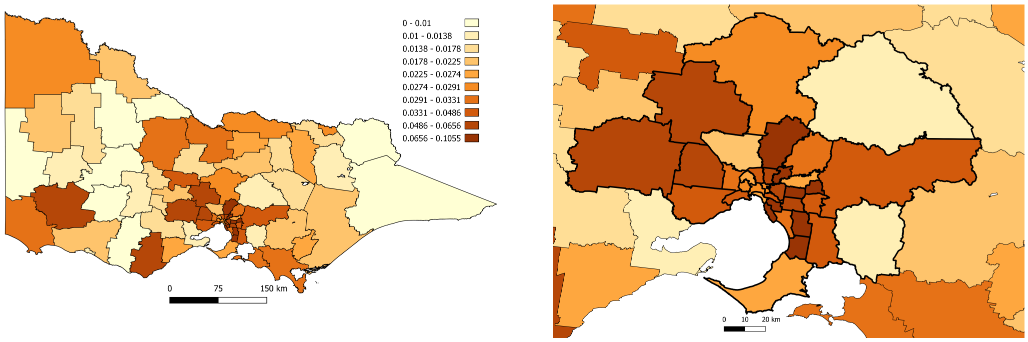
Notes: Measures of supply constraints on residential development applications assessed in Victoria from 2007–2016. *Refusal rate* is the share applications refused by local councils excluding notices of decision, applications that lapsed, were withdrawn or where no final determination was made. *Tacit refusal rate* includes the excluded categories. *Tacit + notice rate* treats notices of decision as a refusal. *Decision time* is the mean number of days from initial submission to a council decision based on the sample in column 1.

In sum, our descriptive statistics document new facts that align with the predictions of the search-theoretic model. First, there is significant dispersion in the rate that homes transfer across the income distribution from sellers to buyers, with significant shares of homes transferring down, and up, the income distribution across locations. Second, we find a significant positive mean for relative income: homes on average transfer *up* the income distribution in contrast to a Walrasian equilibrium or previous models of filtering. Third,

tions but noting that there are outstanding objections. Objectors then have 28 days to appeal. Appeals are referred to statewide tribunal (VCAT) and can be a lengthy and costly process, further delaying applications and can result in a council's initial decision being overturned.

Figure 6: Refusal Rates and The *VicSmart* Planning Instruments

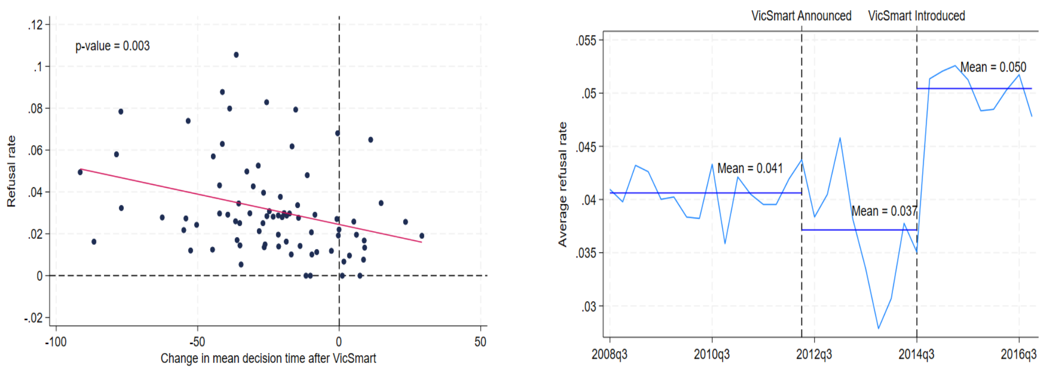
Panel a: Refusal Rates by Council Area



Panel b: The *VicSmart* Planning Instruments

Council Refusal Rate vs. Change in Mean Decision Time

Quarterly Refusal Rate Over Time



Notes: Authors calculations based on 186,042 planning applications assessed between 1 January 2007 to 31 December 2016. *Panel a*(left): council *refusal rate* (τ_g) by decile across the state of Victoria. *Panel a*(right): Greater Melbourne councils highlighted with a bold outline. *Panel b*(left): Scatter of the council *refusal rate* calculated over that period, against the *change in mean decision time* before (1 January 2007–18 September 2014) and after (19 September 2014–31 December 2016) *VicSmart*. *Panel b*(right): Mean quarterly *refusal rate* over time across for all residential planning applications in Victoria.

there is a positive, albeit reduced-form correlation, between relative income and refusal rates across neighbourhoods, and across councils. Fourth, the filtering gradient appears to be declining in the total income of buyers and sellers as implied by the search model.

Identification: To estimate the marginal effects of supply constraints, one could proceed directly by using the local council refusal rate and estimating Equations (6), or (8)–(9). The concern here is that council refusal rates can also be jointly determined by buyer and seller income. For example, older homeowners are incentivised to lodge objections and to vote against urban growth to maintain the value of their homes (Ortalo-Magné and Prat, 2014).

On the buyer side, there is evidence to suggest that supply constraints are more likely to bind in areas with a lower share of undeveloped land and with more favourable amenities (Hilber and Robert-Nicoud, 2013). Thus, buyers with higher incomes pay more to move to supply-constrained areas because they are more desirable. To address this, we use an identification strategy based on a regulatory reform that applied to all local councils in Victoria in 2014.

On 19 September 2014 the *VicSmart* planning reform took effect, which expedited the assessment process for simple planning applications. For eligible applications: (i) the scheme imposed a maximum assessment time of 10 business days; (ii) it removed the ability of local residents to object to or appeal any planning decision made; and (iii) it removed the discretion for councils to refuse them. Not all applications became eligible for *VicSmart*, but those that did include simple land subdivisions, new construction or extensions up to a given threshold value, and permits for land and vegetation clearing.[27]

Councils, however, had strong incentives to respond to this reform heterogeneously. In line with the preferences of the their local constituents, more restrictive councils could respond by refusing an even higher share of planning applications that were not eligible for consideration under VicSmart. Less restrictive councils had no similar incentive. We see strong evidence of this in the data. In the quarter that VicSmart took effect, planning refusal rates increased sharply and remained permanently higher thereafter (Figure 6b (right-panel)). In addition, if councils were constrained in their ability to increase planning delays, as seems likely given the intent of VicSmart, we should also observe larger falls in the mean decision times in more restrictive councils. This is shown in Figure 6b (left-panel) where most councils significantly reduced their decision time after the reform was introduced, and more restrictive councils had larger reductions. We use the change in the mean council decision time and the mean council refusal rate for all residential planning applications assessed before (1 Jan 2007–18 Sep 2014) and after (19 Sep 2014–31 Dec 2016) *VicSmart* took effect as instruments in estimation.

[27] See Appendix A.4 for more detail.

One concern with these instruments is that they might be contaminated by differences in the resources available to councils to assess applications; for example, perhaps larger and more restrictive councils reduced their planning decision times by more as they had more resources to comply with the legislation.[28] For robustness, we consider a third instrument that uses a different source of exogenous variation – historical voting shares. Motivated by Hilber and Vermeulen (2015), voting preferences over the two major national political parties are likely to be correlated with preferences for more or less restrictive housing supply. To ensure exogeneity, it is important that voting shares for national elections are used, as outcomes from state or council elections may be directly impacted by local planning issues.

We use national election voting shares for the two major political parties – the Liberal-National Coalition and the Australian Labor Party – measured on a two-party-preferred basis from the 2001 election as our primary voting instrument. This election is held well before our estimation sample, but still allows accurate geographic matching of voting shares by polling booth to voting shares by council area. In our robustness checks, we also report results using historical voting shares from national elections held in 1998, 2004 and 2007.

5. Estimation Results

We start with Equation (5). The dependent variable is relative income and the included covariates are home age (sale year less construction year), the square of home age, the number of bedrooms, and a measure of home size – log lot size (internal area) for houses (apartments). Table 3 reports estimates of the mean marginal filter rate per home-year (MFR) – $\beta_{age} + 2\beta_{age^2} \times \overline{age}_{it}$ – estimated on the house and apartment samples separately.[29] Table 3 shows the mean MFRs for houses and apartments are significant at +0.32% and

[28] While this has the potential to explain the decline in planning decision times, it does not explain the increase in planning refusal rate after VicSmart took effect.

[29] β_{age} and β_{age^2} denote the linear and quadratic coefficients on home age; $\overline{age}_{it}$ is the corresponding sample mean. In the data, we find a second-order polynomial in age is sufficient to accurately characterize the nonlinear effect of age on relative income – a similar result is obtained in Liu et al. (2021).

+0.44% per home-year, implying that homes on average filter *up* the income distribution as they age. Columns 2–3 and 5–6 show that neither second-home (investor) purchases nor downsizing sales explain the upward filtering observed.[30]

Table 3: OLS Estimates of Filtering

$$\mathcal{R}_{it} = \sum_{j \in J \setminus age} \beta_j h_{ijt} + \beta_{age} age_{it} + \beta_{age^2} age_{it}^2 + \eta_{it}$$

	(1)	(2)	(3)	(4)	(5)	(6)
	Houses			**Apartments**		
	All sales	Excl. investor purchases	Excl. downsizing sales	All sales	Excl. investor purchases	Excl. downsizing sales
Mean Marginal	0.32***	0.34***	0.22***	0.44***	0.47***	0.26***
Filter Rate (%)	(0.05)	(0.06)	(0.05)	(0.10)	(0.12)	(0.10)
P.C. fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Home attributes	Yes	Yes	Yes	Yes	Yes	Yes
RMSE	1.305	1.272	1.224	1.329	1.303	1.257
No. obs	22,237	16,349	19,678	7,402	4,982	6,533

Notes: All specifications include postal code (*P.C.*) fixed effects and controls for home age; home age squared; bedrooms; and log lot size (internal area) for houses (apartments). *Excl. investor purchases* excludes transactions where the buyer declares the home purchased will not be their principal place of residence. *Excl. downsizing sales* excludes transactions where the mean seller age is 65 years or older. *Mean Marginal Filter Rate (%)* is the marginal change in log-buyer less log-seller income of an additional home-year evaluated at the sample mean reported in % points.

Equation (6) additionally controls for the refusal rate interacted with home age (hereafter age). Table 4, column 1, reports OLS estimates with the subsequent columns showing various IV specifications – column 2 where all instruments are used, and subsequent columns excluding one instrument at a time.

Using instruments for the refusal rate lowers estimates of the mean MFR – from +0.34% under OLS to +0.01% when using IV with all three instruments. This change is economically significant. For a mean 40-year old house, it implies that expected relative income drops from approximately +20% to only +2%. By contrast, a one standard deviation increase in

[30] Investor purchases are defined as transactions where the buyer reports that the home purchased will not be their principal place of residence. Downsizing is defined as transactions where the average age of the sellers is 65 years or older, the age at which individuals became eligible for a government-funded pension.

the refusal rate increases the mean MFR by +0.25% per home year, with similar estimates obtained across IV specifications when excluding one instrument at a time, and when using a battery of robustness checks (presented below).

Table 4 presents the second stage IV estimates. Estimates of the first stage are in Appendix Table B2. The first stage coefficient signs on the planning instruments match their theoretical interpretation. Each instrument is highly significant and tests of the null of weak instruments are rejected when using robust weak-instrument tests (Andrews, Stock, and Sun, 2019, Montiel Olea and Pflueger, 2013).

Figure 7a shows quantile estimates using the quantile-IV estimator, Equations (8) and (9). We now see direct evidence of a marginal filter rate that aligns with previous theoretical filtering models and our search-theoretic model when supply constraints are relaxed. The common component in council filter rates, $\beta_{age}(u)$, evaluated at the 0.15 and 0.30 quantiles is large and negative, approximately -2% per home-year (Figure 7a, left-panel). This estimate excludes the effects of local planning refusal on marginal filter rates and quantile-specific council fixed-effects, and is consistent with homes filtering quickly down the income distribution to buyers with lower income than sellers at low relative-income quantiles. At high relative-income quantiles (0.75 and 0.90), however, the marginal filter rate rises and is essentially zero.

The effects of a one standard deviation increase in the refusal rate on the MFR at different relative income quantiles, $\beta_{age,\tau_g}(u) \times \sigma_{\tau_g}$, is close to a mirror image (Figure 7a, right-panel). There are significant positive effects of a higher refusal rate on buyers with low relative incomes. The marginal filter rate increases by +0.12% per home-year in response to a one standard deviation increase in the refusal rate at the 0.15 and 0.30 quantiles, but this effect is negligible at high relative-income quantiles (0.75 and 0.90). Thus, our estimates suggest that the effects of supply constraints on filtering are largest precisely in those areas where buyers have low incomes relative to sellers. In areas where buyer incomes exceed sellers, the effects of supply constraints on the MFR are small.

Table 4: The Effects of Supply Constraints on House Filtering

$$\mathcal{R}_{it} = \sum_{j \in J \backslash age} \beta_j h_{ijt} + \beta_{age} age_{it} + \beta_{age^2} age_{it}^2 + \beta_{age,\tau} \left(age_{it} \times \tau_g \right) + \zeta_{it}$$

	(1)	(2)	(3)	(4)	(5)
	OLS	IV(TSLS) Second Stage			
N=22,237		All instr.	Excl. Δ Dec. time	Excl. Δ Ref. rate	Excl. TPP
Age	0.006***	0.001	0.0001	-0.0003	0.001
	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)
Age squared	-0.3e-04**	-0.1e-04	-0.1e-04	-9.2e-06	-0.1e-04
	(7.9e-06)	(9.9e-06)	(0.1e-04)	(0.1e-04)	(9.9e-06)
Ref. rate × Age	0.033***	0.111***	0.129**	0.137***	0.111***
	(0.009)	(0.034)	(0.064)	(0.045)	(0.034)
Bedrooms	-0.037*	-0.046***	-0.048***	-0.049***	-0.046***
	(0.015)	(0.016)	(0.017)	(0.016)	(0.016)
Log lot size	0.044***	0.063***	0.068***	0.070***	0.064***
	(0.016)	(0.018)	(0.023)	(0.020)	(0.018)
Mean MFR (%)	0.34***	0.01	-0.07	-0.11	0.01
	(0.05)	(0.15)	(0.28)	(0.20)	(0.15)
M.E. of Ref. rate (%)	0.07***	0.25***	0.29**	0.31***	0.25***
	(0.02)	(0.08)	(0.15)	(0.10)	(0.08)
Eff. F-stat.		147.19	54.60	142.90	213.14
5%/10%		22.55/13.97	14.15/9.46	7.46/5.52	18.75/12.16
/20% CV		/9.18	/6.74	/4.39	/8.38

Notes: See notes to Table 1 for variable definitions. This table shows OLS and second-stage IV Two Stage Least Squares (*IV(TSLS)*) estimates where the dependent variable is relative income with all instruments and when excluding one instrument at a time. The Eff. F-stat. is from Montiel Olea and Pflueger (2013) with 5%, 10% and 20% Nagar-bias critical values (CV) with 5% size.

An IV Policy Counterfactual: The previous estimates show planning refusal can explain much of the upward filtering observed from sellers to buyers as homes age. Here we illustrate the magnitude of these effects through a simple estimated counterfactual that ignores general equilibrium effects and the potential for changes in developer, buyer and seller behaviour. Using the benchmark IV estimates that include all instruments (Table 4, column 2), we calculate a counterfactual for predicted relative income if refusal rates were reduced at all councils by one standard deviation, two standard deviations, and when reduced to zero and respecting the constraint that refusal rate in each council must be weakly positive.

Figure 7b, Table row 1, shows that predicted mean relative income is +15.5 log points

(+16.8%) for the benchmark IV model (Equation 6). Reducing refusal rates by one standard deviation reduces the predicted mean to +6.6 log points (+6.8%), two standard deviations to +2.0%, and removing planning refusal altogether to −1.3%. That is, if all council refusal rates were zero, the estimates suggest buyers would have *lower* incomes on average than sellers. The predicted falls in mean relative income are *larger* when we additionally control for postcode and quarter fixed effects, falling to -5.2 log points in that case (Figure 7b, Table row 2).

Why are the effects of lowering planning refusal rates nonlinear? It is partly explained by the fact that refusal rates are bounded below at zero. However, this is not the only explanation. Interaction between the home age distribution and the refusal rate is also important. The home age distribution exhibits positive skewness, which together with the fact that older homes are more frequently sold in areas where refusal rates are higher to higher income buyers, implies positive skewness in the relative income distribution as well. In fact, this correlation is predicted by the search-theoretic model.[31]

Comparing the predicted and counterfactual densities of relative income in Figure 7b confirms this. The left-panel shows the predicted density of relative income in the IV model with all instruments, and when reducing the refusal rate at all councils by 1 standard deviation. The right-panel shows a similar comparison, but now the counterfactual density is calculated when setting the refusal rate at all councils to zero. The difference between the predicted and counterfactual densities in both cases show that higher refusal rates not only increase the predicted mean of relative income, but induce significant positive skewness in the predicted relative income distribution as well.

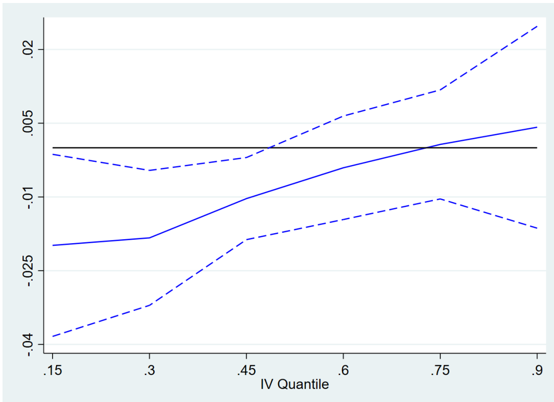
Robustness: We explore the veracity of our results using a wide range of specification

[31]More precisely, the DMP model predicts upward filtering is more likely in locations with more low-quality homes than high-quality homes, and downward filtering in areas with more high-quality homes than low-quality homes. In the data, this corresponds to upward filtering in locations with a higher share of older homes and tighter supply constraints.

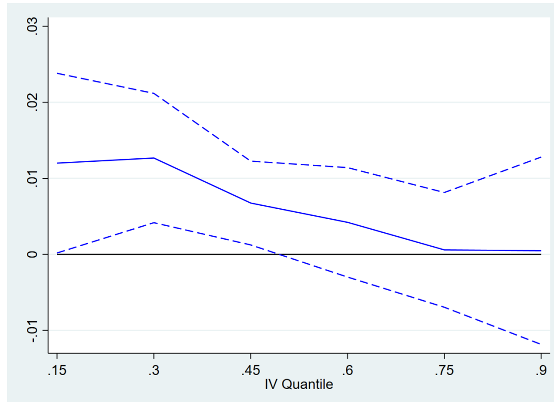
Figure 7: Quantile-IV Estimates and IV Counterfactuals

Panel A: IV Quantile Estimates

MFR by Quantile



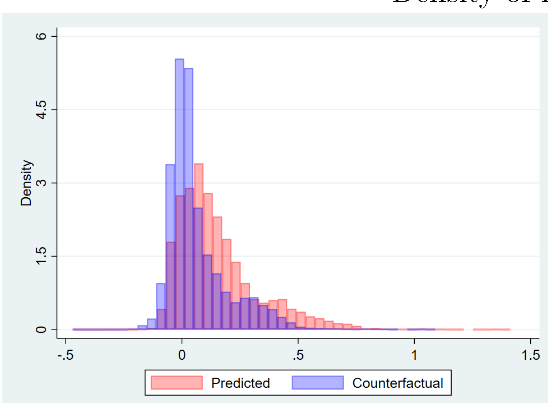
M.E. of Refusal Rate by Quantile

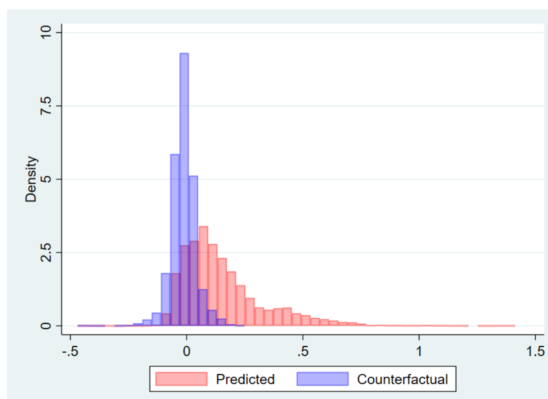


Notes: Second stage quantile-IV estimates with all instruments and excluding the bottom and top 10% of councils by quantile (Chetverikov et al., 2016). *Left*: $\widehat{\beta}_{age}(u)$ – the MFR by quantile. *Right*: $\widehat{\beta}_{age,\tau_g}(u) \times \sigma_{\tau_g}$ – the effect of a 1 S.D. increase in the refusal rate on the MFR by quantile. Dashed lines are robust 90% asymptotic confidence intervals.

Panel B: IV Policy Counterfactuals

Density of relative income





Predicted mean of relative income N=22,237	(1) Benchmark	(2) Reducing constraints by 1 S.D.[a]	(3) Reducing constraints by 2 S.D.[b]	(4) Removing constraints[c]
(1) IV(TSLS)	0.155	0.066	0.020	-0.013
(2) IV(TSLS) with P.C. & time fixed effects	0.155	0.045	-0.012	-0.052

Notes: *IV(TSLS)* uses the two-stage least squares model estimates reported in column 2 of Table 4. *IV(TSLS) with P.C. & time fixed effects* reports mean predictions with additional controls for postal code and quarter fixed effects. [a]All council refusal rates are reduced by 1 S.D. (2.27%) subject to the zero lower bound. [b]The reduction is 2 S.D. again subject to the zero lower bound. [c]Sets all council refusal rates to zero. Predicted densities in the histograms are based on *IV(TSLS)*. *Predicted* is the predicted density from the *Estimation sample*. *Left*: Counterfactual density when reducing the refusal rate in all councils by 1 S.D. as per [a]. *Right*: Counterfactual density when reducing refusal rates in all councils to zero as per [c].

checks with full results reported in Appendix B. Table B3, columns 1 to 4, present the benchmark specifications in Table 4 but now including postcode fixed effects to control for unobserved spatial heterogeneity and using a more narrowly defined measure of the refusal rate; column 5, a restricted sample to councils within the Greater Melbourne area only. The results are similar and, if anything, strengthen our earlier findings that estimated filter rates from sellers to buyers are either zero or negative when instrumenting for local planning refusal.

Table B4, reports estimates for: (i) controlling for both postcode and quarter fixed effects jointly to ensure that seasonality or hot and cold markets within the year are not a confounding factor (Ngai and Tenreyro, 2014); (ii) instrumenting for refusal rates at a more disaggregated geographical level (neighbourhood level as opposed to council-level), allowing for the idea that councils could implement supply constraints heterogeneously within their own jurisdiction; (iii) controlling for changing neighbourhood characteristics over time;[32] and (iv) to capture spatial differences in the demand and supply of homes that may be driven by proximity to Greater Melbourne (and thus population density), we also include the distance to the Melbourne city core as an additional control.

Our main results hold in each case. Estimates of the marginal filter rate instrumenting for the refusal rate vary from -0.40% to -0.04%. The estimated effect of a one standard deviation increase in the refusal rate on the MFR ranges from +0.27% to +0.47% per additional home-year (Table B4, columns 1 to 4), which is a similar range to the estimates reported in Table 4. We also substantiate that our findings are not driven by differences in local topography that

[32]We do so using the percentile change in an index of relative socioeconomic advantage and disadvantage by council, a proxy for whether neighbourhoods were becoming more or less desirable over time. Between 2011 and 2016, we measure the change in each council's relative percentile using the Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD). IRSAD percentiles are calculated by the ABS using principal components on a range of socioeconomic household characteristics such as income, skilled occupations, education, employment etc.

can also act as a barrier to new construction. In Table B4, column 5, we include additional controls for the share of each council covered by water bodies and local variation in ground surface point elevation by council (Saiz, 2010). Again, the results are similar.

To assess the validity of our planning instruments, we use placebo checks that consider alternative timings for when the *VicSmart* reform took effect. The first check brings the date forward by one year (19 September 2013). The second uses the date that the *VicSmart* reforms were announced (07 June 2012), and the third the date that a state government advisory committee was formed with the intent to review local planning laws (14 June 2011). The results in Table B5 show the strength of the planning instruments, as measured by the Effective F-statistic, essentially disappears with these alternative timings. To assess the validity of the two-party-preferred (TPP) vote share from the 2001 national election, we also use TPP voting shares from three other national elections prior to our estimation sample – 1998, 2004 and 2007. Results are similar regardless of the election used with instrument strength retained (Table B6).

Finally, although the search-theoretical model can be generalised to allow for different log-buyer and log-seller income distributions, there is still the concern that selection on buyer and seller characteristics is also highly salient and a potential explanation of our empirical results. To investigate this possibility, we additionally match buyers and sellers listed on transactions to their responses reported in the national Census held in August 2016.[33] The Census data contain information on individual labour force status, occupation, education, mortgage repayments, age and other buyer and seller characteristics. With IV specifications that include these characteristics explaining 31% to 38% of the variation in relative income, our estimates of the MFR vary from −0.28% to −0.25%, and those for the effects of a one standard increase in the refusal rate on the MFR from +0.18% to 0.25% (Table B7, columns 1–5). Additionally including controls for home and seller heterogeneity (Ortalo-Magné and

[33]The Census is a national census of Australian residents held every five years and is distributed to all residents. It surveys a wide range of household socio-economic and demographic characteristics.

Rady, 2008), with nearly half of the variation in relative income now explained (Table B7, column 6), we still find a positive statistical and economically significant effect of local planning refusal on the MFR at +0.17% per home year.

6. Conclusion

We investigate how filtering between buyers and sellers offers new insights on the transfer of homes across the income distribution and on the effects of local supply constraints on those transfers. Using a DMP model of filtering from sellers to buyers, and where new homes are produced by competitive developers, we show that existing homes can filter in either direction depending on the willingness of buyers and sellers to transact. When local supply constraints are tight or the supply of low-quality homes is abundant relative to high-quality homes, the model predicts homes are more likely to transfer up the income distribution from sellers to buyers and a positive mean filter rate overall. However, homes will filter up the income distribution more slowly in areas where both buyers and sellers have higher income. These predictions are in contrast to previous models of filtering that abstract from search frictions and supply constraints, and that predict that homes should filter down the income distribution.

Using a novel data set that matches housing transactions to buyer and seller income and local planning data from Victoria, Australia, we document new evidence on the rate at which homes transfer across the income distribution from sellers to buyers. We find significant dispersion in log-income differences between buyers and sellers across council areas with homes transferring down and up the income distribution. We also find strong evidence that locations with tighter constraints on the building of new homes increase the income differences observed between buyers and sellers and are sufficient to explain the upward filtering of homes on average. In the absence of these constraints, we estimate that the mean home would filter down the income distribution in line with previous theory and as implied by the DMP model. These results offer new insights on the importance of regulatory supply constraints for filtering, and shows how relaxing those constraints offers policymakers another alternative to improve housing affordability through private-market filtering.

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Supplementary Appendices – For Online Publication Only

Appendix A. Filtering Mapping and Data

Appendix A.1. Mapping From Repeat-Buyer to Seller-Buyer Filtering

We first show the mapping from previous estimates of filtering using the repeat log-income of buyers over time (Rosenthal, 2014, Liu et al., 2021), to our estimates that use log-buyer less log-seller income at the point a home is sold. Following Rosenthal, we assume that real buyer income for home i, Y^b_{it}, has a common component, $\mathcal{Y}\left(H_{it,}\omega_t\right)$, and an idiosyncratic component, γ^b_{it}, with total buyer income for home i at time t given by:

$$Y^b_{it} = e^{\gamma^b_{it}}\mathcal{Y}\left(\boldsymbol{H}_{it,}\boldsymbol{\omega}_t\right),$$

and that the structural and neighbourhood attributes of a home, and their associated implicit prices, are constant over time as a home ages, $\boldsymbol{H}_{it} = \boldsymbol{H}_i$ and $\boldsymbol{\omega}_t = \boldsymbol{\omega}$. The change in real log-buyer income between repeat sales of a home, first sold in period t' and then resold in period t, is then:

$$\log\frac{Y^b_{it}}{Y^b_{it'}} = \gamma^b_{it} - \gamma^b_{it'} \tag{A.1}$$

Regressing the change in real log-buyer income between repeat sales on a vector of time-based dummy variables, taking the value -1 when the home is first sold in period t', $+1$ when resold in period t, and 0 in all other periods, provides an empirical estimate of $\gamma^b_{it} - \gamma^b_{it'}$. This estimate is interpreted as the change in real log-buyer income associated with the depreciation of home quality from period t' to period t – typically measured as the number of years between repeat sales. With a large sample of repeat sales over a sufficiently long time period where different homes are resold over different time periods, one can estimate the repeat-buyer filtering gradient using the fact that number of years between repeat sales exactly matches the number of years that each home ages.[34]

To map our estimates of seller-to-buyer filtering to repeat-buyer filtering, we posit the following joint income model for buyers and sellers (identical to the income process discussed in the main text):

$$\log Y_{it}^{j} = \mathbb{1}_{b}\gamma_{it}^{b} + (1 - \mathbb{1}_{b})\,\gamma_{it}^{s} + \log \mathcal{Y}\,(H_{it}, \omega_{t})$$

where $j = b, s$ indexes the $\{buyer, seller\}$, Y_{it}^{j} is real income for market participant j when trading home i at time t, and assuming that buyers and sellers share the same common component in their income $\mathcal{Y}\,(H_{it,}\omega_{t})$. The idiosyncratic components of log-income for buyers and sellers are γ_{it}^{b} and γ_{it}^{s}, and $\mathbb{1}_{b}$ is an indicator function equal to 1 for a log-buyer income observation and 0 for a log-seller income observation. Subtracting log-seller income from log-buyer income, when a home is sold in period t we obtain:

$$\log \frac{Y_{it}^{b}}{Y_{it}^{s}} = \gamma_{it}^{b} - \gamma_{it}^{s} \tag{A.2}$$

which is the assumed data generating process that underpins the regression specification used in Equation (4) in the main text. To see the mapping from Equation (A.2) to repeat-buyer income estimates of filtering, Equation (A.1), we use the following buyer-seller log-income decomposition for any home first sold in period t', and then resold in period t:

$$\log \frac{Y_{it}^{b}}{Y_{it'}^{b}} = \log \frac{Y_{it}^{b}}{Y_{it}^{s}} - \log \frac{Y_{it'}^{b}}{Y_{it'}^{s}} + \log \frac{Y_{it}^{s}}{Y_{it'}^{s}}$$

Imposing the first-order approximation that underlies our baseline empirical specification and similar to that used by Liu et al. (2021), $\log \frac{Y_{it}^{b}}{Y_{it}^{s}} = \gamma + \beta_{age}age_{it} + \beta_{age,\tau}\,(age_{it} \times \tau_{g})\,,$ we

[34]Implicit here is the assumption that significant renovations that improve quality, or tear downs and new builds, are observed and excluded from the sample as these homes would violate the assumption that home attributes are time invariant.

have:

$$\log \frac{Y^b_{it}}{Y^b_{it'}} = \beta_{age} \left(age_{it} - age_{it'}\right) + \beta_{age,\tau} \left(\left(age_{it} - age_{it'}\right) \times \tau_g\right) + \log \frac{Y^s_{it}}{Y^s_{it'}}$$

Applying the assumptions that home attributes and their implicit prices are time invariant ($H_{it} = H_i$ and $\omega_t = \omega$) as assumed in the repeat-buyer income model:

$$\gamma^b_{it} - \gamma^b_{it'} = \beta_{age} \left(t - t'\right) + \beta_{age,\tau} \left(t - t'\right) \tau_g + \gamma^s_{it} - \gamma^s_{it'}$$

Thus, there is a direct mapping from the estimates of repeat-buyer filtering used in Rosenthal, $\gamma^b_{it} - \gamma^b_{it'}$, and our estimates of the marginal seller-to-buyer filter rate (β_{age}), and the marginal effect of supply constraints on the marginal seller-to-buyer filter rate ($\beta_{age,\tau}$). Indeed, restricting to the sample of repeat-sales, one can "back out" the implied repeat-buyer income estimate by subtracting off the real change in log-seller income between repeat-sales of a home with a sufficiently long time series sample and where both buyer and seller income are observed. This should not come as a surprise since a key distinction between using the difference in log-buyer and log-seller income and repeat-buyer income is that the former is in effect measuring the original buyer's income at the point they resell the home, as opposed to the latter that measures the original buyer's income when they first purchased the home.

Several additional points are noteworthy. First, in the absence of any change in the real incomes of sellers over time (and absent supply constraints), the estimate of the marginal filter rate using log-buyer less log-seller income (relative income) is identical to the slope coefficient obtained from the repeat-buyer model if one regresses each sample of pairs of repeat-buyer incomes (that is, for each t' and t) on the number of periods between repeat sales.[35] Second, the marginal effect of supply constraints on filtering, $\beta_{age,\tau}$, can also be identified using real repeat-buyer incomes. Third, when real log-seller incomes change, in particular when they grow over time, the marginal-filter rate estimated from seller to buyers

[35] One can include second-order terms here, as we do in Table 4, to better capture non-linearities in filtering as homes age; or use dummy variables for alternative age groupings as we do in Figure 5.

will be strictly below that estimated using real repeat-buyer income only. Thus, estimates of seller-to-buyer filtering can be used to bound estimates associated with real repeat-buyer income, providing a lower bound in a market where real mean seller incomes are rising and an upper bound when they are falling.

However, there are also important differences between the two measures. One is that the estimates using real repeat-buyer income necessarily require the assumption of time-invariant home attributes and implicit prices, which is not the case for estimates that use the difference in log-buyer and log-seller income at the point a home is sold. This can be an important issue in practice as discussed by Nowak and Smith (2020) who find significant quality changes in home attributes between repeat sales. Second, in general the samples used by the two estimators will be different. Repeat-buyer income estimates require long time series and can only be estimated on homes sold more than once. In practice, this can be a significant data requirement as shown in Liu et al. (2021), where repeat-sales make up less than a fifth of sales overall in their sample, and thus excludes the majority of homes that are only sold once. Using the difference in log-buyer and log-seller income uses the additional information from single sales in estimation, and can be applied on samples with short time series or where only cross-sectional data are available.

Appendix A.2. Matching Housing Transactions to Income

The housing transactions data are sourced from property title transfers provided by the Victorian Department of Treasury and Finance under Australian Research Council Linkage Project LP160101518: "Predicting the Value and Use of Urban Land". Income data are sourced from the personal income taxation database within the Australian Bureau of Statistics (ABS) Multi-Agency Data Integration Project (MADIP). As noted below, housing transactions are matched to the MADIP spline by the the ABS in a secure data environment before being de-identified and accessed by the authors through the ABS DataLab portal.[36]

A deterministic matching algorithm was applied by the ABS in consultation with the authors. The algorithm matches name and address pairs recorded on residential property title transactions to names and address pairs recorded in MADIP. MADIP is a census of all individuals in Australia including those who, between 2006 and 2021, have participated in one or more off: (i) the Medicare Consumer Directory (Medicare the name of the universal national healthcare system of Australia – it covers all citizens and permanent residents); (ii) the personal income tax database maintained by the Australian Taxation Office (ATO); or (iii) the government social security (DOMINO Centrelink) database.[37]

Of the 1,996,660 unique name-address pairs identified in the housing transactions data, exact matches were found for 68.2% of records (approximately 1.36 million records). This is a relatively high unique match rate. For example, Bayer et al. (2016) undertake a similar matching exercise for the San Francisco Bay Area using housing transaction and mortgage data and achieve a unique match rate of about 55%.[38]

Retaining transactions where all individuals (buyers and sellers) are uniquely matched to MADIP (1,040,241 individual property title changes corresponding to 277,529 unique housing transactions), incomes for buyers and sellers are sourced from the ATO personal income taxation database component of MADIP. This database records total income earned before-tax (hereafter income) from tax filings by individual in each taxation (financial) year.

[36]Access to the underlying unit record data is managed by the Australian Bureau of Statistics and the Victorian Department of Treasury and Finance. Further information on obtaining access to the ABS DataLab is provided here: https://www.abs.gov.au/statistics/microdata-tablebuilder/datalab. Associated data disclaimers are reported in Appendix F. MADIP is the precursor to subsequent releases of this dataset, now known as PLIDA.

[37]See Parker (2017) and https://www.abs.gov.au/websitedbs/d3310114.nsf/home/Person+Linkage+Spine for further detail.

[38]Notwithstanding, addresses on housing transactions do not always match the same as the residential address of the parties in MADIP, and housing transactions do not include other demographic information such as gender or date of birth, that are often used by the ABS in other data linkages.

We restrict the sample to matched transactions with up to two buyers and two sellers (the vast majority of transactions),[39] and require total income (for all buyers, and for all sellers) to be positive. We exclude transactions for atypical homes – measured as homes in the top or bottom 1% of the price distribution, the top 1% for bedrooms by home type – house or apartment, the top 5% in terms of lot size for houses and the top 1% in terms of internal area for apartments. This leaves us with 222,375 observations for calculating mean differences in log-buyer and log-seller income over the 2011–2016 sample. Where age of the home is required to estimate the mean marginal filter rate, we restrict the sample to transactions in 2016 where data on age are available. This leaves 33,489 sales for estimation across Victoria, 22,237 of which are house sales and 7,402 are apartment sales.

Appendix A.3. Planning Permit Applications Data and Measuring Supply Constraints

The planning permit applications data are sourced from the Victorian Planning Permit Activity Reporting system (PPARs).[40] We use planning applications where the proposed land use is residential and exclude non-residential and mixed-use applications.[41] The application categories for proposed residential development include: new single homes; new multi-family dwellings (e.g., units, apartments and townhouses); subdivision of land and buildings; changes, extensions or alterations to a building structure or dwelling; new and other building works; consolidation; demolition; vegetation removal; and other subdivisions including changes to easements or realignment of boundaries. In the robustness checks (see Table B3), we also consider a more narrow set of applications excluding vegetation removal and the other (multiple group) application categories.

[39] Transactions with at most two buyers and two sellers make up the vast majority of transactions. Only 18,180 of 1,058,421 uniquely matched title changes involved more than two buyers or more than two sellers.

[40] See the Planning Permit Activity Reporting Data Dictionary, Version 7.9.2 available at: https://www.planning.vic.gov.au/guides-and-resources/council-resources/planning-permit-activity-reporting/guide-to-permit-activity-reporting.

[41] Non-residential includes retail, office, commercial and industrial applications. Mixed-use includes, for example, homes combined with a retail or office premises.

When measuring the refusal rate, we use the share of all permit applications assessed between 2007 and 2016 that are refused outright by the responsible council. Excluded from our baseline refusal rate measure are applications that are yet to be determined, where the application is withdrawn by the applicant, the application lapses or where no final determination is made. The refusal rate by application type is reported in Table 2 (column 1). Refusal rates are higher for new construction (single dwellings + multiple dwellings) at 7.05%, and in particular multiple dwellings at almost 10%. Additionally including the withdrawn, lapsed and applications without a determination - a measure of tacit refusal – increases refusal rates across all applications categories (Table 2, column 2, main text), as does treating Notices of Decision as a form of tacit refusal (Table 2, column 3, main text). Although we use the narrowest, and perhaps the most conservative measure of planning refusal, our estimates are not sensitive to that choice. Table A1 reports estimates of the effects of supply constraints on the MFR using the same specification, instruments and sample in each case, but changing the measure of local planning refusal used allowing for tacit refusal, and tacit refusal plus Notices of Decision (N.O.D). The estimates are similar in each case.

Table A1: Marginal Effects of Supply Constraints with Tacit Refusal

IV(TSLS) – Second stage, dependent variable is log-buyer less log-seller income

	(1) Refusal rate	(2) Tacit refusal rate	(3) Tacit refusal rate + N.O.D
M.E. of Supply Constraints (%)	0.26*** (0.08)	0.30*** (0.08)	0.26*** (0.10)
RMSE	1.310	1.311	1.310
No. obs.	22,237	22,237	22,237

Notes: Estimates are from the second-stage of IV Two Stage Least Squares (*IV(TSLS)*) regressions of the dependent variable (log-buyer less log-seller income) on the local planning refusal rate (either refusal rate, tacit refusal rate or tacit refusal rate + notice of decision as listed in the column heading and defined in Table 2), on house age, house age squared, the log lot size, the number of bedrooms, and using the changes in the mean decision time and local planning refusal rate (before and after *VicSmart*), and two-party preferred vote share from the 2001 Federal election as instruments.

Appendix A.4. VicSmart

To measure exogenous variation in local planning refusal, we use the *VicSmart* planning reform that was introduced on 19 September 2014. While councils are still responsible for assessing *VicSmart* eligible applications, separate application and assessment criteria apply. *VicSmart* applications have a binding 10-day decision requirement,[42] are protected from third party appeals, and have pre-determined approval criteria removing council discretion to reject them. Applications that became eligible for *VicSmart* include boundary re-alignments, simple subdivisions, new construction with an estimated cost of up to $50,000, and minor vegetation removal. 10.3% of all planning applications across Victoria were *VicSmart*-eligible between 19 September 2014 and 31 December 2016. The minimum (maximum) share of applications eligible by council over this period was 0% (28.9%).

Appendix A.5. Federal Electoral Data

In addition to the instruments based on heterogenous responses across councils to VicSmart, we also use historical voting shares at the national level. This approach was first proposed by Hilber and Vermeulen (2015), who find similar evidence that historical nationwide voting shares predict supply restrictiveness in the United Kingdom. Our historical data is derived from national election results for Australia sourced from the Australian Electoral Commission.[43] Historical two-party-preferred voting shares are matched at the pooling booth level to council areas using population concordance weights for the 1998, 2001, 2004 and 2007 national elections.

Appendix A.6. Hydrology and Elevation

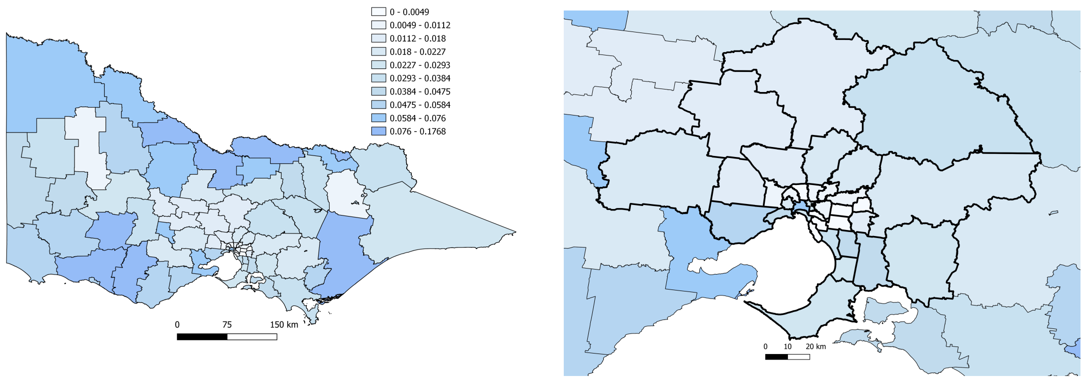
In Table B4 we include additional controls for natural barriers to new housing construction that might otherwise explain constrained local housing supply and that are potentially correlated with regulatory constraints. The natural barriers measured include the fraction

[42] Note if an application is not decided within 10 days it is deemed approved.

[43] See: https://www.aec.gov.au/

of each local planning area covered by hydrological features (lakes, rivers, dams and flats subject to inundation); and, separately, the standard deviation in the elevation of ground surface points to control for changes in ground slope where it becomes more difficult and expensive to build. The hydrological data are sourced from VicMap Hydro Water Area Pologyons (1:25,000) and the elevation data from VicMap Elevation Ground Surface Point (1:25,000).[44] Maps summarising these barriers are reported in Figures A.8 and A.9.

Figure A.8: Council Areas Covered by Hydrological Features



Note: Hydrological area decile shares are reported (i.e. deciles based on the share each of council's physical area covered by lakes, rivers, dams and flats subject to inundation). The hydrological data are sourced from VicMap Hydro water area polygons and use data for 188,779 hydrological features in Victoria. Greater Melbourne councils are highlighted in the right-panel with a bold outline.

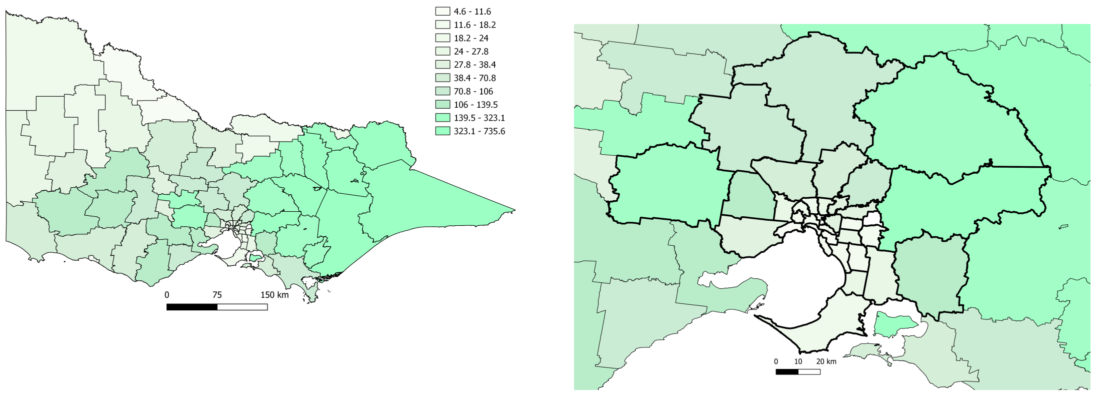
Appendix B. Expanded Tables and Robustness

Appendix B.1. Expanded Tables

Table B1 provides descriptive statistics for the sample 2011-2016 in addition to the estimation sample. It complements Table 1. Table B2 complements Table 4. It shows the coefficient signs on the planning instruments match their theoretical interpretation. A positive change in the mean refusal rate taken before and after the *VicSmart* reform is positively associated with a higher mean refusal rate taken over the full sample: more restrictive

[44]The hydrological and elevation data are sourced from the Victorian Department of Energy, Environment and Climate Action and were accessed via: https://www.data.vic.gov.au/

Figure A.9: Council Area Standard Deviation in Ground Surface Point Elevation



Note: Dispersion in ground surface point elevation by council-decile is reported (measured in metres). The ground surface point elevation data are sourced from VicMap Elevation and are based on data from 334,383 ground surface control points in Victoria. Greater Melbourne councils are highlighted in the right-panel with a bold outline.

councils on average increased their refusal of non-VicSmart eligible applications after the introduction of the reform. In contrast, the change in the mean decision time before and after *VicSmart* is negatively associated with the mean refusal rate over the full sample: in more restrictive councils, a greater fall in mean decision times was observed. Each instrument is highly significant in the first-stage and tests of the null of weak instruments are rejected when using robust weak-instrument tests (Andrews, Stock, and Sun, 2019, Montiel Olea and Pflueger, 2013).

Table B1: Descriptive Statistics

Data	(1) Mean	(2) S.D.	(3) P5	(4) P95
Planning applications (Unbalanced panel, 2007-2016)[a]				
Total No. applications = 186,042, Total No. Councils = 79				
Ref. Rate	0.031	0.023	0.000	0.080
Δ Ref. rate	-0.004	0.026	-0.036	0.030
Δ Dec. time	-23.99	24.58	-77.14	11.12
2001 Electoral data (Total votes matched to council areas = 2,675,481)[b]				
Total No. polling booths = 5,761, Total No. Councils = 79				
TPP	0.53	0.13	0.26	0.75
2011–2016 Matched transactions[c]	**Detached homes**		**Apartments**	
	Mean	S.D.	Mean	S.D.
Bedrooms	3.21	0.68	2.30	0.71
Log size	6.53	0.64	4.55	0.37
Log-buyer income	11.30	0.89	11.22	0.88
Log-seller income	11.13	1.06	11.14	1.06
Log price	13.10	0.55	13.04	0.47
2016 Matched transactions with home age[d]				
Home age	39.15	30.37	27.24	22.52
Bedrooms	3.15	0.64	2.27	0.70
Log size	6.48	0.63	4.55	0.37
Log-buyer income	11.31	0.90	11.24	0.89
Log-seller income	11.16	1.04	11.19	1.05
Log price	13.17	0.55	13.11	0.48

Notes: [a]*Ref. rate* is the mean refusal rate from 2007 to 2016. Δ *Ref. rate* and Δ *Dec. time* are calculated as the change in the mean refusal rate and decision time by council before and after *VicSmart*. [b]*TPP* is the two-party-preferred percentage vote share measured by council for the 2001 national election to the Liberal-National Coalition. [c] Based on 145,789 (41,041) matched house (apartment) sales with complete home attributes. *Log size* is the natural log of the lot size (internal area) for a house (apartment) measured in square metres. Internal area is only recorded for sales in 2016. *Bedrooms* is the number of bedrooms. *Log price* is the natural log of the transaction price. [d] Based on 22,237 (7,402) matched house (apartment) sales for 2016 with data on home age (*Home age*). *Home age* is measured in years since a home was first built.

Table B2: The Effects of Supply Constraints on House Filtering

$$\mathcal{R}_{it} = \sum_{j \in J \setminus age} \beta_j h_{ijt} + \beta_{age} age_{it} + \beta_{age^2} age_{it}^2 + \beta_{age,\tau} (age_{it} \times \tau_g) + \zeta_{it}$$

	(1)	(2)	(3)	(4)	(5)
	OLS	IV(TSLS) Second Stage			
N=22,237		All instr.	Excl. Δ Dec. time	Excl. Δ Ref. rate	Excl. TPP
Age	0.006***	0.001	0.0001	-0.0003	0.001
	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)
Age squared	-0.3e-04**	-0.1e-04	-0.1e-04	-9.2e-06	-0.1e-04
	(7.9e-06)	(9.9e-06)	(0.1e-04)	(0.1e-04)	(9.9e-06)
Ref. rate × Age	0.033***	0.111***	0.129**	0.137***	0.111***
	(0.009)	(0.034)	(0.064)	(0.045)	(0.034)
Bedrooms	-0.037*	-0.046***	-0.048***	-0.049***	-0.046***
	(0.015)	(0.016)	(0.017)	(0.016)	(0.016)
Log lot size	0.044***	0.063***	0.068***	0.070***	0.064***
	(0.016)	(0.018)	(0.023)	(0.020)	(0.018)
Mean MFR (%)	0.34***	0.01	-0.07	-0.11	0.01
	(0.05)	(0.15)	(0.28)	(0.20)	(0.15)
M.E. of Ref. rate (%)	0.07***	0.25***	0.29**	0.31***	0.25***
	(0.02)	(0.08)	(0.15)	(0.10)	(0.08)
		IV(TSLS) First Stage			
Age		0.049***	0.060***	0.053***	0.049***
		(0.002)	(0.002)	(0.002)	(0.001)
Age sq.		-0.0002***	-0.0002***	-0.0002***	-0.0002***
		(9.6-06)	(9.6e-06)	(9.6e-06)	(8.9e-06)
Δ Dec. time × Age		-0.0002***		-0.0002***	-0.0002***
		(0.00001)		(0.00001)	(0.00001)
Δ Ref. rate × Age		0.134***	0.098***		0.134***
		(0.011)	(0.011)		(0.011)
TPP × Age		0.000	-0.008***	-0.004**	
		(0.002)	(0.002)	(0.002)	
Bedrooms		0.108***	0.111***	0.112***	0.108***
		(0.013)	(0.013)	(0.013)	(0.013)
Log lot size		-0.205***	-0.218***	-0.209***	-0.204***
		(0.013)	(0.012)	(0.012)	(0.011)
Eff. F-stat.		147.19	54.60	142.90	213.14
5%/10%		22.55/13.97	14.15/9.46	7.46/5.52	18.75/12.16
/20% CV		/9.18	/6.74	/4.39	/8.38

Notes: See notes to Table B1 for variable definitions. The upper panel shows OLS and second-stage IV Two Stage Least Squares (*IV(TSLS)*) estimates where the dependent variable is relative income. The lower panel shows first-stage estimates where the dependent variable is *Ref. rate* × *Age*. *All instr.* includes all three instruments: columns 3–5 report estimates excluding one instrument at a time. *M.E. of Ref. rate (%)* is the marginal effect of a one standard deviation increase in *Ref. rate* on the *Mean MFR* reported in % points. The Eff. F-stat. is from Montiel Olea and Pflueger (2013) with 5%, 10% and 20% Nagar-bias critical values (CV) with 5% size.

Appendix B.2. Robustness

We report a range of robustness checks discussed in Section 5 of the main text. Table B3, columns 1 to 4, reports estimates from an alternative specification of the IV model discussed in the main text (Table 4), including postcode fixed effects and more a narrow measure of the refusal rate. Compared with Table 4, point estimates suggest a negative filter rate estimated across all specifications ranging from -0.17% per home year to -0.42% per home year. Column 5 reports estimates using councils within the Melbourne metropolitan area only (Greater Melbourne) where the results are similar.

Table B3: Robustness Including Postal Code Fixed Effects

IV(TSLS) – Second stage, dependent variable is log-buyer less log-seller income

	(1) All inst.	(2) Excl. Δ Dec. time	(3) Excl. Δ Ref. rate	(4) Excl. 2001 TPP	(5) All inst. Greater Mel.
Age	-0.001	-0.002	-0.001	-0.002	-0.003
	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)
Ref. rate × Age	0.150**	0.168	0.137*	0.157**	0.152**
	(0.075)	(0.153)	(0.076)	(0.076)	(0.067)
Filter rate (%)	-0.2	-0.3	-0.2	-0.2	-0.4
	(0.3)	(0.5)	(0.3)	(0.3)	(0.3)
M.E. of Ref. rate (%)	0.34**	0.39	0.31*	0.36**	0.35**
	(0.17)	(0.35)	(0.17)	(0.17)	(0.15)
Eff. F-stat.	50.65	15.63	135.79	57.14	56.38
5%	28.45	25.44	13.32	27.82	29.27
/10%	/17.64	/16.09	/8.97	/17.48	/18.10
/20% CV	/11.56	/10.77	/6.45	/11.62	/11.82
RMSE	1.291	1.291	1.290	1.291	1.304
No. obs.	22,237	22,237	22,237	22,237	14,878

Notes: Robust standard errors are reported in parentheses. All specifications include postal code fixed effects and home attribute controls (bedrooms, log lot size, age, and age squared). The refusal rate is measured using a more narrow refusal rate that excludes applications to remove vegetation and applications covering multiple-categories. Variable labels and column headings for the first four columns are the same as those used in Table 4 (see Table 4 notes). The final column restricts the sample to councils within Greater Melbourne only.

Table B4 reports additional specification checks using the change in mean in decision time around *VicSmart* as the only instrument. First, we include postcode and quarter fixed effects to control for any unobserved local neighbourhood effects that might otherwise explain differences in relative income and to control for seasonality in moving patterns (Ngai and Tenreyro, 2014) (column 1). Next we allow for heterogeneity in supply constraints *within* council areas by measuring refusal rates at a more disaggregated level of geography – neighbourhoods that are measured as ABS Statistical Area 2 (SA2s), of which there are 462 in Victoria – and instrument for them using the change in the mean planning application decision time around *VicSmart* also measured at the neighbourhood level (column 2).

In column 3, we control for changes in the socioeconomic characteristics of households, using the change in each council's relative Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD) percentile between 2011 and 2016 again interacted with age.[45] Council areas with an increase in their IRSAD percentile are likely to have become more desirable over time with higher average income and more employment opportunities. In column 4, we control for spatial variation in demand by including the distance of each transaction to the core of Melbourne interacted with age as an additional control. In column 5, we include controls for local topography: (i) age interacted with the fraction of each council's physical area that is covered by water features (e.g. inland lakes, rivers, dams, flats subject to inundation and other hydrological features); and (ii) age interacted with the standard deviation in the elevation of ground surface points within each council. These measures capture natural topographical constraints on building new housing supply (Saiz, 2010).

Table B4 reports similar estimates of filter rates and marginal effects of supply constraints for each specification. Filter rates are small and negative when excluding the effects of supply constraints. In contrast, the marginal effect of the refusal rate on the filter rate is positive and significant with estimates ranging from +0.27% to +0.47% per additional home-year in response to a one standard deviation increase in the refusal rate.

Table B5 reports placebo checks based on the timing around which the planning instru-

[45]See ABS catalogue: 2033.0.55.001. IRSAD percentiles are measured at the sub-neighbourhood (SA1) level and are then re-weighted to council areas using populations weights.

Table B4: Additional Specification Checks

IV(TSLS) – Second stage, dependent variable is log-buyer less log-seller income

N=22,237	(1) P.C. & time FE[a]	(2) SA2 Ref. rate[b]	(3) IRSAD[c]	(4) Dist.[d]	(5) Top.[e]
Age	-0.003	-0.0003	0.001	-0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
Ref. rate × Age	0.205**	0.126**	0.121**	0.184**	0.170**
	(0.092)	(0.057)	(0.057)	(0.077)	(0.082)
Filter rate (%)	-0.40	-0.08	-0.04	-0.29	-0.33
	(0.33)	(0.26)	(0.23)	(0.33)	(0.46)
M.E. of Ref. rate (%)	0.47**	0.29**	0.27**	0.42**	0.39**
	(0.21)	(0.13)	(0.13)	(0.17)	(0.19)
Eff. F-stat.	180.87	132.57	201.83	143.69	143.57
5%	37.42	37.42	37.42	37.42	37.42
/10%	/23.11	/23.11	/23.11	/23.11	/23.11
/20% CV	/15.06	/15.06	/15.06	/15.06	/15.06
RMSE	1.292	1.315	1.311	1.327	1.316

Notes: Robust standard errors are reported in parentheses. All specifications use the change in mean decision time around *VicSmart* as the included instrument. [a]Includes postal code and time fixed effects (FE). [b]Refusal rates are measured (and instrumented for) at the neighbourhood (SA2) level as opposed to council level. [c]Controls for the change in the relative IRSAD percentile for each council between 2011 and 2016 interacted with age. [d]Controls for straight line distance (in metres) to the Melbourne city core (measured using the distances between the SA1 centroid in which the home is located and an SA1 centroid centred on the Melbourne CBD). There are 13,194 SA1s for Victoria represented in the sample. [e]Controls for interactions between age and topography: namely, the fraction of each councils' physical area covered by hydrological features including lakes, rivers, wetlands, and flats subject to inundation; and the standard deviation in ground surface control point elevation within each council. *M.E. of Ref. rate (%)* denotes the marginal effect of a one standard deviation increase in the refusal rate on the filter rate per home-year (measured in % points). See also the notes to Table 4.

ments are calculated. We consider a date one year earlier than when *VicSmart* took effect (19 September 2013), the date when the *VicSmart* reforms were first announced (7 June 2012), and the date a government advisory committee was formed to review planning legislation (4 June 2011). The strength of the planning instruments essentially disappears once any of the alternative dates are used.

Table B6 reports IV(TSLS) results from the second stage and instrument strength when varying the national election data used according to the year that the election was held. Similar results are obtained across multiple election years, confirming the results are not

Table B5: Planning Instrument Relevance

IV(TSLS) – First stage, dependent variable is Ref. rate × Age

N=22,237	(1) *VicSmart* implementation	(2) 1-year before implementation	(3) *VicSmart* announced	(4) Committee announced
Eff. F-stat.	75.82	5.11	0.87	0.83
5%/10%	24.85/15.74	9.87/6.93	12.30/8.37	13.77/9.23
/20% CV	/10.56	/5.22	/6.09	/6.61

Notes: All first stage regressions include postal code and time fixed effects and controls for age, age squared, log land area, and bedrooms and the change in mean decision time and refusal rate instruments (see the definitions in Tables 1a and 1b). *VicSmart implementation* denotes the change in the mean decision time and the change in the mean refusal rate are calculated around 19 September 2014, *1-year before implementation* calculates the changes in both means around 19 September 2013, *VicSmart announced* around 7 June 2012, and *Committee announced* around 4 June 2011. The Eff. F-stat. is based on Montiel Olea and Pflueger (2013) with 5%, 10% and 20% Nagar-bias critical values (CV) with 5% size.

Table B6: Election Instrument Robustness Checks

IV(TSLS) – Second stage, dependent variable is log-buyer less log-seller income

N=22,237	(1) 2001 Federal Election	(2) 1998 Federal Election	(3) 2004 Federal Election	(4) 2007 Federal Election
Age	0.001	0.003	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Ref. rate × Age	0.111***	0.079**	0.108***	0.110***
	(0.034)	(0.032)	(0.034)	(0.034)
Filter rate (%)	0.01	0.14	0.02	0.01
	(0.15)	(0.14)	(0.15)	(0.15)
M.E. of Ref. rate (%)	0.25***	0.18**	0.25***	0.25***
	(0.08)	(0.07)	(0.08)	(0.08)
Eff. F-stat.	147.19	167.04	150.91	150.20
5%/10%	22.55/13.97	22.17/13.76	22.19/13.79	22.31/13.86
/20% CV	/9.18	/9.06	/9.09	/9.12
RMSE	1.310	1.308	1.310	1.310

Notes: Robust standard errors are reported in parentheses. Each specification uses the two-party-preferred vote share (*TPP*) to the Liberal-National Party Coalition as per the election year listed in each column heading. In all specifications the change in mean decision time (Δ *Dec. time*) and the change in the mean refusal rate (Δ *Ref. rate*) around *VicSmart* are also included as instruments. See the notes to Table 4 and Tables B3 to B5.

specific to the 2001 national election only.

Appendix B.3. Controlling for Buyer and Seller Characteristics

Here, we investigate whether the estimates of the marginal effects of supply constraints on filtering are robust to the inclusion of individual-level characteristics of buyers and sellers. To account for them we modify our estimation model by assuming that the idiosyncratic components of income now depend on seller and buyer characteristics ($\mathbf{z}^s_{it}$ and $\mathbf{z}^b_{it}$), with $\gamma^s_{it} = \mathbf{z}^{s\prime}_{it}\vartheta_t + \varsigma^s_{it}$ and $\gamma^b_{it} = \mathbf{z}^{b\prime}_{it}\vartheta_t + \varsigma^b_{it}$. The empirical specification is now:

$$\mathcal{R}_{it} = c + (\mathbf{z}^{b\prime}_{it} - \mathbf{z}^{s\prime}_{it})\vartheta_t + \sum_{q \in \Upsilon \setminus age} c_q x_{iq} + c_{age} age_{it} + c_{age,\tau}\left(age_{it} \times \tau_g\right) + \widetilde{\varsigma}_{it} \qquad \text{(B.1)}$$

The only difference between Equation (B.1) and the benchmark specification Equation (6) used in the main text is that we now additionally control for vectors of observed differences in the characteristics of buyers and sellers. Table B7 reports the results including various sets of controls for differences in buyer and seller characteristics as reported in the 2016 Australian census, and where each model sequentially adds more controls.[46]

Model I includes controls for home attributes (log lot size and bedrooms) and 48 labour force status dummies, one for each unique combination (hereafter combination) of a difference in labour force status reported by buyers and sellers on a transaction. Measured labour force status includes: *Employed full-time*; *Employed part-time*; *Employed away from work*; *Unemployed looking for full-time work*; *Unemployed looking for part-time work*; *Not in the labour force*; *Not stated*; and *Not applicable.* Model II includes 12 dummies (again based on combinations) for differences in the highest level of educational attainment: *Bachelor*; *Diploma*; *Year 12*; *Year 11 or below*; and *Not reported.* Model III includes 65 combinations for differences in the occupation of buyers and sellers at the 1-digit ANZSCO level.

Model IV includes 21 combinations for differences over the range of household monthly mortgage repayments reported – measured in \$150 intervals below \$600, and \$200 intervals

[46]Here, we use an additional linkage step, not only matching housing transactions to income, but to the characteristics of buyers and sellers when surveyed in the 2016 census.

above \$600 and up to the highest value of \$5,000 or more; or *Nil*; or *Not Stated*). Model V controls for the mean difference in buyer and seller age (in years) and for gender. Model VI controls for measures of home and seller heterogeneity including: the difference between the transaction price and the median sale price of all homes in the neighbourhood; the difference between the seller age and the median age of all homeowners in the neighbourhood; and the difference between seller income and the median income of all homeowners in the neighbourhood.

Notwithstanding the increase in the regression's ability to explain differences in buyer and seller income when including controls for differences in buyer and seller characteristics, with the R^2 increasing 0.31 in Model I to 0.49 in Model VI, the estimated marginal effect of local planning refusal (*M.E. of Ref. rate*) remains robust. Using Oster's (2019) calculation assuming equal selection on observables and unobservables and for values of $\overline{R}_{max}$ of 0.6–0.7, the effects of supply constraints remain positive and statistically and economically significant.

Table B7: IV Estimates with Controls for Buyer and Seller Characteristics

IV(TSLS) – Second stage, dependent variable is log-buyer less log-seller income

	(1) Model I.	(2) Model II.	(3) Model III.	(4) Model IV.	(5) Model V.	(6) Model VI.
Age	-0.005^{*}	-0.005^{*}	-0.004^{*}	-0.004^{*}	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age x Ref. rate	0.105^{***}	0.010^{**}	0.080^{**}	0.076^{**}	0.078^{**}	0.072^{**}
	(0.0405)	(0.0404)	(0.0385)	(0.0385)	(0.0382)	(0.0350)
Filter rate (%)	-0.28	-0.28	-0.25	-0.25	-0.20	-0.08
	(0.18)	(0.18)	(0.17)	(0.17)	(0.17)	(0.15)
M.E. of Ref. rate	0.25^{***}	0.24^{**}	0.19^{**}	0.18^{**}	0.19^{**}	0.17^{**}
	(0.097)	(0.097)	(0.092)	(0.092)	(0.092)	(0.084)
Home attributes	Yes	Yes	Yes	Yes	Yes	Yes
Labour force status	Yes	Yes	Yes	Yes	Yes	Yes
Education	No	Yes	Yes	Yes	Yes	Yes
Occupation	No	No	Yes	Yes	Yes	Yes
Mortgage payments	No	No	No	Yes	Yes	Yes
Buy-Sell age diff.	No	No	No	No	Yes	Yes
Seller/home heterogeneity	No	No	No	No	No	Yes
Eff. F-stat	260.49	260.87	260.16	260.74	261.53	257.84
RMSE	1.08	1.08	1.04	1.03	1.03	0.93
R^2	0.31	0.32	0.37	0.37	0.38	0.49

Notes: Estimates based on 17,022 house transactions in Victoria from 2016. Eff. F.stat denotes the effective F-statistic by Montiel Olea and Pflueger (2013). CV denotes critical values are 37.418, 23.109 and 15.062 at the 5%, 10% and 20% measured as percentage of the worst-case possible bias. Coefficients and robust standard errors (in parentheses) are second-stage estimates from an IV(2SLS) regressions of log-buyer less log-seller income with different control groups and where the instrument used in the change in mean decision time before and after the introduction of the VicSmart planning reform. Models relate to the control set as defined in the text. Coefficient values on all combinations of buyer and seller characteristics and home attributes are omitted. Neighbourhoods are measured as SA2s.

Appendix C. Model Proofs

Proposition 3.1:

Proof. (i) Fixing τ fixes P and Z given new home clearing and that the quality-adjusted new home price is equal to marginal cost of acquired unimproved land and building a new home. Using the assumption that F is log-normal to evaluate the quality-adjusted log reservation value of a seller with home quality q_s:

$$\mathcal{V}\left(x_l, q_s\right) = \varepsilon_x^{-1} \log\left(A(x_l) e^{\varepsilon_x x_l} + B\left(x_l, q_s\right) + C\left(q_s\right)\right)$$

where $\mathcal{V}\left(x_l, q_s\right) \equiv \varepsilon_x^{-1} \log \frac{V(q_s, P)}{q_s^{\varepsilon_q}}$, $A\left(x_l\right) \equiv (1-\delta) \times \left(1 - \lambda^S \left(\Phi\left(\frac{x_u - \mu}{\sigma}\right) - \Phi\left(\frac{x_l - \mu}{\sigma}\right)\right)\right)$
$B(x_l, q_s) \equiv (1-\delta)\, \lambda^S e^{\varepsilon_x \mu + \frac{\varepsilon_x^2 \sigma^2}{2}} \frac{\Phi\left(\frac{x_u + \frac{\varepsilon_q}{\varepsilon_x} \log q^{new} - \mu}{\sigma} - \varepsilon_x \sigma\right) - \Phi\left(\frac{x_l + \frac{\varepsilon_q}{\varepsilon_x} \log q_s - \mu}{\sigma} - \varepsilon_x \sigma\right)}{\Phi\left(\frac{x_u \frac{\varepsilon_q}{\varepsilon_x} \log q^{new} - \mu}{\sigma}\right) - \Phi\left(\frac{x_l + \frac{\varepsilon_q}{\varepsilon_x} \log q_s - \mu}{\sigma}\right)}$, $\Phi(.)$is the standard normal CDF, μ and σ denote the mean and standard deviation of log-buyer income, and $C\left(q_s\right) \equiv \frac{\delta Z - (1-\delta) c^s}{(q_s)^{\varepsilon_q}} > 0$. As $\mathcal{V}\left(x_l, q_s\right)$ is continuous in x_l, if $\mathcal{V}\left(x_l, q_s\right) \in [\underline{x}_l, \overline{x}_l]$ with $C\left(q_s\right) > 0$ (Lemma Appendix C.3), then by Brouwer's Fixed Point Theorem there exists at least one fixed point, $x_l = \mathcal{V}\left(x_l, q_s\right)$, for each $q_s \in [\underline{q}, \overline{q}]$. Picking one solution for each q_s is sufficient to solve for a search equilibrium.

(ii) For uniqueness, we use a contraction mapping. Let x_l' and x_l'' be two arbitrary points in $[\underline{x}_l, \overline{x}_l]$. If for each q_s in $[\underline{q}, \overline{q}]$, there exists a constant $k_{q_s} \in (0,1)$ such that $k_{q_s} \left|x_l' - x_l''\right| \geq \left|\mathcal{V}\left(x_l', q_s\right) - \mathcal{V}\left(x_l'', q_s\right)\right|$ for all $x_l', x_l'' \in [\underline{x}_l, \overline{x}_l]$, then by the Contraction Mapping Theorem there exists only one fixed point $x_l = \mathcal{V}\left(x_l, q_s\right)$ for each q_s in $[\underline{q}, \overline{q}]$ and the search equilibrium is unique. A sufficient condition is that there exists a constant $k \in (0,1)$ such that $k \geq k_{q_s}$ with $k_{q_s} \geq \left|\frac{\partial \mathcal{V}(x_l, q_s)}{\partial x_l}\right|$ for all $x_l \in [\underline{x}_l, \overline{x}_l]$ and $q_s \in \left(\underline{q}, \overline{q}\right)$.

Given (i) and (ii) hold, (iii) is implied by the equilibrium strategies of sellers and buyers in the model with search: there exists for each $q_s \in \left[\underline{q}, \overline{q}\right]$, a compact set $[x_l(q_s, P), x_u(P)]$ over which buyers and sellers are willing to trade and thus the distribution of buyer income conditional on trading a home of quality q_s is $F_{x_l, x_u}(x, q_s) \equiv \frac{F(x) - F(x_l(q_s))}{F(x_u) - F(x_l(q_s))}$ for $x \in (x_l, x_u)$, seller home quality has distribution $G_{\underline{q},\overline{q}}$, and seller income is independent of the surplus from trade with distribution F. ■

Proposition 3.2:

Proof. Let $\mathcal{X} \equiv (x_l, x_u)$ denote the interval over which a buyer trades with a seller with home of quality q_s, where for brevity we use the notation $x_l \equiv x_l(q_s, P) = \varepsilon_x^{-1} \log \frac{V^S(q_s,P)}{q_s^{\varepsilon_q}}$ and $x_u \equiv x_u(P) = \varepsilon_x^{-1} \log P$ and noting that $V^B = 0$ in the equilibrium with free buyer entry. Let F be the CDF associated with log-buyer income. We define the truncated CDF F_{x_l,x_u} evaluated at x, given quality q_s and quality-adjusted new home price P, by:

$$F_{x_l,x_u}(x) \equiv \begin{cases} 0 \text{ for } x \in (-\infty, x_l] \\ \frac{F(x)-F(x_l)}{F(x_u)-F(x_l)} \text{ for } x \in (x_l, x_u) \\ 1 \text{ for } x \in [x_u, +\infty) \end{cases}$$

and its corresponding density as $f_{x_l,x_u} \equiv \partial F_{x_l,x_u}/\partial x$ where $F(x_u) > F(x_l)$. Define the expectation of log-buyer income conditional on trade a trading a home of quality q_s as $M(x_l,x_u) \equiv E[X|X \in \mathcal{X}, Q = q_s] = \int_{-\infty}^{+\infty} x dF_{x_l,x_u}(x)$ For (i), differentiating the conditional expectation of log-buyer income with respect to the lower truncation threshold for trade, x_l, we have $\frac{\partial E[X|X\in\mathcal{X},Q=q_s]}{\partial x_l} = f_{x_l,x_u}(x_l)[M(x_l,x_u) - x_l] > 0$ for all $q_s \in (\underline{q}, \overline{q})$. We need to show $\frac{\partial E[\mathcal{R}|Q=q_s]}{\partial x_l}\frac{\partial x_l}{\partial q_s} < 0$ when $\delta Z - (1-\delta)c^s > 0$ and is positive otherwise where $E[\mathcal{R}|Q = q_s] \equiv E[X - Y|X \in \mathcal{X}, Q = q_s]$ is expected log-buyer less log-seller income conditional on trading a home of quality q_s. Since expected seller income is independent of the trade surplus we have $\frac{\partial E[\mathcal{R}|Q=q_s]}{\partial x_l} = \frac{\partial E[X|X\in\mathcal{X},Q=q_s]}{\partial x_l} > 0$. Lemma Appendix C.3 shows $\operatorname{sgn}\left(\frac{\partial x_l}{\partial q_s}\right) = -\operatorname{sgn}(\delta Z - (1-\delta)c^s)$ and thus the result follows.

For (ii), note that an increase in the refusal rate, τ affects the relative income of buyers and sellers through the effect on the quality-adjusted new home price $P \equiv \frac{P^{new}}{q^{new^{\varepsilon q}}}$ and the unimproved value of land Z. Thus, we need to show $\frac{\partial E[\mathcal{R}]}{\partial \tau} = \frac{\partial E[\mathcal{R}]}{\partial P}\frac{\partial P}{\partial \tau} + \frac{\partial E[\mathcal{R}]}{\partial Z}\frac{\partial Z}{\partial \tau} > 0$. Note that seller income is independent of P and the rejection rate τ, thus we need only focus on the sign of $\frac{\partial E[X|X\in\mathcal{X}]}{\partial P}\frac{\partial P}{\partial \tau} + \frac{\partial E[X|X\in\mathcal{X}]}{\partial Z}\frac{\partial Z}{\partial \tau}$. Assume $\frac{\partial P}{\partial \tau} > 0$ and $\frac{\partial Z}{\partial \tau} > 0$ (we verify these assumptions below), from Lemma Appendix C.2 $\frac{\partial E[X|X\in\mathcal{X}|Q=q_s]}{\partial P} > 0$ for all $q_s \in \left(\underline{q}, \overline{q}\right)$. Integrating this derivative over the distribution of the quality of homes offered by sellers we have $\frac{\partial E[X|X\in\mathcal{X}]}{\partial P} = \int_{\underline{q}}^{\overline{q}} \frac{\partial M(x_l,x_u)}{\partial P} dG_{\underline{q}:\overline{q}}\left(q_s\right) > 0$. Lemma Appendix C.7 shows $\frac{\partial E[X|X\in\mathcal{X}]}{\partial Z} > 0$, which establishes the result. We now verify $\frac{\partial P}{\partial \tau} > 0$ and $\frac{\partial Z}{\partial \tau} > 0$. Recall the unique new home price clears the market for new home demand and supply:

$$(1-\tau) \times (1+d) \times \mathcal{S}\delta = \mathcal{B} \int_{\varepsilon_x^{-1} \log P}^{+\infty} dF\left(x\right)$$

Differentiating both sides with respect to the refusal rate, τ, we have that $\frac{\partial P}{\partial \tau} > 0$ whenever $\frac{\partial \mathcal{B}}{\partial \tau} < \frac{\mathcal{B} f(x_u)}{1-F(x_u)} \frac{\partial x_u}{\partial P}$. This requires that the measure of new home buyers is declining in the quality-adjusted new home price as assumed in Lemma Appendix C.4. The proof of Lemma Appendix C.6 verifies $\frac{\partial Z}{\partial \tau} > 0$. ■

Proposition 3.3:

Proof. For (i), we can write the expected value of buyer income conditional on trade for a home of quality q_s as: $E\left[X|X \in \mathcal{X}, Q = q_s\right] = \mu - \sigma \frac{f(x_u)-f(x_l)}{F(x_u)-F(x_l)}$ where $F\left(x_u\right) - F(x_l) > 0$ since $x_l < x_u$ for all $q_s \in \left(\underline{q}, \overline{q}\right)$. With seller income independent of quality: $E\left[\mathcal{R}|Q = q_s\right] = E\left[X|X \in \mathcal{X}, Q = q_s\right] - \mu$. Thus we have $E\left[\mathcal{R}|Q = q_s\right] \leq 0$ (> 0) whenever $f\left(x_u\right) \geq f(x_l)$ $(f\left(x_u\right) < f(x_l))$. For (ii), note that $E\left[\mathcal{R}\right] = -\sigma \int_{\underline{q}}^{\overline{q}} \frac{f(x_u)-f(x_l)}{F(x_u)-F(x_l)} dG^s_{\underline{q},\overline{q}}\left(q_s\right)$, which establishes the result. ■

Proposition 3.5:

Proof. For (i), we take the limit as $\tau \to 1$ from below, which implies $P \to +\infty$. Thus, we have $\lim_{P\to+\infty} E\left[\mathcal{R}\right] = \sigma \int_{\underline{q}}^{\overline{q}} \frac{f(x_l(q_s))}{1-F(x_l(q_s))} dG^s_{\underline{q}:\overline{q}}\left(q_s\right) > 0$. For (ii), note that the conditional expectation for relative income, given home quality q_s, and with log-normal buyer income independent of seller income is $E\left[\mathcal{R}|X \in \mathcal{X}, Q = q_s\right] = M\left(x_l, x_u\right) - \mu$. Thus, it follows that $\frac{\partial E[\mathcal{R}|X\in\mathcal{X},Q=q_s]}{\partial q_s \partial \tau} = \left(\frac{\partial^2 M}{\partial x_l^2} \frac{\partial x_l}{\partial \tau} + \frac{\partial^2 M}{\partial x_l \partial x_u} \frac{\partial x_u}{\partial \tau}\right) \frac{\partial x_l}{\partial q^s} + \frac{\partial M}{\partial x_l} \frac{\partial^2 x_l}{\partial q^s \partial \tau}$. Integrating over the quality distribution $G_{\underline{q},\overline{q}}$ and requiring $\int_{\underline{q}}^{\overline{q}} \frac{\partial E[\mathcal{R}|X\in\mathcal{X},Q=q_s]}{\partial q_s \partial \tau} dG_{\underline{q},\overline{q}}\left(q_s\right) < 0$ yields the result. ■

Proposition 3.6:

Proof. We need to show $\frac{\partial E[\mathcal{R}|Q=q_s]}{\partial\mu\partial q_s} \geq 0 \quad \forall\ q_s \in \left(\underline{q}, \overline{q}\right)$ when $\delta Z - (1-\delta)\, c^s > 0$. Since F is normal, its density is log-concave. Define $W(x_l, x_u) \equiv \int_{-\infty}^{+\infty} \Psi\left(x - M(x_l, x_u)\right) dF_{x_l,x_u}(x)$ where $\Psi : \mathbb{R} \rightarrow \mathbb{R}$ is a convex function. Mailhot (1988),[47] Corollary 3, shows that if two truncated intervals (x_{l2}, x_{u2}) and (x_{l1}, x_{u1}) are such that $(x_{l2}, x_{u2}) \subset (x_{l1}, x_{u1})$, then: (i) The distribution function $F_{x_{l2},x_{u2}}$ is less dispersed than the distribution function $F_{x_{l1},x_{u1}}$, written as:[48]

$$F_{x_{l2},x_{u2}} \overset{disp}{\leq} F_{x_{l1},x_{u1}}$$

and (ii)

$$W(x_{l2}, x_{u2}) \leq W(x_{l1}, x_{u1})$$

for any log-concave distribution F_{x_l,x_u}. Assume Ψ is quadratic so that $\Psi\left(x - M(x_l, x_u)\right) = \left(x - M(x_l, x_u)\right)^2$ and note F normal implies $\frac{\partial E[X|X\in\mathcal{X},Q=q_s]}{\partial\mu} = W(x_l, x_u)$. Since f is also log-concave, applying Theorem 2 and Corollary 3 from Mailhot, we have

$$W(x_{l2}, x_{u1}) \leq W(x_{l1}, x_{u1})$$

and thus

$$\frac{\partial E\left[X|X \in (x_{l2}, x_{u1}), Q = q_s)\right]}{\partial\mu} \leq \frac{\partial E\left[X|X \in (x_{l1}, x_{u1}), Q = q_s)\right]}{\partial\mu}$$

for any $x_{l2} > x_{l1}$ both in $(\underline{x}_l, \overline{x}_l)$ and given $q_s \in (\underline{q}, \overline{q})$. Now define $M_\mu \equiv \frac{\partial M(x_l,x_u)}{\partial\mu}$ and note that M_μ is absolutely continuous in x_l so that the derivative $\frac{\partial M_\mu}{\partial x_l}$ exists with

[47]See Mailhot, L., 1988. Some Properties of Truncated Distributions Connected with Log-Concavity of Distribution Functions. *Applicationes Mathematicae*, 4(20), pp.531-542.

[48]We use Mailhot's defintion, F_X is less than F_Y denoted as $F_X \overset{disp}{\leq} F_Y$, if and only if $\forall$ scalars ϱ_1 and ϱ_2 such that $0 < \varrho_1 \leq \varrho_2 < 1$, we have

$$F_X^{-1}(\lambda_2) - F_X^{-1}(\varrho_1) \leq F_Y^{-1}(\varrho_2) - F_Y^{-1}(\varrho_1)$$

$\lim_{\varepsilon\to0^+}\frac{M_\mu(x_l+\varepsilon,x_u)-M_\mu(x_l,x_u)}{\varepsilon}=\lim_{\varepsilon\to0^-}\frac{M_\mu(x_l+\varepsilon,x_u)-M_\mu(x_l,x_u)}{\varepsilon}$. Consider $(x_l+\varepsilon,x_u)\subset(x_l,x_u)$ for some $\varepsilon>0$ arbitrarily small, we have that $M_\mu(x_l+\varepsilon,x_u)-M_\mu(x_l,x_u)\le0$ so that $\lim_{\varepsilon\to0^+}\frac{M_\mu(x_l+\varepsilon,x_u)-M_\mu(x_l,x_u)}{\varepsilon}\le0$. Thus, given absolute continuity, $\frac{\partial E_X[X|X\in\mathcal{X}|Q=q_s]}{\partial\mu\partial x_l}\le0$. Noting that $x_l=\varepsilon_x^{-1}\log\frac{V^s(q_s,P)}{(q_s)^{\varepsilon q}}$ is differentiable in q_s for all $q_s\in(\underline{q},\overline{q})$ with $\frac{\partial x_l(q_s)}{\partial q_s}<0$ when $\delta Z>(1-\delta)c^s$ (see Lemma Appendix C.3), it follows that $\frac{\partial E[\mathcal{R}|Q=q_s]}{\partial\mu\partial x_l}\frac{\partial x_l}{\partial q_s}\ge0$ for all $q_s\in(\underline{q},\overline{q})$. ■

Corollary Appendix C.1. *In the special case where the direct effects of a change in the quality-adjusted new home price are equal $\frac{\partial x_l}{\partial P}=\frac{\partial x_u}{\partial P}$, an increase in the refusal rate raises the marginal filter rate ($\frac{\partial F}{\partial\tau}>0$).*

Proof. The truncated expectation given log-normality is $E[X|X\in\mathcal{X}]=\mu+\sigma\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)$ where $\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u):=-\frac{\phi(\widetilde{x}_u)-\phi(\widetilde{x}_l)}{\Phi(\widetilde{x}_u)-\Phi(\widetilde{x}_l)}$ and we use the change of variables $\widetilde{x}_l\equiv\frac{x_l-\mu}{\sigma}$ and $\widetilde{x}_u\equiv\frac{x_u-\mu}{\sigma}$. Note that $\frac{\partial\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l}=\frac{\phi(\widetilde{x}_l)}{\Phi(\widetilde{x}_u)-\Phi(\widetilde{x}_l)}\left(\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)-\widetilde{x}_l\right)>0$. The second cross-partial derivative of $\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)$ with respect to quality q^s and the quality-adjusted new home price P is:

$$\frac{\partial\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial q^s\partial P}=\left(\frac{\partial^2\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l^2}\frac{\partial\widetilde{x}_l}{\partial P}+\frac{\partial^2\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l\partial\widetilde{x}_u}\frac{\partial\widetilde{x}_u}{\partial P}\right)\frac{\partial\widetilde{x}_l}{\partial q^s}+\frac{\partial\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l}\frac{\partial^2\widetilde{x}_l}{\partial q^s\partial P}$$

Using the truncated variance $var(X|X\in\mathcal{X})=\sigma^2\left[1-\left(\frac{\partial\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l}+\frac{\partial\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_u}\right)\right]$ and differentiating with respect to the lower truncation limit, $\frac{\partial var(X|X\in\mathcal{X})}{\partial\widetilde{x}_l}=-\sigma\left[\frac{\partial^2\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l^2}+\frac{\partial^2\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_u\partial\widetilde{x}_l}\right]$. Applying the same arguments used in the proof of Proposition 3.5 implies $\frac{\partial var(X|X\in\mathcal{X})}{\partial\widetilde{x}_l}\le0$ and so $\frac{\partial^2\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l^2}+\frac{\partial^2\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l\partial\widetilde{x}_u}\ge0$ after applying Clairaut-Schwarz's Theorem to the second term in the inequality. Next, using the results that $\frac{\partial\widetilde{x}_l}{\partial q^s}=\frac{1}{\sigma}\frac{\partial x_l}{\partial q^s}<0$, $\frac{\partial\widetilde{x}_u}{\partial P}>0$, $\frac{\partial\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial\widetilde{x}_l}>0$, and $\frac{\partial^2\widetilde{x}_l}{\partial q^s\partial P}=\frac{1}{\sigma}\frac{\partial^2x_l}{\partial q^s\partial P}<0$, we have $\frac{\partial^2\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial q^s\partial P}<0$ if $\frac{\partial\widetilde{x}_l}{\partial P}=\frac{\partial\widetilde{x}_u}{\partial P}$. Noting that $\frac{\partial^2E(R|Q=q_s)}{\partial q^s\partial\tau}=\frac{\partial^2E(X|X\in\mathcal{X})}{\partial q^s\partial P}\frac{\partial P}{\partial\tau}$ where $\frac{\partial^2E(X|X\in\mathcal{X})}{\partial q^s\partial P}=\sigma\frac{\partial^2\widetilde{M}(\widetilde{x}_l,\widetilde{x}_u)}{\partial q^s\partial P}$ and $\frac{\partial P}{\partial\tau}>0$ completes the proof. ■

Lemmas used in the above proofs follow.

Lemma Appendix C.2. *For a given home quality $q_s\in(\underline{q},\overline{q})$, expected relative income is increasing in the quality-adjusted new home price.*

$$\frac{\partial\mathbb{E}[\mathcal{R}|\mathcal{Q}=q_s]}{\partial P}>0$$

Proof. Differentiating the expectation of log-buyer income conditional on trading a home of quality q_s with respect to the quality-adjusted new home price, P:

$$\frac{\partial E\left[X|X\in\mathcal{X},Q=q_s\right]}{\partial P}=\frac{\partial x_u}{\partial P}f_{x_l,x_u}(x_u)\left(x_u-M(x_l,x_u)\right)+\frac{\partial x_l}{\partial P}f_{x_l,x_u}(x_l)\left(M(x_l,x_u)-x_l\right) \tag{C.1}$$

Since $\frac{\partial x_u}{\partial P}$ and $\frac{\partial x_l}{\partial P}$ are both positive for all $q_s\in\left(\underline{q},\overline{q}\right)$ (Lemma Appendix C.4) and $x_l<M(x_l,x_u)<x_u$, with seller income independent of existing home quality and the quality-adjusted new home price it follows that $\frac{\partial E[\mathcal{R}|Q=q_s]}{\partial P}>0$. ■

Lemma Appendix C.3. *In an equilibrium where the value of unimproved land is high (low) relative to the costs of search, the lower threshold on buyer income for trade is decreasing (increasing) in home quality:*

$$\operatorname{sgn}\left(\frac{\partial x_l}{\partial q_s}\right)=-\operatorname{sgn}\left(\delta Z-(1-\delta)\,c^s\right)\ \textit{for all}\ q_s\in\left(\underline{q},\overline{q}\right)$$

Proof. Note that the quality-adjusted reservation value of a seller with home quality q_s, $\widetilde{V}^S\left(q_s,P\right)\equiv\frac{V^S(q_s,P)}{q_s^{\varepsilon_q}}$, is:

$$(r+\delta)\,\widetilde{V}^S\left(q_s,P\right)=(1-\delta)\,\lambda^S\int_{x_l}^{x_u}\left(\left(e^x\right)^{\varepsilon_x}-\widetilde{V}^S\right)dF\left(x\right)+\frac{\delta Z-(1-\delta)\,c^s}{\left(q_s\right)^{\varepsilon_q}}$$

Differentiating both sides with respect to q_s

$$\frac{\partial\widetilde{V}\left(q_s,P\right)}{\partial q_s}=-\frac{\varepsilon_q}{\left(q_s\right)^{\varepsilon_q+1}}\frac{\delta Z-(1-\delta)\,c^s}{r+\delta+\lambda^S\left(F\left(x_u\right)-F\left(x_l\right)\right)}$$

Noting that $\varepsilon_q>0$, the denominator is positive and that $x_l\equiv\varepsilon_x^{-1}\log\widetilde{V}\left(q_s,P\right)$ establishes the result. ■

Lemma Appendix C.4. *The lower income truncation threshold is increasing in the quality-adjusted price*

$$\frac{\partial x_l}{\partial P}>0$$

Proof. Note the quality-adjusted seller reservation value $\widetilde{V}^S\equiv\frac{V^S(q_s,P)}{(q_s)^{\varepsilon_q}}$ is given by

$$(r+\delta)\,\widetilde{V}^S=(1-\delta)\left[\lambda^S\int_{x_l}^{x_u}\left(e^{\varepsilon_x x}-\widetilde{V}^S\right)dF\left(x\right)\right]-\frac{(1-\delta)\,c^s-\delta Z}{\left(q_s\right)^{\varepsilon_q}}$$

Differentiating both sides with respect to P

$$\frac{\partial \widetilde{V}^S}{\partial P} = \frac{(1-\delta)\lambda^S f(x_u)\left[\varepsilon_x^{-1}\left(1-\frac{\widetilde{V}^S}{P}\right)\right] + \frac{\delta}{(q_s)^{\varepsilon_q}} + (1-\delta)\frac{\partial \lambda^S}{\partial P}\int_{x_l}^{x_u}\left(e^{\varepsilon_x x} - \widetilde{V}^S\right)dF(x)}{r+\delta+(1-\delta)\lambda^S\left(F(x_u)-F(x_l)\right)} \tag{C.2}$$

Note that the denominator and the first two terms in the numerator are always positive. For the third term, with constant-returns-to-scale in matching we have that $\lambda^S = \mathcal{M}\left(\frac{F(x_u)\mathcal{B}}{\mathcal{S}}, 1\right)$ so that $\frac{\partial \lambda^S}{\partial P} = \frac{\partial \mathcal{M}}{\partial \theta}\frac{\partial F(x_u)\mathcal{B}}{\partial P}\frac{1}{S}$. Appendix C.5 establishes when $\frac{\partial F(x_u)\mathcal{B}}{\partial P} > 0$ which together with $\frac{\partial \mathcal{M}}{\partial \theta} > 0$ is sufficient to establish that $\frac{\partial \widetilde{V}^S}{\partial P} > 0$.[49] Since $x_l = \varepsilon_x^{-1}\log\left(\frac{V(q_s,P)}{q_s^{\varepsilon_q}}\right)$, we have $\frac{\partial x_l}{\partial P} = \varepsilon_x^{-1}\frac{1}{\widetilde{V}(q_s,P)}\frac{\partial \widetilde{V}(q_s,P)}{\partial P} > 0$ as required. ■

Lemma Appendix C.5. *The measure of buyers searching for an existing (new) home is increasing (decreasing) in the quality-adjusted new home price when* $-\frac{f(x_u)}{F(x_u)}\frac{\partial x_u}{\partial P}\mathcal{B} < \frac{\partial \mathcal{B}}{\partial P} < \frac{f(x_u)}{1-F(x_u)}\frac{\partial x_u}{\partial P}\mathcal{B}$. *This holds when the derivative of the buyer search cost function is sufficiently large.*

Proof. The inequality bounds can be verified by differentiation of the measure of existing $F(x_u)\mathcal{B}$ and new $(1-F(x_u))\mathcal{B}$ home buyers with respect to P. Differentiating the expected value of buyer search Eq. 2 in the main text, we have:

$$(1-F(x_u))^2\frac{\partial \mathcal{B}}{\partial P} = \left(\frac{\partial c^B}{\partial B^{new}}\right)^{-1}\left(f(x_u)\frac{\partial x_u}{\partial P}c^B - (1-F(x_u)\mathcal{B}) + f(x_u)\frac{\partial x_u}{\partial P}(1-F(x_u))\right)$$

Thus, when $\frac{\partial c^B}{\partial B^{new}}$ is sufficiently large, $\frac{\partial \mathcal{B}}{\partial P} \in \left(-\frac{f(x_u)}{F(x_u)}\frac{\partial x_u}{\partial P}\mathcal{B}, \frac{f(x_u)}{1-F(x_u)}\frac{\partial x_u}{\partial P}\mathcal{B}\right)$. ■

Lemma Appendix C.6. *The lower log income threshold for trade is increasing in the refusal rate:*

$$\frac{\partial x_l}{\partial \tau} > 0$$

Proof. Note that $\frac{\partial x_l}{\partial \tau} = \frac{\partial x_l}{\partial P}\frac{\partial P}{\partial \tau} + \frac{\partial x_l}{\partial \tau}$. Lemma Appendix C.4 establishes $\frac{\partial x_l}{\partial P} > 0$, Proposition 2.4 establishes $\frac{\partial P}{\partial \tau} > 0$ and given $\frac{\partial x_l}{\partial \tau} = \varepsilon_x^{-1}\frac{\delta}{V(q_s,P)}\frac{\partial Z}{\partial \tau}$ with $\frac{\partial Z}{\partial \tau} = \frac{\partial P}{\partial \tau}/\left(q^{new}\right)^{\varepsilon_q} > 0$, the result follows. ■

[49] Note that this assumption is not necessary. It can be replaced with the weaker assumption that the third term in the numerator of Eq. C.2 is smaller in modulus than the sum of the first two terms, which is necessary and sufficient condition when $\frac{\partial F(x_u)\mathcal{B}}{\partial P} < 0$.

Lemma Appendix C.7. *Expected log-buyer income, conditional on trade, is increasing in the value of unimproved land:*

$$\frac{\partial E\left[X|X\in\mathcal{X}\right]}{\partial Z}>0$$

Proof. Note that $\frac{\partial E[X|X\in\mathcal{X}]}{\partial Z}=\int_{\underline{q}}^{\overline{q}}(\frac{\partial M(x_l,x_u)}{\partial x_l}\frac{\partial x_l}{\partial P}+\frac{M(x_l,x_u)}{\partial x_u}\frac{\partial x_u}{\partial P})\frac{\partial P}{\partial Z}dG_{\underline{q},\overline{q}}\left(q_s\right)$. It is straightforward to show that all terms within the integral are positive for all $q_s\in(\underline{q},\overline{q})$. ■

Appendix D. A Walrasian Equilibrium with Perfect Assortative Matching

Here we characterise the Walrasian equilibrium. Recall we have an exogenous measure of sellers $(1-\delta)\times\mathcal{S}$ who each offer one home of quality q_s drawn from distribution $G_{\underline{q},\overline{q}}$ with compact support $\left[\underline{q},\overline{q}\right]$ and a measure of buyers $\mathcal{B}$ who each demand a single home. Buyer surplus is

$$S^H\left(\widetilde{q}_s,\widetilde{x}\right)=\widetilde{q}_s\times\widetilde{x}-p\left(\widetilde{q}_s\right)$$

where $\widetilde{q}_s=(q_s)^{\varepsilon_q}$ is normalised home quality and $\widetilde{x}=(e^x)^{\varepsilon_x}$ is normalised buyer income. Each seller has an outside option of selling to a developer at price Z, the value of land. We construct a Walrasian equilibrium where all buyers and all sellers meet, and all agents trade.

Appendix D.1. Buyer optimisation

Buyer optimisation implies

$$\frac{\partial S^H\left(\widetilde{q}_s,\widetilde{x}\right)}{\partial\widetilde{q}_s}=\widetilde{x}-\frac{\partial p\left(\widetilde{q}_s\right)}{\partial\widetilde{q}_s}=0 \tag{D.1}$$

That is, the adjusted price gradient must be exactly equal to normalised buyer income for all $\widetilde{q}_s\in\left(\underline{\widetilde{q}},\overline{\widetilde{q}}\right)$ with $\underline{\widetilde{q}}=\left(\underline{q}\right)^{\varepsilon_q}$ and $\overline{\widetilde{q}}=\left(\overline{q}\right)^{\varepsilon_q}$.

Appendix D.2. Solving for the equilibrium mapping from quality to income

Note that our equilibrium implies perfect assortative matching (PAM) as utility from home-ownership is supermodular with $\frac{\partial V^H(\widetilde{q}_s,\widetilde{x})}{\partial\widetilde{q}_s\partial\widetilde{x}}>0$ as shown in Lemma Appendix D.2 below. With PAM, the equilibrium mapping from normalised quality to log-buyer income,

$x(\widetilde{q}_s)$, is strictly increasing ($\frac{\partial x(\widetilde{q}_s)}{\partial \widetilde{q}_s} > 0$). Let x_l^W and x_u^W be the lowest and highest log-buyer income thresholds for trade in the Walrasian equilibrium (these thresholds are determined below). Then the market clearing condition for each quality $\widetilde{q}_s \in \left[\underline{\widetilde{q}}, \overline{\overline{\widetilde{q}}}\right]$ given PAM is

$$\underbrace{(1-\delta) \times \mathcal{S} \times \left[1 - \widetilde{G}(\widetilde{q}_s)\right]}_{\text{Supply with normalised quality above } \widetilde{q}_s} = \underbrace{\mathcal{B} \times \left[1 - \frac{F(x(\widetilde{q}_s)) - F\left(x_l^W\right)}{F\left(x_u^W\right) - F\left(x_l^W\right)}\right]}_{\text{Demand with normalised quality above } \widetilde{q}_s} \tag{D.2}$$

where $x(\widetilde{q}_s) = \varepsilon_x^{-1} \log \widetilde{x}(\widetilde{q}_s)$ and $\widetilde{G}$ is the CDF of normalised home quality, $\widetilde{q}_s = (q_s)^{\varepsilon_q}$. Since F is strictly increasing, we can invert Eq. D.2 to solve for the equilibrium mapping from normalised quality to log-buyer income assuming that all buyers and sellers trade:

$$x(\widetilde{q}_s) = F^{-1}\left(F\left(x_l^W\right) + \left[\widetilde{G}(\widetilde{q}_s)\right]\left[F\left(x_u^W\right) - F\left(x_l^W\right)\right]\right)$$

Appendix D.3. Equilibrium prices

We then substitute this mapping back into the buyer FOC

$$\frac{\partial p(\widetilde{q}_s)}{\partial \widetilde{q}_s} = \exp\left[\varepsilon_x F^{-1}\left(F\left(x_l^W\right) + \left[\widetilde{G}(\widetilde{q}_s)\right]\left[F\left(x_u^W\right) - F\left(x_l^W\right)\right]\right)\right]$$

To determine a unique solution, we assume that the marginal buyer at quality $\overline{\overline{\widetilde{q}}} = (q^{new})^{\varepsilon_q}$ is indifferent between purchasing a new and existing home, which implies

$$p(\widetilde{q}_s) = P^{new} - \int_{\widetilde{q}_s}^{\overline{\overline{\widetilde{q}}}} \exp\left[\varepsilon_x x(r)\right] dr$$

Provided $p(\widetilde{q}_s) \geq Z$ for all $\widetilde{q}_s \in \left[\underline{\widetilde{q}}, \overline{\overline{\widetilde{q}}}\right]$ sellers always prefer to sell their existing home to a buyer than to a developer, and thus all sellers are willing to trade at the Walraisn equilibrium price offered to them. We assume the Walrasian equilibrium trade thresholds are determined by $x_l^W = \underline{x}_l$ and $x_u^W = x_u$ where $\underline{x}_l = x_l(\overline{q})$ and x_u are the lowest and highest log-buyer income trade thresholds for any quality offered by a existing home seller in the model with search. This completes the description of the Walrasian equilibrium. We now state our main proposition.

Proposition Appendix D.1. *In a Walrasian equilibrium where all existing home buyers and sellers trade, (i) the equilibrium price distribution is:*

$$p\left(\widetilde{q}_s\right) = P^{new} - \int_{\widetilde{q}_s}^{\overline{\overline{q}}} \exp\left[\varepsilon_x x(r)\right] dr$$

where $\widetilde{q}_s \equiv q_s^{\varepsilon_q}$ *and* $\widetilde{G}$ *is the CDF of normalised home quality,* $\widetilde{q}_s = (q_s)^{\varepsilon_q}$*.*

(ii) The equilibrium mapping from home quality to log-buyer income implies perfect assortative matching and is given by:

$$x\left(\widetilde{q}_s\right) = F^{-1}\left(F\left(\underline{x}_l\right) + \widetilde{G}\left(\widetilde{q}_s\right)\left[F\left(x_u\right) - F\left(\underline{x}_l\right)\right]\right)$$

(iii) Expected relative inome is increasing in home quality:

$$\frac{\partial E\left[\mathcal{R}|Q = q_s\right]}{\partial q_s} > 0$$

Proof. (i) and (ii) to follow directly the characterisation of the Walrasian equilibrium. For (iii), this follows directly from PAM (Lemma Appendix D.2) and noting:

$$\frac{\partial x\left(\widetilde{q}_s\right)}{\partial q_s} = \frac{g\left(\widetilde{q}_s\right)\left[F\left(x_u\right) - F\left(\underline{x}_l\right)\right]}{f\left(x\left(\widetilde{q}_s\right)\right)} \varepsilon_q q_s^{\varepsilon_q - 1} > 0$$

■

Lemma Appendix D.2. *If* $V^H\left(\widetilde{q}_s, \widetilde{x}\right)$ *is supermodular, then the Walrasian equilibrium existing positive assortative matching with*

$$\frac{\partial x\left(\widetilde{q}_s\right)}{\partial q_s} > 0$$

Proof. From buyer optimisation in the Walraisan equilibrium $\frac{\partial V^H(\widetilde{q}_s,\widetilde{x})}{\partial \widetilde{q}_s} = \frac{\partial p(\widetilde{q}_s)}{\partial \widetilde{q}_s}$. Totally differentiating, we have $\frac{d\widetilde{x}}{d\widetilde{q}_s} = \frac{\frac{\partial^2 p(\widetilde{q}_s)}{\partial \widetilde{q}_s^2} - \frac{\partial^2 V^H(\widetilde{q}_s,y)}{\partial \widetilde{q}_s^2}}{\frac{\partial^2 V^H(\widetilde{q}_s,y)}{\partial \widetilde{q}_s \partial y}}$ Since buyer optimality requires $\frac{\partial^2 V^H(\widetilde{q}_s,\widetilde{x})}{\partial \widetilde{q}_s \partial \widetilde{x}} - \frac{\partial^2 p(\widetilde{q}_s)}{\partial \widetilde{q}_s^2} < 0$ we have $\frac{d\widetilde{x}}{d\widetilde{q}_s} > 0$ if and only if $\frac{\partial^2 V^H(\widetilde{q}_s,y)}{\partial \widetilde{q}_s \partial y} > 0$ for all $\widetilde{q}_s \in \left[\underline{\widetilde{q}}, \overline{\overline{q}}\right]$. Noting that $x\left(q_s\right) = \varepsilon_x^{-1} \log \widetilde{x}$ completes the proof. ■

Appendix E. Seller-to-Buyer Filtering in a Dynamic Model

In this section, we discuss a dynamic model of seller-to-buyer filtering that admits a stationary equilibrium equivalent to the model discussed in the main text. Time is continuous, buyers and sellers are infinitely lived and have a common discount rate $r > 0$. Each seller has one home to sell. The home quality, $q_{s,t}$, is drawn at t, and is specific to the seller. With probability $1 - \delta$ the quality drawn is strictly positive and is retained for the duration of the interval $[t, t+\epsilon)$, and so the seller searchers for buyer who arrives at rate λ^S and incurs search cost c^S. Trade only occurs if the joint trade surplus is positive; otherwise, the seller retains the property and continues to search. With probability δ, the home depreciates to zero quality at t and a developer arrives at rate $\lambda^\dagger$. When meeting a developer, the seller sells the home at a competitively determined price $Z_{t+\epsilon}$. Let $\mathcal{X}_{t+\epsilon} \equiv [x_l(q_{s,t+\epsilon}, P_{t+\epsilon}), x_u(P_{t+\epsilon})]$ be the interval where the joint trade surplus is positive given home quality $q_{s,t+\epsilon}$ and quality-adjusted new home price $P_{t+\epsilon}$. The expected value of selling an existing home at t, $V_t^S \equiv V_t^S(q_{s,t})$, is:

$$V_t^S = \frac{(1-\delta)\,\epsilon}{1+r\epsilon}\left(\lambda^S \int_{\mathcal{X}_{t+\epsilon}} \max\left\{\widetilde{\Pi}_{t+\epsilon}^S - V_{t+\epsilon}^S, 0\right\} dF(x_t) - c^S\right) + \frac{\delta\lambda^\dagger\epsilon(Z_{t+\epsilon} - V_{t+\epsilon}^S)}{1+r\epsilon} + \frac{V_{t+\epsilon}^S}{1+r\epsilon}$$

where $\widetilde{\Pi}_{t+\epsilon}^S \equiv \widetilde{\Pi}^S(x_t; q_{s,t+\epsilon}, P_{t+\epsilon})$ is the seller payoff from trade upon trading with a buyer.

Buyers demand a single home, either newly built or existing, and direct their search conditional on their income that is drawn at t and remains constant over the interval $[t, t+\epsilon)$. Let $\widetilde{X}_{t+\epsilon} \equiv [x_u(P_{t+\epsilon}), +\infty)$. If a buyer's log-income is sufficiently high, $x_t \in \widetilde{X}_{t+\epsilon}$, the buyer searches the new home market and the opportunity to purchase a new home from a developer arrives at rate λ^{new}. If the buyer's log-income (hereafter income) is below $x_u(P_{t+\epsilon})$, the buyer searches for an existing home and meets a seller at rate λ^B. Trade is consummated when the joint trade surplus is positive in both cases. The expected value of buyer search in the existing and new home markets at t, $V_t^{B,E}$ and $V_t^{B,N}$, are given by the Bellman equations:

$$V_t^{B,E} = \frac{\lambda^B \epsilon}{1+r\epsilon}\left(\int_{\mathcal{Q}_{t+\epsilon}}\int_{\mathcal{X}_{t+\epsilon}} \max\left\{\widetilde{\Pi}_{t+\epsilon}^{B,E} - V_{t+\epsilon}^{B}, 0\right\} dF^E(x_t)\, dG_{\underline{q},\overline{q}}(q_{s,t+\epsilon})\right) - \frac{\epsilon c_t^{B,E}}{1+r\varepsilon} + \frac{V_{t+\epsilon}^{B}}{1+r\epsilon}$$
$$V_t^{B,N} = \frac{\lambda^{new}\epsilon}{1+r\epsilon}\left(\int_{\widetilde{X}_{t+\epsilon}} \max\left\{\widetilde{\Pi}_{t+\epsilon}^{B,N} - V_{t+\epsilon}^{B}, 0\right\} dF^N(x_t)\right) - \frac{\epsilon c_t^{B,N}}{1+r\varepsilon} + \frac{V_{t+\epsilon}^{B}}{1+r\epsilon}$$

where the value of buyer search before drawing log-income is $V_t^B \equiv \int_{-\infty}^{x_u(P_{t+\epsilon})} V_t^{B,E} dF(x_t) + \int_{x_u(P_{t+\epsilon})}^{+\infty} V_t^{B,N} dF(x_t)$, $\widetilde{\Pi}_{t+\epsilon}^{B,E} \equiv \widetilde{\Pi}^{B,E}(x_t; q_{s,t+\epsilon}, P_{t+\epsilon})$ is the buyer payoff from purchasing an established home, $\widetilde{\Pi}_{t+\epsilon}^{B,N} \equiv \widetilde{\Pi}^{B,N}\left(x_t; q_{t+\epsilon}^{new}, P_{t+\epsilon}^{new}\right)$ is the payoff from buying a new home, $\mathcal{Q}_{t+\epsilon} \equiv \left[\underline{q}_{t+\epsilon}, \overline{q}_{t+\epsilon}\right]$ is the support for the continuous distribution of existing home quality $G_{\underline{q},\overline{q}} \equiv G_{\underline{q}_{t+\epsilon},\overline{q}_{t+\epsilon}}$, $c^{B,E}$ and $c^{B,N}$ are the respective buyer search costs functions that depend on the measure of buyers searching in each market (arguments are omitted for brevity), and where F^E and F^N are the conditional income distributions for a buyer searching in the existing home, or new home, market.

When trading an existing home of quality $q_{s,t+\epsilon}$, buyers and sellers split the joint surplus from trade. The seller obtains $\Pi_{t+\epsilon}^S - V_{t+\epsilon}^S = \psi\left(V^H(q_{s,t+\epsilon}, x_t) - V_{t+\epsilon}^B - V_{t+\epsilon}^S\right)$ and the buyer $\Pi_{t+\epsilon}^{B,E} - V_{t+\epsilon}^B = (1-\psi)\left(V^H(q_{s,t+\epsilon}, x_t) - V_{t+\epsilon}^B - V_{t+\epsilon}^S\right)$ with $\psi \in [0,1]$.

Assuming that sellers obtain the full surplus from trade and that buyer search costs for existing homes are small ($\psi \to 1^-$ and $c^{B,E} \to 0^+$), in the limit the trading interval is small ($\epsilon \to 0^+$):

$$(r+\delta)V^S(q_s, P) = \delta Z - (1-\delta)c^S + (1-\delta)\lambda^S\left(\int_{x_l}^{x_u} \Pi^S dF(x)\right) + \dot{V}^S(q_s, P) \qquad \text{(E.1)}$$
$$rV^B(P) = \lambda^{new}\int_{x_u}^{\infty} \Pi^B dF(x) - (1 - F(x_u))c^B(B^{new}) + \dot{V}^B(P) \qquad \text{(E.2)}$$

where we omit time subscripts and redefine $\Pi^B \equiv \widetilde{\Pi}^{B,N} - V^B$, $\Pi^S \equiv \widetilde{\Pi}^S - V^S$, and $c^{B,N} \equiv c^B$. In the stationary equilibrium where $\dot{V}^S(q_s, P) = 0$ and $\dot{V}^B(P) = 0$, Equations (E.1) and (E.2) are identical to Equations 1 and 2 discussed in the main text.

Appendix F. Data Disclaimers

Disclaimer: The results of this study are based, in part, on data supplied to the ABS under the Taxation Administration Act 1953, A New Tax System (Australian Business Number) Act 1999, Australian Border Force Act 2015, Social Security (Administration) Act 1999, A New Tax System (Family Assistance) (Administration) Act 1999, Paid Parental Leave Act 2010 and/or the Student Assistance Act 1973. Such data may only used for the purpose of administering the Census and Statistics Act 1905 or performance of functions of the ABS as set out in section 6 of the Australian Bureau of Statistics Act 1975. No individual information collected under the Census and Statistics Act 1905 is provided back to custodians for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes and is not related to the ability of the data to support the Australian Taxation Office, Australian Business Register, Department of Social Services and/or Department of Home Affairs' core operational requirements. Legislative requirements to ensure privacy and secrecy of these data have been followed. For access to PLIDA and/or BLADE data under Section 16A of the ABS Act 1975 or enabled by section 15 of the Census and Statistics (Information Release and Access) Determination 2018, source data are de-identified and so data about specific individuals has not been viewed in conducting this analysis. In accordance with the Census and Statistics Act 1905, results have been treated where necessary to ensure that they are not likely to enable identification of a particular person or organisation.