Interest Rates and Housing Market Dynamics in a Housing Search Model *

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Abstract

We structurally estimate a directed search model of the housing market with mortgages using microdata on home listings and home sales. Estimation is complicated by the significant heterogeneity that even basic mortgages introduce into the search model, but we exploit the insights of Menzio and Shi (2010) to maintain tractability. The estimated model shows that, because of search frictions, housing market conditions are significantly more responsive to mortgage rates than suggested by reduced-form correlations of rates with house prices. In response to a change in interest rates, buyer willingness to pay for the typical home changes by more than twice as much as the average sale price. In contrast, home construction and sales volumes are more rate sensitive than average sale prices, as is true in the data.

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1 Introduction

Fluctuations in housing values have significant consequences for the economy because they influence consumption decisions, residential investment, and financial stability. It is therefore important to understand what drives housing market dynamics. A growing literature has focused on the role of mortgage interest rates, which are a natural factor to examine because most home purchases are financed with large, fixed-rate loans. In addition, mortgage interest rates are a particularly important factor to study because they are the primary channel through which monetary policy will be transmitted to the housing market.

The empirical literature typically estimates the effect of interest rates on housing valuations using reduced-form correlations of interest rates with house prices, identifying causal effects either through monetary policy surprises or through discontinuities in institutional rules. This literature generally finds quite modest effects of interest rates on house prices, with estimates of the semi-elasticity (i.e. the percent house price response to a 100 basis point interest rate shock) in the low to mid single digits.[1] These empirical findings have contributed to a view that monetary policy may be a blunt tool for influencing house price fluctuations, and that macroprudential policies might be better suited for addressing house price movements and financial stability risks (see Bernanke (2010); Yellen (2014)).

There are a few reasons, however, to question this conclusion. First, a benchmark asset market approach to housing valuation (Poterba (1984)), in which the costs of renting and owning are equal in equilibrium, often implies a larger rate elasticity.

[1] Using variation in mortgage rates driven by conforming loan limit rules, Adelino et al. (2012) estimate semi-elasticities ranging from 1 to 9, depending on the time period and the interest rate differential between jumbo and conforming loans. Estimating a VAR model, Del Negro and Otrok (2007) show a semi-elasticity of about 4. More recently, Davis et al. (2018) estimate a semi-elasticity of 3.4 using variation caused by an unexpected change in mortgage premiums charged by the Federal Housing Administration. See Kuttner (2012) for a further review.

Using the asset market approach, Himmelberg et al. (2005) show that the model-implied semi-elasticity can be 20 under reasonable assumptions about key parameters, such as the prevailing interest rate, expected rent price growth, and marginal tax rate.[2] Yet empirical estimates of the semi-elasticity range from 1 to 9. Thus, at first glance, the theory seems to be at odds with the data.[3]

Second, in contrast to house prices, other housing market variables, such as existing home sales and new construction activity, are actually relatively interest rate elastic. If interest rates have only a modest effect on the willingness to pay for housing—as the empirical relationship between house prices and rate changes seems to suggest—then why are home sales and new construction, which should also be driven by buyer valuations for housing, relatively rate elastic?[4]

In this paper, we show that the above facts can be rationalized by adding search frictions, mortgages, and home construction to a standard asset market model. Our estimated housing search model shows that interest rates do have sizable effects on buyer valuations for housing. However, because of search frictions, the sales price response significantly understates the latent valuation response. In particular, the model predicts that an exogenous, unanticipated, and permanent 100 basis point increase in mortgage interest rates will decrease buyer willingness to pay for the typical home by 12 percent, but average sales price will fall by only 5 percent, consistent with

[2] Glaeser et al. (2012) also find semi-elasticities ranging from 10 to 20 in their baseline parameterizations of a user-cost model.

[3] In his summary of the empirical literature on the rate-elasticity of house prices, Kuttner (2012) writes "the estimated effects are uniformly smaller than those implied by the conventional user cost theory of house prices." Glaeser et al. (2012) do show that when the user cost model is extended to include refinancing and volatile interest rates, then the implied semi-elasticity can be reduced substantially, though refinancing either needs to be costless or else subjective discount factors need to be delinked from interest rates. Another strand of the literature shows that broader measures of credit supply other than interest rates (i.e. collateral constraints) have larger effects on house prices (see Favara and Imbs (2015); Maggio and Kermani (2015)).

[4] Among existing homeowners, DiMaggio et al. (forthcoming); Bhutta and Keys (2016) show that changes in interest rates have sizable effects on consumption and equity extraction decisions, also suggestive of a more sensitive response of home buyer demand to changes in rates.

the magnitude of the price elasticity estimated in the existing literature. By contrast, sales volumes and new construction permits are much more rate elastic than prices, which is also true in the data. These are statements about constant-quality homes, so the results are not driven by selection in the types of homes that are sold. Rather, the results will be driven by the behavior of sellers and the tradeoffs they make between list price and time on market.

The model is a directed search and matching model with mortgages and home construction. A main contribution of our paper is that we estimate the model using detailed microdata on the list price choices and selling outcomes of individual sellers from San Diego. In the model, buyers finance home purchases with long-term, fixed-rate mortgages. Thus, homeowners endogenously become differentiated by their interest rate and mortgage amount, which together determine the share of per-period income that a homeowner must allocate to mortgage payment rather than consumption. Homeowners occasionally receive a moving shock and become sellers. The heterogeneous sellers direct their search for a buyer into one of many submarkets, which are effectively list price levels for a given quality-level of housing. Builders, who are differentiated by their construction cost, buy depreciated homes and optimally choose when to start construction to replace the depreciated structure. Once construction is completed, builders face a home selling problem with search frictions just as sellers of existing homes do. The market for new and existing homes is integrated.

To understand the key intuition for our main results, note that the key tradeoff faced by sellers in the model is that listing at a higher price will typically result in a higher sale price but a longer time to sale. When there is a shock to buyer demand (for example, from a decrease in interest rates), the tradeoff between sale price and time-to-sell changes, and sellers will reoptimize on both dimensions. Therefore, not all of the value of the shock gets capitalized into house prices, as some gets reflected in housing liquidity. The quantitative importance of the price versus sale hazard clearing channel depends on parameter values such as search costs and the curvature of the seller's utility function with respect to price. By contrast, new construction activity is more sensitive to interest rates because the building decision is influenced by both expected price *and* expected time-to-sell, as builders also experience search frictions when selling newly built homes.

Introducing even simple mortgage contracts and construction costs into a search model introduces heterogeneity that is usually difficult to accommodate computationally. However, because buyers can freely direct their search toward any submarket in our model, expected buyer utility across submarkets will be equalized. Using the insights of Menzio and Shi (2010, 2011), we show that such a condition allows us to compute the equilibrium of our model without keeping track of the distributions of agent heterogeneity, making the model easily solvable both in and out of steady state. As a result, we are able to estimate the model without imposing the common assumption that our data reflect a steady state, and we can simulate the complete dynamics of our model in response to an interest rate shock from a realistic set of initial conditions.

Related Literature

Our paper contributes to the large literature that uses search models to study the housing market.[5] Although the idea that economic shocks will not be fully reflected in prices is not new to the search literature (i.e. it is emphasized for the housing market in Diaz and Jerez (2013) and Head et al. (2014)) we are the first to try and

[5] See, for example, Burnside et al. (2016); Head et al. (2014); Piazzesi and Schneider (2009); Ngai and Tenreyro (2014); Krainer (2001); Carrillo (2012); Albrecht et al. (2007); Novy-Marx (2009); Diaz and Jerez (2013); Caplin and Leahy (2011); Genesove and Han (2012); Wheaton (1990); Arefeva (2017); Moen et al. (2015); Guren (2018); Ngai and Sheedy (2016); Guren and McQuade (2013).

quantify the effect of interest rates using detailed data on the list price choices and selling outcomes of individual sellers. The advantage of using microdata is that we are able to exploit the rich heterogeneity for informing the quantitative predictions of the model, which lends credence to the final estimates. In addition, the micro data allow us to directly observe key aspects of the model in the data, such as the trade-off between price and time on market and the dependence of the seller's choice of list price on their outstanding loan amount. Other papers that estimate related models of the home selling problem using micro-data on home listings include Merlo et al. (2015); Carrillo (2012); Anenberg (2016); Horowitz (1992). Relative to these papers, we are unique in that buyer valuations and prices are endogenously determined, and that we incorporate new construction into our model.[6]

Another advantage of the structural approach is that it allows us to be explicit about households' expectations associated with the interest rate shock that is used to measure the house price elasticity. In the data, interest rate changes can be anticipated or unanticipated, and temporary or persistent. Such expectations can be difficult to control for in the data but may matter for the size of the price response (e.g. particularly if borrowers can refinance or mortgages are adjustable rate), which complicates the interpretation of some of the reduced-form elasticities. In our main results, we show that a small rate elasticity can be rationalized even when the rate shock is unanticipated and permanent.

Methodologically, our paper is similar to Hedlund (2016) in that he also applies the insights of Menzio and Shi (2010, 2011) to solve a directed search model of the housing market both in and out of steady state. Hedlund (2016) also incorporates mortgages and new construction into his search model, though his main focus is on

[6]Paciorek (2013); Murphy (2017) also model new construction, but they do not consider search frictions as we do in this paper. Most of the macro housing search literature generally treats the housing stock as fixed, and/or considers only steady states. Head et al. (2014) is a recent exception.

foreclosures and the cyclical dynamics of the macroeconomy. In order to maintain tractability given his rich general equilibrium structure, Hedlund (2016) incorporates one-period-lived frictionless intermediaries that intermediate home sales. Our model is more parsimonious compared to the one in Hedlund (2016), and so we do not need to introduce intermediaries to maintain tractability. One consequence is that in our model, the distribution of buy prices and sale prices are guaranteed to line up, net of transaction fees, thus giving a clearer interpretation for how to match micro model moments to the data. Our method for identifying key model objects such as the sale hazard as a function of list price is similar to Guren (2018). Guren (2018) focuses on identifying the concavity of the sale hazard function to show how this can lead to house price momentum. Many of the insights in that paper are also replicated in our model.

Finally, we contribute to the literature on hedonic valuation that builds off the seminal work of Rosen (1974); Bayer et al. (2007); Berry et al. (1995); Bajari and Benkard (2005). The insight of this literature is that consumer preferences over product attributes may be inferred from the pricing of those attributes and from consumers' product choices. This literature has been applied to housing in order to study households' willingness-to-pay for local amenities such as school quality, crime, and pollution.[7] Our contribution to this literature is to provide a framework for studying both the liquidity and the price response to a change in amenities. While our paper focuses on interest rates, our model could be used to obtain more accurate estimates of willingness to pay for a more general set of amenities, in the presence of search frictions.

[7]See, for example, Bayer et al. (2016); Bishop and Murphy (2011); Caetano (2012), Ouazad and Rancière (2013); Kung and Mastromonaco (2015)

2 Motivating Empirical Facts

In this section, we show that home sales and home construction appear to be more rate elastic than home prices. We provide evidence that sales and construction are rate elastic mainly because homebuyer demand is rate elastic. Then, in the remainder of the paper, we turn to a model with search frictions to help us better understand these relationships.

2.1 General Patterns

We examine the correlation between national 30 year fixed rate mortgage rates and several housing market variables of interest. We estimate linear regressions of the following form:

$$log(y_t) - log(y_{t-4}) = \alpha_0 + \alpha_1(r_{t-1} - r_{t-5}) + \alpha_2(X_{t-1} - X_{t-5}) + \epsilon_t \quad (1)$$

where y is the housing market variable of interest, r is the mortgage rate (measured in percentage points), X are other covariates and t indexes the quarter-year. We lag the right hand side variables by one quarter to reflect the fact that housing market variables are measured with some delay. We have over 30 years of data, though the precise number of observations varies with the outcome variable. The mortgage rate is the average quarterly rate in percentage points as reported in the Freddie Mac primary mortgage market survey. For our main results, we include the national unemployment rate in X. α_1 represents the semi-elasticity of y with respect to mortgage rates–that is, the percentage point change in y in response to a 1 percentage point increase in mortgage rates.

Changes in interest rates in equation (1) are likely endogenous, and so the estimate of α_1 should not be interpreted as a causal effect. Rather, the relative estimates of α_1 across outcome variables are simply meant to illustrate the different correlations between changes in rates and outcome variables of interest.

Column 1 of Table 3 displays results for real quality-adjusted house prices, as measured by the Corelogic repeat sales index. The estimated semi-elasticity has the expected sign (negative), but is small in absolute value. Column 2 shows the semi-elasticity when total sales volume of new and existing homes, as reported by the National Association of Realtors, is included as the outcome variable. The estimated semi-elasticity is -8.4, suggesting that sales volume is more rate elastic than house prices. When the number of homes available for sale is divided by sales volume—often referred to as "months supply" in the industry—the estimated semi-elasticity, reported in column 3, is a bit higher in absolute value. This result suggests that the rate elasticity of sales volume is affected by changes in buyer demand—i.e. through homes selling faster or slower—and not just by changes in the number of sellers putting homes on the market. This point is reinforced by column 4, which shows that changes in the number of new listings coming onto the market is actually slightly positively associated with changes in mortgage rates.[8]

Most of the existing literature that estimates the effect of interest rates on housing valuation analyzes only prices, and would miss the liquidity response that is illustrated by the results in columns 2-4. The conceptual framework behind the existing empirical specifications is typically a frictionless asset market approach, where changes to buyer valuations due to rate changes would be fully reflected in price changes. But in such a model there is no scope for homes to remain on the market unsold.[9] In the Appendix,

[8]New listings is for the San Diego CBSA and comes from the CoreLogic listings data that we use to estimate our model and describe below.

[9]For further details of the asset market approach to housing valuation, we refer the reader to the presentation in Fuster and Zafar (2015); Glaeser et al. (2012); Kuttner (2012)

we provide further evidence that 1) mortgage rates affect homebuyer demand and 2) a shock to homebuyer demand from a shock to the mortgage rate is partly cleared through the probability of sale, using an alternative dataset.

Column 5 shows the semi-elasticity when single-family building permits as reported by the Census Bureau is included as the outcome variable in equation 1. The estimated semi-elasticity is -11.5, suggesting that like sales volume, permits are more rate elastic than house prices. Permits could be sensitive to rates for a couple of reasons. First, rates could affect the demand for housing, which should affect the revenue side of a builder's profit function. Second, rates could affect the builder's financing of construction costs, which should affect the cost side of a builder's profit function.[10] To better understand the mechanism through which interest rates influence permit activity, we include interest rates of shorter maturities on the right side of equation 1. The motivation for these additional specifications is that if the demand channel is more important, then permits should be most sensitive to longer maturity rates, as most borrowers finance home purchase with 30 year fixed rate mortgages. If the cost channel is more important, than permits should be more sensitive to shorter-term rates. Builders construct homes relatively quickly and so the short-term rate is more relevant to the cost of financing housing construction. Column 6 show the results. The rate elasticity of permits appears to be entirely driven by the 30 year mortgage rate, suggesting that permits are rate elastic mainly because buyer demand is rate elastic. Our model will therefore focus on this demand channel.

An elastic housing supply curve could help to explain why prices are not as sensitive to rates as new construction.[11] To explore this possibility, we split metropolitan

[10]In the small literature that structurally models the building decision and includes a role for interest rates, interest rates typically affect the building decision through the demand channel. See Paciorek (2013); Murphy (2017).

[11]It is not clear that an elastic housing supply curve could explain why existing home sales are relatively rate elastic, however.

areas into three groups of equal size based on the Saiz (2010) measure of housing supply elasticity. Table 2 shows results where we estimate the regressions shown in Table 1 separately by supply elasticity group. CBSA fixed effects are included. The results are similar in both high and low housing supply elasticity metros suggesting that elastic housing supply alone cannot rationalize the motivating facts that we present in this section.

3 Model

Our approach is to take a standard asset market model and incorporate search, mortgages, and construction as parsimoniously as possible. As in the standard asset market model, we abstract from certain aspects of the market such as endogenous rents, mortgage prepayment/default, buyer heterogeneity, and borrowing constraints. By endogenizing selling and construction decisions in addition to prices, we have predictions for sales volume and construction activity, which are not present in the standard model.

We consider a directed search model of a local housing market where there are $h = 1, 2$ types of housing units (new and old). New homes are produced by builders using undeveloped land, and old homes are held by existing homeowners. New homes become old homes after one ownership spell, and old homes will sometimes depreciate into undeveloped land.

Each period, some builders and some owners will become sellers. Sellers list their houses at $p = p_1, \ldots, p_L$ possible price levels. Buyers will choose which type of house (new or old) to search for, and at what list price level. We define a house type and list price pair, (h, p) as a *submarket*.

Within submarkets, buyers meet sellers via a frictional matching process. Let

$\theta = b/s$ be the ratio of buyers to sellers in the submarket, often referred to as *market tightness*. Then, the probability that a buyer meets a seller is $q_b(\theta)$ and the probability that a seller meets a buyer is $q_s(\theta) = \theta q_b(\theta)$. We assume that q_s and q_b are continuous, that $q_b(0) = 1$ and $q_s(0) = 0$, and that q_b is strictly decreasing while q_s is strictly increasing. In equilibrium, the basic tradeoff faced by the buyer is that searching at higher list prices will typically result in a faster match, whereas the opposite is true for sellers.

3.1 Buyers

Buyers are ex-ante homogeneous. In each period, they may freely enter or exit the local housing market. Let $V^b(x)$ be the value function of entering the housing market when the aggregate state of the economy is x. The aggregate state can take on $x = x_1, \ldots, x_N$ possible values, and evolves according to a first order Markov transition matrix Π. The aggregate state variable encapsulates variables in the economy which affect the housing market, such as mortgage interest rates. Section 3.4 provides the precise definition of x in the equilibrium of our model economy.

Let k be the present value of the buyer's utility if he *does not enter* the housing market. k can be thought of as the outside option of living somewhere else, or of renting forever.[12] In equilibrium,

$$V^b(x) = k \tag{2}$$

as buyers will freely enter the market until the point in which the marginal buyer is indifferent between entry or exit.

Buyers enter the housing market as renters. The per-period cost to renting is *rent*.

[12]For exposition of the model, we treat k as a constant, but it could also be allowed to depend on the aggregate state x. Alternatively, k itself could be an aggregate state variable contained in x.

We assume that rental units come from a separate housing stock than owner-occupied units, and are owned by absentee landlords. Buyers then decide which submarket (i.e. house type and list price) to search in. In submarket (p, h), when the aggregate state is x, the buyer meets a seller with probability $q_b(\theta(p, h, x))$.

After the buyer meets a seller, he discovers an idiosyncratic preference shock ϵ for that particular house, which is drawn from $G_h(\epsilon)$. This preference shock captures the reality that a buyers' valuation is only fully revealed upon physically viewing the house and helps to ensure that not all meetings lead to transactions, consistent with the evidence shown in Genesove and Han (2012) that average viewings per transaction are greater than one. The idiosyncratic preference shock is additive in utility and is consumed at the time of purchase. This assumption simplifies our notation and computation, but due to an exogenous moving assumption which is discussed below, it is equivalent to a model in which the preference shock is additive and consumed over the period of living in the house. After drawing the preference shock, the buyer decides whether or not to purchase the house at the listed price p.[13] If purchased, the buyer becomes an owner and finances the home with a 100% LTV, interest-only, fixed-rate loan that is paid off at the time of resale. This simplifies the analysis without losing the key economic mechanisms of the interest rate affecting buyer valuation through higher borrowing costs, and the mortgage balance affecting the sellers' list price vs. time-on-market tradeoff. We discuss further implications of this assumption, including robustness, in the Appendix. Neither mortgage default nor short sales is allowed. Instead, we model a utility cost to selling while under negative equity. The interest rate r is exogenous and can take on one of $r = r_1, \ldots, r_N$ possible values.

An owner can be described by the price he purchased the house at, p, and the

[13] We abstract away from bargaining from the list price for computational reasons. The assumption that houses sell at list price is a reasonable approximation as in the data, the average, median, and modal transaction price is very close to the list price.

interest rate on his loan r. For each owner, r will be equal to the prevailing market interest rate at the time she purchased the home. Let $V^o(p,r,x)$ be the value function of an owner when the aggregate state is x. A buyer searching at price p when the interest rate is r and the aggregate state is x will therefore purchase if and only if:

$$V^o(p,r,x) + \epsilon \geq k \tag{3}$$

as k is the value of returning to the market as a buyer or of exiting the market.

We can now write the value function of being a buyer as:

$$\begin{aligned} V^b(x) &= u(y - rent) - c_b + \max_{p,h} \beta E_{x',\epsilon|x,h} \Big[\; k + \dots \\ & \dots + q_b(\theta(p,h,x)) \max \Big\{ 0, \; V^o(p,r,x') + \epsilon - k \Big\} \Big] \end{aligned} \tag{4}$$

$u(y - rent)$ is the flow utility from consumption, where y is per-period income and $rent$ is the rental rate. c_b is the cost of searching the market as a buyer, and may be thought of as the time investment of searching through listings and visiting homes. Buyers choose which house type h and list price p to search at. The probability that he meets a seller is $q_b(\theta(p,h,x))$, and if ϵ is high enough, he will purchase the house, getting a surplus of $V^o(p,r,x') + \epsilon - k$ starting next period. Otherwise, he returns to the market as a buyer, or exits the market, both of which give present value k.[14]

[14] We have implicitly assumed that the price and mortgage are locked in at time t, when the search decision is being made, even though the buyer does not start becoming an owner until time $t+1$. This is realistic for our empirical implementation, where the time period is a month, as prices and mortgage contracts are usually locked in a month or two in advance of the closing date.

3.2 Owners

Owners stay in their homes until they receive a moving shock, which happens with probability λ each period.[15] Moving shocks are exogenous, and can be thought of as representing events such as divorce or job change. If an owner does not receive a moving shock, she simply consumes her income minus interest payments, $y - rl$, where l is the loan amount, and moves on to the next period as an owner. Conditional on receiving a moving shock, there is an additional probability α that the house depreciates to undeveloped land. In this case, instead of becoming a seller, the owner immediately receives a liquidation value p_c for the depreciated home, pays off the loan amount l, and transfers ownership of the unit to a builder. The terminal utility for the owner in this situation is $U(p_c - l)$, where U is the utility function used to evaluate net wealth at the time of a move.

Let $V^o(l, r, x)$ and $V^s(l, r, x)$ be the value functions of owners and sellers, respectively. We can write:

$$\begin{aligned} V^o(l,r,x) &= u(y-rl) + \beta E_{x'|x}\Big[(1-\lambda)V^o(l,r,x') + \dots \\ &\quad \dots + \lambda(1-\alpha)V^s(l,r,x') + \lambda\alpha U(p_c - l)\Big] \end{aligned} \tag{5}$$

In words, owners make mortgage payments, consume, and receive housing dividends until they receive a moving shock.[16] Upon receiving a shock, owners either become sellers or receive a liquidation value for the home depending on the realization of a depreciation shock. We now describe the sellers' problem.

[15] Ngai and Sheedy (2016) consider a search model where moving is endogenous. If we allowed for endogenous moving in our model, more sellers would likely decide to list their homes for sale when interest rates fall, which would likely increase the sensitivity of sales volume to rate changes. These extra listings would have no direct effect on prices because buyer entry is elastic in our model, though there may be some indirect effect on prices due to selection on the types of sellers that transact.

[16] Recall that we account for the net present value of the entire housing dividend stream at the time of purchase, so the housing dividend does not appear explicitly in the owner's value function.

3.3 Sellers

Sellers continue to consume their income minus mortgage payments each period. In addition, they pay a per-period search cost c_s, which can be interpreted as including both the time investment of selling a home (listing, showing, etc) and the penalty for not selling the home fast enough (as in the case of moving to a new job).

When an owner first becomes a seller, she chooses a list price to market her home at. In subsequent periods, the seller receives the opportunity to change her list price with probabilityρ.[17] We incorporate this pricing friction to account for the empirical reality that sellers adjust prices only infrequently (see, e.g., Guren (2018); Merlo and Ortalo-Magne (2004)), perhaps due to menu costs, seller inattention, or signaling considerations that might arise in a model where buyers are uncertain over house quality. Our model abstracts from the particular mechanism through the single parameter ρ. However, we will show below that our main results are essentially unchanged when $\rho = 1$ and sellers can adjust prices each period.

Let $V^s(l,r,x)$ be the value function of a seller free to change her list price and let $W^s(l,r,x,p)$ be the value function for a seller currently listing at price p. We can write:

$$V^s(l,r,x) = \max_p W^s(l,r,x,p) \tag{6}$$

and

$$\begin{aligned} W^s(l,r,x,p) \quad = \quad & u(y-rl) - c_s + \beta E_{x'|x}\Big[\kappa(p,h,x)U(p-l) + \dots \\ & \dots + (1-\kappa(p,h,x))\rho V^s(l,r,x') + \dots \\ & \dots + (1-\kappa(p,h,x))(1-\rho)W^s(l,r,x',p)\Big] \end{aligned} \tag{7}$$

[17]In our model, only changes to the aggregate state will incentivize sellers to adjust list prices. There is no duration dependence of list prices that might arise from learning or from a finite selling horizon.

Here, $U(p-l)$ is the utility over net wealth at the time of a move and $\kappa(p,h,x)$ is the probability that the seller meets a willing buyer in submarket (p,h). The probability that the seller meets a willing buyer is given by:

$$\kappa(p,h,x) = q_s(\theta(p,h,x))E_{x',\epsilon|x,h}\Big[V^o(p,r,x') + \epsilon - k \geq 0\Big] \tag{8}$$

i.e. it is the probability that the seller meets a buyer with preference shock ϵ high enough to warrant purchase of the home at price p. Since owners have old houses, $h = 2$ in the seller's problem.

3.4 Builders

Builders can be in three stages of development: 1) sitting on a plot of depreciated land, deciding whether or not to begin development, 2) under construction, and 3) ready to market a completed home. In the first stage, builders start with a plot of land which they acquire for price p_c from owners whose homes depreciate. They are not required to begin development immediately. Rather, this is a decision they make each period based on the aggregate state and on idiosyncratic shocks to startup cost. In the second stage, when the builder has begun development, there is a probability ϕ of completing development each period. When development is complete, builders choose a list price to market the home at, much like sellers of existing homes. Builders have heterogeneous construction costs C, which for simplicity we assume are paid at the time of sale and are learned by builders once construction is completed. We also assume that the price of land, p_c, is paid by the builder at the time of sale.

Let $V^1(x)$ be the value function of a builder sitting on an undeveloped plot of land, let $V^2(x)$ be the value function of a builder in development, and let $V^3(C,x)$ be the value function of a builder who is listing her property for sale. For builders with undeveloped land, there is an additively separable, idiosyncratic cost η to begin development each period. Denote the cdf of η as F_η. The builder's value functions are therefore given by:

$$V^1(x) = \beta E_{\eta,x'|x}\Big[\max\Big\{0,\ V^2(x') - \eta\Big\}\Big] \tag{9}$$

$$V^2(x) = \beta E_{C,x'|x}\Big[(1-\phi)V^2(x) + \phi V^3(C,x')\Big] \tag{10}$$

$$V^3(C,x) = \max_p W^3(C,x,p) \tag{11}$$

$$\begin{aligned} W^3(C,x,p) \;\; = \;\; & -c_c + \beta E_{x'|x}\Big[\kappa(p,h,x)U(p - p_c - C) + \ldots \\ & \ldots + (1-\kappa(p,h,x))\rho V^3(C,x') + \ldots \\ & \ldots + (1-\kappa(p,h,x))(1-\rho)W^3(C,x',p)\Big] \end{aligned} \tag{12}$$

Builders selling completed homes behave similarly to sellers of existing homes. In (12), c_c is the listing and marketing cost for developers.[18] The probability of meeting a willing buyer, $\kappa(p,h,x)$, is the same as in (8). Since developers sell new homes, $h = 1$ in equation (12).

3.5 Equilibrium and Discussion

An equilibrium in the housing market consists of value functions V^o, W^s, V^1, V^2, W^3, and a market-tightness function θ that satisfies equations (2) thru (12). From the value functions and market-tightness, we can derive all the decision rules for agents

[18]Requiring builders to make interest payments on construction costs while the home is for sale in stage 3 would be an additional mechanism that would tend to favor a rate-elasticity of new construction that is larger than the rate-elasticity of prices. We abstract from this for simplicity and because the evidence in Section 2 suggests that the rate-elasticity of buyer demand drives the rate-elasticity of building decisions in the data.

in the economy, at any aggregate state. In the Appendix, we prove the existence of an equilibrium using Brouwer's fixed point theorem.

Even though buyers are ex-ante homogenous and there is only one type of mortgage contract in our model, mortgages and search endogenously generate significant heterogeneity among homeowners and sellers with respect to outstanding loan amount and mortgage rate. Rate heterogeneity arises because there is time-series variation in the market interest rate, and existing homeowners have bought in at different times. Time series variation in the aggregate state also generates loan amount heterogeneity. However, an additional generator of heterogeneity in loan amount is price dispersion—even within a model period where the aggregate state is fixed, loan amount heterogeneity arises because multiple submarkets for a given house type are active in equilibrium.

A special feature of our model is that the equilibrium value functions and market-tightness do not depend on the distribution of agents already present in the economy, nor on the transition dynamics of these distributions. Thus, x depends only on three variables: income, rent, and the market interest rate. This is not a general feature of equilibrium search models, but rather arises out of the indifference condition of the buyers. To develop some intuition for why this is, let us suppose that a positive number of buyers search in submarket (p, h) when the state is x. This implies that (p, h) maximizes (4) in state x. Since $V^b(x) = k$, we can rewrite (4) to give:

$$\theta(p,h,x) = q_b^{-1}\left(\frac{(1-\beta)k - u(y - rent) + c_b}{\beta E_{x',\epsilon|x,h}\left[\max\left\{0,\ V^o(p,r,x') - k + \epsilon\right\}\right]}\right) \tag{13}$$

This shows that, for any submarket in which buyers are willing to search, the equilibrium market-tightness is a function only of p, h, x, and not of the distribution of agents, as long as the owner value function only depends on p and x. In the Appendix, we prove that an equilibrium where V^o depends only on p and x exists. Intuitively, the market-tightness will vary over submarkets in such a way as to make buyers indifferent between searching at a higher list price with higher match probability, or a lower list price with lower match probability. Multiple submarkets can be active at any one time, though the buyers will be indifferent between them. Directed search is important for this feature to hold: if search were undirected, buyers would have to integrate over the distribution of seller types in order to make an entry decision.

Intuitively, the buyers' indifference condition pins down an equilibrium tradeoff curve between list price and sale probability. Heterogeneous sellers then sort along this curve at their optimal list prices. Figure 1 illustrates a hypothetical tradeoff curve between list price and sale hazard, and the optimal choice for a single seller. An interest rate increase reduces buyer valuations at each list price, thus pushing the tradeoff curve downwards, causing the same seller to choose a new combination of optimal list price/sale hazard. Figure 1 shows that the new optimal choice of the seller generally results in both a reduction in list price and sale probability.[19] This prediction is consistent with the empirical evidence documented above and shown in the literature more generally that house prices and probability of sale comove strongly.

The structure of our model is closely related to the directed search models of the labor market in Menzio and Shi (2010, 2011). Menzio and Shi were the first to study the implications of indifference conditions in models of directed search. In their model, firms face a free entry condition on job postings, which regulates the market-tightness to depend only on the aggregate state, and not on the distribution of worker-firm matches within the economy. This is the same role that the free entry condition of buyers plays in our model.

[19] An exception is the special case where the slope of the tradeoff curve is invariant to changes in interest rates. However, if the slope of the indifference curve changes, then we should observe a change in price and sale probability even if the slope of the tradeoff curve does not.

A consequence of dependence only on p, h, x is that the model becomes much more tractable to solve, while still allowing for rich price and volume dynamics. Moreover, the assumption of directed search is appropriate for housing markets: home buyers certainly do not choose which listings to visit at random. The assumption of free entry and exit of buyers is also reasonable for local housing markets, and we note that k could depend on the aggregate state variable, thus allowing for a time-varying indifference condition that could represent changes to the attractiveness of the local market (i.e. through higher wages or amenities).

4 Estimation

4.1 Parametric Assumptions

For estimation, we make the following parametric assumptions. We assume that the matching function is Cobb-Douglass with exponent γ so that the probability that a buyer meets a seller is:

$$q_b(\theta) = \min(1, A\theta^{-\gamma}) \tag{14}$$

and the probability that a seller meets a buyer is:

$$q_s(\theta) = \min(1, A\theta^{1-\gamma}) \tag{15}$$

where $A > 0$ is a scaling parameter. We also assume that per period utility, u, is CRRA with risk aversion parameter, σ:

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma} \tag{16}$$

We write the utility function over terminal wealth as:

$$U(w) = Bu(bw) \tag{17}$$

where B and b are parameters to be estimated. This is a fairly flexible way to model terminal utility over wealth, as it nests the situation in which final net wealth is amortized over either a finite or infinite number of future periods. It also flexibly accommodates other potential reasons for sellers having concave utility over net equity, such as psychological loss aversion or downpayment requirements on future home purchases. To accommodate negative values of wealth, which can occur when the seller sells for a price below the mortgage balance, we allow the utility to become linear for $bw < 1$.

We assume that the match quality draws, ϵ_h, for $h = 1, 2$ the idiosyncratic development cost, η, and construction costs, C, are all iid and normally distributed with means μ_h, μ_η, μ_C and standard deviations σ_h, σ_η, σ_C.

We assume that the buyer's outside option of living somewhere else, k, is equal to the expected value of renting forever:

$$k(x) = u(y - rent) + \beta E_{x'|x} k(x') \tag{18}$$

This amounts to a normalization because the effect of k on buyer decisions is not separately identifiable from the effect of their search cost, c_b. For estimation, we impose $c_b > 0$ so that the utility associated with searching forever as a buyer is less than k. Similarly, we impose lower bounds on c_c, c_s to ensure that sellers do not wish to stay on the market forever as a seller.

We assume that a model period is one month. The aggregate state x includes the market interest rate, rent, and income. We assume that agents expect that these three variables evolve according to a random walk with normally distributed errors. The parameters of this process are calibrated using a procedure and data that we discuss in the Appendix.

4.2 Data and Moments Used for Estimation

We estimate most of the parameters of the model by simulated method of moments, while some of the parameters are set outside of estimation, as described in Table 3. The following discussion describes the data and moments used for estimation while the Appendix provides a discussion of how we choose the parameters that are set outside of estimation.

Our main dataset is from Corelogic on homes listed for sale in the San Diego MSA. For homes listed for sale, the dataset provides information on list prices, initial listing date, and delisting date, among other variables. We observe whether the delisting occurs because of a sale, or whether the delisting occurs because the seller chooses to reverse her decision to market the home for sale. We also obtain a dataset recording all sales transactions in San Diego dating back to 1988, provided by Dataquick. We use the sales dataset to merge on the initial purchase price for each home listing (assuming the home was purchased subsequent to 1988) based on a unique property id. We also use the sales dataset to identify listings that are new construction. The sales dataset has a flag for new construction sales, and so if a listing can be linked to a recent new construction sale, we classify the listing as new construction.

We fit the model to a single cross section of data from the San Diego housing market in 2001. We chose 2001 because our listings data begin in 2000, and we did not want to choose a year during the housing boom or bust when market conditions, as well as other factors that are beyond the scope of our model, were changing rapidly.

Market conditions in 2001 were fairly stable. We include three sets of moments from our data sample. The Appendix describes the weighting matrix that we use to weight the moments in estimation.

The first set of moments are the empirical counterparts to $\kappa(p, h, x)$, which is the sale hazard for each list price, house type (new or old), and aggregate state. In the model, homes are of constant quality, conditional on type. In the data, there are lots of differences in home quality conditional on new or old, so in order to construct empirical moments for $\kappa(p, h, x)$ that reflect *constant quality* variation in the data, we need a strategy for partialling both observed and unobserved house quality.[20]

To do this, we approximate the sale hazard function as a third order polynomial of list price p, where the coefficients are flexible functions of h and x, but also of observed house characteristics z and unobserved quality ϵ:

$$\kappa(p, h, x, z, \epsilon) = g_0(h, x, z) + g_1(h, x, z)p + g_2(h, x, z)p^2 + g_3(h, x, z)p^3 + \epsilon \qquad (19)$$

To obtain constant-quality empirical moments for $\kappa(p, h, x)$, we first estimate (19) using the full sample of listings (including homes that are eventually withdrawn without sale) that are on the market between 2001-2003 in San Diego. Then, we plug in a specific value for x (average mortgage rate, rent, and income in 2001), z (the sample average) and $\epsilon = 0$ to obtain predicted values for $\kappa(p, h, x)$. In practice, we estimate (19) using a linear probability model where the dependent variable is an indicator for whether the listing observation results in a sale in a particular month.

The identification challenge here is that unobserved quality ϵ is likely correlated

[20] In order to be consistent with our model, we assume that all variation in sale hazard conditional on list price, aggregate state, and observed quality is driven by unobserved housing quality. Variation in price conditional on unobserved quality is due to differences in the characteristics of the seller. A valid instrument will therefore be correlated with characteristics of the seller but uncorrelated with unobserved house quality.

with list price p. This would bias the slope of the sale hazard with respect to the list price upwards. To see the intuition for the bias, consider Figure 2(a), which shows the average sale hazard by list price for homes of similar observable quality in our San Diego data. The sale hazard slopes down, so there is a tradeoff between price and sale probability. But in the figure, homes with high list prices are likely a combination of homes that are priced high, conditional on their home quality, and homes that are of high unobserved quality, and are not necessarily priced high. The former type of home would be associated with a low sale hazard, as the high price conditional on quality will attract fewer buyers. The latter would not be since the house is priced high simply because it is of higher quality. This biases the slope of the sale hazard with respect to the list price toward zero.

To address this endogeneity, we follow the identification strategy of Guren (2018) and instrument for p using MSA-level house price appreciation between the month of initial purchase and the current period. This is a valid instrument as long as the timing between purchase and resale is exogenous to unobserved house quality, because it affects the seller's choice of list price while being uncorrelated with unobserved quality. Since we include listing year dummies, the identifying variation thus comes from homeowners who are listing in the same period, but who bought in at different market conditions. Guren (2018) provides a more general defense of the validity of this instrument for estimating the relationship between list price and sale hazard. We provide further details on the estimation of (19) in the Appendix. Figure 2(b) shows our IV estimates and standard errors. The estimated sale hazard is downward sloping, steeper than the slope implied by Figure 2(a), and is somewhat concave. These three findings are qualitatively consistent with the estimates in Guren (2018). We estimate that sellers are less willing to tradeoff a lower sale hazard for a higher price than Guren (2018), which may partly reflect differences in our sample years and metro areas.

The second set of moments is the empirical counterpart to the list price policy function, $p^s(l, r, x)$, for existing homes. This is the seller's optimal list price conditional on the seller's loan amount and outstanding interest rate. In accordance with our model, we use the previous purchase price of the home as the loan amount and the average mortgage rate in the month of initial home purchase as the outstanding interest rate, r.[21] In order to isolate constant-quality variation in the data, we approximate the list price policy function with a third degree polynomial in l, as above:

$$p^s(l, r, x, z, \epsilon) = \psi_0(r, x, z) + \psi_1(r, x, z)l + \psi_2(r, x, z)l^2 + \psi_3(r, x, z)l^3 + \epsilon \tag{20}$$

and evaluate (20) at the sample average of z, $\epsilon = 0$, the sample average of r, and 2001 market conditions. As in the case of the sale hazard function, a potential concern for the estimation of (20) is the correlation between ϵ and l. To see the intuition for the bias, consider Figure 3(a), which shows the average list price choice by purchase price for homes of similar observable quality in our San Diego data. The list price is increasing in the purchase price. But part of this positive slope may reflect the fact that homes that were purchased at higher (lower) prices are of higher (lower) unobserved quality, and thus will naturally have higher (or lower) list prices. Unobserved quality will tend to bias the slope of the empirical list price policy function upwards.

We therefore instrument for l using house price appreciation between the month

[21] The use of purchase price as the measure of outstanding loan amount should bias us against finding a relationship between the list price choice and loan amount in the data, and so it should lower our estimate of seller risk aversion and thus weaken our main results. On the other hand, if sellers evaluate sales prices relative to their purchase price because of anchoring as some evidence suggests (Genesove and Mayer (2001); Bracke and Tenreyro (2016)), then the purchase price is actually the appropriate variable to use.

of initial purchase and two purchases ago. We again refer to the Appendix for further details regarding the estimation of (20). Figure 3(b) shows our IV estimates and standard errors. Our estimates show that the optimal list price is generally increasing in the initial purchase price, but the rate at which it increases with purchase price is less than the rate implied by the raw data shown in Figure 3(a).

We are not able to compute the empirical counterpart to the list price policy function for new constructions, $p^c(C, x)$, because we do not observe the construction costs of builders, C. Instead, we use the data to compute the mean and variance of new construction list prices, adjusted for observable house quality differences, and use those as estimation moments. The Appendix describes the details. The model counterparts we use to these empirical moments are the mean and variance of $p^c(C, x)$, integrated across the distribution of C.

4.3 Identification

The model is highly nonlinear and so almost all parameters affect all outcomes. Nonetheless, here we we provide a discussion of the main features of the data that identify each of our parameters.

The mean and variance of the normal match quality distribution are mainly identified by the mean and range of list prices for which the empirical sale hazards are positive. For example, when there is more variance in match quality draws, sellers will realize positive sale hazards at a larger range of list prices. The mean of the match quality draw for existing homes relative to that for new construction is identified by the difference in the sale hazard for existing homes relative to the sale hazard for new construction homes. In practice, we found that it was difficult to identify both separate means and separate variances for new construction relative to existing homes, so we impose $\sigma_1 = \sigma_2$.

The exponent on the match function, γ, is mainly identified through the slope of the sale hazard function. For example, when γ is low so that the elasticity of the seller's matching probability with respect to the market tightness is higher, then the sale hazard function will be more sensitive to list price, as the market tightness varies by list price. The buyer's search cost, c_b, mainly affects the level of the sale hazard. For example, when buyer search cost is low, a larger number of buyers will find it optimal to enter the housing market, which increases the sale hazard for each level of list price. Since the scale parameter on the matching function, A, has a very similar effect as c_b, we set $A = 0.5$.

The parameters describing the terminal wealth utility function, b,B, σ, are identified mainly by the empirical list price policy function with respect to the outstanding loan amount for existing homes. For example, without risk aversion ($\sigma \to 0$), the list price choice would not depend on loan amount. So the estimate of σ is very sensitive to the slope of the list price policy function with respect to the loan amount. B is partly identified by the level of the list price policy function. A low B would imply that sellers do not place much weight on terminal wealth, and would incentivize a low list price choice. Like B, b affects the relative importance of utility over terminal wealth, but unlike B it also affects the level of wealth for which the utility function switches from linear to concave in wealth. Simulations show that b is separately identified from B through more subtle differences in the moments. For example, changes in B have a larger effect on the sale hazards for lower priced submarkets than b, while the opposite is true for higher priced submarkets. Seller search cost, c_s, is partly identified through its effect on the minimum list price level that is associated with an active submarket for existing homes. For example, if search costs are low, then submarkets with low list prices would not be active, because sellers would never choose to list at such prices as they would be patient enough to hold out for a higher price.

There are three parameters that affect the builders optimal behavior. The mean and variance of constructions costs are mainly identified by the mean and variance of list price choices for builders. Like c_s, the search cost for builders, c_c, is partly identified through its effect on the minimum list price level that is associated with an active submarket, but for new homes. In practice, we find that c_c is also important for helping us to fit the average builder list price observed in the data.

5 Parameter Estimates, Model Fit, and Discussion

Figure 4 shows the model fit for the sale hazards. For the model implied sale hazards, the sale hazards associated with submarkets that are not active—either because no seller would want to list in that submarket or because no buyer would want to visit that submarket—are set to zero. Consistent with the data, we generate a downward sloping and concave sale hazard, so there is a tradeoff between price and sale probability. Sellers will differ in their optimal location on this tradeoff curve due to heterogeneity in outstanding mortgage rate and outstanding loan amount. To see why, note that outstanding mortgage rate and outstanding loan amount help determine the sellers' effective costs of staying on the market through $u(y - rl) - c_s$. Higher costs of staying on the market will tend to cause sellers to move to the left on the tradeoff curve to a point that is associated withlower list prices and faster sale hazards. Outstanding loan amount also affects the sellers marginal utility over price because terminal utility is concave in $p - l$. A higher marginal utility of price favors higher prices and slower sale hazards, all else equal.

Figure 5 shows the model fit for the list price policy function for existing homes. As in the data, the model predicts that the optimal list price is generally increasing in the loan amount, but the slope is less than one. The estimated model generates an increasing relationship between list price and loan amount because the terminal wealth utility function is concave. If sellers were risk-neutral, then the list price would not be increasing in the loan amount, conditional on house quality. List price does not increase with loan amount at a 1-for-1 rate because the probability of sale is decreasing in list price. Beyond a certain level of loan amount, however, the optimal list price begins to flatten out, as in the data (see Figure 3). The reason is simply that for high loan amounts, the optimal list price implied by risk aversion is associated with a non-feasible submarket–i.e. it has a zero sale hazard.

Table 4 shows that we also match the other moments that we use for estimation quite well. Table 3 presents our parameter estimates and standard errors. Following the approach suggested by Lee and Wolpin (2010), standard errors are computed as $(G'WG)^{-1}$ where G is the matrix of derivatives of the moments with respect to the parameters and W is a diagonal matrix where the m^{th} element of the diagonal is equal to the inverse of the squared error associated with the m^{th} moment at the estimated parameter vector. Our estimate of the risk aversion parameter, σ, at around 2 is in line with typical estimates of this parameter in CRRA utility functions. Our estimate of γ implies that the contact elasticity with respect to the market tightness is larger for buyers than it is for sellers.[22] Our estimate of seller search costs, c_s, implies that the cost of staying on the market for an additional month for a typical seller is \$2040.[23]

[22]Our estimate of γ is lower than the estimate in Genesove and Han (2012), who estimate $\gamma = 0.16$ using a completely different approach. Genesove and Han (2012) infer seller contact hazards and the buyer-seller ratio (i.e. market tightness) using the structure of a simple search model and annual survey data on average buyer time-on-market, seller time-on-market, and number of homes visited by buyers. The contact elasticity is then estimated by regressing the contact hazard and buyer-seller ratio on changes in average MSA income, which is treated as a demand shifter.

[23]We compute the payment that leaves the seller indifferent between receiving the price p today and staying on the market and receiving p next period. \$2040 is the payment for a seller with outstanding loan amount of \$200k facing $p = \$300k$.

6 Model Simulations

In this section, we simulate the housing market response to an exogenous full percentage point increase in the mortgage rate. The shock is unexpected because a full percentage point increase in the mortgage rate over one period is a very low probability event according to our calibration of agents' expectations. Because our model is easily solvable outside of steady state, we do not need to conduct our simulations in steady state. We use the aggregate state and distributions of agents from the 2001 San Diego market as the initial conditions. We assume that the aggregate state, x, remains constant for 24 periods (2 years). In period 25, we apply the permanent rate shock. All parameter values are assumed to be invariant to the interest rate shock but we re-solve the model equilibrium after the shock so that the equilibrium sale hazards and list price policy functions adjust to the shock.

Figure 6 plots the response of average log sale prices to the interest rate increase for existing homes. The shock reduces transaction prices by 5 percent over three months. This elasticity is in line with the estimates in the literature discussed in Section 1, which is reassuring since the interest rate elasticity of house prices is not a moment that we target in estimation. From this result, we can conclude that a modest semi-elasticity of house prices with respect to interest rates can be generated simply from a model with search frictions.

The average sale price figure also shows that before and after the interest rate shock, average log transacted house prices are growing at a persistent rate of about 2 percent per year. Interestingly, this growth does not arise from any persistent fundamental process in the model. Rather, the growth arises due to a change in the composition of sellers that are selling in each period as the model moves toward steady state, which happens when all sellers have initial loan amounts that lead them to choose a list price that equals their loan amount. In a companion paper, we explore in more detail the quantitative importance of search frictions and an upward sloping list price policy function for generating house price momentum.

Figure 6 also shows that the price response significantly understates the response in actual housing valuation. We define housing valuation as the price that buyers would be willing to pay (i.e. makes their expected utility equal to k) if the match rate between buyers and sellers in the economy was equal to 1. We still allow buyers to decline to purchase if they receive a low ϵ draw. The details of how we compute this "frictionless price" are provided in the Appendix. Figure 6 shows that housing valuation declines by 11.5 percent in response to the 100 basis point rate shock. This effect is over two times larger than the response in expected sale price.

Figure 6 plots the average transaction rate for existing homes. The transaction rate declines by about 10 percentage points in response to the 100 basis point rate shock. The transaction rate initially overshoots because when the rate shock is realized and buyer demand falls, given the timing in our model, sellers have not adjusted their list prices downward at all, causing the transaction rate to spike down. Once sellers have the opportunity to adjust their price, the transaction rate moves back up somewhat, but is still much lower than the average transaction rate in the lower interest rate regime.

The bottom panel of Figure 6 shows the response of new construction prices, valuations, and permits. As was the case for existing homes, the average price response for new construction homes is lower than the valuation response. The price elasticity is somewhat higher for new constructions than existing homes, a result that we discuss more below. Finally, the figure shows that permits decline by about 15 percent in response to the rate hike. To understand why permits are more rate elastic than prices, first note that prices only reflect part of the elasticity of buyer demand to rate changes. The change in buyer demand gets reflected in sale hazards too. However, the building decision is fully sensitive to the elasticity of buyer demand to rate changes because both prices and sale hazards influence the building decision, as builders face search frictions when selling their newly built homes.

Table 5 summarizes the key model implied rate elasticities reported in this section.

In the Appendix, we show robustness of our main results to a couple of model assumptions. First, we consider the case of no sticky list prices ($\rho = 1$). The results are very similar. The main difference relative to the baseline is that the response to the rate change happens a bit more quickly. Second, we show results for the case of a rate decrease, instead of a rate increase. The results are fairly symmetric. Finally, we consider the robustness of the main result to the assumption of 100% LTV, interest-only mortgages. Using two different approaches to parsimoniously incorporate 80% LTV loans into the model, we find that the basic conclusion that sales prices are less responsive than valuations continues to hold regardless of which assumption is made.

6.1 Discussion

To illustrate the mechanisms behind our main results, the top panel of Figure 8 plots the tradeoff between sale hazard and capital gain for a seller of an existing home with a loan amount of $200k prior to the rate shock when $\rho = 1$.[24] The solid blue line is simply the model generated sale hazard, which matches the data very well as shown in Figure 4. The dotted blue line shows the seller's indifference curve between price and sale hazard implied by our model and parameter estimates. It is downward sloping and convex, reflecting the fact that sellers like price and quicker sales, and

[24] We choose to plot the seller indifference curves for $\rho = 1$ because when list prices are sticky, the indifference curve bends backward due to sellers not wanting to get stuck at a sub-optimal list price.

that seller utility over price is concave.[25] The point of tangency between the solid and dotted lines reflects the seller's optimal choice.

Now consider the solid red line, which reflects the tradeoff following the rate increase according to our model. The red line shifts in because buyer demand is lower following the rate increase. The shift in is larger for high price levels because the effect of rates on buyer demand is stronger for higher priced homes, as the interest rate effectively multiplies the price in the owner's utility function. The optimal point on the tradeoff curve shifts to the southwest—this seller chooses both a smaller capital gain *and* a lower expected sale hazard following the rate shock. So we can see that both prices and sale hazards adjust in response to the interest rate change.

These tradeoff curves focus on the incentives for a particular type of seller. Figure 7 plots the list price policy functions for existing homes for sellers with different purchase prices. For most of the purchase price distribution, the optimal list price is not particularly sensitive to the interest rate level. The main effect of increasing interest rates on the list price policy function is that owners who purchased at very high prices can no longer list at a very high price and still expect to find a buyer with positively probability. They therefore have to reduce their list price significantly. Most owners have lower purchase prices, as is shown by the grey distribution in the figure, and do not change their list prices much in response to the interest rate hike, which explains why on average, the price response is modest.[26]

The concavity of $U(w)$ appears to be important for the quantitative magnitude of this result. The bottom panel of Figure 8 shows that at the optimal list price , the

[25] The seller indifference curves are rather sharply L-shaped because the sellers face a dynamic problem. Marginal tradeoffs around the optimal price and sale hazard are generally not attractive because one could wait a period to try to get the optimal price and sale hazard.

[26] This is partly a function of the initial conditions in our simulation. However, in general, it is reasonable to think in most markets that most sellers will have loan amounts below prevailing prices due to inflation and amortization. Even more so in supply inelastic areas where income growth would also contribute to price growth.

terminal wealth utility function is locally very concave. As a result, when interest rates increase, the marginal disutility of dropping price increases relatively quickly, which causes sellers to adjust more on the sale hazard margin. At the same time, the marginal utility of raising price decreases relatively quickly, and so sellers will not raise their price a lot in response to an interest rate decrease. Indeed, we have found that the list price policy function, and thus average house prices, are more sensitive to interest rates when the risk aversion parameter, σ, is lower.

Finally, we note that Figure 7 also helps to illustrate why average prices of new construction sellers are more rate sensitive than average prices of existing homes. Since our construction cost paramaters imply that the average construction cost plus land cost is higher than the average purchase price, the density of new construction sellers is higher at the region of the list price policy function that is more sensitive to interest rates.

7 Conclusion

We estimate a dynamic equilibrium search model of the housing market with mortgage contracts to study the effects of interest rates on housing market dynamics. Our model structure and parameters are informed by detailed micro data on home listings, and our model can be solved both in and out of steady state despite the rich heterogeneity that arises in the equilibrium of our model. Our main finding is that due to search frictions, the rate elasticity of house prices is modest but it understates the rate elasticity of housing valuations by a factor of two. Our second main finding is that search frictions can explain why home sales and construction are much more rate elastic than house prices.

Taken together, our results suggest that monetary policy—to the extent that it can influence mortgage rates—has stronger effects on housing values than is commonly assumed. The effect on housing values clears through both prices and liquidity of homes in our model. If financial stability depends not just on average prices of transacted homes but on the joint distribution of prices and probability of sale, then an implication of our model for policymakers is that the tradeoff when lowering interest rates between short-run gains in real economic activity and risks to financial stability is stronger than some basic empirical housing relationships would seem to suggest.[27]

References

Adelino, Manuel, Antoinette Schoar, and Felipe Severino, "Credit supply and house prices: evidence from mortgage market segmentation," Technical Report, National Bureau of Economic Research 2012.

Albrecht, James, Axel Anderson, Eric Smith, and Susan Vroman, "Opportunistic Matching in the Housing Market," *International Economic Review*, 2007, *48* (2), 641–664.

Anenberg, Elliot, "Information Frictions and Housing Market Dynamics," *International Economic Review*, 2016, *57* (4), 1449–1479.

Arefeva, Alina, "How Auctions Amplify House-Price Fluctuations," *working paper*, 2017.

Bajari, Patrick and C. Lanier Benkard, "Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach," *Journal of Political Economy*, 2005, *113* (6).

[27]For example, Shleifer and Vishny (2011) argue that liquidity problems were at the heart of the financial crisis. In the housing market more specifically, Hedlund (2016) shows quantitatively that liquidity risk accounts for a large portion of the foreclosure rate.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan, "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, 2007, *115* (4), 588–638.

_ , **Robert McMillan, Alvin Murphy, and Christopher Timmins**, "A Dynamic Model of Demand for Houses and Neighborhoods," *Econometrica*, 2016, *84* (3), 893–942.

Bernanke, Ben, "Monetary Policy and the Housing Bubble," 2010.

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841–890.

Bhutta, Neil and Benjamin J. Keys, "Interest Rates and Equity Extraction during the Housing Boom," *American Economic Review*, July 2016, *106* (7), 1742–74.

_ **and Dan Ringo**, "The Effect of Interest Rates on Home Buying: Evidence from a Discontinuity in Mortgage Insurance Premiums," *working paper*, 2017.

Bishop, Kelly C and Alvin D Murphy, "Estimating the willingness to pay to avoid violent crime: A dynamic approach," *The American Economic Review: Papers and Proceedings*, 2011, *101* (3), 625–629.

Bracke, Philippe and Silvana Tenreyro, "History dependence in the housing market," 2016.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo, "Understanding booms and busts in housing markets," *Journal of Political Economy*, 2016, *124* (4), 1088–1147.

Caetano, Gregorio, "Neighborhood Sorting and the Valuation of Public School Quality," Working Paper, University of Rochester September 2012.

Caplin, Andrew and John Leahy, "Trading Frictions and House Price Dynamics," *Journal of Money, Credit and Banking*, 2011, *43*, 283–303.

Carrillo, Paul E., "An Empirical Stationary Equilibrium Search Model of the Housing Market," *International Economic Review*, 2012, *53* (1), 203–234.

Davis, Morris A, Stephen D Oliner, Tobias Peter, and Edward Pinto, "The Impact of Federal Housing Policy on Housing Demand and Homeownership: Evidence from a Quasi-Experiment," 2018.

Diaz, Antonia and Belen Jerez, "House prices, sales, and time on the market : a search-theoretic framework," *International Economic Review*, 2013, *54* (3), 837–872.

DiMaggio, Marco, Amir Kermani, Ben Keys, Tomask Piskorski, Amit Seru, and Vincent Yao, "Monetary Policy Pass-Through: Household Consumption and Voluntary Deleveraging," *American Economic Review*, forthcoming.

Favara, Giovanni and Jean Imbs, "Credit Supply and the Price of Housing," *American Economic Review*, 2015, *105* (3), 958–92.

Fuster, Andreas and Basit Zafar, "The Sensitivity of Housing Demand to Financing Conditions: Evidence from a Survey," Working Paper, Federal Reserve Bank of New York 2015.

Genesove, David and Christopher Mayer, "Loss Aversion and Seller Behavior: Evidence from the Housing Market," *The Quarterly Journal of Economics*, 2001, *116* (4), 1233–1260.

_ **and Lu Han**, "Search and Matching in the Housing Market," *Journal of Urban Economics*, 2012.

Glaeser, Edward L, Joshua D Gottlieb, and Joseph Gyourko, "Can cheap credit explain the housing boom?," in "Housing and the Financial Crisis," University of Chicago Press, 2012, pp. 301–359.

Guren, Adam, "House Price Momentum and Strategic Complementarity," *Journal of Political Economy*, 2018, *126* (3), 1172–1218.

_ **and Tim McQuade**, *How do foreclosures exacerbate housing downturns?*, Joint Center for Housing Studies, Harvard University, 2013.

Head, Allen, Huw Lloyd-Ellis, and Hongfei Sun, "Search, Liquidity, and the Dynamics of House Prices and Construction," *The American Economic Review*, 2014, *104* (4), 1172–1210.

Hedlund, Aaron, "Illiquidity and its discontents: Trading delays and foreclosures in the housing market," *Journal of Monetary Economics*, 2016, *83*, 1–13.

Himmelberg, Charles, Christopher Mayer, and Todd Sinai, "Assessing high house prices: Bubbles, fundamentals and misperceptions," *The Journal of Economic Perspectives*, 2005, *19* (4), 67–92.

Horowitz, Joel L., "The role of the list price in housing markets: Theory and an econometric model," *Journal of Applied Econometrics*, 1992, *7* (2), 115–129.

Krainer, John, "A Theory of Liquidity in Residential Real Estate Markets," *Journal of Urban Economics*, 2001, *49* (1), 32 – 53.

Kung, Edward and Ralph Mastromonaco, "Credit Constraints and Residential Sorting," *mimeo UCLA*, 2015.

Kuttner, Kenneth N, "Low interest rates and housing bubbles: still no smoking gun," *The Role of Central Banks in Financial Stability: How Has It Changed*, 2012.

Lee, Donghoon and Kenneth I Wolpin, "Accounting for wage and employment changes in the US from 1968–2000: A dynamic model of labor market equilibrium," *Journal of Econometrics*, 2010, *156* (1), 68–85.

Maggio, Marco Di and Amir Kermani, "Credit Induced Boom and Bust," Research Report 2015.

Menzio, Guido and Shouyong Shi, "Block Recursive Equilibria for Stochastic Models of Search on the Job," *Journal of Economic Theory*, 2010, *145* (4), 1453–1494.

_ and _ , "Efficient Search on the Job and the Business Cycle," *Journal of Political Economy*, 2011, *119* (3), 468–510.

Merlo, Antonio and Francois Ortalo-Magne, "Bargaining over residential real estate: evidence from England," *Journal of Urban Economics*, September 2004, *56* (2), 192–216.

_ , _ , and John Rust, "The Home Selling Problem: Theory and Evidence," *International Economic Review*, 2015, *56* (2), 457–484.

Moen, Espen R, Plamen Nenov, and Florian Sniekers, "Buying first or selling first in housing markets," 2015.

Murphy, Alvin, "A Dynamic Model of Housing Supply," *working paper*, 2017.

Negro, Marco Del and Christopher Otrok, "99 Luftballons: Monetary policy and the house price boom across US states," *Journal of Monetary Economics*, 2007, *54* (7), 1962–1985.

Ngai, L. Rachel and Silvana Tenreyro, "Hot and Cold Seasons in the Housing Market," *American Economic Review*, 2014, *104* (12), 3991–4026.

Ngai, Rachel and Kevin Sheedy, "The Decision to Move House and Aggregate Housing-Market Dynamics," Working Paper, LSE 2016.

Novy-Marx, Robert, "Hot and Cold Markets," *Real Estate Economics*, 2009, *37* (1), 1–22.

Ouazad, Amine and Romain Rancière, "Credit Standards and Segregation," 2013. Working Paper.

Paciorek, Andrew, "Supply constraints and housing market dynamics," *Journal of Urban Economics*, 2013, *77*, 11–26.

Piazzesi, Monika and Martin Schneider, "Momentum Traders in the Housing Market: Survey Evidence and a Search Model," *American Economic Review Papers and Proceedings*, 2009, *99* (2), 406–411.

Poterba, James M, "Tax subsidies to owner-occupied housing: an asset-market approach," *The Quarterly Journal of Economics*, 1984, *99* (4), 729–752.

Rosen, Sherwin, "Hedonic Prices and Implicit Markets: Product Differentiation in Perfect Competition," *Journal of Political Economy*, 1974, *82* (1).

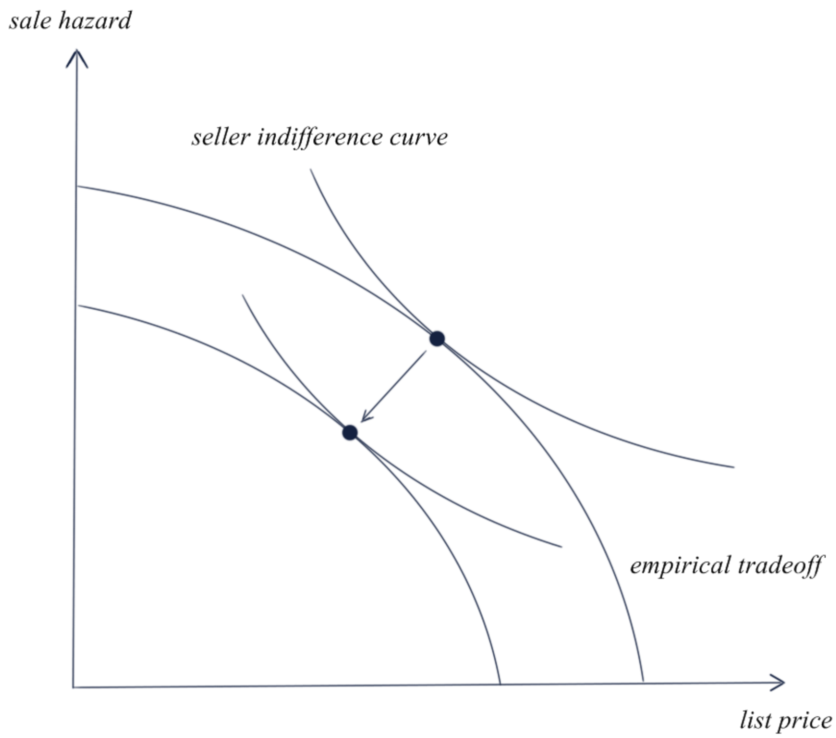
Saiz, Albert, "The geographic determinants of housing supply," *The Quarterly Journal of Economics*, 2010, *125* (3), 1253–1296.

Shleifer, Andrei and Robert Vishny, "Fire sales in finance and macroeconomics," *The Journal of Economic Perspectives*, 2011, *25* (1), 29–48.

Wheaton, William C., “Vacancy, Search, and Prices in a Housing Market Matching Model,” *Journal of Political Economy*, 1990, *98* (6), pp. 1270–1292.

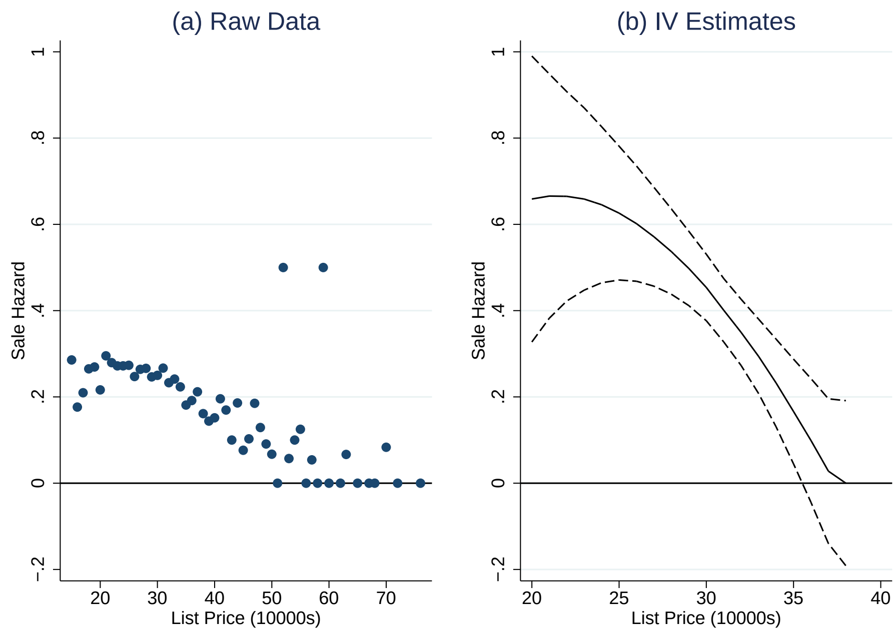
Yellen, Janet, “Monetary Policy and Financial Stability,” 2014.

Figure 1: Intuition for Effect of Interest Rate Change on Price and Sale Hazard



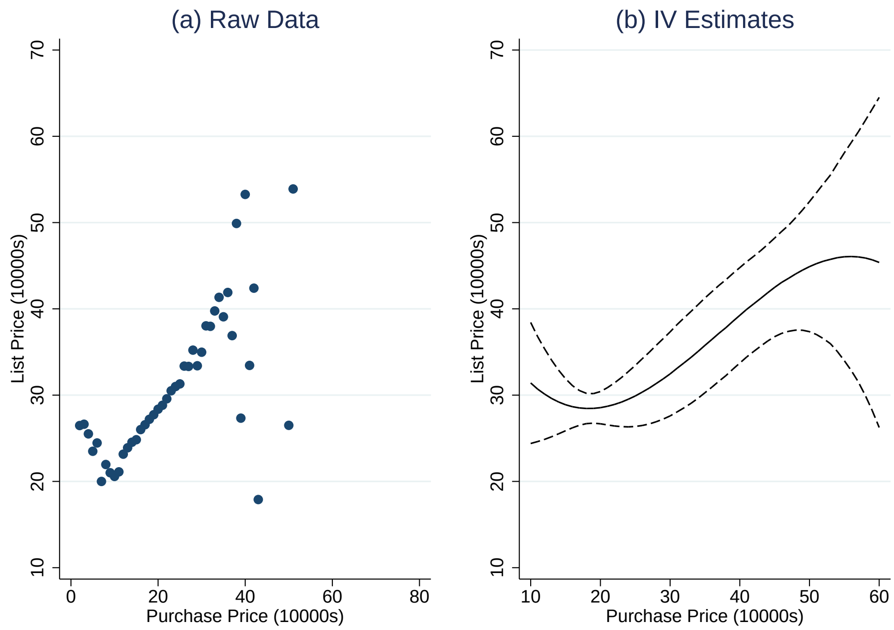
The right-most curves illustrate a hypothetical tradeoff curve between list price and sale hazard, and the optimal choice for a single seller given the seller's indifference curve over price and sale hazard. The left-most curves reflect the tradeoff curve and the indifference curve following an interest rate increase. The effect of an interest rate increase is to reduce buyer valuations at each list price, thus pushing the tradeoff curve downwards, causing the same seller to choose a new combination of optimal list price/sale hazard. The figure shows that the new optimal choice of the seller generally results in both a reduction in list price and sale probability.

Figure 2: Empirical Sale Hazards



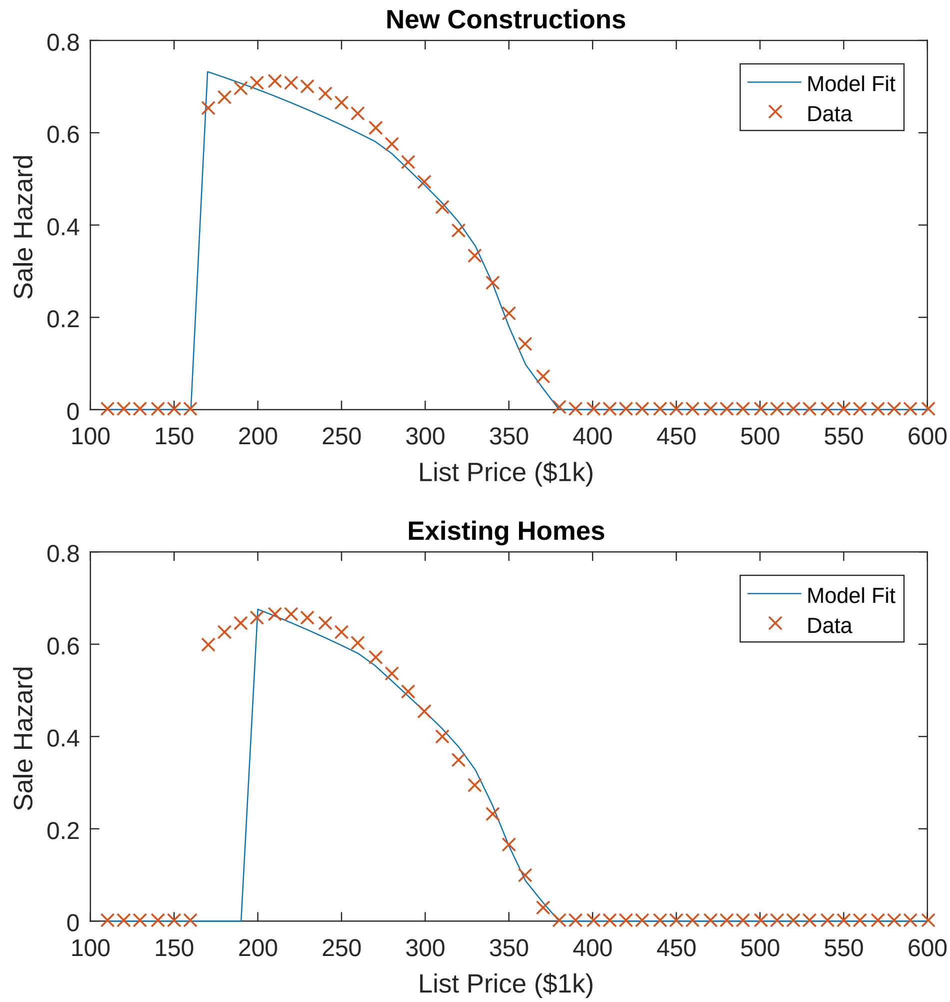
The left figure shows the share of homes on the market at various list price levels in a given month that sell in that month. The data are for homes with observable house quality that is close to the median observable house quality in 2001. For the same type of home, the right figure shows the estimate of sale hazard by list price using the IV regression described in the main text. The dotted lines denote a 95 percent confidence interval.

Figure 3: Empirical List Price Policy Function



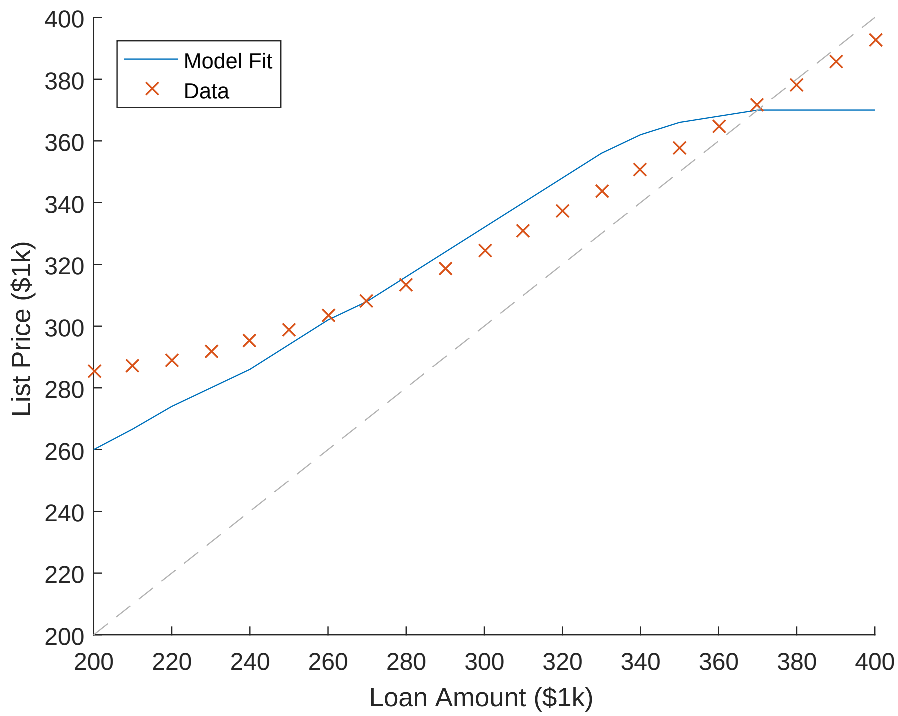
The left figure shows the average list price chosen by sellers with various levels of purchase price–i.e. the price they initially paid for the home. The data are for homes with observable house quality that is close to the median observable house quality in 2001. For the same type of home, the right figure shows the estimate of list price by purchase price using the IV regression described in the main text. The dotted lines denote a 95 percent confidence interval.

Figure 4: Model Fit: Sale Hazards



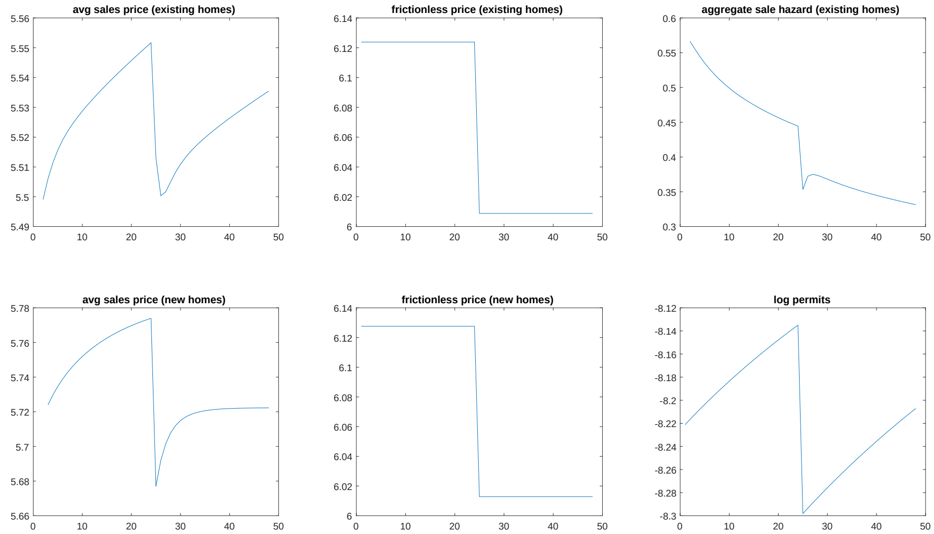
The x's denote the average monthly sale hazard at each list price level that we compute from the data using Equation 19. The solid line denotes the model predictions at our estimated parameters. A sale hazard of zero means that the submarket is not active: either no seller or no buyer would find it optimal to direct their search into that submarket.

Figure 5: Model Fit: List Price Policy Function



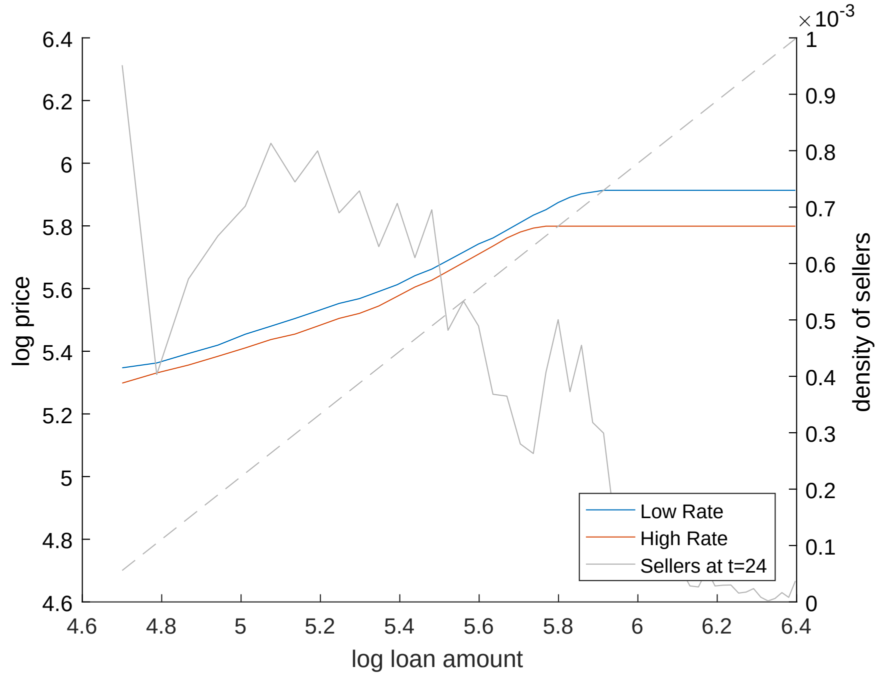
The x's denote the average list price at each loan amount level that we compute from the data using Equation 20. The solid line denotes the model predictions at our estimated parameters. The dotted line is a 45 degree line.

Figure 6: Response to Interest Rate Increase



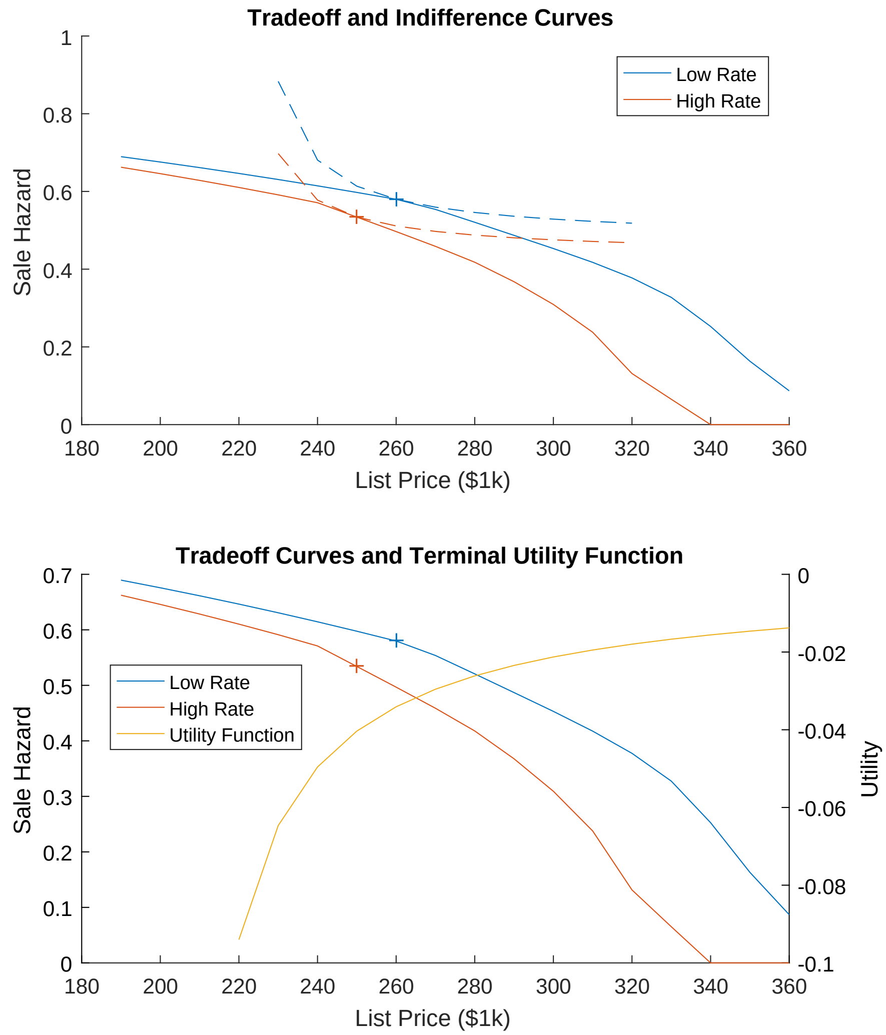
This figure shows simulations from the estimated model. Initial conditions are set to match the 2001 SanDiego market. The aggregate state remains constant until t=24, when there is a 1 percentage point increase in the mortgage rate. The aggregate state remains constant at the higher rate thereafter. The frictionless price is the price that buyers would be willing to pay (i.e. makes their expected utility equal to k) if the match rate between buyers and sellers in the economy was equal to 1. All prices are log prices.

Figure 7: List Price Policy Functions for Existing Homes by Interest Rate



This graph shows the model implied optimal list price choice as a function of loan amount before and after the 1 percentage point interest rate increase in the simulation shown in Figure 6. The grey line shows the distribution of sellers on the market in the period right before the interest rate shock in the simulation.

Figure 8: Tradeoff Between Price and Sale Hazard (Existing Homes)



The top graph shows the model implied optimal list price choice ("+") for a seller of an existing home with a loan amount of $200k before and after the 1 percentage point interest rate increase in the simulation discussed in the text. The seller's indifference curves over price and sale hazard are shown with dotted lines.. The solid lines reflect the tradeoff curve been price and sale hazard that any seller faces in each interest rate regime. The bottom graph shows the same tradeoff curves in the top graph, in addition to the sellers' utility over price, $U(p - \$200k)$.

Table 1: Effects of Interest Rates on Housing Variables

	4-qtr % change in:					
	House Prices	Sales Volume	Months Supply	New Listings	Permits	Permits
4-qtr chg in 30yr FRM	-0.0052**	-0.0835***	0.1079***	0.0843	-0.1176***	-0.1843***
	(0.0026)	(0.0137)	(0.0369)	(0.0457)	(0.0131)	(0.0515)
4-qtr chg in 10yr Treasury						0.0745*
						(0.0385)
4-qtr chg in 2yr Treasury						0.0019
						(0.0421)
Observations	158	106	106	51	175	175

*** p<0.01, ** p<0.05, * p<0.1

Changes are 4-quarter changes. Interest rates are in percentage points. Housing market variables are in logs. House Prices are quality adjusted and come from Corelogic. Sales volume and months supply comes from the National Association of Realtors. Permits come from the Census Bureau. All variables reflection national averages or totals. Newey west standard errors with lag length equal to five quarters in parenthesis.

Table 2: Interaction with Housing Supply Elasticity

	Metro Housing Supply Elasticity		
	Low	Medium	High
Dependent variable: 4-qtr % chg in house prices			
4-qtr chg in 30yr FRM	0.0078***	0.0067***	0.0072***
	(0.0010)	(0.0006)	(0.0006)
Observations	13746	13904	14062
Dependent variable: 4-qtr % chg in sales volume			
4-qtr chg in 30yr FRM	-0.0832***	-0.0483***	0.0013
	(0.0086)	(0.0129)	(0.0145)
Observations	5472	5317	5428
Depndent variable: 4-qtr % chg in permits			
4-qtr chg in 30yr FRM	-0.0905***	-0.0870***	-0.1118***
	(0.0056)	(0.0059)	(0.0080)
Number CBSAs	87	88	89

*** p<0.01, ** p<0.05, * p<0.1

Changes are 4-quarter changes. Interest rates are in percentage points. Housing market variables are in logs. Prices come from Corelogic. Sales volume and months supply comes from the National Association of Realtors. Permits come from the Census Bureau. All variables reflection national averages or totals. CBSA fixed effects are included in each regression. Standard errors are clustered at the CBSA level.

Table 3: Parameter Estimates

Parameter	Description	Value
	Estimated Parameters	
γ	exponent on matching function	0.6809
		(0.0038)
μ_1	mean of match quality draws, new homes	10.4748
		(0.1801)
μ_2	mean of match quality draws, old homes	9.5712
		(0.1267)
σ_1	s.d. of match quality draws	17.9248
		(0.1303)
c_b	buyer search cost	1.0073
		(0.0049)
c_s	seller search cost (owners)	-0.2255
		(0.0372)
σ	coefficient of relative risk aversion	1.9233
		(0.0296)
b	scale parameter on terminal wealth	0.7058
		(0.0041)
B	scale parameter on terminal utility	1.0345
		(0.0042)
μ_C	mean of construction costs	$212k
		(6.7035)
σ_C	s.d. of construction costs	$72k
		(2.3329)
c_c	seller search cost (builders)	0.0408
		(0.0011)
	Parameters Set Outside of Estimation	
μ_η	mean of startup cost shock	70.222
σ_η	s.d. of startup cost shock	52.391
A	scale parameter on matching function	0.50
λ	rate of moving shocks	0.008
ρ	probability of being able to change list price	0.37
β	subjective discount factor (monthly)	0.9957

Table 4: Model Fit - Builder Moments

Moment	Model	Data
Mean of new construction list prices	\$327k	\$327k
S.d. of new construction list prices	\$35k	\$35k

Table 5: Model Implied Elasticities

	Response to 100 bp rate increase
Avg sale price (existing homes)	-5.00%
Frictionless WTP (existing homes)	-11.50%
Permits (new constructions)	-15.40%
Sale hazard (existing homes)	-16.97%

A Existence of equilibrium

Here, we prove the existence of an equilibrium in which the value functions and policy functions depend only on p, r, and x, and do not depend on the distribution of agents in the economy. We consider a computational loop represented by operator T, which acts on V^o and W^s, which are vectors in $\mathbb{R}^{L\times N\times N}$ and $\mathbb{R}^{L\times N\times N\times L}$. The operator T takes an initial value for $V = (V^o, W^s) \in \mathbb{R}^{L^3\times N^4}$, and computes new values using equations (2)-(8). If T has a fixed point, then this proves the existence of an equilibrium. Note that the owner/seller's problem is separable from the builder's problem (i.e. equations (2)-(8) do not depend on the value functions of the builders), so we can first prove the existence of an equilibrium in the owner's problem, then prove the existence of an equilibrium in the builder's problem. The existence proof for an equilibrium in the builder's problem is similar so we omit it.

The proof will proceed in two steps. First, we show the existence of a closed, bounded, and convex set $\mathcal{V} \subset \mathbb{R}^{L^3\times N^4}$ such that if $V \in \mathcal{V}$ then $TV \in \mathcal{V}$. We then show that T is continuous at all $V \in \mathcal{V}$. T and $\mathcal{V}$ therefore satisfy the conditions of Brouwer's Fixed Point Theorem, and there exists a fixed point of T in $\mathcal{V}$.

It is useful first to define a group of operators representing each individual step within the computational loop. The first step is to compute the expected surplus from buyer search, conditional on finding a seller. This is represented by the operator $\mathcal{E} : \mathbb{R}^{L^3\times N^4} \to \mathbb{R}^{L\times N}$ given by:

$$\mathcal{E}V(p, x) = E_{x',\epsilon|x,h=2}\Big[\max\{0,\ V^o(p, r, x') - k + \epsilon\}\Big] \tag{21}$$

The second step is to calculate equilibrium market tightness using the buyer's indifference condition (13). This is represented by the operator $\Theta : \mathbb{R}^{L^3\times N^4} \to \mathbb{R}^{L\times N}$, defined as:

$$\Theta V(p,x) = q_b^{-1}\left(\frac{(1-\beta)k - u(y - rent) + c_b}{\beta \mathcal{E} V(p,x)}\right) \tag{22}$$

Although q_b^{-1} is not formally defined for arguments greater than 1, we allow Θ to return 0 when the term inside q_b^{-1} is greater than 1. This will ensure continuity of Θ and ensure that sellers will not search in those submarkets.

The third step is to calculate the probability that a seller meets a buyer using equation (8). This is represented by the operator $K : \mathbb{R}^{L^3 \times N^4} \to \mathbb{R}^{L \times N}$:

$$KV(p,x) = q_s(\Theta V(p,x)) E_{x',\epsilon|x,h=2}\Big[V^o(p,r,x') - k + \epsilon \geq 0\Big] \tag{23}$$

The fourth step is to compute the new value of T^s, using equation (7). This is represented by the operator $T^s : \mathbb{R}^{L^3 \times N^4} \to \mathbb{R}^{L^2 \times N^2}$, defined as:

$$\begin{aligned} T^s V(l,r,x,p) &= u(y - rl) - c_s + \beta E_{x'|x}\Big[KV(p,x)U(p-l) + \dots \\ &\quad \dots + (1 - KV(p,x))\rho \max_{p'} W^s(l,r,x',p') + \dots \\ &\quad \dots + (1 - KV(p,x))(1-\rho) W^s(l,r,x',p)\Big] \end{aligned} \tag{24}$$

The final step is to compute the new value of V^o, using equation (5). This is represented by the operator $T^o : \mathbb{R}^{L^3 \times N^4} \to \mathbb{R}^{L \times N^2}$, defined as:

$$\begin{aligned} T^o V(l,r,x) &= u(y - rl) + \beta E_{x'|x}\Big[(1-\lambda)V^o(l,r,x') + \dots \\ &\quad \dots + \lambda(1-\alpha)\max_{p} W^s(l,r,x',p) + \lambda\alpha U(p_c - l)\Big] \end{aligned} \tag{25}$$

And the operator $T : \mathbb{R}^{L^3 \times N^4} \to \mathbb{R}^{L^3 \times N^4}$ is simply defined by:

$$TV = (T^o V,\ T^s V) \tag{26}$$

A.1 Proof of boundedness

The first step is to show the existence of a closed, bounded, and convex set $\mathcal{V}$ such that if $V \in \mathcal{V}$ then $TV \in \mathcal{V}$. Let us define:

$$\begin{aligned} \underline{W}^s &= u(y - \bar{r}\bar{p}) - c_s + \beta \min\left\{\frac{u(y-\bar{r}\bar{p}) - c_s}{1-\beta},\ U(\underline{p} - \bar{p})\right\} && (27) \\ \bar{W}^s &= u(y - \underline{r}\underline{p}) - c_s + \beta \max\left\{\frac{u(y-\underline{r}\underline{p}) - c_s}{1-\beta},\ U(\bar{p} - \underline{p})\right\} && (28) \end{aligned}$$

and

$$\begin{aligned} \underline{V}^o &= \frac{u(y - \bar{r}\bar{p}) + \lambda(1-\alpha)\underline{W}^s + \lambda\alpha U(p_c - \bar{p})}{1-\beta(1-\lambda)} && (29) \\ \bar{V}^o &= \frac{u(y - \underline{r}\underline{p}) + \lambda(1-\alpha)\bar{W}^s + \lambda\alpha U(p_c - \underline{p})}{1-\beta(1-\lambda)} && (30) \end{aligned}$$

where $\bar{r}$ and $\bar{p}$ are the highest possible interest rates and price levels, respectively, and $\underline{r}$ and $\underline{p}$ are the lowest. Let $\mathcal{V} = [\underline{V}^o, \bar{V}^o]^{L \times N^2} \times [\underline{W}^s, \bar{W}^s]^{L^2 \times N^2}$. $\mathcal{V}$ is closed, bounded, and convex. Since $KV(p, x) \in [0, 1]$ for any p, x and any V, it is easy to show using equation (24) that if $V \in \mathcal{V}$ then $T^s V(l, r, x, p) \in [\underline{W}^s, \bar{W}^s]$ for any l, r, x, p. Similary, we can use equation (25) to show that if $V \in \mathcal{V}$, then $T^o V(l, r, x) \in [\underline{V}^o, \bar{V}^o]$ for any l, r, x. Therefore, if $V \in \mathcal{V}$ then $TV \in \mathcal{V}$.

A.2 Proof of continuity

The second condition of Brouwer's Fixed Theorem is that T is continuous at each $V \in \mathcal{V}$. To show this, we simply need to show that the operators given in equations (21)-(25) are continuous. As a reminder, the definition of continuity for a mapping $T : X \to Y$ from normed vector space X to normed vector space Y is:

Definition 1. $T : X \to Y$ is continuous at $x \in X$ if for all $\rho > 0$, there exists $\delta > 0$ such that for any $y \in X$, $\|x - y\| < \delta$ implies $\|Tx - Ty\| < \rho$. If T is continuous at all $x \in X$ then we simply say T is continuous in X.

Let $\|\cdot\|$ be the sup-norm. We will simply demonstrate that the operator $\mathcal{E}$ is continuous. The continuity of the rest of the operators follow from the continuity of $\mathcal{E}$. Given $\rho > 0$, we let $\delta = \rho/2$. Let $V, \tilde{V} \in \mathcal{V}$ such that $\left\|V - \tilde{V}\right\| < \delta$. We write:

$$\mathcal{E}V(p,x) = \sum_{x'|x} \pi_{x'|x} \left\{ \int_{k - V^o(p,r,x')}^{\infty} \left[\epsilon - k + V^o(p,r,x')\right] g(\epsilon) d\epsilon \right\} \tag{31}$$

and so:

$$\begin{aligned}\mathcal{E}V - \mathcal{E}\tilde{V} \quad = \quad & \sum_{x'|x} \pi_{x'|x} \Bigg\{ \\ & \int_{k - \max\{V^o, \tilde{V}^o\}}^{k - \min\{V^o, \tilde{V}^o\}} \left[\epsilon - k + \max\{V^o, \tilde{V}^o\}\right] g(\epsilon) d\epsilon \\ & + \int_{k - \min\{V^o, \tilde{V}^o\}}^{\infty} \left[V^o - \tilde{V}^o\right] g(\epsilon) d\epsilon \end{aligned} \tag{32}$$

Now note that:

$$
\begin{aligned}
& \int_{k-\max\{V^o,\tilde{V}^o\}}^{k-\min\{V^o,\tilde{V}^o\}} \Big[\epsilon - k + \max\{V^o, \tilde{V}^o\}\Big] g(\epsilon) d\epsilon \\
\leq\ & \int_{k-\max\{V^o,\tilde{V}^o\}}^{k-\min\{V^o,\tilde{V}^o\}} \Big[\max\{V^o, \tilde{V}^o\} - \min\{V^o, \tilde{V}^o\}\Big] g(\epsilon) d\epsilon \\
\leq\ & \delta \int_{k-\max\{V^o,\tilde{V}^o\}}^{k-\min\{V^o,\tilde{V}^o\}} g(\epsilon) d\epsilon \leq \delta
\end{aligned}
\tag{33}
$$

and:

$$
\int_{k-\max\{V^o,\tilde{V}^o\}}^{k-\min\{V^o,\tilde{V}^o\}} \Big[\epsilon - k + \max\{V^o, \tilde{V}^o\}\Big] g(\epsilon) d\epsilon \geq 0 > -\delta \tag{34}
$$

Further note that:

$$
\int_{k-\min\{V^o,\tilde{V}^o\}}^{\infty} \Big[V^o - \tilde{V}^o\Big] g(\epsilon) d\epsilon \leq \delta \int_{k-\min\{V^o,\tilde{V}^o\}}^{\infty} g(\epsilon) d\epsilon \leq \delta \tag{35}
$$

and:

$$
\int_{k-\min\{V^o,\tilde{V}^o\}}^{\infty} \Big[V^o - \tilde{V}^o\Big] g(\epsilon) d\epsilon \geq -\delta \int_{k-\min\{V^o,\tilde{V}^o\}}^{\infty} g(\epsilon) d\epsilon \geq -\delta \tag{36}
$$

Together, this implies that if $\left\|V - \tilde{V}\right\| < \delta$, then $\left\|\mathcal{E}V - \mathcal{E}\tilde{V}\right\| < 2\delta = \rho$, as desired.

B Micro Evidence for Rate Elasticity of Home Buyer Demand

In this subsection, we use a novel microdataset to provide further, model-free evidence that 1) mortgage rates affect homebuyer demand and 2) a shock to homebuyer demand from a shock to the mortgage rate is partly cleared through the probability of sale.

Our dataset, provided by a private vendor called Optimal Blue, records applications for mortgage rate locks at a daily frequency. Buyers who apply for rate locks usually do so between the sale agreement date, which is when the buyer and seller tentatively agree upon a price and other terms, and the sale closing date, which is when the buyer pays the seller and takes ownership of the home. A mortgage rate lock is a guarantee by a lender to a borrower that the borrower can obtain mortgage financing at the locked in mortgage rate, regardless of what happens to mortgage rates subsequently. A rate lock is usually valid for a specified number of days. Our dataset covers the time period from 2013-2016. About 25 percent of originated purchase mortgages over this time period appear in our dataset.

We estimate the following regression on our locks dataset:

$$log(NumLocks_t) - log(NumLocks_{t-2}) = \alpha_0 + \alpha_1(r_{t+L} - r_{t+L-2}) + \epsilon_t \tag{37}$$

where $NumLocks_t$ is the total number of rate lock applications on day t and r is the 10-year treasury rate on day t, which we use as a proxy for the mortgage rate since daily mortgage rate data are difficult to obtain. Table 6 presents the results. Two-day changes in interest rates are strongly negatively associated with the two-day change in the number of rate lock applications. A 10 basis point increase in the interest rate is associated with a 8.3 percent drop in applications. Interestingly, the correlation only holds when the changes are contemporaneous: columns 2-5 show that for $L \neq 0$, the correlation is zero. This result strongly suggests that the response in applications for $L = 0$ is due to movements in the interest rate, rather than some unobserved factor.

Why do the number of applications drop (rise) when mortgage rates rise (drop) ? There are a few possibilities. One, purchase agreements may be less frequent when rates rise and some buyers may apply for rate locks on (or just after) the agreement date. Two, buyers may back out of purchase agreements when rates rise, possibly because the buyer cannot obtain financing at the higher rate or no longer wants to pay the negotiated price because the debt service burden is too high under the higher rate. Third, buyers may be timing the date of their purchase agreements and/or rate locks to coincide with low interest rates. In contrast, a supply response is not a likely possibility. It is highly unlikely that sellers are adjusting their decision to list their homes for sale, or that builders are choosing when to market new constructions, at such a high, 2-day, frequency.

Bhutta and Ringo (2017) find support for the first two channels. Using the same rate lock data merged with HMDA data, they find that following an interest rate decrease due to an unexpected policy change at the Federal Housing Administration, applications for rate locks that eventually led to closed purchase originations increased almost immediately and remained elevated for some time. They provide further evidence that the increase in originations was due to both fewer loan denials and additional applications for rate locks. They find that average prices did not change much following the policy change.

The high frequency evidence from the locks data strongly suggests that buyer demand responds to changes in mortgage rates, and that this change in demand is not just reflected in prices. Increases (decreases) in rates appear to decrease (increase) both quantities and prices. A framework for measuring the effect of mortgage rates on the housing market that is motivated by a frictionless model and only analyzes house prices would miss this quantity response.

C Discussion of 100% LTV, interest-only mortgage assumption

In this subsection, we discuss the motivation and likely implications of our assumption of 100% LTV, interest-only mortgages for our main results.In our San Diego data, the average LTV is 88 percent and there are sizable mass points in the LTV distribution at 96.5 (the FHA maximum) and 100 percent. The modal LTV is 80 percent. How would our main results change if we assumed 80 percent LTVs instead of 100% LTVs?

None of the mechanisms in our model that generate our key qualitative results depend on the 100% LTV assumption. However, the quantitative results may change if we were to introduce wealth and savings into the model to allow for 80% LTVs. But it is not clear whether our main quantitative result – the difference between the model-implied average house price and latent buyer valuation elasticity – would be larger or smaller than in our baseline estimates.

With 80% LTVs, the elasticity of home buyer valuations should be lower than what we find in our baseline estimates. Future consumption is not as sensitive to current interest rates when only 80 percent of the purchase price needs to be financed with a fixed-rate mortgage. However, we also expect that the average house price elasticity would be lower than in our baseline estimates. Due to concavity of the terminal wealth utility function, sellers with lower outstanding loan amounts change their list price by less in response to an interest rate change than sellers with high loan amounts. This result is illustrated in Figure 7. The intuition for the effect of having interest-only loans is similar. Allowing for amortization would lower the outstanding loan amounts of sellers, implying a lower price elasticity with respect to changes in interest rates.

To support our intuition of the likely effects of introducing 80% LTVs, we conduct two model simulations using our estimated paramater values, but allowing for 80 percent LTVs. In the first simulation, we assume that the buyer finances her downpayment from her lifetime income at a rate of $1-\beta$, where β is the discount factor. In the second simulation, we simply endow each buyer with exactly enough wealth to make a 20 percent downpayment. In the first simulation, the results are very similar to our main results shown in Table 5. The average sale price and frictionless price elasiticies were both slightly lower than in our baseline. In the second simulation, the average sale price elasticity falls below 2 while the frictionless price elasticity remained at about 10. So in both simulations with 80% LTVs, we continue to find that the average price elasticity significantly understates the elasticity of buyer willingness to pay.

In summary, because we are not clearly biasing our main quantitative results in a particular direction with our assumption on the mortgage contract and because our assumption of 100% LTV is not too far from reality for the typical borrower, we choose to take advantage of the computational savings and model parsimony that 100% LTV mortgages provide. The advantage of assuming a 100% LTV is that we do not need to model wealth and savings for a downpayment. The advantage of assuming away amortization is that we do not need to keep track of how long each homeowner has lived in the house in the state space.

D Parameters Set Outside of Estimation

We first discuss calibration of the mean and variance of builder startup costs, μ_η, σ_η. These two parameters affect the probability of building, but they do not have any effect on the moments we use in estimation, which are list price choices and sale hazards. To calibrate these two parameters, we match our model (post-estimation) to two additional moments related to the overall model probability of building, i.e. $E_C[V^2(C, x) - \eta \geq V^1(x)]$. To get the empirical counterpart to the model implied probability of building, we first collected an estimate of the stock of potential infill parcels in San Diego, L, from the California Statewide Infill Study conducted by the Institute of Urban and Regional development.[28] Infill parcels are those in developed, residential areas of San Diego that are economically underutilized (e.g. have a low improvement-value-to-land-value ratio) or in some cases are vacant. These parcels would not include undeveloped land in the periphery of San Diego. One can roughly equate this estimate to the stock of depreciated homes in our model that have not yet been developed by builders. To get the empirical counterpart to $E_C[V^2(C, x) - \eta \geq V^1(x)]$, we compute $Permits/4L = 0.0103$ (i.e. the monthly build rate). We obtain data on monthly single-family construction permits for San Diego from the Census. Since permits reflect all types of new construction, we divide permits in each year by four to reflect an estimate from the Infill Study of the share of total construction in San Diego that is infill construction.[29]

Since there are two parameters that govern the probability of building, μ_η, σ_η, we need one additional building moment to separately identify the two parameters. If rather than including a second building moment we instead assume values for either μ_η or σ_η, then we found that our results are qualitatively unchanged, but the elasticity of permits with respect to interest rates implied by our estimated model becomes unrealistically large. The additional moment that we use is the probability of building in response to a 1 percentage point increase in the mortgage rate over the

[28] The study and data are available here: http://communityinnovation.berkeley.edu/reports/Future_of_Infill_Vol_2.pdf.

[29] The estimate of L from the infill study is for 2004. Since we fit our model to 2001 data, we back out the stock of undeveloped land, L_t, according to $L_t = L_{t-1} - \frac{Permits_t}{4} + \lambda\alpha H$ where $\lambda\alpha$ as defined above is the depreciation rate, H is an estimate of the size of the housing stock in SanDiego from the 2000 census, and $Permits$ is total building permits in San Diego from the census.

2001 mortgage rate. We apply the elasticity estimate from Table 1 to determine the probability of building in the higher interest rate regime, which gives us a monthly build rate of 0.0088. The model counterpart is simply $E_C[V^2(C, x') - \eta \geq V^1(x')]$ where x' is the state vector reflecting the 1 percentage point increase in the mortgage rate.

The permit elasticity estimate from Table 1 relies on time series interest rate variation, and so it is likely biased downward due to endogeneity of interest rate changes in the data. All of the moments that we use in estimation are based on cross-sectional data. However, our only main result that is sensitive to μ_η, σ_η is the simulated elasticity of permits with respect to a change in interest rates.[30] Our goal in modeling home construction is to show that in a rational model with search frictions, home construction can be more rate elastic than house prices, and more in line with the rate elasticity of buyer valuations. We deliver this result with reasonable, calibrated builder parameters.

We set λ, the probability of a moving shock, equal to 0.008 to reflect that moving occurs once every 10 years on average, in line with estimates from the American Housing Survey. We set α, the probability of depreciation conditional on moving shock, equal to 0.05. We set $\phi = \frac{1}{6}$ so that the average construction time from start to completion is 6 months, to match the average time-to-build reported by the Census. We set monthly rent and monthly income income equal to \$1383 and \$4591, respectively, based on San Diego income and rent data from Zillow and BEA data. We set the monthly interest rate equal to .00581 to reflect the average monthly 30 year fixed rate mortgage rate in 2001 from the Freddie Mac survey. We calibrate $\rho = 0.37$ using an auxiliary dataset on San Diego home listings from 2008-2013 from

[30]Because of our model assumptions, particularly that of buyer free entry, the optimal behavior of buyers and sellers of existing homes, who determine our main results, are not sensitive to the decisions of builders.

Altos Research. In these data, for all homes that are on the market for at least one month, we find that 37 percent of the time, the average list price in a particular month is different from the average list price in the previous month. We set p_c, the price of undeveloped land, equal to \$70,500 based on simple hedonic regression using our main dataset that we describe Appendix C. In practice, our estimate of $p_c$has little effect on our results because we estimate μ_C and these two parameters enter additively in the builders' terminal utility function. Finally we set the monthly discount factor to $\beta = 0.95^{1/12}$.

To calibrate agents expectations on future rent, income, and interest rate changes, we use monthly, national rental inflation data from the BLS (1983-2016); monthly, national average private, nonfarm hourly wage data from the BLS (2006-2016); and monthly mortgage rates from the Freddie Mac Survey (1983-2016), respectively. We assume that at a monthly frequency, agents expect that percentage changes in rents, incomes, and rates are uncorrelated. This assumption is roughly consistent with the data: the correlation between monthly changes in rates and rents is -0.02, monthly changes in rents and changes in wages is 0.1, and monthly changes in rates and changes in wages is 0.03. We set the variances on the rent, income, and rate processes to match the variance of monthly changes observed for each respective series in the data.

E Construction of Empirical Moments

First, we describe how we define the two home types in our model–existing and new homes–in our data. In the data, we summarize the multiple dimensions of house quality into a single variable by running a hedonic regression of log initial list price on observable house characteristics, including a dummy variable for new construction, zip code fixed effects, and quarter-by-year fixed effects. We use San Diego listings data from 2001-2003 to estimate this regression. The predicted value from this regression, net of the quarter-by-year fixed effects and the new construction dummy, is our definition of house quality, q. We define an existing home in our model as a home with the median quality among homes listed in 2001. We define a new home as the quality of an existing home plus the coefficient on the new construction dummy from the hedonic regression, which is about 3 percent. We define p_c, the price of undeveloped land, as the median quality among homes listed in 2001, less the contribution to quality of house characteristics (e.g. sqft, number of bathrooms) but inclusive of the contribution of zip code fixed effects and land.

Our first goal is to estimate $\partial\kappa(p, h, x)/\partial p$. To this end, we estimate the following regression using our sample of listings between 2001-2003:

$$\begin{aligned} sell_{it} &= \delta_{y(t)} + \alpha_1 q_i + \alpha_2 q_i^2 + \alpha_3 q_i^3 + \alpha_4 (p_i - q_i)\delta_{y(t)} + \alpha_5 (p_i - q_i) q_i + \alpha_6 (p_i - q_i)^2 q_i + \ldots \\ &\quad \ldots + \alpha_7 (p_i - q_i)^2 \delta_{y(t)} + \alpha_8 (p_i - q_i)^3 q_i + \alpha_9 (p_i - q_i)^3 \delta_{y(t)} + \epsilon_{it} \end{aligned} \tag{38}$$

where $sell_{it}$ is a dummy variable equal to 1 if listing i sells in month t. $\delta_{y(t)}$ is a set of listing year fixed effects meant to proxy for the aggregate state, x, meaning that, for example, the coefficient on $p_i - q_i$ is allowed to vary with the aggregate state. p is the list price. To see the source of endogeneity, note that $p - q$ will be positively correlated with unobserved house quality, leading to a correlation with the error term.

We instrument for the endogenous $p-q$ terms using $log(P_t) - log(P_{t_0})$ where P_t is the Corelogic house price index for San Diego in the year/month of listing t and $P_{t_0}$is the house price index for San Diego for the year/month in which the seller initially purchased the home. In practice, we use a sixth order polynomial of the instrument and estimate the model using 2SLS. As in Guren (2018), the first stage is strongly significant: more house price appreciation since purchase results in a lower list price choice on average. We group list prices into $10,000 bins and compute the average sale hazard associated with each bin according to the estimated equation (38).

Our second goal is to estimate $\partial p^s(l,r,x)/\partial l$. To this end, we estimate the following regression using our sample of listings between 2001-2003:

$$\begin{aligned} p_{it} &= \delta_{y(t)} + \alpha_1 q_i + \alpha_2 q_i^2 + \alpha_3 q_i^3 + \alpha_4 r_i + \alpha_5 l_i + ... \\ &\quad \ldots + \alpha_6 l_i q_i + \alpha_7 l_i^2 + \alpha_8 l_i^2 q_i + \alpha_9 l_i^3 + \alpha_{10} l_i^3 q_i + \epsilon_{it} \end{aligned} \tag{39}$$

where $p_{it}$is the seller's list price choice. l is the seller's outstanding loan amount, equal to the purchase price in our model. r is the sellers outstanding mortgage rate, equal to the mortgage rate at the time of purchase in our model. The other variables are defined as above. The source of endogeneity is the same as described above. The purchase price will be positively correlated with unobserved house quality, and unobserved quality enters the error term because it has a direct effect on the list price. Our estimates of $\alpha_5 - \alpha_{10}$ will be biased upward if we estimate (39) by OLS. Therefore, we instrument for l using $log(P_{t_0}) - log(P_{t_0'})$ where $P_{t_0}$is the house price index for San Diego for the year/month in which the seller initially purchased the home and $P_{t_0'}$is the house price index for San Diego for the year/month two transactions prior to listing. In practice, we use a sixth order polynomial of the instrument and estimate the model using 2SLS. We group purchase prices into $10,000 bins and compute the average list price associated with each bin according to the estimated equation (39).

Finally, to get the mean and standard deviation of list prices for new construction homes, we first run the following regression on the sample of new construction listings:

$$p_{it} = \delta_{y(t)} + \alpha_1 q_i + \alpha_2 q_i^2 + \alpha_3 q_i^3 + \epsilon_{it} \tag{40}$$

We estimate this equation using weighted least squares to account for heteroskedasticity. We get the standard deviation of list prices from the RMSE of this regression. Thus, we are partialing out observable quality differences in new construction homes before computing the standard deviation.[31] We get the mean list price by evaluating equation (40) at the q associated with an existing home.

E.1 Weighting Matrix Used for Estimation of the Model

We use a diagonal weighting matrix. For the sale hazard moments, we weight each list price bin by the inverse of the square of the standard error of the average sale hazard as implied by our estimates of equation (38). For the list price moments for existing homes, we weight each purchase price bin by the inverse of the square of the standard error of the average list price as implied by our estimates of equation (39). For purchase price bins that are associated with list price choices that result in a zero sale hazard according to equation (39), we set the weight equal to zero. In practice, these purchase price bins already receive low weight because they are associated with high standard errors, but we further lower the weight to zero because no seller would ever choose a list price that is associated with a zero sale hazard in our model. We give equal weight to the mean and standard deviation of list price choices for new construction. We set the scale on the weights so that the sum of the weights for these two moments is equal to the sum of all of the weights associated with the moments

[31] We cannot account for unobserved quality in new construction homes because there is no price appreciation since purchase to form an instrument for new construction. However, we expect that unobserved quality for new construction homes is much less of a concern than for existing homes. In practice, differences in unobserved quality comes from renovations/maintenance/depreciation, which would not typically be applicable for new construction homes.

for list price choices for existing homes. Our results are robust to other choices of weights for these two moments.

F Details on Solving the Model

To solve the model, we iterate on the following loop until convergence. Given an initial guess of the value functions,

1. Compute $\theta(p,h)$ using (13)

2. Compute $\kappa(p,h)$ using (8)

3. Compute V^b using (4)

4. Compute $V^s(l,r)$ and $W^s(l,r,p)$ using (6,7)

5. Compute $V^o(l,r)$ using (5)

6. Compute $V^3(C)$ and $W^3(C,p)$ using (11,12)

7. Compute V^2 using (10)

8. Compute V^1 using (9)

In implementing this loop, we set loan, price, and construction cost grids to each run from \$10k to \$600k in \$10k increments. We solve the model for four different interest rate levels: the average 2001 interest rate, a one standard deviation positive shock to the interest rate, a one standard deviation negative shock to the interest rate, and the average prevailing interest rate among sellers who enter the market in 2001; for two different rent levels: the average 2001 rent and a one standard deviation positive shock to the rent; and for two different income levels: average 2001 income and a one standard deviation positive shock to this income.

G Calculation of Frictionless Price

To compute the frictionless price, we re-solve the model equilibrium assuming that the probability of a match for a buyer or seller is always one, regardless of the market tightness. We still assume that the buyer receives an idiosyncratic preference shock ϵ and may reject the purchase if ϵ is too low. That is, for each type of housing h, we find the price $p_h^{wtp}(x)$ that solves the following:

$$k(x) = u(y - rent) - c_b + \beta E_{x',\epsilon|x}\Big[\ k + \max\Big\{0,\ V^o(p_h^{wtp}, r, x') + \epsilon - k\Big\}\Big] \quad (41)$$

where

$$\begin{aligned} V^o(l, r, x) &= u(y - rl) + \beta E_{x'|x}\Big[(1-\lambda)V^o(l, r, x') + \dots \\ &\quad \dots + \lambda(1-\alpha)V^s(l, r, x') + \lambda\alpha U(p_c - l)\Big] \end{aligned} \quad (42)$$

and

$$\begin{aligned} V^s(l, r, x) &= u(y - rl) - c_s + \beta E_{x'|x}\Big[\kappa(h, x)U(p_h^{wtp} - l) + \dots \\ &\quad \dots + (1 - \kappa(h, x))V^s(l, r, x')] \end{aligned} \quad (43)$$

and

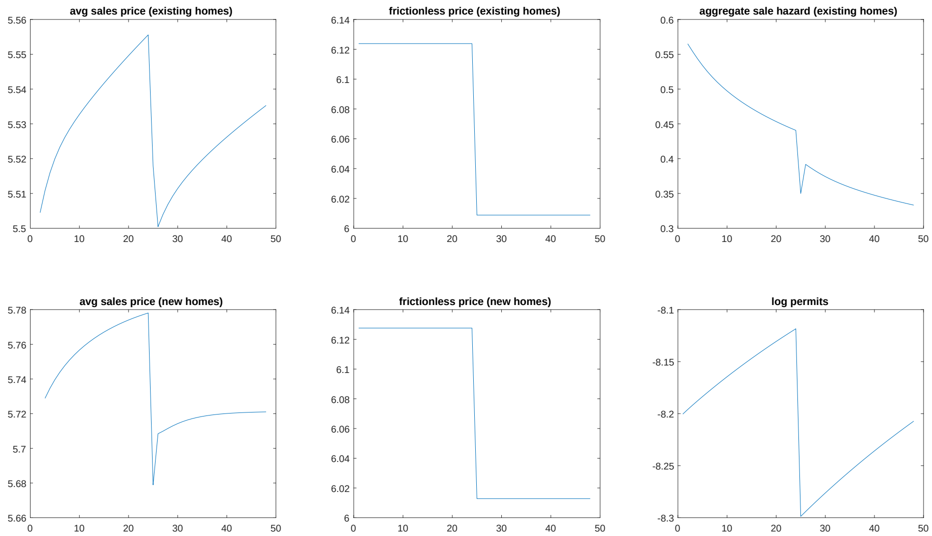
$$\kappa(h, x) = E_{x',\epsilon|x,h}\Big[V^o(p_h^{wtp}, r, x') + \epsilon - k(x) \geq 0\Big]. \quad (44)$$

In words, $p^{wtp}(x)$ is the price that the buyer can get without any search frictions given the aggregate state x. Thus, p^{wtp} can be interpreted as a willingness to pay for housing. Since the calculation in (41) depends on the owners value function, V^o, we re-solve V^o using equations (42)-(44). (42) has the same structure as in the baseline model. (43) says that all sellers post the frictionless price upon mismatch. (44) says that the probability of a seller meeting a buyer is one, but the buyer may reject the match if ϵ is not high enough. The frictionless price that we compute is an equilibrium price in a model where the probability of a match is always equal to one.

H Additional Model Simulation Results

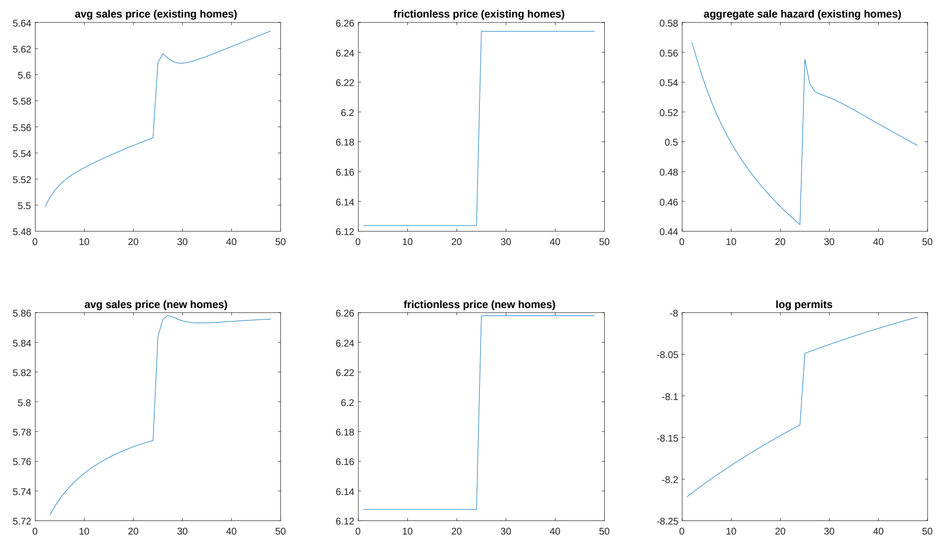
We simulate the housing market response to an exogenous and unexpected full percentage point *decrease* in the mortgage rate. Figure A.2 shows the results. The results are largely symmetric to the results shown in Figure 6. Finally, we repeat our baseline simulations shown in Figure 6 for the case where list prices are not sticky (i.e. $\rho = 1$). Figure A.1 shows the results. They are similar to the baseline results.

Figure A.1: Response to Interest Rate Increase, No Sticky List Prices



This graph shows simulations from the estimated model when list prices are not sticky ($\rho = 1$). Initial conditions are set to match the 2001 SanDiego market. The aggregate state remains constant until t=24, when there is a 1 percentage point increase in the mortgage rate. The aggregate state remains constant at the higher rate thereafter. The frictionless price is defined as the price that would leave buyers indifferent over being in a market where the probability of matching with a seller is one, and being in the market described in our baseline model where the probability of matching is generally less than one in equilibrium. All prices are log prices.

Figure A.2: Response to Interest Rate Decrease



This graph shows simulations from the estimated model. Initial conditions are set to match the 2001 SanDiego market. The aggregate state remains constant until t=24, when there is a 1 percentage point decrease in the mortgage rate. The aggregate state remains constant at the higher rate thereafter. The frictionless price is defined as the price that would leave buyers indifferent over being in a market where the probability of matching with a seller is one, and being in the market described in our baseline model where the probability of matching is generally less than one in equilibrium. All prices are log prices.

Table 6: Effect of Interest Rates in Mortgage Rate Locks Data

	2-day % change in # mortgage locks				
	L=0	L=1	L=2	L=3	L=-5
r_{t+L} - r_{t+L-2}	-0.8281***	-0.0290	-0.1550	0.1550	-0.0206
	(0.2049)	(0.2643)	(0.2413)	(0.2624)	(0.2660)
Observations	742	741	740	739	737

Shows regressions of 2-day change in the log(# mortgage rate lock applications) on 2-day changes in the 10-year treasury rate (r). Mortgage rate lock applications data come from Optimal Blue. The sample period is 2013-2016.