House Price Momentum and Strategic Complementarity

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Abstract

House price changes are positively autocorrelated over two to three years, a phenomenon known as momentum. While several frictions that cause momentum have been identified, existing explanations cannot quantitatively explain the magnitude of momentum found in the data. This paper introduces, empirically grounds, and quantitatively analyzes an amplification mechanism that can generate substantial momentum from a broad class of small frictions. The amplification is due to a concave demand curve in relative price, which implies that increasing the quality-adjusted list price of a house priced above the market average rapidly reduces its probability of sale, but cutting the price of a below-average priced home only slightly improves its chance of selling. This creates a strategic complementarity that incentivizes sellers to set their list price close to others'. Consequently, frictions that cause slight insensitivities to changes in fundamentals lead to prolonged adjustments because sellers gradually adjust their price to stay near the average. I provide new micro empirical evidence for the concavity of demand—which is often used in macro models with strategic complementarities—by instrumenting a house's relative list price with a proxy for the seller's equity and nominal loss. I find significant concavity, which I embed in an equilibrium housing search model. Quantitatively, the calibrated model amplifies frictions that cause momentum by a factor of two to three.

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1 Introduction

A puzzling and prominent feature of housing markets is that aggregate price changes are highly positively autocorrelated, with a one percent annual price change correlated with a 0.30 to 0.75 percent change in the subsequent year (Case and Shiller, 1989).[1] This price momentum lasts for two to three years before prices mean revert, a time horizon far greater than most other asset markets. Substantial momentum is surprising both because most pricing frictions dissipate quickly and because predictable price changes should be arbitraged away by households, either by altering their bidding and bargaining or by re-timing their purchase or sale. Indeed, while several papers have explained momentum by introducing frictions into models of housing markets, these frictions need to be unpalatably large to quantitatively explain house price momentum.

This paper introduces, empirically grounds, and quantitatively analyzes an amplification mechanism for a variety of underlying frictions that can generate substantial momentum without the need for implausibly-large frictions. The mechanism relies on a strategic complementarity among list-price-setting sellers that makes the optimal list price for a house depend positively on the prices set by others. Strategic complementarities of this sort are frequently used in macroeconomic models, but there is limited empirical evidence of their importance or strength. In analyzing momentum in the housing market, I provide direct micro empirical evidence for a prominent strategic complementarity in the macroeconomics literature and, using a calibrated equilibrium search model, demonstrate that its ability to amplify underlying frictions is quantitatively significant.

The propagation mechanism I introduce relies on two components: costly search and a demand curve that is concave in relative price. Search is inherent to housing because no two houses are alike and idiosyncratic taste can only be learned through costly inspection. Concave demand in relative price implies that the probability a house sells is more sensitive to list price for houses priced above the market average than below the market average. While concave demand may arise in housing markets for several reasons, I focus on the manner in which asking prices direct buyer search. The intuition is summarized by an advice column for sellers: "Put yourself in the shoes of buyers who are scanning the real estate ads...trying to decide which houses to visit in person. If your house is overpriced, that will be an immediate turnoff. The buyer will probably clue in pretty quickly to the fact that other houses look like better bargains and move on."[2] In other words, the probability that a house is visited by buyers decreases rapidly as a home's list price rises relative to the market average. This generates a concave demand curve in relative price because at high relative prices buyers are on the margin of looking and purchasing, while at low relative prices they are mostly on the margin of purchasing.

Concave demand incentivizes list-price-setting sellers—who have market power due to search frictions—to set their list prices close to the mean list price. Intuitively, raising a house's relative list price reduces the probability of sale and profit dramatically, while lowering its relative price increases

[1] See also Cutler et al. (1991), Head et al. (2014), and Glaeser et al. (2014).

[2] "Settling On The Right List Price for Your House," Ilona Bray, http://www.nolo.com/legal-encyclopedia/listing-house-what-price-should-set-32336-2.html.

the probability of sale slightly and leaves money on the table. In a rational expectations equilibrium with identical sellers, all sellers change their prices simultaneously and no gradual adjustment arises from the incentive to be close to the mean. However, modest frictions that generate differential insensitivities of prices to changes in fundamentals cause protracted price adjustments because sellers optimally adjust their list price gradually so their price does not stray too far from the market average. Importantly, this strategic complementarity amplifies *any* friction that generates heterogeneity in the speed of adjustment, a class that includes most of the frictions proposed by the literature, such as staggered pricing, backward-looking expectations, learning, and the gradual spread of sentiment. This paper is focused on the degree of amplification, and is agnostic as to which particular friction is at work in practice.

To evaluate the concavity of the effect of unilaterally changing a house's relative quality-adjusted price on its probability of sale, I turn to micro data on listings for the San Francisco Bay, Los Angeles, and San Diego metropolitan areas from 2008 to 2013. I address bias caused by unobserved quality by instrumenting a house's relative list price with the amount of local price appreciation since the seller purchased. Sellers with less appreciation since purchase set a higher price for two reasons. First, sellers often use the equity they extract from their current home to make a down payment on their next home (Stein, 1995; Genesove and Mayer, 1997). When the amount of extracted equity is low, sellers are on a down payment constraint, each dollar of equity extracted can be leveraged heavily, and the seller's marginal utility of cash on hand is high. Conversely, with higher equity extraction, the down payment constraint is less likely to be binding, each dollar extracted is not leveraged to the same extent, and the seller's marginal utility of cash on hand is lower. Given their higher marginal utility of cash on hand, sellers extracting less equity set a higher list price. Second, home sellers exhibit nominal loss aversion (Genesove and Mayer, 2001). Local appreciation since purchase is a noisy proxy for the exact appreciation of any given house, so there is a negative relationship between appreciation since purchase and both the probability and size of a nominal loss and hence the list price a seller sets. Because I compare listings within a ZIP code and quarter, the supply-side variation based on appreciation since purchased identifies the curvature of demand if unobserved quality is independent of when a seller purchased their home.

The instrumental variable estimates reveal a statistically and economically significant concave demand curve that is highly robust to various controls, sample restrictions, and proxies for unobserved quality and date of purchase. My findings about the concavity of demand are also robust to other sources of relative price variation that are independent of appreciation since purchase.

To assess the strength of this propagation mechanism, I embed concave demand in a Diamond-Mortensen-Pissarides equilibrium search model and consider two separate frictions cited by the literature to assess the amplification mechanism's ability magnify frictions. First, I consider staggered pricing whereby overlapping groups of sellers set prices that are fixed for multiple periods (Taylor, 1980). Concave demand induces sellers to only partially adjust their prices when they have the opportunity to do so, and repeated partial adjustment manifests itself as momentum. Second, I introduce a small fraction of backward-looking rule-of-thumb sellers as in Campbell and

Mankiw (1989) and Gali and Gertler (1999). Backward-looking expectations are frequently discussed as a potential cause of momentum (*e.g.*, Case and Shiller, 1987; Case et al. 2012), but some observers have voiced skepticism about widespread non-rationality in housing markets given the financial importance of housing transactions for most households. With a strategic complementarity, far fewer backward-looking sellers are needed to explain momentum because the majority of forward-looking sellers adjust their prices gradually so they do not deviate too much from the backward-looking sellers (Haltiwanger and Waldman, 1989; Fehr and Tyran, 2005). This, in turn, causes the backward-looking sellers to observe more gradual price growth and change their price by less, creating a two-way feedback that amplifies momentum.

I calibrate the parameters of the model that control the shape of the demand curve to match the micro empirical estimates and the remainder of the model to match steady state and time series moments. I find that a two-month staggered pricing friction without concavity is amplified into four to six months of gradual adjustment, and between a half and a third as many backward-looking sellers are needed to explain the amount of momentum in the data with concavity relative to without concavity. I conclude that concave demand amplifies underlying frictions by a factor of between two and three.

The amplification mechanism adapts two ideas from the macro literature on goods price stickiness to frictional asset search. First, the concave demand curve is similar to "kinked" demand curves (Stiglitz, 1979) which, since the pioneering work of Ball and Romer (1990) has been frequently cited as a potential source of real rigidities. In particular, a "smoothed-out kink" extension of Dixit-Stiglitz preferences proposed by Kimball (1995) is frequently used to tractably introduce real rigidities through strategic complementarity in price setting. Second, the repeated partial price adjustment caused by the strategic complementarity is akin to Taylor's (1980) "contract multiplier." A lively literature has debated the importance of strategic complementarities and kinked demand in particular for propagating goods price stickiness by analyzing calibrated models, by assessing whether the ramifications of strategic complementarities are borne out in micro data (Klenow and Willis, 2006), by examining exchange-rate pass through for imported goods (*e.g.,* Gopinath and Itshoki, 2010; Nakamura and Zerom, 2010), and by estimating the response of firms' pricing to their own costs and the prices of their competitors, instrumenting costs prices with exchange rates (Amiti et al., 2016). My analysis of housing markets adds to this literature by directly estimating a concave demand curve and assessing its ability to amplify frictions in a calibrated model.

The remainder of the paper proceeds as follows. Section 2 provides facts about momentum and describes why existing explanations cannot quantitatively explain momentum. Section 3 analyzes micro data to assess whether housing demand curves are concave. Section 4 presents the model. Section 5 calibrates the model to the micro estimates and assesses the degree to which strategic complementarity amplifies momentum. Section 6 concludes.

2 Momentum: Facts and Explanations

Since the pioneering work of Case and Shiller (1989), price momentum has been considered one of the most puzzling features of housing markets. While other financial markets exhibit momentum, the housing market is unusual for the 8 to 14 quarter horizon over which it persists.[3]

House price momentum has consistently been found across cities, countries, time periods, and price index measurement methodologies (Cho, 1996; Titman et al., 2014). Figure 1 shows two nation-wide measures of momentum for the CoreLogic repeat-sales house price index for 1976 to 2013 and a third measure for the same index across 103 cities.[4] Panel A shows that autocorrelations are positive for 11 quarterly lags of the quarterly change in the price index adjusted for inflation and seasonality. Panel B shows an impulse response in log levels to an initial one percent price shock estimated from an AR(5). In response to the shock, prices gradually rise for two to three years before mean reverting. Finally, panel C shows a histogram of AR(1) coefficients estimated separately for 103 metropolitan area repeat-sales house price indices from CoreLogic using a regression of the annual change in log price on a one-year lag of itself as in Case and Shiller (1989):

$$\Delta_{t,t-4} \ln p = \beta_0 + \beta_1 \Delta_{t-4,t-8} \ln p + \varepsilon. \tag{1}$$

β_1 is positive for all 103 cities, and the median city has an annual AR1 coefficient of 0.60.[5] Appendix B replicates these facts for a number of countries, price series, and measures of autocorrelation and consistently finds two to three years of momentum.

Momentum is a puzzle because forward-looking models have a strong arbitrage force that eliminates momentum, even with short sale constraints. In Walrasian models, this works through potential buyers and sellers re-timing their transactions, while in search models it works through the outside options of buyers and sellers. Construction also serves as an arbitrage force. Furthermore, momentum cannot be empirically explained by serially correlated changes in fundamentals. Case and Shiller (1989) argue that momentum cannot be explained by autocorrelation in interest rates, rents, or taxes, and Capozza et al. (2004) find significant momentum after accounting for six comprehensive measures of fundamentals in a vector error correction model. Pulling together the empirical and theoretical arguments, Glaeser et al. (2014) estimate a dynamic spatial equilibrium model and find that "there is no reasonable parameter set" consistent with short-run momentum.

In recent years, a number of frictions have been added to models of the housing market to explain momentum. These frictions fall into four main categories.

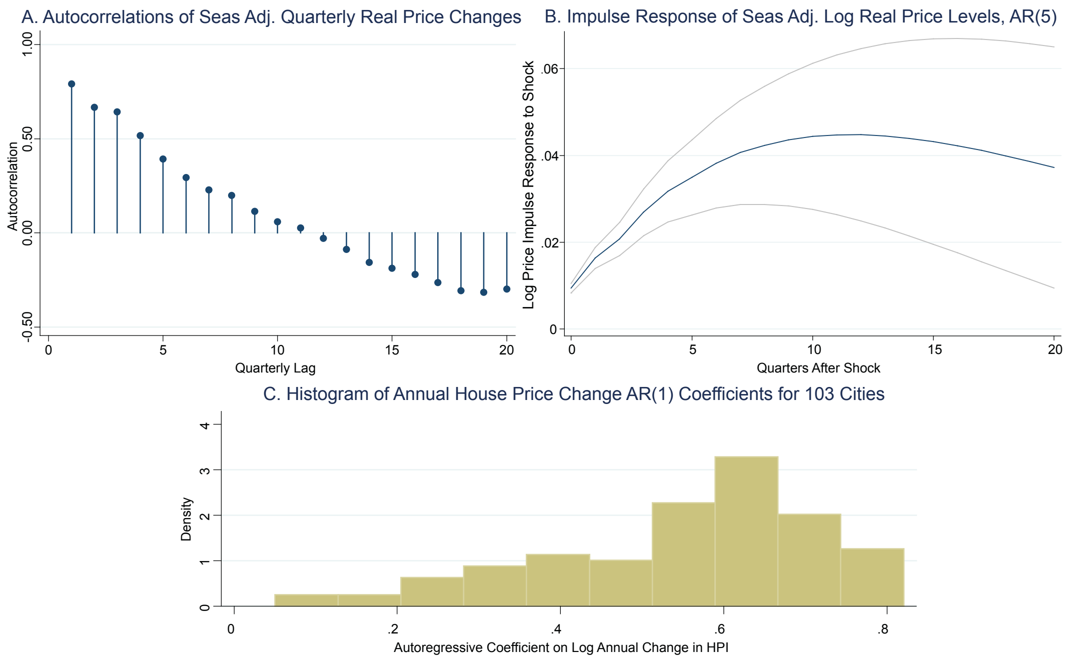
First, gradual learning about market conditions by sellers can create momentum. Anenberg (2014) structurally estimates a partial equilibrium model with learning and finds an annual AR(1) coefficient of 0.165, which is about a quarter of the median city in the CoreLogic data. The inability

[3]See Cutler et al. (1991) and Moskowitz et al. (2012) for analyses of time series momentum for different assets.

[4]As discussed in Appendix B, price indices that measure the median price of transacted homes display momentum over roughly two years as opposed to three years for repeat-sales indices. Appendix B also shows that there is no evidence of an asymmetry in falling markets relative to rising markets, although the test for asymmetry has limited statistical power.

[5]This paper does not attempt to explain the variation in momentum across MSAs.

Figure 1: Momentum in Housing Prices



Notes: Panel A and B show the autocorrelation function for quarterly real price changes and an impulse response of log real price levels estimated from an AR(5) model, respectively. The IRF has 95% confidence intervals shown in grey. An AR(5) was chosen using a number of lag selection criteria, and the results are robust to altering the number of lags. Both are estimated using the CoreLogic national repeat-sales house price index from 1976-2013 collapsed to a quarterly level, adjusted for inflation using the CPI, and seasonally adjusted. Panel C shows a histogram of annual AR(1) coefficients of annual house price changes as in regression (1) estimated separately on 103 CBSA division repeat-sales house price indices provided by CoreLogic. The local HPIs are adjusted for inflation using the CPI. The 103 CBSAs and their time coverage, which ranges from 1976-2013 to 1995-2013, are listed in Appendix A.

of learning to explain the amount of momentum in the data reflects the fact that Bayesian learning about buyer valuations happens relatively quickly. One would need to dramatically slow down learning with an extreme parameterization to generate three years of momentum.

Second, Head et al. (2014) demonstrate that search frictions can generate momentum by making the adjustment of market tightness gradual in response to shocks to fundamentals. In a boom in their model, most sellers sell but only some buyers buy, so the number of searching buyers “builds up” as buyers persistently enter, which causes market tightness to rise over time as more houses are rented out to accommodate the growing mass of buyers and fewer houses are listed for sale. Head et al. calibrate their model and obtain only 40 percent of the autocorrelation in the data over one year and no momentum over two years. Over 85 percent of the price impulse response occurs in the first quarter after a shock in contrast to the impulse response in Figure 1, in which under 25 percent occurs in the first quarter.

Third, a behavioral finance literature hypothesizes that investors initially under-react to news due to behavioral biases (Barberis et al., 1998, Hong and Stein, 1999) or loss aversion (Frazzini,

2006) and then "chase returns" due to extrapolative expectations about price appreciation. Both extrapolative expectations and loss aversion are considered to be important forces in the housing market (Case and Shiller, 1987; Genesove and Mayer, 2001). Recently, Glaeser and Nathanson (2016) have provided a behavioral theory of momentum in which agents neglect to account for the fact that previous buyers were learning from prices and instead take past prices as direct measures of demand. Their calibrated model can match quantitatively explain momentum when all agents are behavioral and observe prices with a somewhat-long six-month lag. Momentum is dampened to a third of the observed amount when half of sellers are fully rational, and recent survey and experimental evidence suggest that under half of agents expectations appear to be substantially extrapolative (Kuchler and Zafar, 2016; Armona et al. 2016).

Fourth, Burnside et al. (2015) show that in a model with belief heterogeneity, momentum could result from optimism and pessimism that gradually spreads through social interactions, akin to epidemiological models of the spread of disease. In their model, agents with tighter priors are more likely to convert others to their beliefs, and in order to generate sufficient momentum, the relative confidence of optimists and pessimists must be extremely close so that the relative number of optimists grows gradually over the course of a decade instead of suddenly in an "epidemic." This tight parameter restriction could be relaxed with the amplification mechanism presented here.[6]

For all four types of frictions, the degree of friction necessary to match the amount of momentum in the data is unpalatably large. This paper introduces a strategic complementarity in pricing that amplifies the effect of any friction that generates heterogeneity in beliefs, a class that includes learning, backward-looking sellers, and gradually spreading beliefs, among others. With the additional momentum provided by the strategic complementarity, the frictions identified by the literature are able to quantitatively explain momentum with substantially more reasonable parameterizations.

3 The Concavity of Demand in the Housing Market

I propose an amplification channel for momentum based on search and a concave demand curve in relative price. Search is a natural assumption for housing markets, but the relevance of concave demand requires further explanation.

A literature in macroeconomics argues that strategic complementarities among goods producers can amplify small pricing frictions into substantial price sluggishness by incentivizing firms to set prices close to one another. Because momentum is similar to price stickiness in goods markets, I hypothesize that a similar strategic complementarity may amplify house price momentum. There are several reasons why concave demand may arise in housing markets. First, buyers may avoid visiting homes that appear to be overpriced. Second, buyers may infer that underpriced homes are lemons. Third, a house's relative list price may be a signal of seller type, such as an unwillingness

[6]Burnside et al. obtain such a parameter restriction through a simulated method of moments procedure. Their data implies that the change in the number of optimists is growing at a decreasing rate between 7 and 10 years after the start of the boom (assumed to be 1996), which implies a very gradual spread of optimism. This estimation strategy does not provide any direct evidence inconsistent with the strategic complementarity presented here because their model with a strategic complementarity in price setting could fit the same data with a faster spread of optimism.

to negotiate (Albrecht et al., 2016). Fourth, homes with high list prices may be less likely to sell quickly and may consequently be more exposed to the tail risk of becoming a "stale" listing that sits on the market without selling (Taylor, 1999). Fifth, buyers may infer that underpriced homes have a higher effective price than their list price because their price is likely to be increased in a bidding war (Han and Strange, 2016). Sixth, the law of one price—which would create a step-function demand curve—may be smoothed into a concave demand curve by uncertainty about what a house is worth.

Nonetheless, concrete evidence is needed for the existence of concave demand in housing markets before it is adopted as an explanation for momentum. Consequently, this section assesses whether demand is concave by analyzing micro data on listings matched to sales outcomes for the San Francisco Bay, Los Angeles, and San Diego metropolitan areas from April 2008 to February 2013.[7]

3.1 Empirical Approach

3.1.1 Econometric Model

To keep the analysis transparent, the unit of observation is a listing associated with an initial log list price, p, and the outcome of interest is a summary statistic of the time to sale distribution, d. In the main text, d is an indicator for whether the house sells within 13 weeks, with a withdrawal counting as a non-sale, and I vary the horizon and use time to sale for d in robustness checks. The data consist of homes, denoted with a subscript h, from markets defined by a location ℓ (a ZIP code in the data) and time period t (a quarter in the data).

The relevant demand curve for list-price-setting sellers is the effect of unilaterally changing a house's quality-adjusted list price relative to the average list price in the area on its probability of sale. To simplify notation, I combine the average list price in location ℓ at time t and the quality-adjustment for house h into a single "target" list price for house h, $\tilde{p}_{h\ell t}$. $\tilde{p}_{h\ell t}$ has two additive components: the average log list price in location ℓ at time t, represented by a fixed effect $\xi_{\ell t}$, and quality $q_{h\ell t}$ that is only partially observable to the econometrician:

$$\tilde{p}_{h\ell t} = \xi_{\ell t} + q_{h\ell t}. \tag{2}$$

I model the probability of sale $d_{h\ell t}$ as being a potentially nonlinear function of $p_{h\ell t} - \tilde{p}_{h\ell t}$ net of a market-specific effect and an error term:

$$d_{h\ell t} = g\left(p_{h\ell t} - \tilde{p}_{h\ell t}\right) + \psi_{\ell t} + \varepsilon_{h\ell t}. \tag{3}$$

The demand curve in relative price $g(\cdot)$ is assumed to be invariant across markets defined by a location and time net of an additive fixed effect $\psi_{\ell t}$ that represents local market conditions. $\varepsilon_{h\ell t}$ is an error term that represents luck in finding a buyer and is assumed to be independent of $p_{h\ell t} - \tilde{p}_{h\ell t}$.[8]

[7] These areas were selected because both the listings and transactions data providers are based in California, so the matched dataset for these areas is of high quality and spans a longer time period.

[8] Traditionally, endogeneity concerns stem from the correlation of the error term $\varepsilon_{h\ell t}$ with price. This source of

I call $p_{h\ell t} - \tilde{p}_{h\ell t}$ the seller's log relative markup, as it represents the "markup" a seller is asking over the quality-adjusted average list price for a house in location ℓ at time t.

If $q_{h\ell t}$ were observable, one could directly estimate (3), but quality $q_{h\ell t}$ almost certainly has an important unobserved component that is likely positively correlated with price, leading to an estimated demand curve that is less elastic than the true demand curve. To surmount this challenge, I use a non-linear instrumental variable approach that traces out the demand curve using plausibly exogenous supply-side variation in seller pricing behavior. I also use an "OLS" approach that assumes away unobserved quality to assess how the instrument affects the measured shape of $g(\cdot)$.

Formally, I model quality as a linear function of observed measures of quality $X_{h\ell t}$ and quality unobserved by the econometrician $u_{h\ell t}$:

$$q_{h\ell t} = \beta X_{h\ell t} + u_{h\ell t}. \tag{4}$$

Combining (2) and (4), the reference price $\tilde{p}_{h\ell t}$ can be written as:

$$\tilde{p}_{h\ell t} = \xi_{\ell t} + \beta X_{h\ell t} + u_{h\ell t}. \tag{5}$$

I use two observed measures of quality $X_{h\ell t}$ in my baseline specification and introduce other measures and more flexible functional forms for $X_{h\ell t}$ in robustness tests. First, I use a repeat-sales predicted price $\hat{p}^{repeat}_{h\ell t} = \log\left(P_{h\ell\tau}\frac{\phi_{\ell t}}{\phi_{\ell\tau}}\right)$, where $P_{h\ell\tau}$ is the price at the previous sale date τ and $\phi_{\ell t}$ is a ZIP code-level repeat-sales house price index index. Second, I use a hedonic predicted price $\hat{p}^{hedonic}_{t}$, which is the sum of the static value of a house's hedonic characteristics and a date of sale fixed effect, both estimated within a ZIP code. The construction of both indices follows standard practice and is detailed in Appendix A.

Unobserved quality $u_{h\ell t}$ introduces two difficulties in identifying $g(\cdot)$. First, there is an endogeneity problem as unobserved quality and price are likely positively correlated. Second, unobserved quality creates a measurement error problem because the true $\tilde{p}_{h\ell t}$ is not observable. Both of these problems may lead to bias in the estimated $g(\cdot)$.

I identify $g(\cdot)$ in the presence of unobserved quality by introducing an instrumental variable $z_{h\ell t}$ which is described in the next section that generates supply-side variation in $p_{h\ell t} - \tilde{p}_{h\ell t}$ and that is independent of unobserved quality. To allow for nonlinearity in the first stage, I let $z_{h\ell t}$ affect price through a flexible function $f(\cdot)$. Then $g(\cdot)$ is identified if:

Condition 1.

$$z_{h\ell t} \perp (u_{h\ell t}, \varepsilon_{h\ell t})$$

and

$$p_{h\ell t} = f(z_{h\ell t}) + \tilde{p}_{h\ell t} = f(z_{h\ell t}) + \xi_{\ell t} + \beta X_{h\ell t} + u_{h\ell t}. \tag{6}$$

bias is absent here as the effect of demand shocks on average price levels is absorbed into $\xi_{\ell t}$ and the effect of prices on aggregate demand is absorbed into $\psi_{\ell t}$.

The first half of Condition 1 is an exclusion restriction that requires $z_{h\ell t}$ have no direct effect on the outcome, either through fortune in finding a buyer $\varepsilon_{h\ell t}$ or through unobserved quality $u_{h\ell t}$. I discuss this assumption when I introduce the instrument in subsection 3.1.2. The second part of Condition 1 requires that $z_{h\ell t}$ is the only reason for variation in $p_{h\ell t} - \tilde{p}_{h\ell t}$, which is effectively a no measurement error assumption. I discuss this assumption and the robustness of my results to measurement error in subsection 3.1.3.

Under Condition 1, $p_{h\ell t} - \tilde{p}_{h\ell t} = f(z_{h\ell t})$, and $g(\cdot)$ can be estimated by a two-step procedure that estimates equation (6) by OLS as a first stage and then uses the predicted $f(z_{h\ell t})$ as $p_{h\ell t} - \tilde{p}_{h\ell t}$ to estimate equation (3) as a second stage by OLS. Both equations weighted by the inverse standard deviation of the error in the repeat-sales index to account for the reduced precision of the predicted prices in areas with fewer transactions, and I use a quintic polynomial for $f(\cdot)$. I show that neither of these assumptions matters for my results in robustness tests.

I assess the degree of concavity in two ways. First, I use a quadratic $g(\cdot)$ and test whether the quadratic term is statistically distinguishable from zero. To account for spatial correlation, I calculate standard errors by block bootstrapping the entire procedure and clustering on 35 units defined by the first three digits of the ZIP code (ZIP-3). The bootstrapped 95 percent confidence interval is my preferred test for concavity. Second, to visualize the data, I construct a binned scatter plot, which approximates $g(\cdot)$ using indicator variables for the 25 equally-sized bins of $p_{h\ell t} - \tilde{p}_{h\ell t}$, as detailed in Appendix C. I also overlay a third-order polynomial fit with pointwise 95 percent confidence bands.

3.1.2 Instrument

Due to search frictions, home sellers face a trade-off between selling at a higher price and selling faster. Sellers with a higher marginal utility of cash on hand will choose a higher list price and longer time on the market. My instrument takes advantage of two sources of variation in the marginal utility of cash on hand that are plausibly independent of unobserved quality.

The first source of variation is that sellers who extract less equity upon sale on average have a higher marginal utility of cash on hand. This is the case because many sellers many sellers use the equity they extract from sale for the down payment on their next home (Stein, 1995). At low levels of equity extraction, households are on a down payment constraint, and each dollar of equity extracted is used towards the next down payment and leveraged, making the marginal utility of cash on hand is high. By contrast, sellers extracting significant equity have enough cash on hand that they no longer face a binding down payment constraint. Because they do not leverage up each additional dollar of equity they extract, their marginal utility of cash on hand is lower. The presence of a binding down payment constraint depends on an individual seller's liquid asset position and their access to credit, but on average sellers that extract more equity have a less binding down payment constraint, lower marginal utility of cash on hand, and set lower list prices.

The second source of variation is loss aversion. Using data on condominiums in Boston in the 1990s, Genesove and Mayer (2001) show that sellers experiencing a nominal loss set higher list prices, attain a higher selling price, and take longer to sell.

I use one instrument to capture the effect of both of these sources of variation: the log of appreciation in the ZIP repeat-sales house price index since purchase $z_{h\ell t} = \log\left(\frac{\phi_{\ell t}}{\phi_{\ell \tau}}\right)$, where ϕ is the repeat-sales house price index, t is the period of listing, and τ is the period of previous sale. For loss aversion, $z_{h\ell t}$ is a proxy for whether the seller is facing a nominal loss and how large the loss will be because it measures average appreciation in the local area rather than the appreciation of any particular house. For equity extraction, financing and refinancing decisions make the equity of sellers endogenous. $z_{h\ell t}$ is isomorphic to equity if all homeowners take out an identical mortgage and do not refinance and is thus an instrument for the exogenous component of equity. I am agnostic as to the importance of each source of variation in the first stage relationship.

For the instrument to be relevant, $f(z_{h\ell t})$ must be have a significant effect on $p_{h\ell t}$ in the first stage equation (6). I show below that the first stage is strong and has the predicted effect of lowering the list price when appreciation since purchase is high.[9] Importantly, it is smooth and monotonic, so nonlinearity in $f(z_{h\ell t})$ does not drive the results on $g(\cdot)$.

The exclusion restriction for the instrument to be valid is $z_{h\ell t} \perp (u_{h\ell t}, \varepsilon_{h\ell t})$ in Condition 1, which requires that appreciation since purchase $z_{h\ell t}$ have no direct effect on the probability of sale $d_{h\ell t}$, either through the error term $\varepsilon_{h\ell t}$ or through unobserved quality $u_{h\ell t}$. If this is the case, $z_{h\ell t}$ only affects probability of sale through the relative markup $p_{h\ell t} - \tilde{p}_{h\ell t}$. Because I use ZIP $\times$ quarter of listing fixed effects $\xi_{\ell t}$, the variation in $z_{h\ell t}$ comes from sellers who sell at the same time in the same market but purchase at different points in the cycle. Condition 1 can thus be interpreted as requiring that unobserved quality be independent of when the seller purchased.

This assumption is difficult to test because I only have a few years of listings data, so flexibly controlling for when a seller bought weakens the effect of the instrument on price in equation (6) and widens the confidence intervals to the point that any curvature is not statistically significant. Nonetheless, I evaluate the identification assumption in five ways in robustness tests in Appendix C. First, I include observable measures of quality in $X_{h\ell t}$. Second, I show that the observable measures of quality are either uncorrelated with the date of purchase (bedrooms and bathrooms) or roughly linear in date of purchase (age, rooms, lot size) and do not appear to vary systematically with the housing cycle. This implies that any unobservables sorted in the same way as these observables would be captured by a linear time trend. This motivates my third test, which includes a linear time trend in date of purchase or time since purchase. Fourth, I limit the sample to sellers who purchased prior to 2004 and again include a linear time trend, eliminating variation from sellers who purchased near the peak of the bubble or during the bust. In all of these tests, the results remain robust, although standard errors widen with smaller sample sizes. Fifth, I show that the shape of

[9] In the first stage regression, appreciation since purchase enters both through $z_{h\ell t} = \log\left(\frac{\phi_{\ell t}}{\phi_{\ell \tau}}\right)$ and through $X_{h\ell t}$, which includes $\hat{p}^{repeat}_{h\ell t} = \log\left(P_{h\ell\tau}\frac{\phi_{\ell t}}{\phi_{\ell\tau}}\right) = \log(P_{h\ell\tau}) + z_{h\ell t}$. The coefficient on $\log(P_{h\ell\tau})$ and $z_{h\ell\tau}$ entering through $\hat{p}^{repeat}_{h\ell t}$ are restricted to be the same. $f(z_{h\ell t})$ is identified in the first stage through the differential coefficient on $z_{h\ell t}$ and $\log(P_{h\ell\tau})$. I address concerns that the identification of $f(z_{h\ell t})$ is coming from introducing $\hat{p}^{repeat}_{h\ell t}$ linearly but $z_{h\ell t}$ nonlinearly in the first stage by introducing $\hat{p}^{repeat}_{h\ell t}$ with a polynomial of the same order as $f(\cdot)$ in robustness tests, and the results are virtually unchanged.

the estimated demand curve is similar for IV and OLS, which assumes away unobserved quality, although OLS results in a far more inelastic demand curve due to bias created by the positive correlation of price with unobserved quality. If in spite of these robustness tests, homes with very low appreciation since purchase are of substantially lower unobserved quality despite their higher average list price, my identification strategy would overestimate the amount of curvature in the data.[10]

To make the exclusion restriction more plausible, I focus on sellers for whom the exogenous variation is cleanest and consequently exclude four groups from the main analysis sample. I relax these exclusions in robustness tests. First, I drop houses sold by banks after a foreclosure (often called REO sales), as the equity of the foreclosed-upon homeowner should not affect the bank's list price. Second, many individuals who have had negative appreciation since purchase are not the claimant on the residual equity in their homes—their mortgage lender is. For these individuals, appreciation since purchase is directly related to their degree of negative equity, which in turn affects the foreclosure and short sale processes of the mortgage lender or servicer. Because I am interested in time to sale as determined by the market rather than how long a mortgage servicer takes to approve a sale, I exclude these individuals based on two proxies for equity detailed when I describe the data in the next subsection. Second, investors who purchase, improve, and flip homes typically have a low appreciation in their ZIP code since purchase but improve the quality of the house in unobservable ways, violating the exclusion restriction. To minimize the effect of investors, I exclude sellers who previously purchased with all cash, a hallmark of investors. Third, I drop sellers who experience extreme price drops since purchase (over 20 percent) as these are unusual sellers who only have positive equity if they took out a very unusual initial mortgage.

3.1.3 Measurement Error

The second part of Condition 1 requires that $z_{h\ell t}$ is the only reason for variation in $p_{h\ell t} - \tilde{p}_{h\ell t}$. This is a strong assumption because there may be components of liquidity that are unobserved or other reasons that homeowners list their house at a price different from $\tilde{p}_{h\ell t}$, such as heterogeneity in discount rates. If the second part of Condition 1 did not hold, the estimates would be biased because the true $p_{h\ell t} - \tilde{p}_{h\ell t}$ would equal $f(z_{h\ell t}) + \zeta_{h\ell t}$, and the unobserved measurement error $\zeta_{h\ell t}$ enters $g(\cdot)$ nonlinearly. This is an issue because the measurement error induced by unobserved quality is non-classical. In (6), unobserved quality is a residual that is independent of observed quality $\beta X_{h\ell t}$, and so the measurement error induced by $u_{h\ell t}$ is Berkson measurement error, in which the measurement error is independent of the observed component, rather than classical measurement error, in which the measurement error is independent of the truth $\tilde{p}_{h\ell t}$. An instrument such as $z_{h\ell t}$ can address classical measurement error in a non-linear setting, but it cannot address Berkson measurement error, which is why an additional assumption is necessary.

[10] One potential concern is that sellers with higher appreciation since purchase improve their house in unobservable ways with their home equity. However, this would create a positive first stage relationship between price and appreciation since purchase while I find a strong negative relationship.

I use two strategies to show that the bias created by measurement error does not cause significant spurious concavity. First, I prove that if the measurement error created by other sources of variation in the relative markup $p_{h\ell t} - \tilde{p}_{h\ell t}$ is independent of the variation induced by the instrument, the measurement error would not cause spurious concavity. Intuitively, noise in $p_{h\ell t} - \tilde{p}_{h\ell t}$ would cause the observed probability of sale at each observed $p_{h\ell t} - \tilde{p}_{h\ell t}$ to be an average of the probabilities of sale at true $p_{h\ell t} - \tilde{p}_{h\ell t}$s that are on average evenly scrambled. Consequently, the curvature of a monotonically-decreasing demand curve is preserved. An analytical result can be obtained if the true $g(\cdot)$ is a polynomial regression function as in Hausman et al. (1991):

Lemma 1. *Consider the econometric model described by (3) and (5) and suppose that:*

$$z_{h\ell t} \perp (u_{h\ell t}, \varepsilon_{h\ell t}), \tag{7}$$

$$p_{h\ell t} = f(z_{h\ell t}) + \zeta_{h\ell t} + \tilde{p}_{h\ell t}, \tag{8}$$

$\zeta_{h\ell t} \perp f(z_{h\ell t})$, *and the true regression function* $g(\cdot)$ *is a third-order polynomial. Then estimating* $g(\cdot)$ *assuming that* $p_{h\ell t} = f(z_{h\ell t}) + \tilde{p}_{h\ell t}$ *yields the true coefficients of the second- and third-order terms in* $g(\cdot)$*. If* $g(\cdot)$ *is a second-order polynomial, the same procedure yields the true coefficients of the first- and second-order terms.*

Proof. See Appendix C. □

While a special case, Lemma 1 makes clear that the bias in the estimated concavity is minimal if $\zeta_{h\ell t} \perp f(z_{h\ell t})$.

Second, while spurious concavity is a possibility if the measurement error created by other sources of variation in the relative markup were correlated with the instrument, the amount of concavity generated would be far smaller than the concavity I observe in the data. Appendix C presents Monte Carlo simulations that show that if the instrument captures most of the variation in the relative markup $p_{h\ell t} - \tilde{p}_{h\ell t}$ at low levels of appreciation since purchase but very little of the variation at high levels of appreciation since purchase, spurious concavity arises because the slope of $g(\cdot)$ is attenuated for low relative markups but not high relative markups. However, to spuriously generate a statistically-significant amount of concavity, one would need a perfect instrument at low levels of appreciation since purchase and all of the variation in price at high levels of appreciation since purchase to be measurement error. Because this is implausible, I conclude that spurious concavity due to measurement error is not driving my findings.

3.2 Data

I combine data on listings with data on housing characteristics and transactions. The details of data construction can be found in Appendix A. The listings data come from Altos Research, which every Friday records a snapshot of homes listed for sale on multiple listing services (MLS) from several publicly available web sites and records the address, MLS identifier, and list price. The housing characteristics and transactions data come from DataQuick, which collects and digitizes public records from county register of deeds and assessor offices. This data provides a rich one-time snapshot of housing characteristics from 2013 along with a detailed transaction history of each property from 1988 to August 2013 that includes transaction prices, loans, buyer and seller names and characteristics, and seller distress. I limit my analysis to non-partial transactions of single-family existing homes as categorized by DataQuick.

I match the listings data to a unique DataQuick property ID. To account for homes being de-listed and re-listed, listings are counted as contiguous if the same house is re-listed within 90 days and there is not an intervening foreclosure. If a matched home sells within 12 months of the final listing date, it is counted as a sale, and otherwise it is a withdrawal. The matched data includes 78 percent of single-family transactions in the Los Angeles area and 68 percent in the San Diego and San Francisco Bay areas. It does not account for all transactions due to three factors: a small fraction of homes (under 10%) are not listed on the MLS, some homes that are listed in the MLS contain typos or incomplete addresses that preclude matching to the transactions data, and Altos Research's coverage is incomplete in a few peripheral parts of each metropolitan area.

I limit the data to homes listed between April 2008 and February 2013.[11] I drop cases in which a home has been rebuilt or significantly improved since the transaction, the transaction price is below $10,000, or a previous sale occurred within 90 days. I exclude ZIP codes with fewer than 500 repeat sales between 1988 and 2013 because my empirical approach requires that I estimate a local house price index. These restrictions eliminate approximately five percent of listings.

As discussed above, the instrumental variables analysis omits REO sales, investors who previously purchased with all cash, individuals who experience extreme price declines, and individuals with substantial negative equity. I create two different IV samples that identify listings in which the seller has substantial negative equity in two different ways. First, I create a proxy for the equity of all sellers at listing using DataQuick data on the history of mortgage liens against each property along with the loan amount, loan type (fixed or adjustable rate), and an estimate of the interest rate based on loan and property characteristics. The data does not indicate when mortgages are prepaid and omits several features the payment schedule. Consequently, I follow DeFusco (2015) and create a "debt history" for each listed property that estimates the outstanding mortgage debt by making assumptions about unobserved mortgage characteristics and when liens are paid off as detailed in Appendix A. Because the resulting proxy for seller equity is noisy, in the first IV sample I exclude sellers with less than -10 percent estimated equity, and I vary this cutoff in robustness tests. I create a second IV sample by excluding listings in which DataQuick has flagged the sale as a likely short sale or withdrawn listings that are subsequently foreclosed upon in the next two years.

[11] The Altos data begins in October 2007 and ends in May 2013. I allow a six month burn-in so I can properly identify new listings, although the results are not substantially changed by including October 2007 to March 2008 listings. I drop listings that are still active on May 17, 2013, the last day for which I have data. I also drop listings that begin less than 90 days before the listing data ends so I can properly identify whether a home is re-listed within 90 days and whether a home is sold within six months. The Altos data for San Diego is missing addresses until August 2008, so listings that begin prior to that date are dropped. The match rate for the San Francisco Bay area falls substantially beginning in June 2012, so I drop Bay area listings that begin subsequent to that point.

Table 1: Summary Statistics For Listings Micro Data

Sample	All	Prior Trans	IV	IV2	All	Prior Trans	IV	IV2
Only houses that sold?	No	No	No	No	Yes	Yes	Yes	Yes
Transaction	72.30%	74.60%	68.70%	62.70%	100%	100%	100%	100%
Prior Transaction	62.70%	100%	100%	100%	64.70%	100%	100%	100%
REO	22.40%	27.80%	0%	0%	28.70%	35.60%	0%	0%
Short Sale or Subsequent Foreclosure	19.40%	23.60%	13.50%	0%	19.80%	24.30%	15.90%	0.00%
Estimated Equity < -10%	30.90%	49.30%	100%	88.40%	31%	47.90%	100.00%	94.20%
Initial List Price	$644,556	$595,137	$859,648	$861,254	$580,150	$548,132	$824,239	$845,253
Transaction Price					$532,838	$501,588	$758,803	$781,091
Weeks on Market					15.32	16.46	14.01	12.86
Sold Within 13 Wks	44.30%	42.90%	44.80%	42.90%	61.20%	57.50%	0.652	0.685
Beds	3.283	3.239	3.337	3.328	3.264	3.229	3.327	3.322
Baths	2.185	2.126	2.331	2.316	2.141	2.102	2.31	2.308
Square Feet	1,811	1,732	1,969	1,953	1,759	1,702	1943.6	1944.1
N	663,976	416,373	140,344	137,238	480,258	310,758	96,400	86,033

Notes: Each column shows summary statistics for a different sample of listings. The four samples used are the full sample of listings matched to a transaction, houses with an observed prior transaction (or if the observed prior transaction is not counted as a sales pair, for instance because there is evidence the house was substantially renovated), and the first and second IV samples. The first set of four columns provides summary statistics for all listed homes regardless of whether they sell The second four columns limits the summary statistics to houses that sell. The data covers listings between April 2008 and February 2013 in the San Francisco Bay, Los Angeles, and San Diego areas as described in Appendix A. REOs are sales of foreclosed homes and foreclosure auctions. Short sales and subsequent foreclosures include cases in which the transaction price is less than the amount outstanding on the loan and withdrawals that are subsequently foreclosed on in the next two years. The estimation procedure for equity is described in Appendix A, and a -10 percent threshold is chosen because the equity measure is somewhat noisy.

The data set consists of 663,976 listings leading to 480,258 transactions. I focus on the 416,373 listings leading to 310,758 transactions with an observed prior transaction in the DataQuick property history going back to 1988. The two IV samples are substantially smaller because of the large number of REO sales and listings by negative equity sellers from 2007 to 2013. Roughly 28 percent of listings with an observed prior transaction sample are REO sales, and dropping these leads to approximately 300,000 listings. Another 34,000 sales by likely investors who initially purchased with all cash. Of the remaining 266,000 listings, roughly 126,000 have estimated equity at listing under -10% or appreciation since purchase under -20%, so the first IV sample consists of 140,344 listings leading to 96,400 transactions. Roughly 129,000 of the 266,000 listings are flagged as a short sale by DataQuick, subsequently foreclosed upon, or have appreciation since purchase under -20%, leading to a second IV sample of 137,238 listings leading to 86,033 transactions. Table 1 provides summary statistics for the subsamples that I use in the analysis.

3.3 Results

Figure 2 shows first and second stage binned scatter plots for both IV samples: IV sample one which excludes extreme negative equity sellers, and IV sample two which excludes short sales and withdrawals that are subsequently foreclosed upon. The results are similar for both samples. As shown in panel A, the first stage is strong, smooth, and monotonic. This is the variation that identifies the shape of demand and is the x-axis of panel B. The first stage is strong with a joint F statistic for the third order polynomial of the instrument in (6) of 206 in the baseline specification for IV sample one. Panel B shows a clear concave relationship in the second stage, with very inelastic demand for relatively low priced homes and elastic demand for relatively high priced homes. This curvature is also visible in the cubic polynomial fit.

Table 2 shows regression results when $g(\cdot)$ is approximated by quadratic polynomial. Columns 3 and 5 show the IV results for each IV sample. In both cases, there is clear concavity: the quadratic term is negative and highly significant, and the bootstrapped 95 percent confidence interval for the quadratic term is bounded well away from zero.

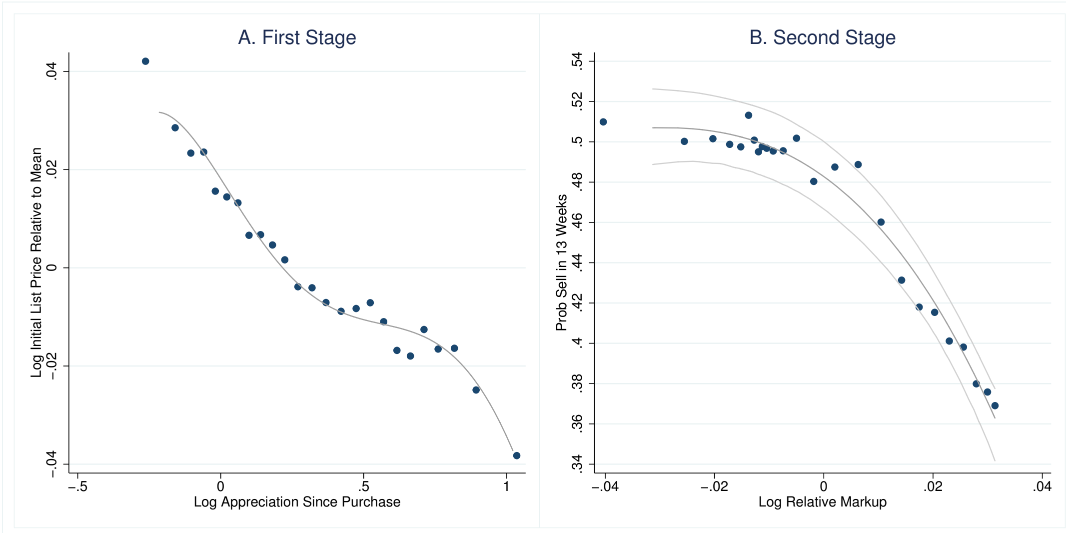
As a point of comparison, Column 1 shows the OLS results that assume away unobserved quality for the full set of sales with a observed prior transaction. The fixed effects are at the ZIP $\times$ quarter $\times$ REO seller $\times$ short seller level to prevent distressed sales from biasing the results. Columns 2 and 4 show similar OLS results for IV sample one and IV sample two. Reassuringly, concavity is not unique to the IV specification. In all three samples, OLS displays clear and significant concavity, and binned scatter plots in Appendix C show that most of the difference across samples is from extreme quantiles that do not drive concavity in the IV specification. The expected bias is also present: the demand curve is flatter because $\tilde{p}_{h\ell t}$ is positively correlated with $p_{h\ell t}$ due to omitted unobserved quality. Finally, while there is slightly more concavity in the IV samples, the 95 percent confidence intervals on the quadratic terms overlap. This suggests that the concavity found in the IV samples is not due to sample selection.

At the mean price, the sample one estimates imply that raising one's price by one percent reduces the probability of sale within 13 weeks by approximately 2.7 percentage points on a base of 48 percentage points, a reduction of 5.6 percent. This corresponds to a one percent price hike increasing the time to sale by five to six days. By contrast, increasing the list price by five percent reduces the probability of sale within 13 weeks by 21.5 percentage points, a reduction of 45 percent. These figures are slightly smaller than those found by Carrillo (2012), who estimates a structural search model of the steady state of the housing market with multiple dimensions of heterogeneity using data from Charlottesville, Virginia from 2000 to 2002. Although we use very different empirical approaches, in a counterfactual simulation, he finds that a one percent list price increase increases time on the market by a week, while a five percent list price increase increases time on the market by nearly a year. Carrillo also finds small reductions in time on the market from underpricing, consistent with the nonlinear relationship found here.

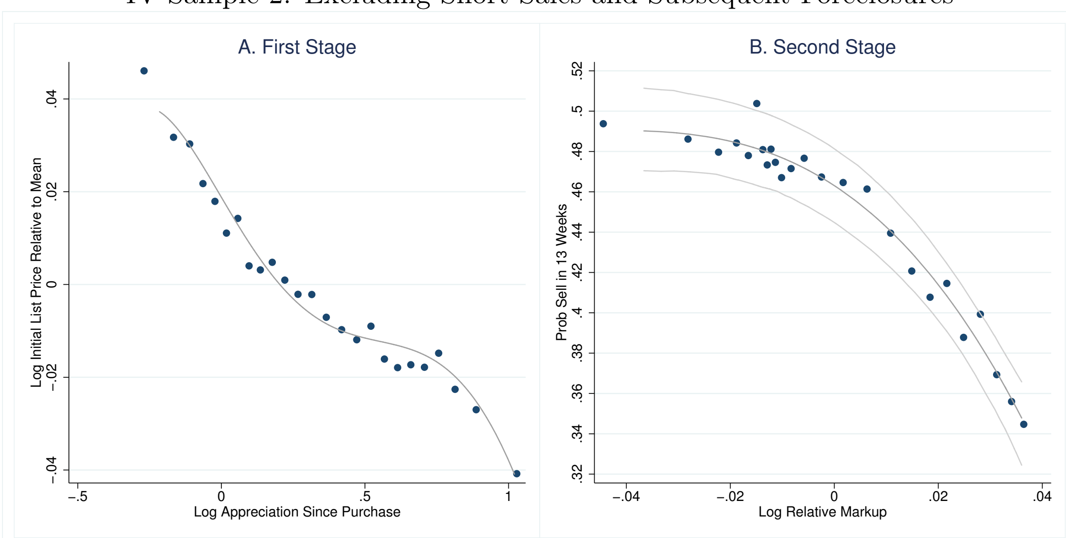
Appendix C shows the finding of concavity is highly robust. Across both samples, the results are robust across geographies, time periods, and specifications, although in a handful of cases restricting

Figure 2: Instrumental Variable Estimates of the Effect of List Price on Probability of Sale

IV Sample 1: Excluding Low Estimated Equity



IV Sample 2: Excluding Short Sales and Subsequent Foreclosures



Notes: For both samples, Panel B shows a binned scatter plot of the probability of sale within 13 weeks net of ZIP $\times$ first quarter of listing fixed effects (with the average probability of sale within 13 weeks added in) against the estimated log relative markup $p - \tilde{p}$. It also shows an overlaid cubic fit of the relationship, as in equation (3). To create the figure, a first stage regression of the log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and repeat sales and hedonic log predicted prices, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup. The figure splits the data into 25 equally-sized bins of this estimated relative markup and plots the mean of the estimated relative markup against the mean of the probability of sale within 13 weeks net of fixed effects for each bin, as detailed in Appendix C. Before binning, the top and bottom 0.5 percent of the log sale price residual and any observations fully absorbed by fixed effects are dropped. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. IV sample 1 drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The grey bands indicate a pointwise 95-percent confidence interval for the cubic fit created by block bootstrapping the entire procedure on 35 ZIP-3 clusters. Panel A shows the first stage relationship between the instrument and log initial list price in equation (6) by residualizing the instrument and the log initial list price against the two predicted prices and fixed effects, binning the data into 25 equally-sized bins of the instrument residual, and plotting the mean of the instrument residual against the mean of the log initial list price residual for each bin. The first-stage fit is overlaid. N = 140,344 observations for IV sample 1 and 137,238 observations for IV sample 2 prior to dropping unique zip-quarter cells and winsorizing.

Table 2: The Effect of List Price on Probability of Sale: Regression Results

Dependent Variable: Sell Within 13 Weeks					
	(1)	(2)	(3)	(4)	(5)
Estimator	OLS	OLS	IV	OLS	IV
Sample	All With Prior Obs	IV Sample 1: Prior Obs Excluding REO, Investors, $<$ -10 % Estimated Equity $>$ 20% Depreciation		IV Sample 2: Prior Obs Excluding REO, Investors, Short Sales $>$ 20% Depreciation	
Controls	ZIP$\times$ Quarter FE Repeat and Hedonic Predicted Price, Distress FE	ZIP X Quarter FE Repeat and Hedonic Predicted Price		ZIP X Quarter FE Repeat and Hedonic Predicted Price	
Constant	0.461***	0.496***	0.480***	0.475***	0.461***
	(0.005)	(0.009)	(0.008)	(0.011)	(0.009)
Linear	-0.216***	-0.293***	-2.259***	-0.295***	-1.932***
	(0.016)	(0.021)	(0.346)	(0.034)	(0.291)
Quadratic	-0.634***	-1.062***	-40.955***	-0.802***	-29.208***
	(0.088)	(0.188)	(10.271)	(0.227)	(7.206)
Quadratic Bootstrapped 95% CI	[-0.832, -0.498]	[-1.518, -0.825]	[-69.168, -28.758]	[-1.319, -0.490]	[-48.241, -20.496]
N	416,373	140,344	140,344	137,238	137,238

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial. This relationship represents the effect of the log relative markup on the probability of sale within 13 weeks. For IV, a first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. For OLS, quality is assumed to be perfectly measured by the hedonic and repeat-sales predicted prices and have no unobserved component. Consequently, the log list price is regressed on fixed effects and the predicted prices and uses the residual as the estimated relative markup into equation (3), as described in Appendix C. Both procedures are weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. For column 1, the full set of listings with a previous observed transaction are used. To prevent distressed sales from biasing the results, the fixed effects are at the quarter of initial listing x ZIP x distress status level. Distress status corresponds to three groups: normal sales, REOs (sales of foreclosed homes and foreclosure auctions), and short sales (cases where the transaction price is less than the amount outstanding on the loan and withdrawals that are subsequently foreclosed on in the next two years). IV sample 1 drops sales of foreclosures, sales of homes with more than a 20 negative appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The number of observations listed is prior to dropping observations that are unique to a ZIP-quarter cell and winsorizing.

to a smaller sample leads to insignificant results. The results are also robust to time trends in date of purchase, limiting the sample to sellers who purchased before the bubble, controlling for other measures of quality and nearby foreclosures, using different functional forms for $f(\cdot)$ and for the observables $X_{h\ell t}$, allowing for differential sorting by letting β vary across time and space, accounting for the uniqueness of a house in its neighborhood, and accounting for different price tiers within ZIP codes, and using alternate measures of whether a house sells quickly. Finally, the results are robust to changing the criteria for inclusion in each IV sample and to using transaction prices rather than list prices, which assuages concerns that bargaining or price wars undo the concavity in list price. Appendix C also shows that concavity is clearly visible in the reduced-form relationship between the instrument and probability of sale, providing further reassurance that the concavity is not being driven by the first stage. The instrumental variable results thus provide evidence of demand concave in relative price for these three MSAs from 2008 to 2013.[12]

4 A Search Model of House Price Momentum

This section introduces an equilibrium search model with concave demand which I calibrate to my micro evidence to quantitatively assess how much concave demand can amplify small frictions that create momentum. The model builds on search models of the housing market, such as Wheaton (1990), Krainer (2001), Novy-Marx (2009), Piazzesi and Schneider (2009), Genesove and Han (2012), Ngai and Tenreyro (2013), and Head et al. (2014). I first introduce a model of a metropolitan area with a fixed population and housing stock, describe the housing market, and show how sellers set list prices. I then add two frictions that create some initial momentum, staggered price setting and backward-looking rule-of-thumb sellers, and define equilibrium. Table 3 summarizes the notation.

4.1 Setting

Time is discrete and all agents are risk neutral. Agents have a discount factor of β. There is a fixed housing stock of mass one, no construction, and a fixed population of size N.[13]

There are four types of homogenous agents: a mass B_t of buyers, S_t of sellers, H_t of homeowners, and R_t of renters. Buyers, sellers, and homeowners have flow utilities (inclusive of search costs) b, s, and h and value functions V_t^b, V_t^s, and V_t^h, respectively. Buyers and sellers are active in the housing market, which is described in the next section. The rental market, which serves as a reservoir of potential buyers, is unmodeled. Each agent can own only one home, which precludes short sales and investor-owners. Sellers and buyers are homogenous but sellers may differ in their list prices.

Each period with probability λ^h and λ_t^r, respectively, homeowners and renters receive shocks that cause them to separate from their current house or apartment, as in Wheaton (1990). A

[12] Aside from the tail end of my sample, this period was a depressed market. The similarity between my results and Carrillo's provide some reassurance that the results I find are not specific to the time period, but I cannot rule out that the nonlinearity would look different in a booming market.

[13] Construction is omitted for parsimony, as it would work against momentum with or without concavity, leaving the relative amount of amplification roughly unchanged. See Head et al. (2014) for a model with construction.

Table 3: Notation in the Model

Variable	Description	Note
	Masses	
N	Total Population (Housing Stock Mass One)	
B_t	Endogenous Mass of Buyers	Value Fn V_t^b
S_t	Endogenous Mass of Sellers	Value Fn V_t^s
R_t	Endogenous Mass of Renters	
H_t	Endogenous Mass of Homeowners	Value Fn V_t^h
	Flow Utilities	
b	Flow Utility of Buyer (Includes search cost)	
s	Flow Utility of Seller (includes search cost)	
h	Flow Utility of Homeowner	
	Moving Shock Probabilities	
λ^h	Prob Homeowner Gets Shock	
λ_t^r	Prob Renter Gets Shock	Exogenous Driving Process
	Other Fixed Parameters	
β	Discount Factor	
L	Probability Seller Leaves Metro Area	
V^0	PDV of Exiting Metro Area	
	Utilities	
ε	Match-Specific One-Time Utility Benefit	$\sim F(\varepsilon)$
υ_h	Permanent House Quality	Mean Zero
	Stochastic Draws	
$\eta_{h,t}$	Noise in υ_h in Binary Signal About Quality, IID Common to All Buyers in Period t	$\sim G(\eta)$
	Parameters / Values	
θ_t^m	Market Tightness $= B/S$ in Submarket $m = \{f, d\}$	Endogenous
$\tilde{\theta}_t$	Vector of θ^m s	Endogenous
$q^m(\theta_t^m)$	Prob. Seller Meets Buyer in m (Matching Fn)	Endogenous
ξ^m	Constant in Matching Function in m	
γ	Matching Function Elasticity in all ms	
p_t	List Price Adjusted for Permanent Quality	Endogenous
Ω_t	Distribution of Prices	Endogenous
ε_t^*	Threshold ε for Purchase	Endogenous
μ	Threshold for Binary Signal	
	Distribution Parameters	
$\underline{\varepsilon}, \bar{\varepsilon}$	Bounds of Dist of $F(\varepsilon)$, Uniform With Mass Point	
χ	Size of Mass Point of Uniform Dist at $\bar{\varepsilon}$	
σ	Generalized Normal Variance Parameter	
ζ	Generalized Normal Shape Parameter	

renter who gets a shock enters the market as a homogenous buyer. A homeowner who gets a shock leaves the MSA with probability L, in which case they become a seller and receive a net present value of V^0 for leaving, and remains in the city with probability $1-L$. If they remain in the city, they simultaneously become a buyer and a homogenous seller. These two roles are assumed to be quasi-independent so that the value functions do not interact and no structure is put on whether agents buy or sell first, as in Ngai and Tenreyro (2013) and Guren and McQuade (2015). Because the population is constant, every time a seller leaves the city they are replaced by a new renter.

I defer the laws of motion that formalize the system until after I have defined the probabilities of purchase and sale. The value function of the homeowner is:

$$V_t^h = h + \beta E_t \left[\lambda^h \left[V_{t+1}^s + LV^0 + (1-L)\, V_{t+1}^b \right] + \left(1-\lambda^h\right) V_{t+1}^h \right]. \tag{9}$$

4.2 The Housing Market

The search process occurs at the beginning of each period and unfolds in three stages. First, sellers post list prices $\hat{p}_t$. Second, buyers observe a noisy binary signal about each house's quality relative to its price. Buyers direct their search either towards houses that appear reasonably-priced for their quality or towards houses that appear to be overpriced for their quality, which defines two sub-markets: follow the signal (submarket f) or do not follow the signal (submarket d). After choosing a submarket, buyers search randomly within the submarket an stochastically find a house to inspect. Third, matched buyers inspect the house and decide whether to purchase it.

At the inspection stage, buyers observe their idiosyncratic valuation for the house ε, which is match-specific, drawn from $F(\varepsilon)$ at inspection, and realized as utility at purchase. They also observe the house's permanent quality υ_h, which is common to all buyers, mean-zero, gained by a buyer at purchase, and lost by a seller at sale. I assume all sales occur at list price, or equivalently that risk neutral buyers and sellers expect that the average sale price will be an affine function of the list price. Letting $p_t \equiv \hat{p}_t - \upsilon_h$ be the quality-adjusted list price, the buyer purchases if his or her surplus from doing so $V_t^h + \varepsilon - p_t - b - \beta V_t^b$ is positive. This leads to a threshold rule to buy if $\varepsilon > p_t + b + \beta V_{t+1}^b - V_t^h \equiv \varepsilon_t^*(p_t)$ and a probability of purchase given inspection of $1 - F(\varepsilon_t^*)$.

The assumption that houses sell at list price is made for tractability.[14] [15] While clearly a simplification, it is a reasonable approximation in two ways. First, for average and median prices it is realistic: Appendix D shows that in the merged Altos-DataQuick micro data, the modal transaction price is the list price, and the average and median differences between the list and transaction price are less than 0.03 log points and do not vary much across years. Second, conditional on unobserved quality, the difference between initial list and transaction prices does not vary with the initial list

[14] This assumption restricts what can occur in bargaining or a price war. Several papers have considered the role of various types of bargaining in a framework with a list price in a steady state search model, including cases in which the list price is a price ceiling (Chen and Rosenthal, 1996; Haurin et al., 2010), price wars are possible (Han and Strange, 2016), and list price can signal seller type (Albrecht et al., 2016).

[15] An important feature of the housing market is that most price changes are decreases. Consequently, the difference between the initial list price and the sale price fluctuates substantially over the cycle as homes that do not sell cut their list price. I abstract from such duration dependence to maintain a tractable state space.

price. To show this, Appendix D uses the IV procedure in Section 3 replacing $d_{h\ell t}$ with the difference between list and transaction prices. There is no strong relationship between relative quality-adjusted list prices and transaction prices, and if anything setting an average price results in a slightly higher transaction price. Consequently, the list price is the best predictor of the transaction price from the perspective of a list-price-setting seller. Since utility is linear, adding adding empirically-realistic *ex-post* bargaining that maintains the mean transaction price as the list price would not alter the seller's list price setting incentives as shown in Appendix D.

At the signal stage, buyers observe a binary signal from their real estate agent or from advertisements that reveals whether each house's quality-adjusted price relative to the average quality-adjusted price is above a threshold μ. However, quality υ_h (or equivalently the observation of the average price) is subject to mean zero noise $\eta_{h,t} \sim G(\cdot)$, where $G(\cdot)$ is assumed to be a fixed distribution.[16] This noise, which represents how well a house is marketed in a given period, is common to all buyers but independent and identically distributed across periods. The signal thus indicates a house is reasonably priced if,

$$p_t - E_{\Omega_t}[p_t] - \eta_{h,t} \leq \mu,$$

where Ω_t is the cumulative distribution function of list prices and the notation $E_{\Omega_t}[\cdot]$ represents an expectation with respect to the distribution of prices Ω_t rather than an intertemporal expectation. Consequently, a house with quality-adjusted price p_t appears reasonably priced and is searched by buyers in submarket f with probability $1 - G(p_t - E_{\Omega_t}[p_t] - \mu)$ and is searched by buyers in submarket d with probability $G(p_t - E_{\Omega_t}[p_t] - \mu)$. I assume that search is more efficient if buyers follow the signal than if they do not because they have the help of a realtor or are looking at better-marketed homes. In equilibrium, buyers follow a mixed strategy and randomize whether they search submarket f or d so that the value of following the signal is equal to the value of not following it. I consider an equilibrium in which all buyers choose the same symmetric strategy with a probability of following the signal of ϕ_t.

After choosing a submarket, buyers search randomly within that sub-market and cannot direct their search to any particular type of home within that market. The probability a house in submarket m meets a buyer is determined according to a constant returns to scale matching function, $q^m(\theta_t^m)$, where θ_t^m is the ratio of buyers to sellers in submarket $m = \{f, d\}$. The probability a buyer meets a seller is then $q^m(\theta_t^m)/\theta_t^m$. The matching function captures frictions in the search process that prevent all reasonably-priced homes and all buyers from having an inspection each period. For instance, buyers randomly allocating themselves across houses may miss a few houses, or there may not be a mutually-agreeable time for a buyer to visit a house in a given period.

The mass of sellers in the f submarket is S_t times the weighted average probability that any given seller is in the f submarket $E_\Omega[1 - G(\cdot)]$, and the mass of sellers in the d submarket is

[16] Because the signal reveals no information about the house's permanent quality υ_h, posted price $\hat{p}_t$, or match quality ε_m, the search and inspection stages are independent.

similarly $S_t E_\Omega [G(\cdot)]$. Consequently, the market market tightness in the f and d submarkets is:

$$\begin{aligned} \theta_t^f &= \frac{B_t^{follow}}{S_t^f} = \frac{B_t \phi_t}{S_t E_{\Omega_t} [1 - G(p_t - E_{\Omega_t}[p_t] - \mu)]} \\ \theta_t^d &= \frac{B_t^{do\ not\ follow}}{S_t^d} = \frac{B_t (1-\phi_t)}{S_t E_{\Omega_t} [G(p_t - E_{\Omega_t}[p_t] - \mu)]}. \end{aligned}$$

The probability a buyer who follows the signal buys a house is then:

$$\begin{aligned} Pr\,[\text{Buy}|\text{Follow}] &= \frac{q^f\left(\theta_t^f\right)}{\theta_t^f} \int \frac{1 - G(p_t - E_{\Omega_t}[p_t] - \mu)}{E_{\Omega_t}[1 - G(p_t - E_{\Omega_t}[p_t] - \mu)]} (1 - F(\varepsilon_t^*(p_t)))\, d\Omega_t(p_t) \\ &= \frac{q^f\left(\theta_t^f\right)}{\phi_t \theta_t} \int (1 - G(p_t - E_{\Omega_t}[p_t] - \mu))(1 - F(\varepsilon_t^*(p_t)))\, d\Omega_t(p_t) \\ &= \frac{1}{\phi_t \theta_t} E_{\Omega_t}\left[d^f\left(p_{t,}\Omega_t, \tilde{\theta}_t\right)\right], \end{aligned}$$

where $\theta_t = B_t/S_t$ is the aggregate market tightness, and

$$d^f\left(p_t, \Omega_t, \tilde{\theta}_t\right) = q^f\left(q_t^f\right)(1 - G(p_t - E_{\Omega_t}[p_t] - \mu))(1 - F(\varepsilon_t^*(p_t))), \tag{10}$$

is the demand curve faced by a seller in the f submarket. Similarly, the probability a buyer buys if they do not follow the signal is:

$$Pr\,[\text{Buy}|\text{Do Not Follow}] = \frac{1}{(1-\phi_t)\theta_t} E_{\Omega_t}\left[d^d(p_{t,}\Omega_t, \theta_t, \phi_t)\right],$$

where,

$$d^d\left(p_t, \Omega_t, \tilde{\theta}_t\right) = q^d\left(\theta_t^d\right) G(p_t - E_{\Omega_t}[p_t] - \mu)(1 - F(\varepsilon_t^*(p_t))), \tag{11}$$

is the demand curve faced by a seller in the d submarket.

Note that the demand curve faced by sellers, which is the *ex-ante* probability of sale for a house with a list price p_t, can be written as:

$$\begin{aligned} d\left(p_t, \Omega_t, \tilde{\theta}_t\right) &= Pr\,[Good\ Signal]\, Pr\,[Sell|Good\ Signal] + Pr\,[Bad\ Signal]\, Pr\,[Sell|Bad\ Signal] \\ &= d^f\left(p_t, \Omega_t, \tilde{\theta}_t\right) + d^d\left(p_t, \Omega_t, \tilde{\theta}_t\right). \end{aligned} \tag{12}$$

Similarly, the total probability a buyer buys given the ϕ_t randomization strategy is:

$$\begin{aligned} Pr\,[Buy] &= \phi_t \frac{1}{\phi_t \theta_t} E_{\Omega_t}\left[d^f\left(p_{t,}\Omega_t, \tilde{\theta}_t\right)\right] + (1-\phi_t)\frac{1}{(1-\phi_t)\theta_t} E_{\Omega_t}\left[d^d(p_{t,}\Omega_t, \theta_t, \phi_t)\right] \\ &= \frac{1}{\theta_t} E_{\Omega_t}\left[d\left(p_t, \Omega_t, \tilde{\theta}_t\right)\right]. \end{aligned}$$

Given these probabilities of purchase and sale, the stock of buyers is equal to the stock of buyers who failed to buy last period plus the stock of renters and flow of new entrants who decide to buy, while the stock of sellers is equal to those sellers who failed to sell last period plus homeowners who put their house up for sale. These are formalized by:

$$B_t = \left(1 - \frac{1}{\theta_{t-1}} E_{\Omega_{t-1}} \left[d\left(p_{t-1}, \Omega_{t-1}, \tilde{\theta}_{t-1}\right)\right]\right) B_{t-1} + \lambda^r_{t-1} R_{t-1} + (1 - L)\, \lambda^h H_{t-1} \tag{13}$$

$$S_t = \left(1 - E_{\Omega_{t-1}} \left[d\left(p_{t-1}, \Omega_{t-1}, \tilde{\theta}_{t-1}\right)\right]\right) S_{t-1} + \lambda^h H_{t-1}. \tag{14}$$

Because there are mass one of homes that can either be owned by a homeowner or up for sale and mass N of agents who can either be renters, homeowners, or buyers,

$$1 = H_t + S_t \tag{15}$$

$$N = R_t + B_t + H_t. \tag{16}$$

These equations together with (13) and (14) implicitly define laws of motion for H_t and R_t.

When a buyer buys, they receive the expected surplus $E\left[\varepsilon - \varepsilon^*_t | \varepsilon > \varepsilon^*_t\right]$ where ε^*_t is a function of p_t. The value of a buyer who follows, $V^{b,f}_t$, a buyer who does not follow $V^{b,d}_t$, and a buyer prior to choosing a submarket V^b_t, are:

$$V^{b,f}_t = b + \beta E_t V^b_{t+1} + \frac{1}{\phi_t \theta_t} E_{\Omega_t} \left[d^f \left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon^*_t | \varepsilon > \varepsilon^*_t\right]\right] \tag{17}$$

$$V^{b,d}_t = b + \beta E_t V^b_{t+1} + \frac{1}{(1-\phi_t)\,\theta_t} E_{\Omega_t} \left[d^d \left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon^*_t | \varepsilon > \varepsilon^*_t\right]\right] \tag{18}$$

$$V^b_t = \max\left\{V^{b,f}_t, V^{b,d}_t\right\}.$$

In equilibrium, buyers are indifferent between the two markets, so $V^{b,f}_t = V^{b,d}_t$ or:

$$\frac{E_{\Omega_t} \left[d^f \left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon^*_t | \varepsilon > \varepsilon^*_t\right]\right]}{E_{\Omega_t} \left[d^d \left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon^*_t | \varepsilon > \varepsilon^*_t\right]\right]} = \frac{\phi_t}{1-\phi_t}. \tag{19}$$

This pins down the fraction of buyers who go to submarket f, ϕ_t. V^b_t can then be rewritten as:

$$V^b_t = b + \beta E_t V^b_{t+1} + \frac{1}{\phi_t \theta_t} E_{\Omega_t} \left[d^f \left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon^*_t | \varepsilon > \varepsilon^*_t\right]\right]. \tag{20}$$

Sellers have rational expectations but set their list price before $\eta_{h,t}$ is realized and without knowing the valuation of the particular buyer who visits their house. The demand curve they face is $d\left(p_t, \Omega_t, \tilde{\theta}_t\right)$, so the seller value function is:

$$V^s_t = s + \beta E_t V^s_{t+1} + \max_{p_t} \left\{ d\left(p_t, \Omega_t, \tilde{\theta}_t\right) \left[p_t - s - \beta E_t V^s_{t+1}\right]\right\}. \tag{21}$$

I solve for the seller's optimal price in the next subsection.

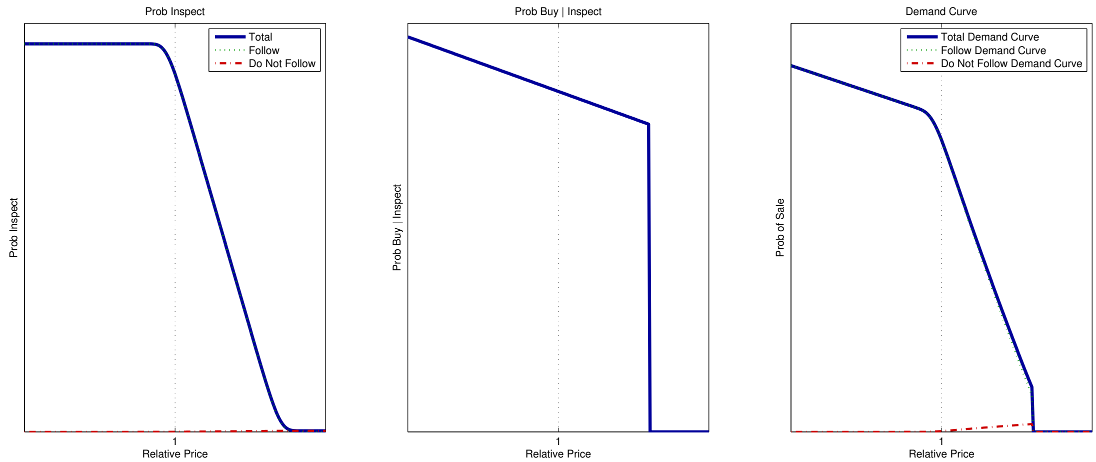
I parameterize the model by assuming distributions for $F(\cdot)$, the distribution of idiosyncratic match quality, and $G(\cdot)$, the noise in the signal. I assume that $F(\varepsilon_m)$ is a uniform distribution on $[\underline{\varepsilon}, \bar{\varepsilon}]$ with a mass point of mass χ at $\bar{\varepsilon}$. In Figure 2, the demand curve for below average priced homes is very flat, which implies a very low density of $F(\cdot)$ at the margin. If there were not a mass point at the top of $F(\cdot)$, the low density would imply a very large upper tail conditional expectation $E[\varepsilon - \varepsilon^* | \varepsilon > \varepsilon^*]$, which in turn implies a very high value of future search to buyers. Adding a mass point allows me to control the value of future search and target a realistic buyer search cost. In practice, this means that there are many buyers who like the property, many who do not, and a few in between. For $G(\cdot)$ I use a type 1 generalized normal distribution with a PDF of $g(x) = \frac{\zeta}{2\sigma\Gamma(1/\zeta)} e^{-(|x-\mu|/\sigma)^{\zeta}}$. This is the same as a normal if the shape parameter ζ is equal to two. When $\zeta > 2$, the PDF is more flat topped" which results in a CDF that is more kinked rather than smoothly s-shaped. This allows me to capture a feature of Figure 2: the demand curve, which inherits the properties of the CDF $G(\cdot)$, is somewhat kinked. These two distributions provide a close fit to the microdata. I also assume that the matching function is Cobb-Douglas $q^m(\theta) = \xi^m \theta^{\gamma}$, as is standard in the housing search literature, with $\xi^f > \xi^d$. While these functional form assumptions matter somewhat for the precise quantitative predictions of the model, they are not necessary for the intuitions it illustrates.

This setup leads to a locally concave demand curve with considerable curvature in the neighborhood of the average price At below average prices, the house receives a good signal with near certainty and the demand curve is dominated by the trade-off between idiosyncratic match quality ε_m and price, so demand is less elastic. At above average prices, the demand curve is dominated by the fact that perturbing the price affects whether the house gets a good signal or a bad signal, in which case it ends up in a market with few buyers who match with less efficiency. To illustrate how the demand curve is built up from its various components, Figure 3 shows the shapes of the probability of inspection $q\left(\theta_t^f\right)(1 - G(p_t - E_{\Omega_t}[p_t] - \mu)) + q\left(\theta_t^d\right) G(p_t - E_{\Omega_t}[p_t] - \mu)$, the probability of purchase conditional on inspection $1 - F(\varepsilon^*(p_t))$, and the overall demand curve faced by sellers $d(p_t, \Omega_t, \theta_t)$, equal to the product of the first two panels. The probability of inspection and overall demand curve are split into the f and d components, revealing that the d submarket has negligible effect on the overall demand curve because it has few buyers. Note that the axes are switched from a standard Marshallian supply and demand diagram to be consistent with the empirical estimates.

4.3 Price Setting

The strategic complementarity enters through the seller's optimal price. Sellers have monopoly power due to costly search, and the optimal pricing problem they solve in equation (21) is the same as that of a monopolist facing the demand curve d except that the marginal cost is replaced by the seller's outside option of searching again next period $s + \beta E_t V_{t+1}^s$. The optimal pricing strategy is a markup over this outside option $s + \beta V_{t+1}^s$, and the markup varies inversely with relative price, creating a strategic complementarity. With an initial friction that generates some heterogeneity in the speed of adjustment, the strategic complementarity causes quick adjusters to adjust their price

Figure 3: The Concave Demand Curve in the Model



Notes: The figures are generated using calibration described in Section 5. All probabilities are calculated assuming all other sellers are setting the steady state price and considering the effect of a unilateral deviation. The first panel shows the total probability of inspection and the components coming form the f and d submarkets, with the f submarket almost entirely overlapping the total and the d submarket essentially zero because few buyers are in the d submarket. The second panel shows the probability of purchasing given inspection. The third panel shows the demand curve, which is the product of the two. Again, the f submarket demand curve d^f is essentially on top of the total demand curve d and d submarket demand curve d^d is near zero. Note that the axes are swapped from the traditional Marshallian supply and demand diagram in order to be consistent with the empirical analysis in Section 3.

more gradually when fundamentals change: $s+\beta V^s_{t+1}$ jumps upon the change in fundamentals, but raising the list price above the market average erodes the markup, so the optimal price does not change much on impact.

To formalize these intuitions in my model, I focus on a symmetric equilibrium.[17] Sellers do not internalize that their choice of p_t affects the average price, which they treat as given. Seller optimization implies:

Lemma 2. *The seller's optimal list price at the interior optimum is:*

$$\begin{aligned} p_t &= s+\beta E_t V^s_{t+1} + E_t\left[\frac{-d\left(p_t,\Omega_t,\tilde{\theta}_t\right)}{\frac{\partial d\left(p_t,\Omega_t,\tilde{\theta}_t\right)}{\partial p_t}}\right] \\ &= s+\beta E_t V^s_{t+1} + \frac{1}{\frac{f(\varepsilon^*_t)}{1-F(\varepsilon^*_t)} + \frac{g\left(p_t-E_{\Omega_t}[p_t]-\mu\right)}{1-G\left(p_t-E_{\Omega_t}[p_t]-\mu\right)}\left(1-\frac{1}{G\left(p_t-E_{\Omega_t}[p_t]-\mu\right)}\frac{d^d\left(p_t,\Omega_t,\tilde{\theta}_t\right)}{d\left(p_t,\Omega_t,\tilde{\theta}_t\right)}\right)}, \end{aligned} \tag{22}$$

where d^d is defined by (11) and d is defined by (12).

[17] Although the seller's problem may not be globally concave, I focus on an interior optimum and later check that the interior optimum is the global optimum by simulation. This turns out not to be a concern in the baseline calibration in Figure 3 as the mass point in the idiosyncratic taste distribution occurs before the probability of inspection curve flattens. In some alternate calibrations, the mass point is further out, and the demand curve is non-concave.

Proof. See Appendix E. □

In equation (22), the seller markup is written as an additive markup equal to the reciprocal of the semi-elasticity of demand, $\frac{-d(p_t,\Omega_t,\theta_t)}{\frac{\partial d(p_t,\Omega_t,\theta_t)}{\partial p_t}}$. The semi-elasticity, in turn, is equal to the sum of the hazard rates of the idiosyncratic preference distribution $F(\cdot)$ and the distribution of signal noise $G(\cdot)$ adjusted for the share of sales that occur in the d submarket, the term in parenthesis. This creates a local strategic complementarity because the elasticity of demand rises as relative price increases, causing the optimal additive markup to fall and pushing sellers to set prices close to those of others. Mathematically, this works through relative price $p_t - E_{\Omega_t}[p_t]$ entering the hazard rate of the signal $G(\cdot)$, which is rising in relative price so the additive markup is falling in relative price.[18]

However, in a rational expectations equilibrium in which all sellers can set their price flexibly, all sellers choose the same list price and $p_t = E_{\Omega_t}[p_t]$, so there is no change in relative prices to affect the markup. A shock to home values thus causes list price to jump proportionally to the seller's outside option, and there is no momentum. In the terminology of Ball and Romer (1990), concave demand is a real rigidity that only amplifies nominal rigidities.

Consequently, I introduce frictions that generate some heterogeneity in the insensitivity of prices to fundamentals. As discussed in Section 2, there are several frictions that the literature has identified that act in such a manner, and I am agnostic as to which underlying frictions are at work in practice. In this paper I separately introduce two tractable, transparent, and well-understood frictions, a small fraction of rule-of-thumb sellers and staggered pricing, and demonstrate concave demand's ability to amplify each of them. I call these the "rule of thumb model" and the "staggered pricing model" and define their equilibria separately. I leave a formal analysis of other frictions that may interact with concave demand to future work.

4.4 Source of Insensitivity 1: A Small Fraction of Rule-of-Thumb Sellers

Since Case and Shiller (1987), sellers with backward-looking expectations have been thought to play an important role in housing markets. Previous models assume that all agents have backward-looking beliefs (*e.g.*, Berkovec and Goodman, 1996), but some observers have found the notion that the majority of sellers are non-rational unpalatable given the financial importance of housing transactions for many households. Indeed, recent evidence from surveys and experiments finds significant heterogeneity in backward-looking expectations: Kuchler and Zafar (2016) analyze survey expectations and find significant extrapolation by lower-educated households that make up 44 percent of the sample but minimial extrapolation by higher-educated households, and Armona et al. (2016) estimate that 41 percent of households are extrapolators using an experimental intervention. Consequently, I introduce a small number of rule-of-thumb sellers, as in Campbell and Mankiw (1989), and assess quantitatively what fraction of sellers is needed to be non-rational to explain the momentum in data, similar to Gali and Gertler (1999).

[18] Because few buyers are in the d submarket, the term in parenthesis is near unity.

I assume that at all times a fraction $1-\alpha$ of sellers are of type R (rational) and set their list price p_t^R rationally according to Lemma 2 and (22) but a fraction α of sellers are of type E (extrapolator) and use a backward-looking rule of thumb to set their list price p_t^E. Specifically, they set their price equal to the most recently observed price plus a fraction of the most recently observed inflation:

$$p_t^E = \frac{p_{t-2} + p_{t-3} + p_{t-4}}{3} + \psi \left(\frac{p_{t-2} + p_{t-3} + p_{t-4}}{3} - \frac{p_{t-5} + p_{t-6} + p_{t-7}}{3} \right), \tag{23}$$

where p_t is the transaction-weighted average price at time t:

$$p_t = \frac{\alpha d_t^E p_t^E + (1-\alpha)\, d_t^R p_t^R}{\alpha d_t^E + (1-\alpha)\, d_t^R}. \tag{24}$$

Such a rule is a common assumption in models with backward-looking expectations and in the New Keynesian literature and is frequently motivated by limited knowledge, information costs, and extrapolative biases (*e.g.*, Hong and Stein, 1999; Fuster et al. 2010).[19]

For tractability and parsimony, I assume that regardless of whether rational or backward-looking sellers sell faster, inflows adjust so that α of the active listings are houses owned by backward-looking sellers at all times. To conserve notation, in the model with rule of thumb sellers, S_t refers to the total number of sellers, but V_t^s is now the value function for the rational sellers. V_t^s remains as in equation (21), and the value function of a buyer remains (20), but now there are two prices p_t^E and p_t^R in the market.

4.5 Source of Insensitivity 2: Staggered Price Setting

Prices in housing markets are adjusted only infrequently, with the median price lasting two months as shown in the Altos listings data in Appendix D. This is the case because it takes time to market a house and collect offers, and lowering the price frequently can signal that the house is of poor quality. While likely not the most important pricing friction in housing markets, infrequent price adjustment has the virtue of being familiar and tractable. I introduce it into the baseline model by assuming that groups of sellers set prices in a staggered fashion as in Taylor (1980).

In particular, I assume there are N groups of sellers that set prices every N periods, typically using $N = 2$ in monthly simulations. Denote the prices p_t, value functions V_t^s, seller masses S_t, and purchase thresholds ε_t of a vintage of sellers that set prices $\tau = \{0, ..., N-1\}$ periods ago by τ superscripts. Buyers receive the same signals buyer's problem and value function remain the same, while the seller's value function is as in (21), except the value function for $V_t^{s,\tau}$ has V_{t+1}^s terms replaced by $V_{t+1}^{s,\tau+1}$ for $\tau = \{0, N-2\}$ and by $V_{t+1}^{s,0}$ for $\tau = N-1$.

Seller optimization implies an optimal list price that is reminiscent of Taylor or Calvo pricing:

[19] I use three-month lag to match the lag with which house price indices are released. I use three-month averages to correspond to how major house price indices are constructed and to smooth out saw-tooth patterns that emerge with non-averaged multi-period lags. I microfound such a rule using a model of limited information and near rationality in Appendix E

Lemma 3. *If posted prices last N periods, the seller's optimal reset price p_t^0 is:*

$$p_t^0 = \frac{\sum_{\tau=0}^{N-1} \beta^\tau D_t^\tau \left(p_t^0\right) \Psi_t^\tau \varphi_t^\tau}{\sum_{\tau=0}^{N-1} \beta^\tau D_t^\tau \left(p_t^0\right) \Psi_t^\tau} \tag{25}$$

where $D_t^j(p) = E_t \left[\prod_{\tau=0}^{j-1} \left(1 - d^\tau \left(p, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)\right)\right] d\left(p, \Omega_{t+j} + \tilde{\theta}_{t+j}\right)$ is the expected probability the house is sold j periods after the price is set, $\Psi_t^\tau = E_t \left[\frac{\frac{-\partial d\left(p_t, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)}{\partial p_t}}{d\left(p_t, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)}\right]$ is the expected semi-elasticity of demand with respect to price after τ periods from Lemma 2, $\varphi_t^\tau = s + E_t V_{t+\tau+1}^{s,\tau+1} + \frac{1}{\Psi_t^\tau}$ is the expected optimal flexible reset price τ periods after the price is set, and $V_{t+N}^{s,N} = V_{t+N}^{s,0}$.

Proof. See Appendix E. □

As is standard in staggered pricing models, the optimal price is a weighted average of the optimal flexible prices that are expected to prevail on the equilibrium path until the seller can reset his or her price. The weight put on the optimal flexible price in period $t + \tau$ is equal to the discounted probability of sale in period $t + \tau$ times the semi-elasticity of demand in period $t + \tau$. Intuitively, the seller cares more about periods in which probability of sale is higher but also about periods in which demand is more elastic because perturbing price has a larger effect on profit.

In addition to the new price setting rule, the law of motion for sellers (14) needs to be altered to N different laws of motion for each of the the N groups of sellers each with separate prices. These modifications are relegated to Appendix E.

4.6 Equilibrium

I add a stochastic shock process to the model to examine its dynamic implications. The results do not depend qualitatively or qualitatively depend on the particular shock used, but the positive correlation between price and volume in the data implies that demand-side shocks dominate. For simplicity, I use a shock to the entry rate of renters λ_t^r so that a positive shock causes the entry of potential buyers into the market, increasing demand and pushing up prices.[20] An example of such a shock would be a change in credit standards for new homeowners or changes in the price expectations of renters. I implement the shock by assuming that λ_t^r follows a mean-reverting AR(1) process:

$$\lambda_t^r = \bar{\lambda}^r + \rho\left(\lambda_{t-1}^r - \bar{\lambda}^r\right) + u_t \text{ with } u_t \sim N\left(0, \sigma_\eta^2\right) \text{ and iid.} \tag{26}$$

An equilibrium with a fraction α of backward-looking sellers is defined as:[21]

[20] See Guren (2015), a previous working paper version of this paper, for a model with an endogenous entry decision whereby agents who receive shocks have the opportunity to pay a randomly-drawn fixed cost to avoid entry. The working paper shows how momentum interacts with endogenous entry to explain the relationships between price, volume, and inventory in the data, in particular the strong "housing Phillips curve" relationship between price changes and inventory levels.

[21] An analogous equilibrium with N groups of backward-looking sellers is defined in Appendix E. Aside from switching $i \in \{E, R\}$ for $\tau = \{0, ..., N-1\}$, it differs from the above definition of an equilibrium with backward-looking sellers in three key ways. First, prices are (25) for sellers that can reset their prices and fixed for sellers that

Definition 1. Equilibrium with a fraction α of backward-looking sellers is a set of prices p_t^i, demands $d\left(p_t^i, \Omega_t, \tilde{\theta}_t\right)$, and purchase cutoffs $\varepsilon_t^{*,i}$ for each type of seller $i \in \{E, R\}$, a transaction-weighted average price p_t, rational seller, buyer, homeowner, and renter value functions V_t^s, V_t^b, V_t^h, a probability that buyers follow the signal ϕ_t, stocks of each type of agent B_t, S_t, H_t, and R_t, and a shock to the flow utility of renting x_t satisfying:

1. Optimal pricing for rational sellers (22) and the pricing rule (23) for backward-looking sellers, which depends on lagged transaction-weighted average prices (24);
2. Optimal purchasing decisions by buyers: $\varepsilon_t^{*,i} = p_t^i + b + \beta V_{t+1}^b - V_t^h$;
3. The demand curve for each type of seller $i \in \{E, R\}$ in the f submarket (10), the d submarket, (11), and the aggregate (12), all of which result from buyer search behavior;
4. The value functions for buyers (20), rational sellers (21), homeowners (9);
5. The laws of motion for buyers (13) and sellers (14) and the closed system conditions for homes (15) and people (G) that implicitly define the laws of motion for homeowners and renters;
6. Buyers are indifferent across markets (19);
7. All agents have rational expectations that λ_t^r evolves according the AR(1) process (26).

The model cannot be solved analytically, so I simulate it numerically using a log-quadratic approximation pruning higher-order terms as in Kim et al. (2008) around a steady state described in Appendix E in which $u_t = 0 \ \forall \ t$ implemented in Dynare (Adjemian et al., 2013).[22] Appendix G shows that the impulse responses are almost identical in an exactly-solved deterministic model with an unexpected permanent shock, so approximation error is minimal.

5 Amplification of Momentum in the Calibrated Model

To quantitatively assess the degree to which concave demand curves amplify house price momentum, this section calibrates the model to the empirical findings presented in Section 3 and a number of aggregate moments.

5.1 Calibration

In order to simulate rule of thumb model, 22 parameters listed in Table 5 must be set. The staggered pricing model requires two fewer parameters. This section describes the calibration procedure and targets, with details in Appendix F. Because a few parameters are based on limited data

cannot. Second, the laws of motion for each vintage of sellers in the Appendix replace the laws of motion in the text. Third, the value functions for each vintage of sellers are similarly altered.

[22] Because of the mass point in the $F(\cdot)$ distribution, the model is not smooth. However, a perturbation approach is appropriate because the mass point at $\bar{\varepsilon}$ is virtually never reached (less than 0.1 percent of the time in simulations).

and subject to some uncertainty, I use the baseline calibration for exposition and use 14 different parameterizations to determine a plausible range for the amplification of each underlying friction.

Three components of the calibration control the shape of the demand curve and thus have a first-order impact on momentum: the local density of the idiosyncratic quality distribution $F(\cdot)$ controls the elasticity of demand for low-priced homes that are certain to be visited; σ and ζ, the variance and shape parameters of the signal distribution, control how much the elasticity of demand changes as relative price increases; and μ, the threshold for being overpriced, controls where on the curve the average price lies. The other parameters have a second order effect on momentum. Consequently, the first step of the calibration sets these three components to match the instrumental variable binned scatter plot from Section 3. The second step calibrates the rest of the model to match steady state and time series moments.

For the first step, I approximate the probability of sale as a function of a few key parameters, the relative list price I observe in the data, and a fixed effect that absorbs the aggregate market conditions so that the model can be directly compared to my empirical specification. This allows me to approximate the model demand curve out of steady state with the heterogeneity in the data for the purposes of calibration and then conduct dynamic simulations with the heterogeneity suppressed to maintain a tractable state space. Specifically, Appendix E shows that the probability of sale at the time the list price is posted can be approximated as:

$$d\left(p_t - E_{\Omega_t}[p_t]\right) \approx \kappa_t \left(1 - F\left(\varepsilon^*_{mean} + p_t - E_{\Omega_t}[p_t]\right)\right) \times \left[\begin{array}{l} \left(\frac{\phi_{mean}}{E_{\Omega_t}\left[1-G\left(p_t - E_{\Omega_t}[p_t]-\mu\right)\right]}\right)^{\gamma}\left[1 - G\left(p_t - E_{\Omega_t}[p_t] - \mu\right)\right] \\ +\frac{\xi^d}{\xi^f}\left(\frac{(1-\phi_{mean})}{E_{\Omega_t}\left[G\left(p_t - E_{\Omega_t}[p_t]-\mu\right)\right]}\right)^{\gamma} G\left(p_t - E_{\Omega_t}[p_t] - \mu\right) \end{array}\right], \tag{27}$$

where κ_t is a fixed effect that summarizes the state of the market at time t, and ε^*_{mean} and ϕ_{mean} are the mean values of these variables over the cycle. Appendix E also explains why the approximation error is small. I solve for ϕ_{mean} by approximating it by its steady state value using a steady-state version of (19). (27) is then used to simulate the probability of sale in three months for each $p - E_\Omega[p_t]$, and the density of $F(\cdot)$, μ, and σ are chosen to minimize the mean squared error between the simulated demand curve and the IV binned-scatter plot with κ_t chosen match the average probability of sale.[23] [24] [25]

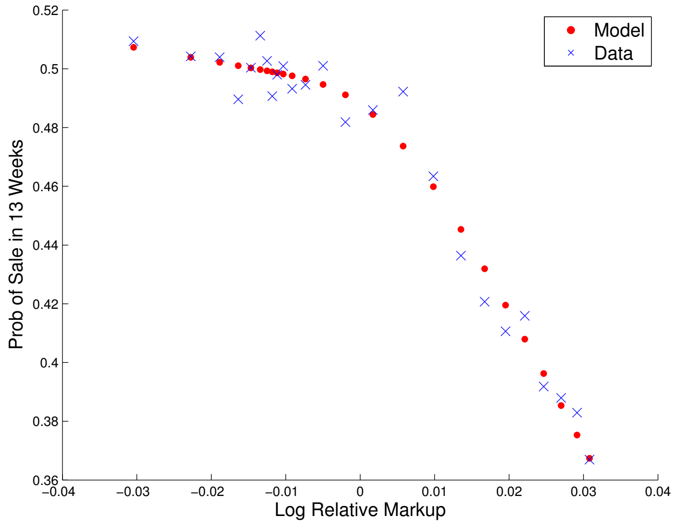
Evaluating (27) requires values for $\frac{\xi^d}{\xi^f}$, ε^*_{mean}, and a parametrization of $F(\cdot)$ given its density.

[23]To minimize the importance of outliers, 2.5 percent of the data is Winsorized from each end rather than 0.5 percent in Section 3.

[24]Setting ζ by minimizing the distance between the model and data leads to a very large ζ that leads to numerical error when the dynamic model is solved using perturbation methods. Consequently, I choose $\zeta = 8$, which gets nearly all the way to the improvement in mean squared error from increasing ζ above two while reducing numerical error. The results are not sensitive to this choice of ζ.

[25]Through equations (21) and (22), the seller search cost is determined by the elasticity of demand given the steady state price and probability of sale. In Figure 2, the zero point is just on the inelastic side of the demand curve, yielding an extremely high seller search cost. Because the zero point corresponding to the average price is not precisely estimated and depends on the deadline used for a listing to count as a sale, I use a zero point within one percent of the estimated zero point that gives a more plausible demand elasticity and seller search cost.

Figure 4: Model Fit Relative to Instrumental Variable Estimates



Notes: The Xs are the binned scatter plot from the IV specification with 2.5 percent of the data from each end Winsorized to reduce the effects of outliers. The dots are the simulated probabilities of sale in three months at each price calculated using (27) and approximating ϕ_t by its steady state value using (19) as described in the text.

The baseline values are described here, and the parameters are permuted below. I assume $\varepsilon^*_{mean} =$ \$100k, which I show in robustness tests is a normalization that has no impact on the economics of the model. I also assume a value of $\xi^d/\xi^f = 1/2$. This has no analog in the data, and I show in robustness checks that it is of minimal importance for my quantitative results.[26] To fully parameterize $F(\cdot)$, I introduce two additional moments that along with the assumed ε^*_{mean} and density pin down $\underline{\varepsilon}$, $\bar{\varepsilon}$, and χ: the average fraction of home inspections that lead to a purchase $1 - F(\varepsilon^*_{mean})$ and the average mean excess function $E[\varepsilon - \varepsilon^*_{mean} | \varepsilon > \varepsilon^*_{mean}]$. The average fraction of home inspections that lead to a purchase is set to 1/10 to match buyer surveys from National Association of Realtors surveys analyzed by Genesove and Han (2012). The mean excess function is selected to match a reasonable target for the buyer flow cost of 0.75 percent of the purchase cost of the house per month, so that the average seller incurs 3 percent of the purchase cost as search costs, and this parameter is varied in robustness tests.

Figure 4 shows the IV binned scatter plot for the first IV sample alongside the model's predicted three-month probability of sale for the (F density, σ, μ) that minimize the distance between the model and the data. The demand curve in the calibrated model captures the curvature in the data well.

The second step in the calibration sets the remaining parameters to match steady state moments listed in the first three panels of Table 4 as detailed in Appendix F. These targets are either from

[26] I choose a value of 1/2 to limit the degree of non-convexity in the model. If ξ^d is high enough relative to ξ^f, sellers may have an incentive to deviate and set a price of $\bar{\varepsilon}$ when prices are rising and buyers visit rarely. Appendix E shows numerically that with $\xi^d/\xi^f = 1/2$ this never happens. Empirically, I rule out a substantially higher ξ^d because the stronger incentive to deviate would generate asymmetries in house prices not present in the data.

Table 4: Calibration Targets For Baseline Calibration

Steady State Parameter or Moment	Value	Source / Justification
	Parameters	
γ (Matching Function Elasticity)	0.8	Genesove and Han (2012)
L (Prob. Stay in MSA)	0.7	Anenberg and Bayer (2015)
	Aggregate Targets	
Annual Discount Rate	5%	
Time on Market for Sellers	4 Months	Approx average parameter value in literature
Time on Market for Buyers	4 Months	$\approx$ Time to sell (Genesove and Han, 2012)
Homeownership Rate	65%	Long run average, 1970s-1990s
Time in House For Owner Occupants	9 Years	American Housing Survey, 1997-2005
Prob Purchase | Inspect	0.1	Mean buyer visits 10 homes (Genesove and Han, 2012)
	Assumed Values	
Steady State Price	$760k	Average transaction price in IV sample
h (Flow Utility of Homeowner)	$6.78k	2/3 of House Falue From Flow Util (Normalization)
ξ^d/ξ^f	0.5	Limited Incentive to "Fish"
ε^* in steady state	$100k	Normalization
b/P (Flow Utility of Buyer Rel To Price)	.75% of Price	Average total buyer search costs 3% of price
ψ	0.4	Based on Case et al. (2012)
	Time Series Moments	
SD of Annual Log Price Changes	0.065	CoreLogic national HPI adjusted for CPI, 1976-2013
ρ (Monthly Persistence of AR1 Shock)	0.950	Head et al. (2014, 2016) Autocorr of Local Pop Growth

Table 5: Calibrated Parameter Values for Baseline Rule of Thumb Model

Parameter	Interpretation	Value	Parameter	Interpretation	Value
β	Monthly Discount Factor	0.996	-b/P	Flow Util of B (search cost)/Price	0.75%
γ	Matching Fn Elasticity	0.8	-s/P	Flow Util of S (search cost)/Price	2.1%
ξ^f	Matching Fn Efficiency, Follow	2.540	$\bar{\varepsilon}$	Upper Bound of F Dist	$ 161 k
ξ^d	Matching Fn Efficiency, Defy	1.270	$\underline{\varepsilon}$	Lower Bound of F Dist	-$5,516 k
λ^h	Monthly Prob H Moving Shock	0.009	χ	Weight of Mass Point at $\bar{\varepsilon}$	0.090
$\bar{\lambda^r}$	Ave Monthly Prob R Moving Shock	0.013	σ	Variance Param in $G(\cdot)$	39.676
N	Population	1.484	ζ	Shape Param in $G(\cdot)$	8
L	Prob Leave MSA	0.7	μ	Threshold for Signal	39.676
ψ	AR(1) Param in Rule of Thumb	0.4	σ_η	SD of Innovations to AR(1) shock	0.00004
V^0	NPV of Leaving MSA	$2,776 k	ρ	Persistence of AR(1) shock	0.950
h	Flow Util of H	$6.783 k	α	Fraction Backward Looking	0.299

Notes: These parameters are for the baseline calibration. The calibration is monthly.

other papers or are long-run averages for the U.S. housing market, such as the homeownership rate, the average amount of time between moves for buyers and renters, and the average time on the market for buyers and sellers. The more speculative targets are varied in robustness tests.

To calibrate the driving shock process which controls the rate at which renters become buyers, I match two time series moments as indicated by the bottom panel of Table 4. The monthly persistence of the shock is set to match the persistence of local income shocks as in Glaeser et al. (2014). The variance of the iid shock is set to match the standard deviation of annual log price changes in stochastic simulations.

For the backward-looking model, I adjust α and recalibrate the model until the impulse response to the renter entry shock matches the matches the 36 months of positively autocorrelated price changes in the AR(5) impulse response estimated on the CoreLogic national house price index in Section 2. Table 5 summarizes the baseline calibrated parameter values for the backwards-looking model. For the staggered pricing model, I use $N = 2$ groups in a monthly calibration to match the median time to adjust price in the data described in Appendix D. Because I cannot generate enough momentum to match the data using the staggered pricing model, I use the backward-looking calibration procedure and then report results that take out backward-looking sellers and add staggering.

5.2 Quantitative Results on Amplification

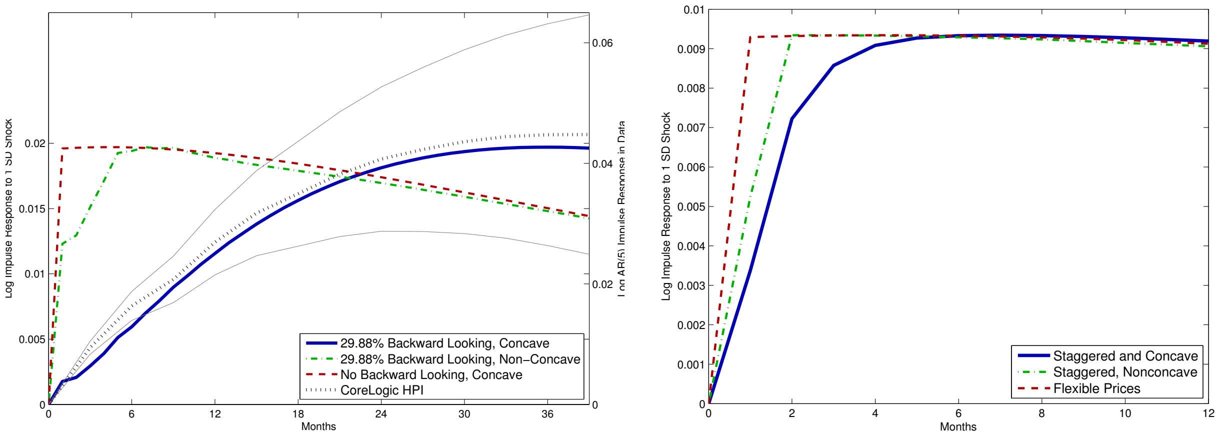
To assess the degree of momentum in the data and in the model, I compare the calibrated rule of thumb and staggered pricing models to a frictionless model and to calibrated models with either backward-looking sellers and staggered pricing but no concavity. The simulations without concavity use a demand curve with the same steady state probability of sale and additive markup for the average house as the concave model, but the markup is constant regardless of the relative price as detailed in Appendix E.

Figure 5 shows the impulse responses graphically by plotting impulse responses under the baseline calibration. The impulse response is computed as the average difference between two sets of simulations that use the same sequence of random shocks except for one period in which an additional standard deviation shock is added. Impulse responses for downward shocks are approximately symmetric and shown in Appendix G.

Panel A shows these impulse responses for rule of thumb model. The solid line shows the model impulse response that attains a 36 month impulse response with 30 percent backward-looking sellers, while the dotted line shows the estimated AR(5) impulse response from the CoreLogic data with the 95 percent confidence interval shown as thin grey lines. The two impulse responses nearly identical: they both jump very little on impact and rise smoothly before flattening out at 36 months. The dashed line shows the model without backward-looking sellers but with concave demand. In this case, the optimal price jumps nearly all the way to its peak level immediately. There is essentially no momentum because there is no initial stickiness for the strategic complementarity to amplify. The dash-dotted line shows the non-concave demand impulse response. Prices jump over half of

Figure 5: Price Impulse Response Functions: Model and Data

A: Rule of Thumb Model B: Staggered Pricing Model



Notes: Panel A figure shows impulse responses to a one standard deviation shock to the renter probability of becoming a buyer in the rule of thumb model with and without concavity as well as a fully-flexible model ($\alpha = 0$). The calibration removing concave demand maintains the steady state markup and probability of sale as described in Appendix E.. Also shown on the right vertical axis in the figure in the dotted black line and with grey 95% confidence intervals is the impulse response to a one standard deviation price shock estimated from a quarterly AR(5) for the seasonally and CPI adjusted CoreLogic national house price index for 1976-2013, as in Figure 1. The vertical axes of the model and AR(5) are different because the AR(5) is a quarterly shock, while the model is a monthly shock. Panel B shows impulse responses to a one standard deviation shock to the renter probability of becoming a buyer in the staggered pricing model as well as a model with no staggering and a model with no concavity. Simulated impulse responses are calculated by differencing two simulations of the model from periods 100 to 150, both of which use identical random shocks except in period 101 in which a one standard deviation negative draw is added to the random sequence, and then computing the average difference over 100 simulations.

the way to their peak value upon the impact of the shock and continue to rise for seven months, at which point they begin to mean revert. One can generate a 36 month impulse response without concave demand, but this requires 74 percent of sellers to be backward looking.[27] [28]

Far fewer backward-looking sellers are needed to match the data with concave demand in the rule-of-thumb model because the strategic complementarity creates a two-way feedback. When a shock occurs, the backward-looking sellers are not aware of it for several months, and the rational sellers only slightly increase their prices so that they do not dramatically reduce their chances of attracting a buyer. When the backward-looking sellers do observe increasing prices, they observe a much small increase than in the non-concave case and gradually adjust their price according to their AR(1) rule, reinforcing the incentives of the rational sellers not to raise their prices too quickly.

Panel B shows similar impulse responses for the staggered model. Again, the solid line shows the

[27]The 30 percent backward-looking sellers I find are necessary to explain the data is slightly below the 40 to 50 percent of the population that is significantly extrapolative found by Kuchler and Zafar (2016) and Armona et al. (2016). This is likely the case because the model excludes several strong arbitrage forces that work against momentum such as construction and endogenous entry, which would increase the necessary fraction of backward-looking sellers. 30 percent is also of the same order of magnitude as Gali and Gertler (1999), who find find that 26 percent of firms are backward looking in a structurally estimated New Keynesian model.

[28]Because rational sellers are incentivized to "imitate" the backward-looking sellers, the loss from failing to optimize for the backward-looking sellers is relatively small, on average under half a percent of the sales price.

model with concave demand, the dashed line shows the model with flexible prices, and the dash-dotted line shows the model without concavity. Without both concave demand and staggering, reset prices jump on impact and reach a convergent path to the stochastic steady state as soon as all sellers have reset their prices, as indicated by the dotted red line and the dashed green line. In combination, however, the two-month staggered pricing friction is amplified into seven months of autocorrelated price changes. While this is only one sixth of the momentum observed in the data, this experiment reveals concave demand to be a powerful amplification mechanism.

The gradual impulse response results from sellers only partially adjusting their list prices when they have the opportunity to do so in order to not ruin their chances of attracting a buyer by being substantially overpriced. Repeated partial adjustment results in serially correlated price changes that last far beyond the point that all sellers have reset their price.[29]

Table 6 summarizes the amount of amplification generated by concave demand in the calibrated model by showing summary statistics for the amplification of momentum that compare the concave model impulse response to the nonconcave model impulse response under 14 different calibrations. For the rule of thumb model, amplification is measured as the ratio of the fraction of backward-looking sellers α without concavity to α with concavity. For the staggered model, amplification is measured as the ratio of the maximum period of the impulse response with concavity to the maximum period without concavity. In the model without concavity, this is always two periods because prices fully adjust once all sellers have had the opportunity to change their price. To capture the number of periods with nontrivial autocorrelation, my preferred measure of amplification replaces the number of periods to reach the maximum with number of periods to reach 99 percent of the maximum. For the baseline calibration, both the rule of thumb and staggered pricing models amplify both frictions by a factor of 2.5. Table 6 reveals that this is a robust finding, as across a broad range of calibrations and for both frictions, concave demand robustly amplifies momentum by a factor of two to three.

The parameter that most affects the degree of amplification is the seller's search cost. This is the case because search costs create market power for list-price-setting sellers. As search costs fall, the market power of these sellers is eroded, and the incentive to set once's price close to the market average, which enters as an additive markup in equation (22), shrinks relative to changes in market conditions, which enters through the seller's outside option of searching again next period.

The seller search cost is pinned down by the elasticity of demand at the average price and is 2.1 percent of the average sale price per month. The average seller, who is on the market for four months, thus incurs search costs equal to 8.4 percent of the transaction price. This is a plausible figure given six-percent realtor fees, maintenance and staging costs to get the house into condition for listing, the nuisance of listing ones house, and the fact that many sellers need to sell quickly due to the high costs of holding multiple houses. Nonetheless, because a 2.1 percent monthly seller

[29] With staggered pricing there are further dynamic incentives because price resetters leapfrog sellers with fixed prices and are subsequently leapfrogged themselves. The interested reader is referred to Appendix G.3 for a detailed discussion of the dynamic intuition with staggered pricing.

Table 6: Summary Statistics for Amplification of Momentum Across Different Calibrations

	Rule of Thumb Model			Staggered Pricing Model			
	α Concave	α Nonconcave	Amplification	Max Period	Amplification	99% of Max Period	Amplification
IV Sample 1 (Baseline)	0.2988	0.7406	2.479	7	3.5	5	2.5
IV Sample 2	0.2637	0.7188	2.726	8	4	6	3
-b/P of 0.25%	0.2988	0.7422	2.484	7	3.5	5	2.5
-b/P of 1.25%	0.2988	0.7375	2.468	7	3.5	5	2.5
-s/P of 1.0%	0.4062	0.7664	1.887	6	3	4	2
-s/P of 1.5%	0.3496	0.757	2.165	6	3	5	2.5
-s/P of 2.5%	0.2715	0.7188	2.648	7	3.5	6	3
$\varepsilon^* = \$50k$	0.2988	0.7375	2.468	7	3.5	5	2.5
$\varepsilon^* = \$150k$	0.2988	0.7375	2.468	7	3.5	5	2.5
h 1/2 of Flow Util	0.2988	0.7406	2.479	7	3.5	5	2.5
h 4/5 of Flow Util	0.2988	0.7375	2.468	7	3.5	5	2.5
$\xi^d/\xi^f = 0.75$	0.3145	0.7453	2.370	7	3.5	5	2.5
$\psi = 0.3$	0.2617	0.7008	2.678	N/A	N/A	N/A	N/A
$\psi = 0.5$	0.3457	0.7852	2.271	N/A	N/A	N/A	N/A

Notes: Each row shows a different robustness check. The entire model is recalibrated given the indicated parameter change. The first column shows α, the share of backward-looking sellers necessary for a 36-month price impulse response in the rule of thumb model, and the second column shows the required α in a model with no concavity. For the no concavity case, the demand cure is calibrated to maintain the steady state markup and probability of sale as described in Appendix E. The amplification column shows the ratio of the first to the second column. The third and fifth columns show the period in which the maximum price and 99% of the maximum price are reached in the staggered pricing model with the same calibration. The fourth and sixth columns report the ratio of the maximum and 99% of the maximum period in the staggered model to the model without concavity, which results in a two-month impulse response as prices fully adjust once all sellers have the opportunity to do so. Because the seller search cost is pinned down by the elasticity of demand along with the probability of sale and price, the robustness checks that vary s/p alter the binned scatter plot that is used for the calibration by slightly scaling the probability of sale relative to its median value to obtain a more or less elastic demand curve, as described in Appendix F. This approach was chosen because it errs on the side of reducing the amount of concavity.

search cost may be considered high, I vary it in robustness tests.[30] When I do so, I find that the factor of amplification falls to 1.89 (2.0 for staggered) for a monthly search cost of 1.0 percent of the purchase price and rises to 2.65 (3.0 for staggered) when I raise the seller search cost to 2.5 percent of the purchase price.

The other parameters that are calibrated to somewhat speculative targets and consequently altered in Table 6 have a smaller effect on the factor of amplification.[31] I thus conclude that concave demand amplifies both frictions by a factor of two to three.

[30] Because the seller search cost is pinned down by the elasticity of demand, in order to vary it I must alter the binned-scatter plot to which I calibrate to obtain a more elastic demand curve. To do so, I stretch the probability of sale around its median value. I take this approach as opposed to compressing the relative list price because it reduces the concavity slightly while compressing the relative list price increases concavity, and I do not want to artificially increase concavity.

[31] Calibrating to IV sample two yields a slightly higher degree of amplification. Although the demand curve is slightly less concave in IV sample two, it is more inelastic, yielding a larger seller search cost. With a seller search cost equal to what I use for IV sample one, I would obtain slightly less amplification than for IV sample one.

5.3 Amplification of Other Frictions

Because concave demand induces sellers to set their list price close to the market average, it amplifies *any* friction that creates heterogeneity in the speed of adjustment by list-price-setting sellers. Beyond the two frictions I incorporate in my model to quantitatively assess the amplification of momentum created by list-price-setting sellers, concave demand would amplify momentum created by learning in a model with incomplete information or by the gradual spread of sentiment in a model with belief disagreement. Although formally modeling these channels is beyond the scope of this paper, it is worth briefly discussing why each of these frictions would be amplified.

In Burnside et al.'s (2015) model of gradually-spreading sentiment, momentum arrises from the gradual conversion of pessimists to optimists through social interactions. With a strategic complementarity, the optimistic agents would not want to raise their price too much relative to pessimists, creating the same amount of momentum with more rapid social dynamics.

With incomplete information and learning, strategic complementarities can cause very gradual price adjustment even if first-order learning occurs somewhat rapidly as in Anenberg (2014) because the motive to price close to others makes higher order beliefs matter. Learning about higher order beliefs is more gradual—which in turn makes price adjustment more gradual—because agents must learn not only about fundamentals but also about what everyone else has learned as in a Keynesian beauty contest. Such a model has the potential to quantitatively explain momentum without appealing to non-rationality. For instance, Anenberg (2014) obtains about a quarter of the momentum in the data from learning. If the degree of amplification of learning is similar to what I find for staggered pricing and backward-looking sellers, this would come close to explaining the amount of momentum observed in the data.

6 Conclusion

The degree and persistence of autocorrelation in house price changes is one of the housing market's most distinctive features and greatest puzzles, and existing explanations rely on unpalatably large frictions to quantitatively explain momentum. This paper introduces a mechanism that amplifies many proposed frictions into substantial momentum, allowing the needed frictions to be of a plausible magnitude. Search and concave demand in relative price together imply that increasing one's list price above the market average is costly, while lowering one's list price below the market average has little benefit. This strategic complementarity induces sellers to set their list prices close to the market average. Consequently, frictions that cause heterogenous insensitivity to changes in fundamentals can lead to prolonged autocorrelated price changes as sellers slowly adjust their list price to remain close to the mean.

I provide evidence for concave demand in micro data and introduce an equilibrium search model with concave demand that is calibrated to match the amount of concavity in the micro data. Quantitatively, concave demand amplifies momentum created by staggered pricing and a fraction of backward-looking rule of thumb sellers by a factor of two to three. Importantly, concave demand amplifies any other pricing frictions that creates heterogeneity in the speed of price adjustment because the incentive to price close to the average makes sellers who would change their price quickly instead respond sluggishly. Assessing which frictions are relevant is an important path for future research.

Beyond the housing market, this paper shows how a central idea in macroeconomics—that strategic complementarities can greatly amplify modest frictions—can be applied in new contexts. These contexts can, in turn, serve as empirical laboratories to study macroeconomic phenomena for which micro evidence has proven elusive. In particular, many models with real rigidities (Ball and Romer, 1990) use a concave demand curve. This paper provides new evidence that a concave demand curve in relative price is not merely a theoretical construct and can have a significant effect on market dynamics.

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Appendix For "The Causes and Consequences of House Price Momentum"

Adam M. Guren · May 26, 2016

This Appendix provides a number of details relegated from the main text. The Appendix is structured as follows:

- Section A provides details on the data and the procedures used to clean it. Section A.1 focuses on the data used in the time series analysis in Section 2 of the main text, while Section A.2 details the DataQuick and Altos matched microdata as well as the house price indices used in estimation in Section 3 of the main text.
- Section B provides a number of facts about momentum in the time series data sets described in Appendix A beyond the basic analysis in Section 2 of the main text.
- Section C provides econometric proofs and robustness tests related to the micro evidence for concave demand presented in Section 3 of the main text. This includes many robustness and specification tests for the main IV analysis as well as robustness tests for the OLS specifications and analysis of the robustness of the results to other sources of markup variation, which may induce measurement error.
- Section D provides facts about prices from the matched Altos-DataQuick microdata to support some of the assumptions made in the model. In particular, it provides evidence to support the assumption that the average house is sold at list price by comparing list prices with transaction prices in the DataQuick and Altos matched microdata. It also provides evidence on the frequency of price change to motivate the staggered pricing friction calibration.
- Section E provides details and proofs related to the backward-looking and staggered price models as well as the non-concave model.
- Section F details the calibration procedure for the model parameters and shocks.
- Section G provides additional simulation results and robustness checks, including a downward price shock and a deterministic shock so that the model solution is not approximated.

A Data

A.1 Time Series Data

A.1.1 National and Regional Data

In the main text, the national-level price series is the CoreLogic national repeat-sales house price index. This is an arithmetic interval-weighted house price index from January 1976 to August 2013. The monthly index is averaged at a quarterly frequency and adjusted for inflation using the Consumer Price Index, BLS series CUUR0000SA0.

Other price and inventory measures are used in Appendix B. The price measures include:

- A median sales price index for existing single-family homes. The data is monthly for the whole nation from January 1968 to January 2013 and available on request from the National Association of Realtors.

- The quarterly national "expanded purchase-only" HPIs that only includes purchases and supplements the FHFA's database from the GSEs with deeds data from DataQuick from Q1 1991 to Q4 2012. This is an interval-weighted geometric repeat-sales index.
- The monthly Case-Shiller Composite Ten from January 1987 to January 2013. This is an interval-weighted arithmetic repeat-sales index.
- A median sales price index for all sales (existing and new homes) from CoreLogic from January 1976 to August 2013.

For annual AR(1) regressions, I use non-seasonally-adjusted data. For other specifications, use seasonally-adjusted data. I use the data provider's seasonal adjustment if available and otherwise seasonally adjust the data using the Census Bureau's X-12 ARIMA software using a multiplicative seasonal factor.

A.1.2 City-Level Data

The city level data set consists of local repeat-sales price indices for 103 CBSA divisions from CoreLogic. These CBSAs divisions include all CBSAs divisions that are part of the 100 largest CBSAs which have data from at least 1995 onwards. Most of these CBSAs have data starting in 1976. Table A1 shows the CBSAs and years. This data is used for the annual AR(1) regression coefficient histogram in Figure 1 and is adjusted for inflation using the CPI.

A.2 Micro Data

The matched listings-transactions micro data covers the San Francisco Bay, San Diego, and Los Angeles metropolitan areas. The San Francisco Bay sample includes Alameda, Contra Costa, Marin, San Benito, San Francisco, San Mateo, and Santa Clara counties. The Los Angeles sample includes Los Angeles and Orange counties. The San Diego sample only includes San Diego County. The data from DataQuick run from January 1988 to August 2013. The Altos data run from October 2007 to May 2013. I limit my analysis to April 2008 to February 2013, as described in footnote 11.

A.2.1 DataQuick Characteristic and History Data Construction

The DataQuick data is provided in separate assessor and history files. The assessor file contains house characteristics from the property assessment and a unique property ID for every parcel in a county. The history file contains records of all deed transfers, with each transfer matched to a property ID. Several steps are used to clean the data.

First, both data files are formatted and sorted into county level data files. For a very small number of properties, data with a typo is replaced as missing.

Second, some transactions appear to be duplicates. Duplicate values are categorized and combined into one observation if possible. I drop cases where there are more than ten duplicates, as this is usually a developer selling off many lots individually after splitting them. Otherwise, I pick the sale with the highest price, or, if as a tiebreaker, the highest loan value at origination. In practice, this affects very few observations.

Third, problematic observations are identified. In particular, transfers between family members are identified and dropped based on a DataQuick transfer flag and a comparison buyer and seller names. Sales with prices that are less than or equal to one dollar are also counted as transfers. Partial consideration sales, partial sales, group sales, and splits are also dropped, as are deed transfers that are part of the foreclosure process but not actually transactions. Transactions that appear to be

Table A1: CBSAs in CoreLogic City-Level Price Data Set

CBSA Code	Main City Name	Start	End	32820	Memphis, TN	1984	2013
10420	Akron, OH	1978	2013	33124	Miami, FL	1976	2013
10580	Albany, NY	1992	2013	33340	Milwaukee, WI	1976	2013
10740	Albuquerque, NM	1992	2013	33460	Minneapolis, MN	1976	2013
10900	Allentown, PA	1976	2013	34980	Nashville, TN	1976	2013
12060	Atlanta, GA	1976	2013	35004	Nassau, NY	1976	2013
12420	Austin, TX	1976	2013	35084	Newark, NJ-PA	1976	2013
12540	Bakersfield, CA	1976	2013	35300	New Haven, CT	1985	2013
12580	Baltimore, MD	1976	2013	35380	New Orleans, LA	1976	2013
12940	Baton Rouge, LA	1992	2013	35644	New York, NY	1976	2013
13140	Beaumont, TX	1993	2013	36084	Oakland, CA	1976	2013
13644	Bethesda, MD	1976	2013	36420	Oklahoma City, OK	1976	2013
13820	Birmingham, AL	1976	2013	36540	Omaha, NE	1990	2013
14484	Boston, MA	1976	2013	36740	Orlando, FL	1976	2013
14860	Bridgeport, CT	1976	2013	37100	Ventura, CA	1976	2013
15380	Buffalo, NY	1991	2013	37764	Peabody, MA	1976	2013
15764	Cambridge, MA	1976	2013	37964	Philadelphia, PA	1976	2013
15804	Camden, NJ	1976	2013	38060	Phoenix, AZ	1976	2013
16700	Charleston, SC	1976	2013	38300	Pittsburgh, PA	1976	2013
16740	Charlotte, NC	1976	2013	38900	Portland, OR	1976	2013
16974	Chicago, IL	1976	2013	39100	Poughkeepsie, NY	1976	2013
17140	Cincinnati, OH	1976	2013	39300	Providence, RI	1976	2013
17460	Cleveland, OH	1976	2013	39580	Raleigh, NC	1976	2013
17820	Colorado Springs, CO	1976	2013	40060	Richmond, VA	1976	2013
17900	Columbia, SC	1977	2013	40140	Riverside, CA	1976	2013
18140	Columbus, OH	1976	2013	40380	Rochester, NY	1991	2013
19124	Dallas, TX	1977	2013	40484	Rockingham County, NH	1990	2013
19380	Dayton, OH	1976	2013	40900	Sacramento, CA	1976	2013
19740	Denver, CO	1976	2013	41180	St. Louis, MO	1978	2013
19804	Detroit, MI	1989	2013	41620	Salt Lake City, UT	1992	2013
20764	Edison, NJ	1976	2013	41700	San Antonio, TX	1991	2013
21340	El Paso, TX	1977	2013	41740	San Diego, CA	1976	2013
22744	Fort Lauderdale, FL	1976	2013	41884	San Francisco, CA	1976	2013
23104	Fort Worth, TX	1984	2013	41940	San Jose, CA	1976	2013
23420	Fresno, CA	1976	2013	42044	Santa Ana, CA	1976	2013
23844	Gary, IN	1992	2013	42644	Seattle, WA	1976	2013
24340	Grand Rapids, MI	1992	2013	44140	Springfield, MA	1976	2013
24660	Greensboro, NC	1976	2013	44700	Stockton, CA	1976	2013
24860	Greenville, SC	1976	2013	45060	Syracuse, NY	1992	2013
25540	Hartford, CT	1976	2013	45104	Tacoma, WA	1977	2013
26180	Honolulu, HI	1976	2013	45300	Tampa, FL	1976	2013
26420	Houston, TX	1982	2013	45780	Toledo, OH	1976	2013
26900	Indianapolis, IN	1991	2013	45820	Topeka, KS	1985	2013
27260	Jacksonville, FL	1976	2013	46060	Tucson, AZ	1976	2013
28140	Kansas City, MO	1985	2013	46140	Tulsa, OK	1981	2013
28940	Knoxville, TN	1977	2013	47260	Virginia Beach, VA	1976	2013
29404	Lake County, IL	1982	2013	47644	Warren, MI	1976	2013
29820	Las Vegas, NV	1983	2013	47894	Washington, DC	1976	2013
30780	Little Rock, AR	1985	2013	48424	West Palm Beach, FL	1976	2013
31084	Los Angeles, CA	1976	2013	48620	Wichita, KS	1986	2013
31140	Louisville, KY	1987	2013	48864	Wilmington, DE	1976	2013
32580	McAllen, TX	1992	2013	49340	Worcester, MA	1976	2013

corrections or with implausible origination loan to value ratios are also flagged and dropped. Properties with implausible characteristics (<10 square feet, < 1 bedroom, < 1/2 bathroom, implausible year built) have the implausible characteristic replaced as a missing value.

From the final data set matched to Altos, I only use resale transactions (as opposed to new construction or subdivisions) of single-family homes, both of which are categorized by DataQuick.

For the purposes of estimating the equity for each house when it is listed, I also create a secondary dataset that includes not only the history of deed transfers but also the history of mortgage liens for each property. This data includes the value, lender, interest rate type (adjustable- or fixed-rate), as well as the initial interest rate on the loan as estimated by DataQuick using the date of origination of the loan and loan characteristics together with other proprietary data on interest rates. The estimated interest rate is not available until 1995 for most counties in California. The data is cleaned identically to the main data set for transfers. For the loan data, duplicates, group sales, split properties, partial sales, partial consideration sales, and loans that are less than $10,000 are dropped.

A.2.2 Altos Research Listings Data Construction and Match to DataQuick

The Altos research data contains address, MLS identifier, house characteristics, list price, and date for every week-listing. Altos generously provided me access to an address hash that was used to parse the address fields in the DataQuick assessor data and Altos data and to create a matching hash for each. Hashes were only used that appeared in both data files, and hashes that matched to multiple DataQuick properties were dropped.

After formatting the Altos data, I match the Altos data to the DataQuick property IDs. I first use the address hash, applying the matched property ID to every listing with the same MLS identifier (all listings with the same MLS ID are the same property, and if they do not all match it is because some weeks the property has the address listed differently, for instance "street" is included in some weeks but not others). Second, I match listings not matched by the address hash by repeatedly matching on various combinations of address fields and discarding possible matches when there is not a unique property in the DataQuick data for a particular combination of fields, which prevents cases where there are two properties that would match from being counted as a match. I determine the combinations of address fields on which to match based on an inspection of the unmatched observations, most of which occur when the listing in the MLS data does not include the exact wording of the DataQuick record (*e.g.*, missing "street"). The fields typically include ZIP, street name, and street number and different combinations of unit number, street direction, and street suffix. In some cases I match to the first few digits of street number or the first word of a street name. I finally assign any unmatched observations with the same MLS ID as a matched observation or the same address hash, square feet, year built, ZIP code, and city as a matched observation the property ID of the matched observation. I subsequently work only with matched properties so that I do not inadvertently count a bad match as a withdrawal.

The observations that are not matched to a DataQuick property ID are usually multi-family homes (which I drop due to the problematic low match rate), townhouses with multiple single-family homes at the same address, or listings with typos in the address field.

I use the subset of listings matched to a property ID and combine cases where the same property has multiple MLS identifiers into a contiguous listing to account for de-listings and re-listings of properties, which is a common tactic among real estate agents. In particular, I count a listing as contiguous if the property is re-listed within 13 weeks and there is not a foreclosure between the de-listing and re-listing. I assign each contiguous listing a single identifier, which I use to match to transactions.

In a few cases, a listing matches to several property IDs. I choose the property ID that matches to a transaction or that corresponds to the longest listing period. All results are robust to dropping the small number of properties that match to multiple property IDs.

I finally match all consolidated listings to a transaction. I drop transactions and corresponding listings where there was a previous transaction in the last 90 days, as these tend to be a true transaction followed by several subsequent transfers for legal reasons (*e.g.*, one spouse buys the house and then sells half of it to the other). I first match to a transaction where the date of last listing is in the month of the deed transfer request or in the prior three months. I then match unmatched listings to a transaction where the date of last listing is in the three months after the deed transfer request (if the property was left on the MLS after the request, presumably by accident). I then repeat the process for unmatched listings for four to 12 months prior and four to 12 months subsequent. Most matches have listings within three months of the last listing. The matching procedure takes care to make sure that listings that match to a transaction that is excluded from the final sample (for instance due to it being a transfer or having an implausible sale price) are dropped and not counted as unmatched listings.

For matched transactions, I generate two measures of whether a house sold within a given time frame. The first, used in the main text, is the time between the date of first listing and the date of filing of the deed transfer request. The second, used in robustness checks in Appendix C, is the time between date of first listing and the first of the last listing date or the transfer request.

Figure A1 shows the fraction of all single-family transactions of existing homes for which my data accounts in each of the three metropolitan areas over time. Because the match rates start low in October 2007, I do not start my analysis until April 2008, except in San Diego where almost all listings have no listed address until August 2008. Besides that, the match rates are fairly stable, except for a small dip in San Diego in mid-2009 and early 2012 and a large fall off in the San Francisco Bay area after June 2012. I consequently end the analysis for the San Francisco Bay area at June 2012. Figures A2, A3, and A4 show match rates by ZIP code. One can see that the match rate is consistently high in the core of each metropolitan area and falls off in the outlying areas, such as western San Diego county and Escondido in San Diego, Santa Clarita in Los Angeles, and Brentwood and Pleasanton in the San Francisco Bay area.

A.2.3 Construction of House Price Indices

I construct house price indices largely following Case and Shiller (1989) and follow sample restrictions imposed in the construction of the Case-Shiller and Federal Housing Finance Administration (FHFA) house price indices.

For the repeat sale indices, I drop all non-repeat sales, all sales pairs with less than six months between sales, and all sales pairs where a first stage regression on year dummies shows a property has appreciated by 100 percent more or 100 percent less than the average house in the MSA. I estimate an interval-corrected geometric repeat-sales index at the ZIP code level. This involves estimating a first stage regression:

$$p_{h\ell t} = \xi_{h\ell} + \phi_t + \varepsilon_{h\ell t}, \tag{A1}$$

where p is the log price of a house h in location ℓ at time t, $\xi_{h\ell}$ is a sales pair fixed effect, ϕ_t is a time fixed effect, and $\varepsilon_{h\ell t}$ is an error term.

I follow Case and Shiller (1989) by using a GLS interval-weighted estimator to account for the fact that longer time intervals tend to have a larger variance in the error of (A1). This is typically implemented by regressing the square of the error term $\varepsilon_{h\ell t}^2$ on a linear (Case-Shiller index) or

Figure A1: Match Rates by Month of Transaction

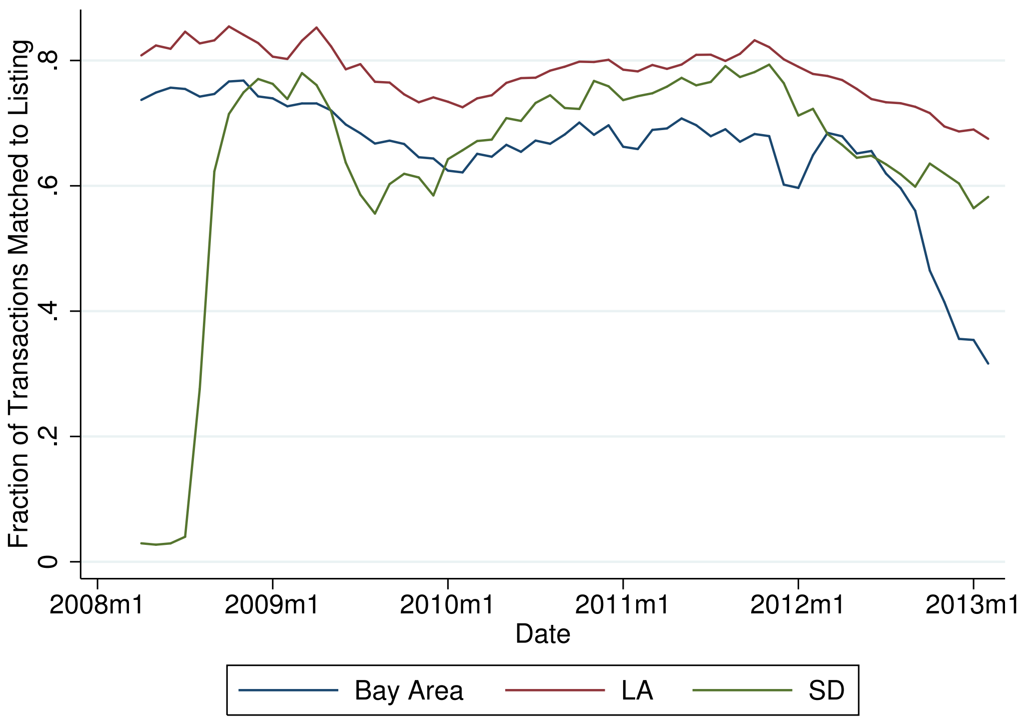


Figure A2: Match Rates by ZIP Code: Bay Area

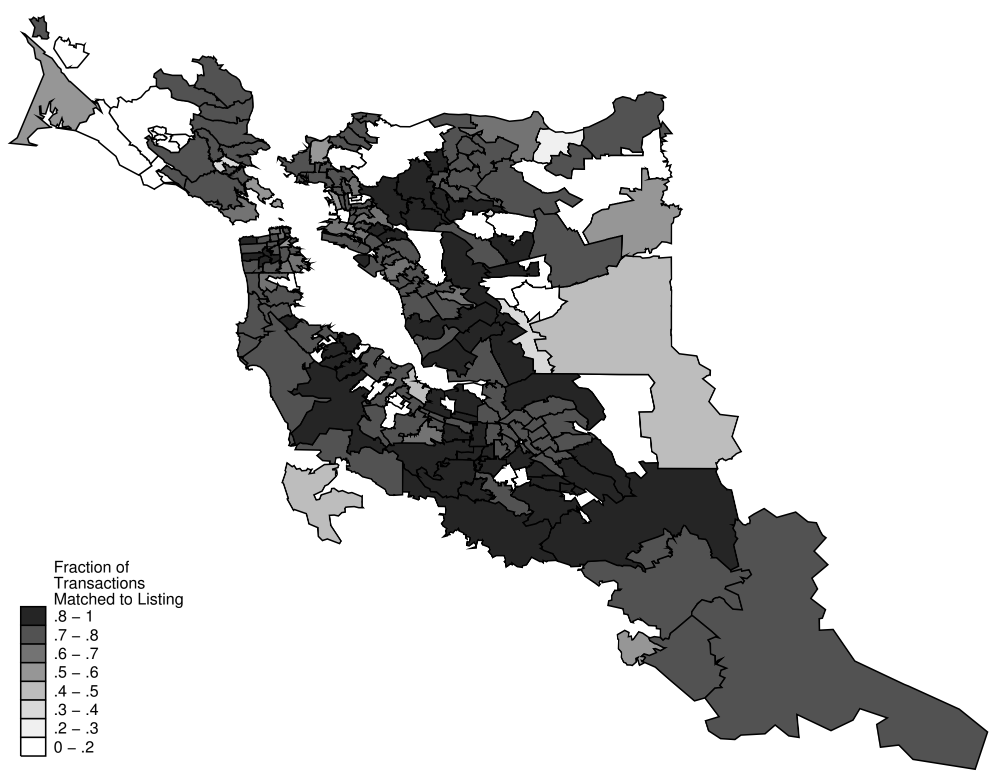


Figure A3: Match Rates by ZIP Code: Los Angeles

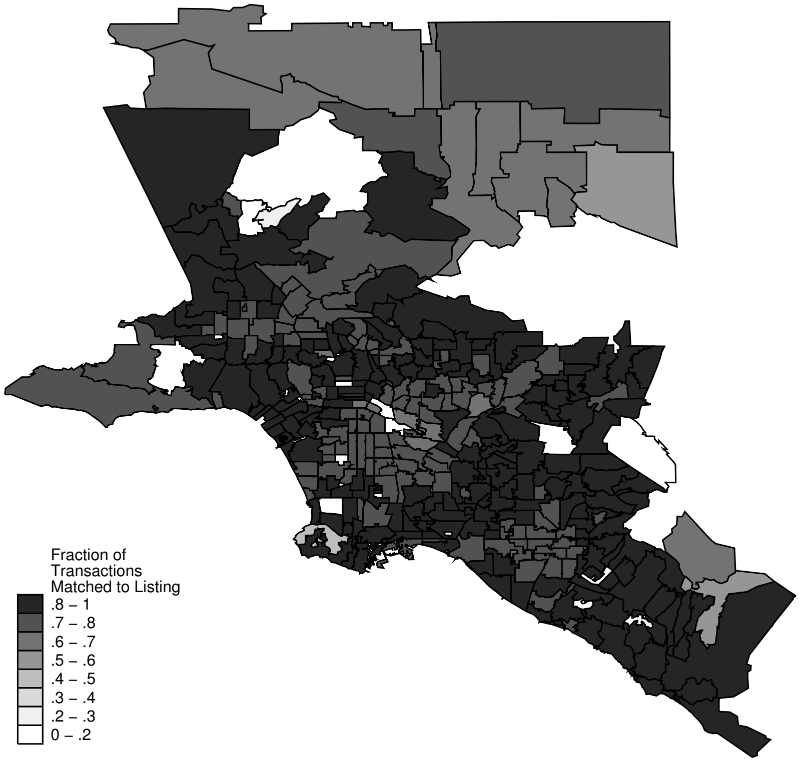
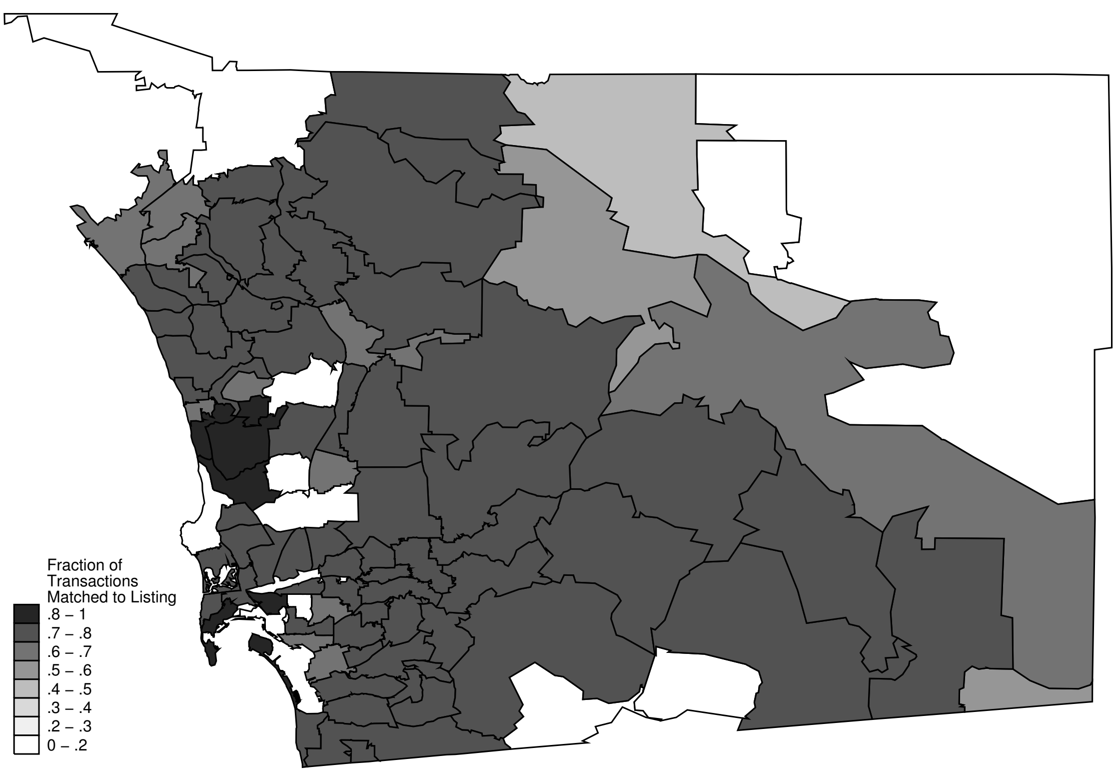


Figure A4: Match Rates by ZIP Code: San Diego



quadratic (FHFA) function of the time interval between the two sales. The regression coefficients are then used to construct weights corresponding to $\frac{1}{\sqrt{\hat{\varepsilon}^2_{h\ell t}}}$ where $\hat{\varepsilon}^2_{h\ell t}$ is a predicted value from the interval regression. I find that the variance of the error of (A1) is non-monotonic: it is very high for sales that occur quickly, falls to its lowest level for sales that occur approximately three years after the first sale, and then rises slowly over time. This is likely due to flippers who upgrade a house and sell it without the upgrade showing up in the data. Consequently, I follow a non-parametric approach by binning the data into deciles of the time interval between the two sales, calculate the average $\varepsilon^2_{h\ell t}$ for the decile $\bar{\varepsilon}^2_{h\ell t}$, and weight by $\frac{1}{\sqrt{\bar{\varepsilon}^2_{h\ell t}}}$. The results are nearly identical using a linear interval weighting.

$\exp(\phi_t)$ is then a geometric house price index. The resulting indices can be quite noisy. Consequently, I smooth the index using a 3-month moving average, which produced the lowest prediction error of several different window widths. The resulting indices at the MSA level are very comparable to published indices by Case-Shiller, the FHFA, and CoreLogic.

The log predicted value of a house at time t, $\hat{p}_t$, that sold originally at time τ for P_τ is:

$$\hat{p}_t = \log\left(\frac{\exp\left(\hat{\phi}_t\right)}{\exp\left(\hat{\phi}_\tau\right)} P_\tau\right).$$

For the hedonic house price indices, I use all sales and estimate:

$$p_{i\ell t} = \phi_t + \beta X_i + \varepsilon_{i\ell t}, \tag{A2}$$

where X_i is a vector of third-order polynomials in four housing characteristics: age, bathrooms, bedrooms, and log (square feet), all of which are winsorized at the one percent level by county for all properties in a county, not just those that trade. Recall that these characteristics are all recorded as a single snapshot in 2013, so X_i is not time dependent. I do not include a characteristic if over 25 percent of the houses in a given geography are missing data for a particular characteristic. Again $\exp(\phi_t)$ is a house price index, which I smooth using a 3-month moving average. The log predicted price of a house is:

$$\hat{p}_{it} = \hat{\beta} X_i + \hat{\phi}_i.$$

For homes that are missing characteristics included in an area's house price index calculation, I replace the characteristic with its average value in a given ZIP code.

For my analysis, I use a ZIP code level index, but all results are robust to alternatively using a house price index for all homes within one mile of the centroid of a home's seven-digit ZIP code (roughly a few square blocks). I do not calculate a house price index if the area has fewer than 500 sales since 1988. This rules out about 5% of transactions, typically in low-density areas far from the core of the MSA. For each ZIP code, I calculate the standard deviation of the prediction error of the house price index from 1988 to 2013 and weight most specifications by the reciprocal of the standard deviation.

A.2.4 Construction of the Final Analysis Samples

I drop listings that satisfy one of several criteria:

1. If the list price is less than $10,000;

2. If the assessed structure value is less than five percent of the assessed overall value;

Table A2: Share of Sample Accounted For By Each MSA and Year

Sample	All All	Prior Trans All	All Transactions	Prior Trans Transactions
SF Bay	26.99 %	26.59 %	27.86 %	27.31 %
Los Angeles	58.76 %	59.52 %	57.47 %	58.35 %
San Diego	14.25 %	13.89 %	14.67 %	14.34 %
2008	18.17 %	20.06 %	16.48 %	18.26 %
2009	20.66 %	20.90 %	21.06 %	21.38 %
2010	23.88 %	23.45 %	23.56 %	23.08 %
2011	21.09 %	20.37 %	21.60 %	20.95 %
2012	14.90 %	14.00 %	15.94 %	15.05 %
2013	1.30 %	1.21%	1.36 %	1.27 %

Notes: Each cell indicates the percentage of each sample accounted for by each MSA (above the line) or by each year of first listing (below the line).

3. If the data shows the property was built after the sale date or there has been "significant improvement" since the sale date;

4. If there was an implausibly large change in the house's value, indicating a typo or large renovation;

5. If there is a previous sale within 90 days.

Each observation is a listing, regardless of whether it is withdrawn or ends in a transaction. The outcome variable is sold within 13 weeks, where withdrawn listings are counted as not transacting. The price variable is the initial list price. The predicted prices are calculated for the week of first listing by interpolation from the monthly index values. The sample is summarized in Table 1 in the main text, and the fraction of the sample accounted for by each MSA and year are summarized in Table A2.

A.2.5 Estimation of Equity Positions at Date of Listing

I estimate the equity position of the seller at date of listing for each listing in the final sample using the DataQuick data on both transactions and mortgage liens together with the listing dates for each property. While the data on mortgages is rich—it contains every lien, and I am able to observe loan amounts, loan type (fixed or adjustable rate), and DataQuick's estimated mortgage interest rate—I do not have enough data to perfectly calculate equity for three reasons. First, I only observe new mortgage liens and cannot tell which mortgages have been prepaid or replaced. I thus cannot definitely know whether a new mortgage is a refinance, consolidation, or a second mortgage. Second, I do not observe some features of the mortgage, such as the frequency and time of reset, the margin over one-year LIBOR (or a similar index) to which an adjustable rate mortgage resets, the interest rate path (e.g. teaser rates or balloon mortgages), whether the mortgage is interest only, and whether the borrower is current on their mortgage payments or has prepaid. Finally, if a mortgage is a home equity line of credit, I do not observe its draw down. There are also cases where loan type or interest rate are missing.

Because of these data limitations, I follow a procedure to estimate equity similar to DeFusco (2015) and make several assumptions that allow me to estimate the equity of each home. In particular I assume:

1. Assumptions about mortgages:

    (a) All adjustable rate mortgages are 5/1 ARMs (among the most popular ARMs) that amortize over 30 years that reset to a 2.75% margin over one-year LIBOR on the date of reset, which according to the Freddie Mac Primary Mortgage Market Survey is roughly the average historical margin.

    (b) All fixed rate mortgages and mortgages of unknown type are 30 year fixed rate mortgages.

    (c) All mortgages with a missing DataQuick estimated interest rate (most are prior to 1995) are assigned an interest rate equal to the average interest rate on a 30-year fixed rate mortgage in the month of origination from the Freddie Mac Primary Mortgage Market Survey.

2. All borrowers are current on their mortgage, have not prepaid their mortgage unless they move or refinance, and all home equity lines of credit are drawn down immediately. Consequently, the mortgage balance at listing can be computed by amortizing all outstanding loans to the date of listing.

3. All houses can have at most two outstanding mortgages at one time (the DataQuick data includes up to three in a given history entry, and I choose the largest two). Mortgages are estimated to be a first or second mortgage according to several rules:

    (a) Initial mortgage balances:

        i. If a property has an observed prior transaction, the initial mortgage balance is the mortgage amount associated with that transaction (the mortgage balance used to estimate the cumulative loan to value ratio)

        ii. If the house has no observed prior transactions but there are observed mortgage liens, a new loan is counted as a first mortgage if it is greater than or equal to 50% of the hedonic value of the house (computed using the ZIP hedonic price index described above) at the time of purchase and a second mortgage if it is less than 50%.

        iii. If the house has no observed prior transactions and no observed new mortgage liens since 1988, there is no mortgage balance by 2008 when the sample starts. Since we are interested in screening out houses with negative equity, this is a harmless assumption as any homeowner with no new mortgage liens in 20 years has a very low mortgage balance and very high equity.

    (b) If a new lien record shows two mortgages simultaneously taken out, both outstanding mortgage "slots" are updated unless the two mortgages have the same value (a likely duplicate in the records) or both are very small (less than half of the outstanding mortgage balance together), in which case they are likely a second and third mortgage and only the larger of the two is counted as a second mortgage.

    (c) If a new lien record shows one new mortgage, then:

        i. If the property has no mortgage, it is a first mortgage.

        ii. If the property only has a second mortgage (only for homes with no observed prior transaction), the new mortgage is a first mortgage if it is over half of the hedonic estimated value and otherwise a second mortgage.

        iii. If the property has no second mortgage, the new mortgage is a second mortgage if it is less than half the estimated first mortgage balance and otherwise the new mortgage is a refinancing of the first mortgage.

Table A3: The Robustness of Momentum Across Price Measures and Metrics

Price Measure	Annual AR(1) Coefficient	1 Year Lagged Autocorr of Quarterly Δp	2 Year Lagged Autocorr of Quarterly Δp	Lag in Which Quarterly Δp Autocorr is First < 0	Quarter of Peak of AR(5) IRF	Quarter of Peak Value of Lo-MacKinlay Variance Ratio
CoreLogic Repeat	0.665	0.516	0.199	12	12	19
Sales HPI, 1976-2013	(0.081)					
Case-Shiller	0.670	0.578	0.251	14	11	20
Comp 10, 1987-2013	(0.088)					
FHFA Expanded	0.699	0.585	0.344	14	11	18
HPI, 1991-2013	(0.089)					
NAR Median	0.458	0.147	0.062	12	6	16
Price, 1968-2013	(0.103)					
CoreLogic Median	0.473	0.215	0.046	11	7	16
Price, 1976-2013	(0.082)					

Notes: Each row shows six measures of momentum for each of the five house price indices, which are detailed in Appendix A. The first row shows the AR(1 coefficient for a regression of the annual change in log price on a on-year lag of itself estimated on quarterly data, as in equation (1), with robust standard errors in parenthesis. The second and third columns show the one and two year lagged autocorrelations of the quarterly change in log price. The fourth column shows the quarterly lag in which the autocorrelation of the quarterly change in log price is first negative. The fifth column indicates the quarter in which the impulse response function estimated from an AR(5), as in Section 2, reaches its peak. Finally, the last column shows the quarterly lag for which the Lo-MacKinlay variance ratio computed as in equation (A3) reaches its peak.

iv. If there is currently a second mortgage, there are two cases:
   A. If the balance is greater than the total current combined mortgage balance minus \$10,000 (for error), this is a mortgage consolidation. Replace the first mortgage with the new mortgage and eliminate the second mortgage.
   B. Otherwise, the loan for which the outstanding balance is closest to the new loan amount is replaced, unless the loan is closer to the second mortgage and under 25% of the second mortgage balance in which case it is a third mortgage and is dropped, as I assume that houses have up to two mortgages for simplicity.

Given the above assumptions, I calculate the mortgage balance at each listing and merge this into the final data set. Equity at listing is then calculated as

$$\text{Equity} = 1 - \frac{\text{Mortgage Balance}}{\text{Predicted Value}}.$$

The rules for determining a first and second mortgage appear to be a reasonable approximation for equity based on a visual inspection of at loan histories for many houses in the data set. There will be some noise due to inaccuracies about the loan interests rate, amortization schedule, what is a first versus second mortgage, error in the home's predicted value, et cetera, but the estimated mortgage balance at listing shoudl be a good proxy for the seller's equity position in most cases.

B Momentum

To assess the robustness of the facts about house price momentum presented in Section 2, Table A3 shows several measures of momentum for five different national price indices. The indices are

Table A4: Testing For Asymmetry in Momentum

Dependent Variable: Annual Change in Log Price Index at CBSA Level		
Specification	With Interaction	Without Interaction
Coefficient on Year-Lagged	0.614***	0.591***
Annual Change in Log Price	(0.011)	(0.020)
Coefficient on Interaction With		0.045
Positive Lagged Change		(0.031)
CBSA Fixed Effects	Yes	Yes
CBSAs	103	103
N	13,188	13,188

Notes: *** p<0.001. Each column shows a regression of the annual change in log price on a one-year lag of itself and CBSA fixed effects. In column two, the interaction between the lag of annual change in log price with an indicator for whether the lag of the annual change in log price is also included as in equation (A4). The regressions are estimated on the panel of 103 CBSAs repeat-sales price indices described in Appendix A. Robust standard errors are in parentheses.

the CoreLogic National repeat-sales house price index discussed in the main text, the Case-Shiller Composite Ten, the FHFA expanded repeat-sales house price index, the National Association of Realtors' national median price for single-family homes, and CoreLogic's national median price for all transactions. The first column shows the coefficient on an AR(1) in log annual price change run at quarterly frequency as in equation (1).[1] The next two columns show the one- and two-year lagged autocorrelations of the quarterly change in log price. The fourth column shows the quarterly lag in which the autocorrelation of the quarterly change in log price is first negative. The fifth column shows the quarter subsequent to a shock in which the impulse response from an estimated AR(5) estimated in log levels, as in Section 2, reaches its peak value. Finally, the sixth column shows the quarterly lag in which the Lo-MacKinlay variance ratio statistic reaches its peak value. This statistic is equal to,

$$V(k) = \frac{var\left(\sum_{t=1}^{t-k+1} r_{t-k+1}\right)/k}{var(r_t)} = \frac{var\left(\log(p_t) - \log(p_{t-k})\right)/k}{var\left(\log(p_t) - \log(p_{t-1})\right)}, \tag{A3}$$

where $r_t = \log(p_t) - \log(p_{t-1})$ is the one-period return. If this statistic is equal to one, then there is no momentum, and several papers have used the maximized period of the statistic as a measure of the duration of momentum.

Table A3 shows evidence of significant momentum for all price measures and all measures of momentum. The two median price series exhibit less momentum as the IRFs peak at just under two years and the two-year-lagged autocorrelation is much closer to zero.

Table A4 tests for asymmetry in momentum. Many papers describe prices as being primarily sticky on the downside (*e.g.*, Leamer, 2007; Case, 2008). To assess whether this is the case, I turn to the panel of 103 CBSA repeat-sales price indices described in Appendix A, which allows for a more powerful test of asymmetry than using a single national data series. I estimate a quarterly

[1] Case and Shiller (1989) worry that the same house selling twice may induce correlated errors that generate artificial momentum in regression (1) and use $\Delta p_{t,t-4}$ from one half of their sample and $\Delta p_{t-4,t-8}$ from the other. I have found that this concern is minor with 25 years of administrative data by replicating their split sample approach with my own house price indices estimated from the DataQuick micro data.

Table A5: Momentum Across Countries

Country	AR(1) Coefficient	N	Country	AR(1) Coefficient	N
Australia, 1986-2013	0.217*	100	Netherlands, 1995-2013	0.951***	67
	(0.108)			(0.079)	
Belgium, 1973-2013	0.231**	154	Norway, 1992-2013	-0.042	79
	(0.074)			(0.091)	
Denmark, 1992-2013	0.412***	78	New Zealand, 1979-2013	0.507***	127
	(0.110)			(0.075)	
France, 1996-2013	0.597***	62	Sweden, 1986-2013	0.520***	103
	(0.121)			(0.100)	
Great Britain, 1968-2013	0.467***	173	Switzerland, 1970-2013	0.619***	167
	(0.079)			(0.082)	

Notes: * p< 0.05, ** p<0.01, *** p<0.001. Each row shows the AR(1) coefficient for a regression of the annual change in log price on an annual lag of itself, as in equation (1), estimated on quarterly, non-inflation-adjusted data from the indicated country for the indicated time period. Robust standard errors are in parentheses, and N indicates the number of quarters in the sample. The BIS identifiers and series descriptions are listed for each country. Australia: Q:AU:4:3:0:1:0:0, residential property for all detached houses, eight cities. Belgium Q:BE:0:3:0:0:0:0, residential property all detached houses. Denmark: Q:DK:0:2:0:1:0:0, residential all single-family houses. France: Q:FR:0:1:1:6:0, residential property prices of existing dwellings. Great Britain: Q:GB:0:1:0:1:0:0, residential property prices all dwellings from the Office of National Statistics. Netherlands: Q:NL:0:2:1:1:6:0, residential existing houses. Norway: Q:NO:0:3:0:1:0:0, Residential detached houses. New Zealand: Q:NZ:0:1:0:3:0:0, residential all dwellings. Sweden: Q:SE:0:2:0:1:0:0, owner-occupied detached houses. Switzerland: Q:CH:0:2:0:2:0:0, owner-occupied single-family houses.

AR(1) regression of the form:

$$\Delta_{t,t-4} \ln p_c = \beta_0 + \beta_1 \Delta_{t-4,t-8} \ln p_c + \beta_2 \Delta_{t-4,t-8} \ln p_c \times 1 \left[\Delta_{t-4,t-8} \ln p_c > 0\right] + \phi_c + \varepsilon, \qquad \text{(A4)}$$

where c is a city. If momentum is stronger on the downside, the interaction coefficient β_2 should be negative. However, Table A4 shows that the coefficient is insignificant and positive. Thus momentum appears equally strong on the upside and downside when measured using a repeat-sales index.

B.1 Across Countries

Table A5 shows annual AR(1) regressions as in equation (1) run on quarterly non-inflation-adjusted data for ten countries. The data come from the Bank for International Settlements, which compiles house price indices from central banks and national statistical agencies. The data and details can be found online at http://www.bis.org/statistics/pp.htm. I select ten countries from the BIS database that include at least 15 years of data and have a series for single-family detached homes or all homes. Countries with per-square-foot indices are excluded. With the exception of Norway, which shows no momentum, and the Netherlands, which shows anomalously high momentum, all of the AR(1) coefficients are significant and between 0.2 and 0.6. Price momentum thus holds across countries as well as within the United States and across U.S. metropolitan areas.

C Micro Evidence For Concave Demand

C.1 Binned Scatter Plots

Throughout the analysis, I use binned scatter plots to visualize the structural relationship between list price relative to the reference list price and probability of sale. This section briefly describes how they are produced.

Recall that the econometric model is:

$$d_{h\ell t} = g\left(p_{h\ell t} - \tilde{p}_{h\ell t}\right) + \psi_{\ell t} + \varepsilon_{h\ell t}, \tag{A5}$$

where $p_{h\ell t} - \tilde{p}_{h\ell t}$ is equal to $f\left(z_{h\ell t}\right)$ in:

$$p_{h\ell t} = f\left(z_{h\ell t}\right) + \beta X_{h\ell t} + \xi_{\ell t} + u_{h\ell t}. \tag{A6}$$

To create the IV binned scatter plots. I first estimate $f\left(z_{h\ell t}\right)$ by (A6) and let $p_{h\ell t} - \tilde{p}_{h\ell t} = f\left(z_{h\ell t}\right)$. I drop the top and bottom 0.5 percentiles of $p_{h\ell t} - \tilde{p}_{h\ell t}$ and ZIP-quarter cells with a single observation and create 25 indicator variables ζ_b corresponding to 25 bins q of $p_{h\ell t} - \tilde{p}_{h\ell t}$. I project sale within 13 weeks $d_{h\ell t}$ on fixed effects and the indicator variables:

$$d_{h\ell t} = \psi_{\ell t} + \zeta_b + \nu_{h\ell tq} \tag{A7}$$

I visualize $g\left(\cdot\right)$ by plotting the average $p_{h\ell t} - \tilde{p}_{h\ell t}$ for each bin against the average $d_{h\ell t} - \psi_{\ell t}$ for each bin, which is equivalent to ζ_b.

C.2 Proof of Lemma 1

Recall that the Lemma assumes that:

$$\begin{gathered} z_{h\ell t} \perp \left(u_{h\ell t}, \varepsilon_{h\ell t}\right), \\ p_{h\ell t} = f\left(z_{h\ell t}\right) + \zeta_{h\ell t} + \tilde{p}_{h\ell t}, \end{gathered}$$

$\zeta_{h\ell t} \perp f\left(z_{h\ell t}\right)$, and that the true regression function $g\left(\cdot\right)$ is a third-order polynomial. Because of the fixed effect $\xi_{h\ell t}$ in $\tilde{p}_{h\ell t}$, $\zeta_{h\ell t}$ can be normalized to be mean zero. Using the third-order polynomial assumption, the true regression function is:

$$g\left(p_{h\ell t} - \tilde{p}_{h\ell t}\right) = E\left[d_{h\ell tq} | f\left(z_{h\ell t}\right) + \zeta_{h\ell t}, \psi_{\ell t}\right] = \beta_1\left(f\left(z_{h\ell t}\right) + \zeta_{h\ell t}\right) + \beta_2\left(f\left(z_{h\ell t}\right) + \zeta_{h\ell t}\right)^2 + \beta_3\left(f\left(z_{h\ell t}\right) + \zeta_{h\ell t}\right)^3.$$

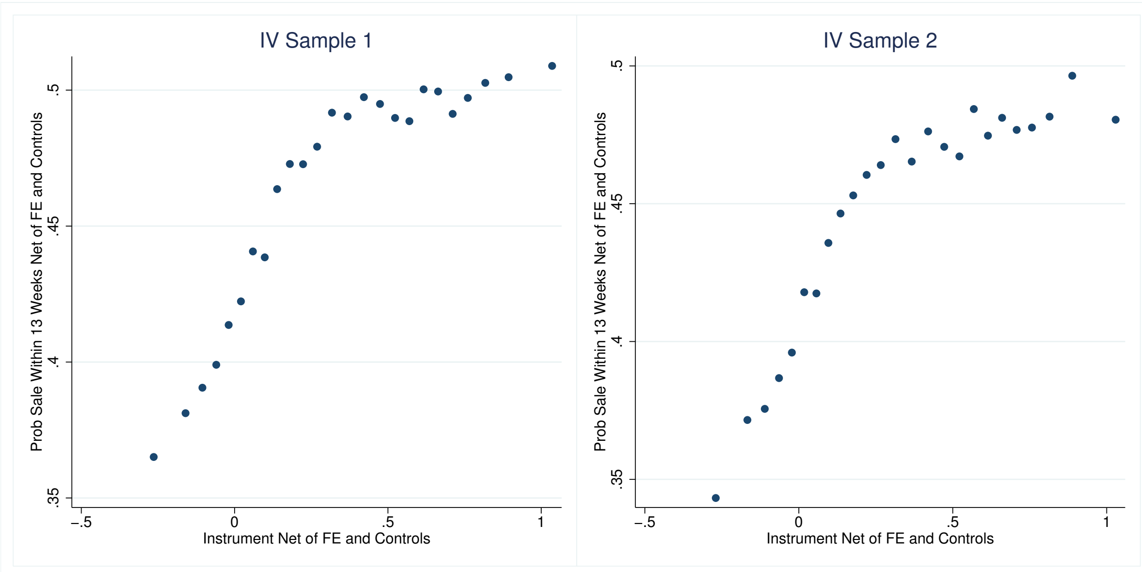
However, $\zeta_{h\ell t}$ is unobserved, so I instead estimate:

$$\begin{aligned} E\left[d_{h\ell tq} | f\left(z_{h\ell t}\right), \psi_{\ell t}\right] = & \beta_1 f\left(z_{h\ell t}\right) + \beta_2 f\left(z_{h\ell t}\right)^2 + \beta_3 f\left(z_{h\ell t}\right)^3 \\ & + \beta_1 E\left[\zeta_{h\ell t} | f\left(z_{h\ell t}\right)\right] + 2\beta_2 E\left[f\left(z_{h\ell t}\right)\zeta_{h\ell t}\right] + \beta_2 E\left[\zeta_{h\ell t}^2 | f\right] \\ & + 3\beta_3 f\left(z_{h\ell t}\right) E\left[\zeta_{h\ell t}^2 | f\right] + 3\beta_3^2 f\left(z_{h\ell t}\right) E\left[\zeta_{h\ell t} | f\right] + \beta_3 E\left[\zeta_{h\ell t}^3 | f\right]. \end{aligned}$$

However, because $\zeta_{h\ell t} \perp f\left(z_{h\ell t}\right)$, $E\left[\zeta_{h\ell t} | f\left(z_{h\ell t}\right)\right] = 0$, $E\left[f\left(z_{h\ell t}\right)\zeta_{h\ell t}\right] = 0$, and $E\left[\zeta_{h\ell t}^2 | f\right]$ and $E\left[\zeta_{h\ell t}^3 | f\right]$ are constants. The $\beta_2 E\left[\zeta_{h\ell t}^2 | f\right]$ and $\beta_3 E\left[\zeta_{h\ell t}^3 | f\right]$ terms will be absorbed by the fixed effects $\psi_{\ell t}$, leaving:

$$E\left[d_{h\ell tq} | f\left(z_{h\ell t}\right), \psi_{\ell t}\right] = \beta_1 f\left(z_{h\ell t}\right) + \beta_2 f\left(z_{h\ell t}\right)^2 + \beta_3 f\left(z_{h\ell t}\right)^3 + 3\beta_3 f\left(z_{h\ell t}\right) E\left[\zeta_{h\ell t}^2 | f\right].$$

Figure A5: Reduced-Form Relationship Between the Instrument and the Outcome Variable



Notes: This figure shows the reduced-form relationship between the instrument on the x-axis and the probability of sale within 13 weeks on the y axis. Both are residualized against ZIP $\times$ first quarter of listing fixed effects and the repeat-sales and hedonic predicted prices, and the means are added back in. Before binning, the top and bottom 0.5 percent of the log sale price residual and any observations fully absorbed by fixed effects are dropped. This plot of the reduced form shows the basic concave relationship that the IV approach, although the downward-sloping first stage flips and shrinks the x-axis. The left panel shows IV sample 1, which drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The right panel shows IV sample 2, which does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year..

Thus when one estimates $g(\cdot)$ by a cubic polynomial of $f(z_{h\ell t})$,

$$d_{h\ell tq} = \gamma_1 f(z_{h\ell t}) + \gamma_2 f(z_{h\ell t})^2 + \gamma_3 f(z_{h\ell t})^3 + \psi_{\ell t} + \varepsilon_{h\ell t},$$

one recovers $\gamma_1 = \beta_1 + 3\beta_3 E\left[\zeta_{h\ell t}^2 | f\right]$, $\gamma_2 = \beta_2$, and $\gamma_3 = \beta_3$, so the true second- and third-order terms are recovered.

For the quadratic case, I estimate

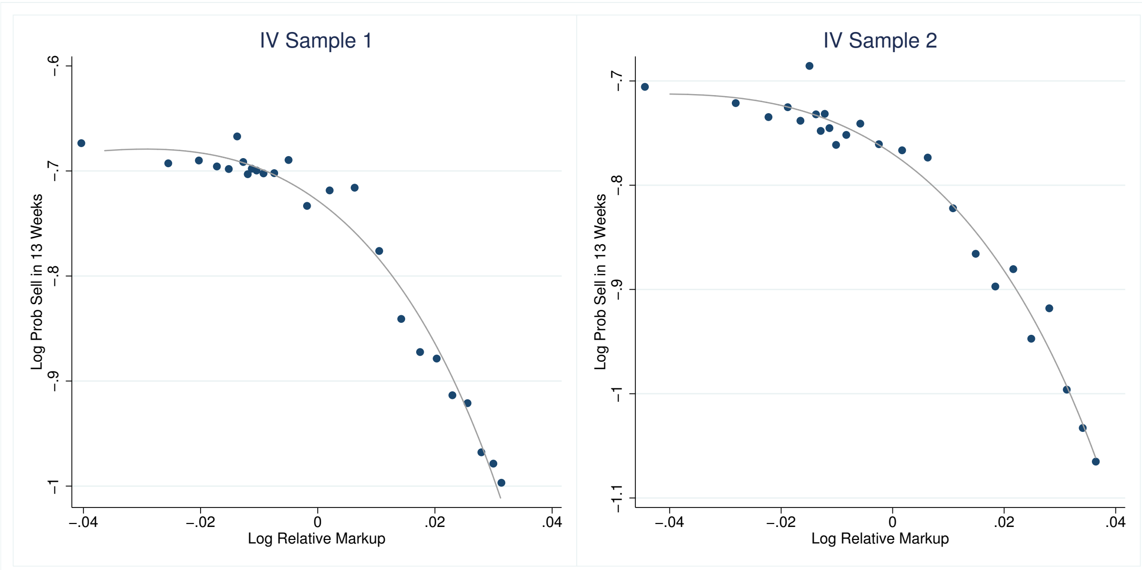
$$\begin{aligned} E\left[d_{h\ell tq} | f(z_{h\ell t}), \psi_{\ell t}\right] &= \beta_1 f(z_{h\ell t}) + \beta_2 f(z_{h\ell t})^2 + \beta_3 f(z_{h\ell t})^3 \\ &\quad + \beta_1 E\left[\zeta_{h\ell t} | f(z_{h\ell t})\right] + 2\beta_2 E\left[f(z_{h\ell t})\zeta_{h\ell t}\right] + \beta_2 E\left[\zeta_{h\ell t}^2 | f\right] \\ &= \beta_1 f(z_{h\ell t}) + \beta_2 f(z_{h\ell t})^2 . \end{aligned}$$

and so $\gamma_1 = \beta_1$ and $\gamma_2 = \beta_2$ and the true first- and second-order terms are recovered.

C.3 Instrumental Variable Robustness and Specification Tests

This section provides robustness and specification tests for the IV estimates described in Section 3. All robustness tests are shown for both IV sample 1 and IV sample 2, although the results are similar across samples.

Figure A6: Instrumental Variable Estimates With Probability of Sale Axis in Logs



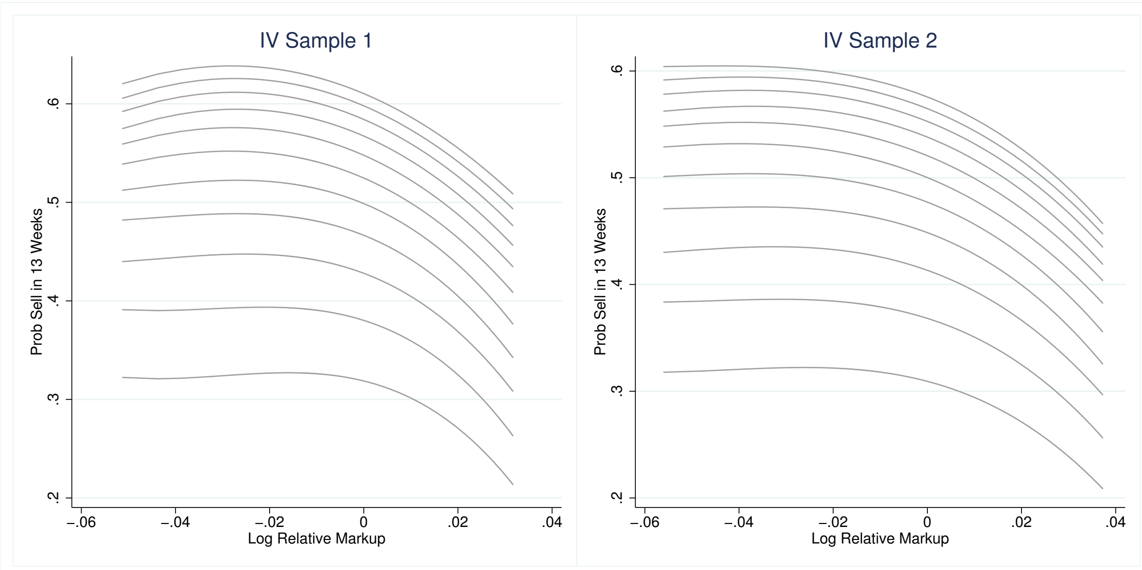
Notes: For both samples, the figure shows a binned scatter plot of the log of the probability of sale within 13 weeks net of ZIP × first quarter of listing fixed effects (with the average probability of sale within 13 weeks added in) against the estimated log relative markup $p - \tilde{p}$. It also shows an overlaid cubic fit of the relationship, as in equation (3). To create the figure, a first stage regression of the log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and repeat sales and hedonic log predicted prices, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup. The figure splits the data into 25 equally-sized bins of this estimated relative markup and plots the mean of the estimated relative markup against the log of the mean of probability of sale within 13 weeks net of fixed effects for each bin, as detailed in Appendix C. The log transformation is applied at the end as the y variable is binary. Before binning, the top and bottom 0.5 percent of the log sale price residual and any observations fully absorbed by fixed effects are dropped. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. IV sample 1 drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The grey bands indicate a pointwise 95-percent confidence interval for the cubic fit created by block bootstrapping the entire procedure on 35 ZIP-3 clusters. N = 140,344 observations for IV sample 1 and 137,238 observations for IV sample 2 prior to dropping unique zip-quarter cells and winsorizing.

Figure A5 shows the reduced-form relationship between the instrument and outcome variable when both are residualized against fixed effects and the repeat-sales and hedonic predicted price. The estimates presented in the main text rescale the instrument axis into price (and in the process flip and shrink the x axis), but the basic concave relationship between probability of sale and appreciation since purchase is visible in the reduced form. The clear concave relationship in the reduced form is important because it ensures that nonlinearities in the first stage are not driving the overall concave relationship (although one could surmise this from the smooth and monotonic first stage).

Figure A6 shows IV binned scatter plots when the y-axis is rescaled to a logarithmic scale so that the slope represents the elasticity of demand. The demand curve is still robustly concave.

Figure A7 shows third-order polynomial fits varying the number of weeks that a listing needs

Figure A7: Instrumental Variable Estimates: Varying The Sell-By Date



Notes: For both samples, the figure shows third-order polynomial fits of equation (3) for the probability of sale by eleven different deadlines (6, 8, 10, 12, 14, 16, 18, 20, 22, 24, and 26 weeks) net of fixed effects (with the average probability of sale added in) against the estimated log relative markup. To create the figure, a first stage regression of the log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and repeat sales and hedonic log predicted prices, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup before equation (3) is run. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. IV sample 1 drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. N = 140,344 observations for IV sample 1 and 137,238 observations for IV sample 2 prior to dropping unique zip-quarter cells and winsorizing.

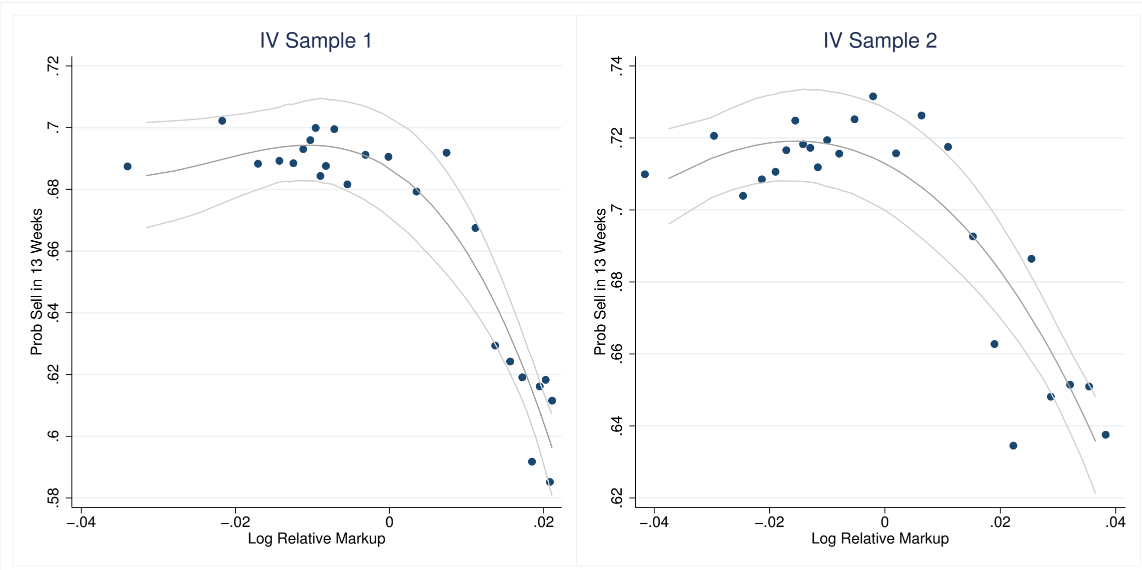
to sell within to count as a sale from six weeks to 26 weeks. Concavity is evident regardless of the deadline used for the binary y-variable.

Figure A8 shows the IV binned scatter plot and a third-order polynomial fit when the sample is limited to transactions and transaction prices are used rather than initial list prices. Substantial concavity is still present, assuaging concerns that the concavity in list prices may not translate into a strategic complementarity in transaction prices. The upward slope in the middle of the figure is not statistically significant.

Figure A9 shows third-order polynomial fits for each ZIP-3 in the data set with over 2,000 observations, so that the cubic polynomial is estimated with some degree of confidence. These ZIP-3s form the core of my analysis sample. The pointwise standard errors on each line are fairly wide and are not shown, but one can see that almost all of the ZIP-3s there is substantial curvature.

Figure A10 provides some evidence on the exclusion restriction by showing how observed quality varies with time since purchase. In particular, it shows plots of six measures of observed quality residualized against zip by quarter of listing fixed effects (with the mean added back in) against the date of the previous transaction for both of the IV samples. For both samples, there is no clear relationship between bedrooms and bathrooms and original sale date. To the extent to which unob-

Figure A8: Instrumental Variable Estimates: Transaction Prices

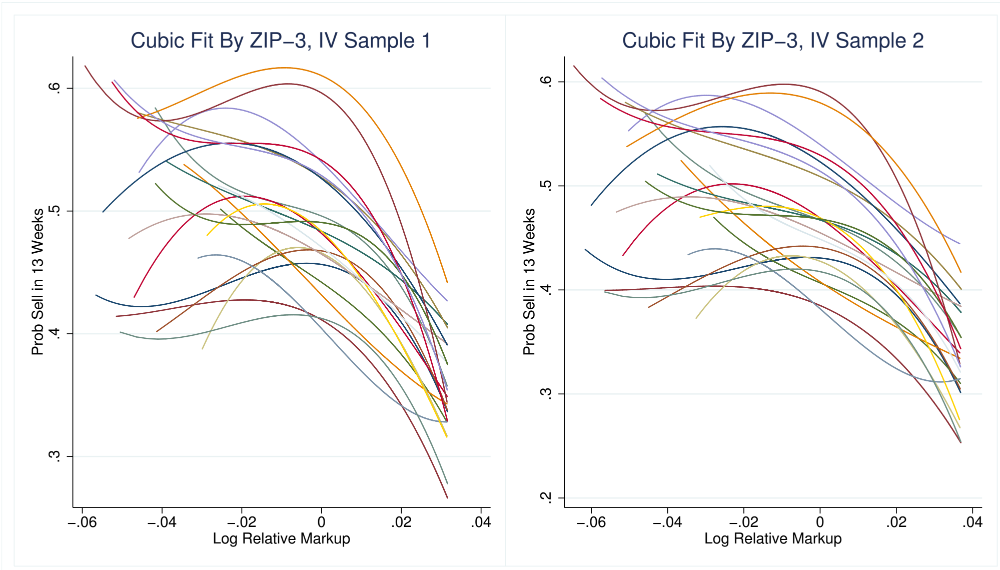


Notes: For both samples, the figure shows a binned scatter plot of the probability of sale within 13 weeks net of ZIP $\times$ first quarter of listing fixed effects (with the average probability of sale within 13 weeks added in) against the estimated log relative markup $p - \tilde{p}$ measured using transaction prices rather than list prices. It also shows an overlaid cubic fit of the relationship, as in equation (3). To create the figure, a first stage regression of the log transaction price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and repeat sales and hedonic log predicted prices, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup. The figure splits the data into 25 equally-sized bins of this estimated relative markup and plots the mean of the estimated relative markup against the mean of the probability of sale within 13 weeks net of fixed effects for each bin, as detailed in Appendix C. Before binning, the top and bottom 0.5 percent of the log sale price residual and any observations fully absorbed by fixed effects are dropped. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. IV sample 1 drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The grey bands indicate a pointwise 95-percent confidence interval for the cubic fit created by block bootstrapping the entire procedure on 35 ZIP-3 clusters. N = 96,400 observations for IV sample 1 and 86,033 observations for IV sample 2 prior to dropping unique zip-quarter cells and winsorizing.

served quality varies with these observed measures of quality, this is consistent with the exclusion restriction. There is a weak negative relationship between log square feet and original sale date, but there are strong negative relationships between lot size, rooms, age, and original sale date. Age is slightly nonmonotonic as it rises post 2005, but otherwise the results are more or less linear, and do not strongly vary with the housing cycle. To the extent to which unobserved quality varies with these observed measures of quality, these results imply that a linear time trend would pick up the effects of unobservables. This motivates a robustness check using a linear time trend in date of purchase (or time since purchase) below.

Tables A6, A8, A10, A12, A14, and A16 present various robustness and specification tests of the main IV specification for IV sample 1 (column 3 of Table 2). Tables A7, A9, A11, A13, A15, and A17 repeat the same robustness tests for IV sample 2 (column 5 of Table 2). For all robustness

Figure A9: Instrumental Variable Estimates: Best Fit Polynomial By ZIP-3

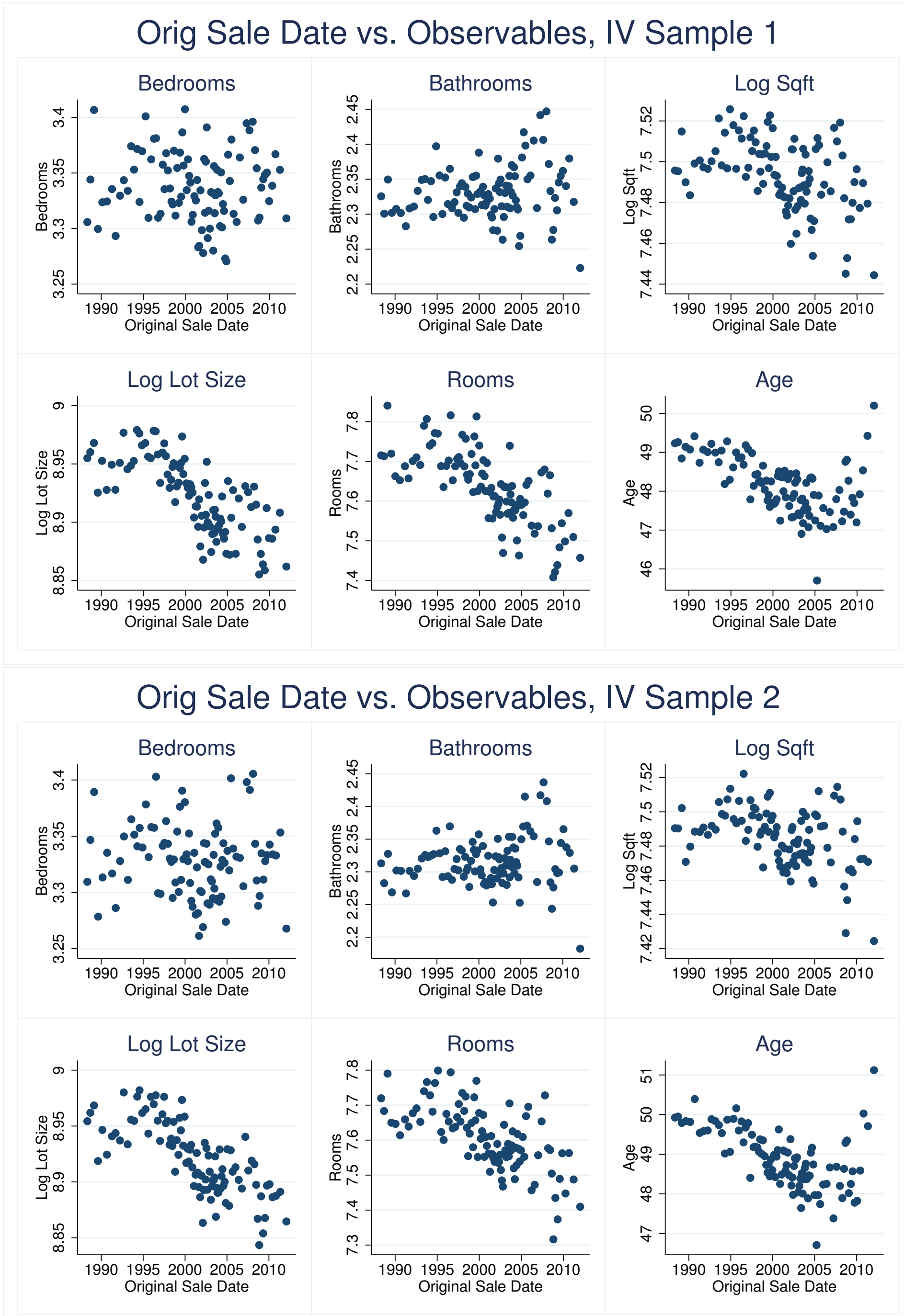


Notes: For both samples, the figure shows for each ZIP-3 with over 2,000 observations a cubic fit of the log of the probability of sale within 13 weeks net of ZIP $\times$ first quarter of listing fixed effects (with the average probability of sale within 13 weeks added in) against the estimated log relative markup $p - \tilde{p}$ as in equation (3). To create the figure, a pooled first stage regression of the log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and repeat sales and hedonic log predicted prices, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated for each ZIP-3 with over 2,000 observations. For each ZIP-3, the x-axis of the best-fit polynomial reflects the 1st to 99th percentiles of the log relative markup in that ZIP. IV sample 1 drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year.

tables, each row in the tables represents a separate regression, with the specifications described in the Appendix text. Coefficients for a quadratic polynomial in the log relative markup and a bootstrapped 95 percent confidence interval for the quadratic term are reported as in the main text. The robustness and specification checks consistently show evidence of significant concavity, although in a few specifications the bootstrapped confidence intervals widen when the sample size is reduced to the point that the results are no longer significant.

Tables A6 and A7 evaluate the exclusion restriction that unobserved quality is independent of when a seller purchased. The first two specifications add a linear trend in date of purchase or time since purchase in $X_{h\ell t}$ along with the two predicted prices, thus accounting for any variation in unobserved quality that varies linearly in date of purchase or time since purchase. To the extent that unobserved quality varies with date of purchase in the same way that lot size, rooms, and age do n Figure A10, a linear time trend will help control for unobserved quality. If anything, adding a linear time trend strengthens the finding of concavity, with more negative point estimates on the quadratic term. The next three rows limit the sample to homes purchased before the bust (before 2005), after 1994, and in a window from 1995 to 2004. Finally, the last two rows add linear time trends to the purchased before 2005 sample. In all cases, the bootstrapped 95 percent confidence intervals for the quadratic term continue to show significant concavity, and if anything the point

Figure A10: Observed Quality (Residualized Against ZIP-Quarter FE) By Original Sale Date



Notes: For both samples, the figure shows binned scatter pots of six observed measures of quality versus the original sale date. For each figure, the quality measure (but not the original sale date) is residualized against zip by quarter of listing dummies and the mean is added back in to create a residualized quality measure. The data is then binned into 100 bins of the original sale date and the mean residualized quality is plotted against the mean original sale date for each bin. IV sample 1 drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year.

Table A6: IV Sample 1 Robustness 1: Controls for Time Since Purchase

Dependent Var: Sell Within 13 Weeks					
Specification	Quadratic Polynomial Coefficients			Quadratic Coefficient	
(Details In Text)	Constant	Linear	Quadratic	Bootstrapped 95% CI	Obs
Linear Trend in	0.476***	-3.360***	-64.978*	[-141.455,-28.643]	140,344
Date of Purchase	(0.008)	(0.660)	(27.420)		
Linear Trend in	0.476***	-3.381***	-65.428*	[-143.701,-28.427]	140,344
Time Since Purchase	(0.008)	(0.671)	(27.992)		
Purchased Pre 2005	0.492***	-2.357***	-93.245*	[-220.122,-44.835]	107,980
	(0.008)	(0.631)	(46.725)		
Purchased Post 1994	0.475***	-2.474***	-45.538***	[-63.142,-32.285]	122,818
	(0.003)	(0.137)	(7.809)		
Purchased 1995-2004	0.489***	-2.992***	-136.931*	[-306.78,-75.278]	90,454
	(0.009)	(0.656)	(60.586)		
Pre 2005 With Trend	0.493***	-1.818***	-66.248**	[-129.257,-35.281]	107,980
in Date of Purchase	(0.008)	(0.382)	(24.604)		
Pre 2005 With Trend	0.493***	-1.833***	-67.119**	[-130.846,-35.509]	107,980
in Time Since Purchase	(0.008)	(0.388)	(25.041)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

estimate on the quadratic term are more negative.

Tables A8 and A9 show various specification checks. The first set of regressions limit the analysis to ZIP-quarter cells with at least 15 and 20 observations to evaluate whether small sample bias in the estimated fixed effect $\xi_{h\ell t}$ could be affecting the results. In both cases, the results appear similar to the full sample and the bootstrapped confidence interval shows a significantly negative quadratic term, which suggests that bias in the estimation of the fixed effects is not driving the results. The second set introduces $X_{h\ell t}$, the vector of house characteristics that includes the repeat-sales and hedonic predicted prices, as a quadratic, cubic, quartic, and quintic function instead of linearly. The assumed linearity of these characteristics is not driving the results. In particular, introducing $z_{h\ell t}$ nonlinearly and $\hat{p}^{repeat}_{h\ell t}$ linearly is not driving the results, as when $z_{h\ell t}$ and $\hat{p}^{repeat}_{h\ell t}$ are both introduced as fifth-order polynomials the results are virtually unchanged. Finally, the third set considers different specifications for the flexible function of the instrument $f(z_{h\ell t})$ in the first stage, which is quintic in the baseline specification. Again, the order of $f(\cdot)$ does not appear to alter the finding of significant concavity.

Table A10 and A11 show various robustness checks. These include:

- House Characteristic Controls: This specification includes a third-order polynomial in age, log square feet, bedrooms, and bathrooms in $X_{h\ell t}$ along with the predicted prices.

- Alternate Time To Sale Definition: Instead of measuring time to sale as first listing to the

Table A7: IV Sample 2 Robustness 1: Controls for Time Since Purchase

Dependent Var: Sell Within 13 Weeks					
Specification (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
Linear Trend in Date of Purchase	0.458***	-2.673***	-42.695*	[-91.130,-21.180]	137,238
	(0.009)	(0.532)	(18.076)		
Linear Trend in Time Since Purchase	0.458***	-2.684***	-42.910*	[-92.536,-21.014]	137,238
	(0.009)	(0.538)	(18.339)		
Purchased Pre 2005	0.471***	-2.523***	-90.567*	[-185.042,-51.624]	105,775
	(0.010)	(0.651)	(37.485)		
Purchased Post 1994	0.455***	-2.077***	-30.401***	[-41.221,-20.681]	120,229
	(0.002)	(0.122)	(5.241)		
Purchased 1995-2004	0.465***	-2.987***	-111.862*	[-252.84,-72.415]	88,766
	(0.010)	(0.730)	(46.582)		
Pre 2005 With Trend in Date of Purchase	0.472***	-2.014***	-66.436**	[-124.922,-37.902]	105,775
	(0.009)	(0.427)	(20.940)		
Pre 2005 With Trend in Time Since Purchase	0.472***	-2.026***	-66.965**	[-127.425,-38.101]	105,775
	(0.009)	(0.434)	(21.340)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 2, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

filing of the deed transfer request, this specification measures time to sale as first listing to the first of the deed transfer request or the last listing.

- 18 and 10 Weeks to Sale: This specification varies sell-by deadline for the binary y-variable from 13 weeks to 10 and 18 weeks, respectively.
- No Weights: This specification does not weight observations by the inverse standard deviation of the repeat-sales house price index prediction error at the ZIP level.
- No Possibly Problematic Observations: A small number of listings are matched to multiple property IDs and I use an algorithm described in Appendix A to guess of which is the relevant property ID. Additionally, there are spikes in the number of listings in the Altos data for a few dates, which I have largely eliminated by dropping listings that do not match to a DataQuick property ID. Despite the fact that these two issues affect a very small number of observations, this specification drops both types of potentially problematic observations to show that they do not affect results.
- By Time Period: This specification splits the data into two time periods, February 2008 to June 2010 and July 2010 to February 2013.
- By MSA: This specification runs separate regressions for the San Francisco Bay, Los Angeles, and San Diego areas.

Table A8: IV Sample 1 Robustness 2: Specification Checks

Dependent Var: Sell Within 13 Weeks					
Specification	Quadratic Polynomial Coefficients			Quadratic Coefficient	
(Details In Text)	Constant	Linear	Quadratic	Bootstrapped 95% CI	Obs
Only FE Cells With	0.483***	-2.381***	-35.437**	[-62.362,-20.101]	99,594
At Least 15 Obs	(0.010)	(0.381)	(10.862)		
Only FE Cells With	0.484***	-2.364***	-33.537**	[-62.418,-14.822]	79,304
At Least 20 Obs	(0.011)	(0.439)	(12.313)		
Predicted Prices	0.480***	-2.317***	-42.381***	[-65.556,-30.138]	140,344
Introduced as Quadratic	(0.008)	(0.322)	(9.229)		
Predicted Prices	0.481***	-2.323***	-43.270***	[-66.779,-30.618]	140,344
Introduced as Cubic	(0.008)	(0.318)	(9.276)		
Predicted Prices	0.481***	-2.307***	-42.764***	[-66.865,-30.291]	140,344
Introduced as Quartic	(0.008)	(0.317)	(9.297)		
Predicted Prices	0.480***	-2.300***	-42.420***	[-66.052,-30.379]	140,344
Introduced as Quintic	(0.008)	(0.318)	(9.256)		
Linear Fn of Instrument	0.490***	-2.425***	-70.956***	[-121.787,-51.831]	140,344
	(0.008)	(0.360)	(17.669)		
Quadratic Fn of Instrument	0.489***	-2.288***	-67.890***	[-112.521,-49.987]	140,344
	(0.009)	(0.354)	(15.904)		
Cubic Fn of Instrument	0.478***	-2.206***	-36.511***	[-63.469,-24.76]	140,344
	(0.008)	(0.343)	(10.339)		
Quartic Fn of Instrument	0.480***	-2.236***	-42.040***	[-72.821,-28.122]	140,344
	(0.008)	(0.350)	(11.795)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

The results continue to show concavity, although in some specifications it is weakened by the smaller sample size and no longer significant. In particular, in San Diego the confidence intervals are so wide that nothing can be inferred. The insignificance is in large part because the standard errors are created by block bootstrapping on ZIP-3 clusters, so in San Diego there are very few effective observations. Additionally, in the second half of the sample, the result is weakened although still significant.

Table A12 and A13 show various robustness checks. These include:

- Beta varies by MSA-Year or MSA-Quarter: In this specification, β, the control for observables in the first stage relationship which is assumed fixed across MSAs and years in the baseline specification, is estimated separately for each MSA-year or MSA-quarter rather than in a pooled regression. This accounts for potentially differential sorting between households and homes across space and time.

- Only Low All Cash Share ZIPs: This specification limits the sample to ZIP codes where less than 10 percent of buyers buy in all cash (a hallmark of investors).

Table A9: IV Sample 2 Robustness 2: Specification Checks

Dependent Var: Sell Within 13 Weeks					
Specification	Quadratic Polynomial Coefficients			Quadratic Coefficient	
(Details In Text)	Constant	Linear	Quadratic	Bootstrapped 95% CI	Obs
Only FE Cells With	0.471***	-1.964***	-25.751***	[-44.255,-14.298]	94,447
At Least 15 Obs	(0.011)	(0.280)	(7.209)		
Only FE Cells With	0.474***	-1.971***	-24.945**	[-47.136,-9.286]	72,579
At Least 20 Obs	(0.013)	(0.336)	(9.568)		
Predicted Prices	0.461***	-2.000***	-30.532***	[-45.069,-21.543]	137,238
Introduced as Quadratic	(0.009)	(0.265)	(6.103)		
Predicted Prices	0.461***	-2.018***	-31.192***	[-45.058,-22.07]	137,238
Introduced as Cubic	(0.009)	(0.263)	(6.071)		
Predicted Prices	0.461***	-2.009***	-30.829***	[-44.901,-21.843]	137,238
Introduced as Quartic	(0.009)	(0.263)	(6.082)		
Predicted Prices	0.461***	-2.007***	-30.730***	[-44.938,-21.915]	137,238
Introduced as Quintic	(0.009)	(0.264)	(6.113)		
Linear Fn of Instrument	0.471***	-2.107***	-52.619***	[-91.046,-38.946]	137,238
	(0.009)	(0.301)	(13.492)		
Quadratic Fn of Instrument	0.469***	-1.964***	-49.855***	[-86.671,-36.932]	137,238
	(0.009)	(0.296)	(12.585)		
Cubic Fn of Instrument	0.459***	-1.908***	-26.688***	[-47.592,-18.009]	137,238
	(0.009)	(0.287)	(7.610)		
Quartic Fn of Instrument	0.461***	-1.921***	-29.661***	[-50.928,-20.422]	137,238
	(0.009)	(0.292)	(7.981)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 2, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

- Uniqueness Controls: This specification drops households that appear to be unique in their ZIP code in an effort to get a more homogenous sample. Uniqueness is defined three ways. First, if beds, baths, square feet, lot size, rooms, or year built is more than 2 standard deviations from the mean value (e.g. unique on one dimension). Second, the same metric with a threshold of 1.5 standard deviations. Third, if the average squared value of a house's Z score for these characteristics is above 2. Note that if a characteristic is missing for a house, it is not counted as having a high Z score.

- Tier Controls: This specification uses a ZIP code level repeat sales house price index as in the main estimation to estimate the value of all homes based on their most recent transaction. It then splits each ZIP code into two or four tiers based on the estimated value of the house and makes the fixed effects $\xi_{\ell t}$ and $\psi_{\ell t}$ to be ZIP-quarter-tier level instead of the ZIP-quarter level in the baseline specification.

The results show that the concavity is not affected by any of the above controls, although confidence intervals do widen when fewer observations are used (only low all cash share ZIPs) or when more

Table A10: IV Sample 1 Robustness 3: Miscellaneous Robustness Tests

Dependent Var: Sell Within 13 Weeks Unless Otherwise Indicated					
Specification (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
House Characteristic Controls	0.481***	-2.514***	-50.595***	[-80.123,-33.569]	133,671
	(0.008)	(0.366)	(12.066)		
Alternate Time to Sale Defn	0.511***	-2.140***	-36.433***	[-59.576,-25.285]	140,344
	(0.010)	(0.320)	(9.014)		
Dep Var: 18 Weeks	0.547***	-2.205***	-40.078***	[-65.127,-27.644]	140,344
	(0.007)	(0.340)	(9.607)		
Dep Var: 10 Weeks	0.425***	-2.132***	-41.778***	[-71.622,-29.343]	140,344
	(0.007)	(0.321)	(11.095)		
No Weights	0.466***	-1.868***	-34.965***	[-58.351,-23.906]	140,344
	(0.008)	(0.312)	(8.778)		
No Poss Problematic Obs	0.485***	-2.231***	-40.822***	[-68.327,-29.289]	135,858
	(0.007)	(0.340)	(9.944)		
No Short Interval Between Prev Trans and Listing	0.481***	-2.278***	-41.368***	[-69.123,-28.903]	139,580
	(0.008)	(0.356)	(10.562)		
First Listed 2008-7/2010	0.453***	-2.190***	-30.295**	[-55.285,-10.604]	69,240
	(0.012)	(0.346)	(11.216)		
First Listed 7/2010-2013	0.502***	-2.248***	-44.960*	[-94.677,-26.093]	71,104
	(0.008)	(0.372)	(18.294)		
Bay Area	0.511***	-2.609***	-36.537**	[-70.887,-19.171]	39,550
	(0.016)	(0.633)	(13.883)		
Los Angeles	0.463***	-1.940***	-47.637**	[-85.803,-24.353]	82,803
	(0.008)	(0.415)	(15.634)		
San Diego	0.494***	-4.374***	-100.529	[-100.529,483.072]	17,991
	(0.018)	(0.451)	(132.245)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

Table A11: IV Sample 2 Robustness 3: Miscellaneous Robustness Tests

Dependent Var: Sell Within 13 Weeks Unless Otherwise Indicated					
Specification (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
House Characteristic Controls	0.462***	-2.145***	-36.076***	[-53.821,-25.145]	130,958
	(0.010)	(0.293)	(7.669)		
Alternate Time to Sale Defn	0.487***	-1.897***	-27.126***	[-44.842,-18.793]	137,238
	(0.011)	(0.285)	(6.575)		
Dep Var: 18 Weeks	0.519***	-1.951***	-27.989***	[-43.7,-18.914]	137,238
	(0.009)	(0.301)	(6.431)		
Dep Var: 10 Weeks	0.411***	-1.800***	-29.772***	[-50.912,-21.054]	137,238
	(0.009)	(0.271)	(7.714)		
No Weights	0.444***	-1.628***	-24.665***	[-42.218,-16.763]	137,238
	(0.010)	(0.278)	(6.326)		
No Poss Problematic Obs	0.466***	-1.903***	-29.225***	[-49.197,-20.982]	132,835
	(0.009)	(0.292)	(7.299)		
No Short Interval Between Prev Trans and Listing	0.462***	-1.942***	-29.580***	[-49.421,-20.53]	136,342
	(0.009)	(0.295)	(7.450)		
First Listed 2008-7/2010	0.438***	-2.088***	-27.212**	[-49.764,-14.762]	69,603
	(0.012)	(0.362)	(8.898)		
First Listed 7/2010-2013	0.483***	-1.695***	-28.092*	[-61.53,-14.924]	67,635
	(0.010)	(0.273)	(12.574)		
Bay Area	0.505***	-2.343***	-34.164*	[-74.646,-15.522]	37,742
	(0.020)	(0.591)	(16.990)		
Los Angeles	0.438***	-1.722***	-29.972*	[-59.485,-8.72]	81,998
	(0.009)	(0.350)	(11.803)		
San Diego	0.474***	-3.329***	-49.741	[-547.966,103.933]	17,498
	(0.017)	(0.667)	(110.829)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 2, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

Table A12: IV Sample 1 Robustness 4: Miscellaneous Robustness Tests II

Dependent Var: Sell Within 13 Weeks Unless Otherwise Indicated					
Specification	Quadratic Polynomial Coefficients			Quadratic Coefficient	
(Details In Text)	Constant	Linear	Quadratic	Bootstrapped 95% CI	Obs
Beta Varies By MSA-Year	0.481***	-2.442***	-48.770***	[-78.037,-33.523]	140,344
	(0.008)	(0.351)	(11.218)		
Beta Varies by MSA-Quarter	0.481***	-2.466***	-50.577***	[-78.156,-33.86]	140,344
	(0.008)	(0.349)	(11.185)		
Only Low All Cash Share ZIPs	0.512***	-3.163***	-47.394*	[-103.288,-24.069]	58,171
	(0.011)	(0.521)	(19.797)		
Uniqueness: Any Characteristic	0.494***	-2.341***	-44.000***	[-70.292,-31.184]	116,495
Over 2 SD From Mean	(0.008)	(0.377)	(10.148)		
Uniqueness: Any Characteristic	0.504***	-2.384***	-47.284***	[-80.995,-33.281]	90,085
Over 1.5 SD From Mean	(0.009)	(0.384)	(12.678)		
High Aggregate Uniqueness Index	0.502***	-2.820***	-58.017***	[-98.104,-38.305]	92,645
	(0.008)	(0.484)	(15.291)		
FE: Quarter x ZIP x	0.480***	-2.321***	-43.091***	[-69.675,-28.318]	140,030
Top or Bottom Tier in ZIP	(0.008)	(0.327)	(10.839)		
FE: Quarter x ZIP x	0.480***	-2.516***	-45.689***	[-72.385,-22.595]	140,030
Tier Quartile in ZIP	(0.008)	(0.332)	(12.072)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

Table A13: IV Sample 2 Robustness 4: Miscellaneous Robustness Tests II

Dependent Var: Sell Within 13 Weeks Unless Otherwise Indicated					
Specification (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
Beta Varies By MSA-Year	0.461***	-2.099***	-35.003***	[-52.123,-23.767]	137,238
	(0.009)	(0.292)	(7.399)		
Beta Varies by MSA-Quarter	0.462***	-2.103***	-35.346***	[-52.401,-24.195]	137,238
	(0.009)	(0.292)	(7.412)		
Only Low All Cash Share ZIPs	0.500***	-2.554***	-35.700*	[-78.086,-17.256]	55,232
	(0.013)	(0.457)	(15.817)		
Uniqueness: Any Characteristic Over 2 SD From Mean	0.477***	-2.076***	-33.991***	[-51.256,-24.2]	113,714
	(0.009)	(0.306)	(7.129)		
Uniqueness: Any Characteristic Over 1.5 SD From Mean	0.487***	-2.124***	-37.348***	[-61.747,-26.938]	88,003
	(0.010)	(0.319)	(9.079)		
High Aggregate Uniqueness Index	0.484***	-2.474***	-44.945***	[-77.341,-29.962]	90,815
	(0.010)	(0.412)	(11.603)		
FE: Quarter x ZIP x Top or Bottom Tier in ZIP	0.462***	-2.019***	-30.136***	[-48.423,-17.66]	136,654
	(0.009)	(0.285)	(7.814)		
FE: Quarter x ZIP x Tier Quartile in ZIP	0.464***	-2.200***	-34.143***	[-54.441,-13.74]	136,654
	(0.010)	(0.273)	(10.228)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 2, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

fixed effects are added.

The top section of Tables A14 and A15 show results for the subset of homes that transact for three different outcome variables. First, it shows the main sale within 13 weeks outcome, for which the concavity is still significant. The second two specifications show results using weeks on the market as the outcome variable, for which concavity is indicated by a positive quadratic term rather than a negative term when probability of sale is the dependent variable. For both the baseline and alternate weeks on the market definitions, there is significant concavity.

The bottom section of Tables A14 and A15 show results for different sample restrictions. The top row includes investors who previously purchased with all cash. The concavity is somewhat weakened, which is not surprising as these sellers, who have had low appreciation since purchase, likely upgrade the house in unobservable ways, which should make these low appreciation (and by the instrument, high list price) houses sell faster, reducing the concavity.

For IV sample 1, the next four rows of Table A14 show results when the estimated equity threshold for inclusion in the sample is changed, while the last two rows show results when short sales and houses subsequently foreclosed upon are excluded and when houses with negative appreciation since purchase are excluded.[2] While the results are robust, they are weaker when we condition on a higher equity requirement. This is the case both because shrinking sample sizes expand confidence intervals and because the point estimate on the quadratic term drops a bit as the lowest appreciation since purchase borrowers have non-zero equity and are less sensitive to the instrument. Nonetheless, the results are either significantly concave or just barely insignificant at the 95 percent confidence level, making clear that the finding of concavity is not being driven by the sample selection criteria.

For IV sample 2, the bottom three rows of table A15 impose an estimated equity requirement of varying levels on IV sample 2. Again, the results are a bit weaker for higher equity requirements but are still significant.

Finally Tables A16 and A17 show results controlling for the number of nearby foreclosures (within 1 and 0.25 miles) over the entire downturn and over the past year. The results are very stable, indicating that the concavity cannot be explained by nearby foreclosure sales. These results are largely unchanged if one looks at other distance thresholds.

C.4 Ordinary Least Squares

An alternative to IV is to assume that there is no unobserved quality and thus no need for an instrument. This ordinary least squares approach implies that:

$$\tilde{p}_{h\ell t} = \xi_{\ell t} + \beta X_{h\ell t},$$

and so $p_{h\ell t} - \tilde{p}_{h\ell t}$ is equal to the regression residual $\eta_{h\ell t}$ in:

$$p_{h\ell t} = \xi_{\ell t} + \beta X_{h\ell t} + \eta_{h\ell t}, \tag{A8}$$

which can be estimated in a first stage and plugged into the second stage equation:

$$d_{h\ell t} = g\left(\eta_{h\ell t}\right) + \psi_{\ell t} + \varepsilon_{h\ell t}.$$

[2]For a few of the specifications with a high equity threshold, houses with less than 10 percent negative appreciation since purchase (rather than negative 20 percent) are dropped. This is done so that the stricter equity requirement does not make it so that the houses with the lowest appreciation since purchase are essentially all sellers who previously purchased with abnormally high down payments and who should be far less responsive to the instrument.

Table A14: IV Sample 1 Robustness 5: Transactions Only and Relaxing Sample Restrictions

Dependent Variable (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
Sell Within 13 Weeks	0.680***	-1.991***	-56.791**	[-102.866,-35.732]	96,400
	(0.007)	(0.325)	(17.277)		
Weeks on Market	12.959***	69.766***	2,008.614***	[1333.398,3282.778]	96,400
	(0.217)	(9.739)	(492.627)		
Weeks on Market	11.130***	57.628***	1,758.968***	[1149.601,2919.092]	96,400
Alternate Defn	(0.407)	(7.678)	(436.691)		
Including Investors Who Prev	0.480***	-1.553***	-21.995*	[-45.709,-12.182]	169,147
Purchased With All Cash	(0.007)	(0.272)	(8.594)		
Keeping Estimated Equity	0.451***	-3.215***	-49.967***	[-89.533,-31.677]	158,217
> -30%	(0.008)	(0.477)	(15.030)		
Keeping Estimated Equity	0.464***	-3.054***	-54.223***	[-95.958,-36.222]	150,932
> -20%	(0.008)	(0.450)	(15.497)		
Keeping Estimated Equity	0.498***	-1.410***	-22.902**	[-39.058,-1.223]	113,717
> 0 % †	(0.009)	(0.266)	(8.845)		
Keeping Estimated Equity	0.512***	-1.001***	-15.918*	[-26.834,2.268]	99,640
> 10% †	(0.009)	(0.216)	(6.893)		
Dropping Short Sales and	0.499***	-1.360***	-23.190**	[-39.136,-5.792]	107,896
Subsequent Foreclosure †	(0.010)	(0.236)	(8.128)		
Dropping Short Sales and	0.475***	-1.132***	-29.955**	[-55.902,-16.12]	102,342
Neg Appreciation Since Purch	(0.010)	(0.300)	(10.174)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing. The rows with a † indicate that rather than excluding households who had less than negative 20 percent appreciation since purchase from the sample, households with less than negative 10 percent appreciation since purchase have been excluded. This is done so that the stricter equity requirement does not make it so that the houses with the lowest appreciation since purchase have essentially all sellers who previously purchased with abnormally high down payments.

Table A15: IV Sample 2 Robustness 5: Transactions Only and Relaxing Sample Restrictions

Dependent Variable (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
Sell Within 13 Weeks	0.710***	-0.910***	-23.200***	[-37.92,-12.298]	86,033
	(0.007)	(0.131)	(6.773)		
Weeks on Market	11.953***	28.944***	753.945***	[474.25,1126.112]	86,033
	(0.212)	(4.313)	(167.095)		
Weeks on Market	10.278***	22.794***	714.468***	[480.683,1051.453]	86,033
Alternate Defn	(0.354)	(3.660)	(145.799)		
Including Investors Who Prev	0.463***	-1.442***	-18.225**	[-35.973,-10.607]	166,595
Purchase With All Cash	(0.008)	(0.263)	(6.580)		
Keeping Estimated Equity	0.477***	-1.815***	-24.651***	[-39.623,-15.414]	129,481
> -30%	(0.009)	(0.257)	(6.090)		
Keeping Estimated Equity	0.482***	-1.685***	-21.100***	[-33.209,-10.933]	126,501
> -20%	(0.009)	(0.236)	(5.508)		
Keeping Estimated Equity	0.488***	-1.483***	-13.854*	[-23.383,-1.408]	121,369
> -10 %	(0.009)	(0.209)	(5.434)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 2, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

Table A16: IV Sample 1 Robustness 6: Controls for Nearby Foreclosures

Dependent Variable (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
Control For Foreclosures	(0.008)	(0.339)	(12.415)		
Within .25 Miles Over Entire Downturn	0.479***	-2.301***	-41.762**	[-78.965,-30.086]	140,344
Control For Foreclosures	(0.008)	(0.358)	(13.021)		
Within 1 Mile Over Entire Downturn	0.479***	-2.308***	-41.484**	[-78.457,-29.78]	140,344
Control For Foreclosures	(0.008)	(0.342)	(12.338)		
Within .25 Miles in Past Year	0.479***	-2.293***	-41.415**	[-78.461,-29.906]	140,344
Control For Foreclosures	(0.008)	(0.359)	(13.025)		
Within 1 Mile in Past Year	0.479***	-2.303***	-41.487**	[-78.618,-29.784]	140,344
	(0.008)	(0.357)	(12.944)		

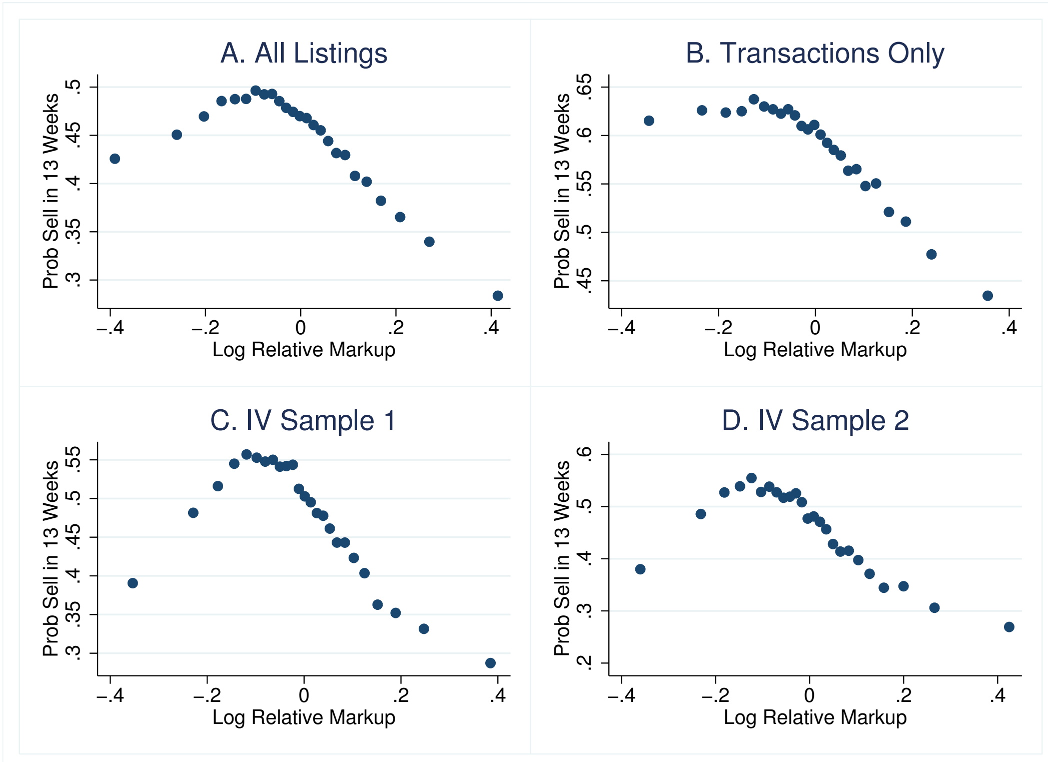
Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

Table A17: IV Sample 2 Robustness 6: Controls for Nearby Foreclosures

Dependent Variable (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
Control For Foreclosures	0.460***	-1.965***	-28.984***	[-55.093,-20.726]	137,238
Within .25 Miles Over Entire Downturn	(0.009)	(0.284)	(8.664)		
Control For Foreclosures	0.460***	-1.952***	-28.402***	[-53.095,-20.356]	137,238
Within 1 Mile Over Entire Downturn	(0.009)	(0.277)	(8.325)		
Control For Foreclosures	0.460***	-1.956***	-28.846***	[-55.099,-20.525]	137,238
Within .25 Miles in Past Year	(0.009)	(0.285)	(8.663)		
Control For Foreclosures	0.460***	-1.944***	-28.266***	[-53.067,-20.276]	137,238
Within 1 Mile in Past Year	(0.009)	(0.279)	(8.337)		

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when g(·) in equation (3) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (3), which is estimated by OLS. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 2, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

Figure A11: The Effect of List Price on Probability of Sale: Ordinary Least Squares



Notes: Each panel shows a binned scatter plot of the probability of sale within 13 weeks against the log relative markup. The OLS methodology assumes no unobserved quality. To create each figure, a first stage regression of log list price on fixed effects at the ZIP x first quarter of listing level x seller distress status level and repeat sales and hedonic log predicted prices, as in (A8), is estimated by OLS. Distress status corresponds to three groups: normal sales, REOs (sales of foreclosed homes and foreclosure auctions), and short sales (cases where the transaction price is less than the amount outstanding on the loan and withdrawals that are subsequently foreclosed on in the next two years). The residual is used as the relative markup in equation (3), which is estimated by OLS. The figure splits the data into 25 equally-sized bins of the estimated relative markup and plots the mean of the estimated relative markup against the log of the mean of the probability of sale within 13 weeks net of fixed effects for each bin. Before binning, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Panel A uses all listings with a prior observed sale N=416,373. Panel B uses listings with a prior observed sale that lead to transactions N = 310,758. Panel C uses IV sample 1,which drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. For panel C, N=140,344. Panel D uses IV sample 2 does away with the estimated equity requirement in IV sample 1 and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. For panel D, N=137,2387. In all cases, he number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

Given the importance of unobserved quality, this is likely to provide significantly biased results, but it is worth considering as a benchmark as discussed in the main text. This section provides additional OLS results to show that the findings in columns one, two, and four of Table 2 are robust.

Table A18: Ordinary Least Squares Robustness

Dependent Var: Weeks on Market					
Specification (Details In Text)	Quadratic Polynomial Coefficients Constant	Linear	Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
House Characteristic Controls	0.460*** (0.005)	-0.184*** (0.010)	-0.612*** (0.068)	[-0.769,-0.506]	399,423
Alternate Time to Sale Defn	0.514*** (0.013)	-0.222*** (0.014)	-0.530*** (0.080)	[-0.703,-0.402]	416,373
Dep Var: 18 Weeks	0.542*** (0.005)	-0.180*** (0.015)	-0.595*** (0.080)	[-0.773,-0.467]	416,373
Dep Var: 10 Weeks	0.393*** (0.004)	-0.218*** (0.012)	-0.467*** (0.074)	[-0.633,-0.352]	416,373
Hedonic Predicted Price Only	0.470*** (0.006)	-0.176*** (0.012)	-0.391*** (0.091)	[-0.578,-0.236]	663,976
Low REO ZIPs	0.470*** (0.013)	-0.331*** (0.026)	-0.382* (0.174)	[-0.752,-0.147]	134,666
Low Short Sale ZIPs For Predicted Price	0.476*** (0.016)	-0.325*** (0.022)	-0.433* (0.172)	[-0.765,-0.146]	109,249
Only FE Cells With At Least 20 Obs	0.460*** (0.008)	-0.250*** (0.014)	-0.481*** (0.099)	[-0.715,-0.336]	251,945
Predicted Prices Introduced as Cubic	0.459*** (0.004)	-0.212*** (0.011)	-0.596*** (0.059)	[-0.725,-0.495]	416,373
Beta Varies By MSA-Year	0.458*** (0.005)	-0.199*** (0.012)	-0.543*** (0.070)	[-0.704,-0.437]	416,373
First Listed 2008-7/2010	0.451*** (0.008)	-0.289*** (0.013)	-0.452*** (0.084)	[-0.637,-0.31]	223,429
First Listed 7/2010-2013	0.465*** (0.005)	-0.106*** (0.018)	-0.595*** (0.069)	[-0.757,-0.499]	192,944
Bay Area	0.478*** (0.010)	-0.213*** (0.015)	-0.573*** (0.081)	[-0.728,-0.414]	110,719
Los Angeles	0.446*** (0.005)	-0.199*** (0.019)	-0.495*** (0.110)	[-0.755,-0.336]	247,818
San Diego	0.473*** (0.008)	-0.196*** (0.030)	-0.718*** (0.025)	[-0.759,-0.677]	57,836

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Each row shows regression coefficients when g(.) in equation (3) is approximated using a quadratic polynomial. Quality is assumed to be perfectly measured by the hedonic and repeat-sales predicted prices and have no unobserved component. Consequently, the log list price is regressed on fixed effects and the predicted prices and uses the residual as the estimated relative markup into equation (3), as described in Appendix C. The fixed effects at the quarter of initial listing x ZIP x distress status level. Distress status corresponds to three groups: normal sales, REOs (sales of foreclosed homes and foreclosure auctions), and short sales (cases where the transaction was less than the amount outstanding on the loan and withdrawals that are subsequently foreclosed on in the next two years). The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is Winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The number of observations listed is prior to dropping observations that are unique to a ZIP-quarter cell and winsorizing. The appendix text details each specification.

Because the OLS sample may include distressed sales, I take a conservative approach and include fixed effects at the ZIP $\times$ quarter $\times$ distress status level. Distressed status is defined as either non-distressed, REO, or a short sale (or withdrawn listing subsequently foreclosed upon). The results would look similar if ZIP $\times$ quarter fixed effects were used and an additive categorical control for distressed status were included in $X_{h\ell t}$.

First, Figure A11 shows binned scatter plots for OLS for all listings, transactions only, and each of the IV samples. In each, a clear pattern of concavity is visible, but as discussed in the main text, the upward slope on the left indicates the presence of substantial unobserved quality—particularly among homes that do not sell—and thus the need for an instrument.[3] The concavity is only slightly stronger in the IV samples, assuaging concerns about sample selection. Importantly, most of the differences occur in the extremely low log relative markup quantiles, which do not look like outliers in the IV binned scatter plot, assuaging concerns about sample selection driving some of the findings of concavity.

Table A18 shows a number of robustness and specification checks. Those different from the IV specification checks described previously are:

- House Characteristic Controls: As with IV, this includes a third-order polynomial in age, log square feet, bedrooms, and bathrooms, but it also includes additive fixed effects for quintiles of the time since purchase distribution in $X_{h\ell t}$.
- Hedonic predicted price only: Drops the repeat-sales house price index from $X_{h\ell t}$. This expands the sample to all listings in the data rather than only those with a prior observed sale.
- Low REO ZIPs: Only includes ZIP codes with less than 20 percent REO sale shares from 2008 to 2013. (REO is a sale of a foreclosed property.)
- Low Short ZIPs: Only includes ZIP codes with less than 20 percent short sale shares from 2008 to 2013. (A short sale occurs when a homeowner sells their house for less than their outstanding mortgage balance and must negotiate the sale with their lender.)
- No REO or Short Sale: Drops REOs, short sales, and withdrawn sales subsequently foreclosed upon homes, thus only leaving non-distressed sales.
- Transactions only: Drops houses withdrawn from the market.
- IV Subsample: Drops homes with negative appreciation since purchase, REOs, and homes previously purchased with all cash.

All specifications show significant concavity.

C.5 Robustness to Other Sources of Markup Variation

In my estimation, I assume $\zeta_{h\ell t} = 0$, that is that there are no other sources of markup variation that manifest themselves as Berkson measurement error. While this is not realistic, I argue that if $\zeta_{h\ell t} \neq 0$ and $\zeta_{h\ell t} \perp f(z_{h\ell t})$, using a quadratic or cubic polynomial for $g(\cdot)$ will lead to unbiased estimates of the coefficient on the quadratic or cubic terms. This appendix relaxes these assumptions to assess the robustness of the econometric strategy to other sources of markup variation entering

[3] An alternative explanation is that in the later years of my sample I do not have follow-up data on foreclosures, so some withdrawn short sales are counted as non-distressed. This may explain some of the upward slope, as the upward slope is concentrated in non-withdrawn properties, high short sale ZIP codes, and the later years of my sample.

$g(\cdot)$ nonlinearly when $\zeta_{h\ell t}$ is independent of the instrument and when $\zeta_{h\ell t}$ is correlated with the instrument.

Recall that I want estimate the non-linear effect of the relative markup $p_{h\ell t} - \tilde{p}_{h\ell t}$ on the probability of sale $d_{h\ell t}$. The reference price is $\tilde{p}_{h\ell t} = \xi_{\ell t} + q_{h\ell t}$, where $\xi_{\ell t}$ is the average price in location ℓ at time t. $q_{h\ell t}$ is quality defined as $q_{h\ell t} = \beta X_{h\ell t} + u_{h\ell t}$ where $u_{h\ell t}$ is unobserved quality and $X_{h\ell t}$ are observable measures of quality. Unobserved quality affects $q_{h\ell t}$, which in turn affects $\tilde{p}_{h\ell t}$.

Unobserved quality is problematic for two reasons. First, it is likely correlated with price. This endogeneity problem is the main issue I address through instrumental variables. Second, one cannot observe $\tilde{p}_{h\ell t}$ directly, so there is a measurement error problem. In a classical measurement error setup in which the error is independent of the true value, the instrumental variable would solve this issue as well. However, here by construction I have that $\beta X_{h\ell t}$, the observed quality, is independent of $u_{h\ell t}$, the unobserved quality. In other words, the measurement error is independent of the proxy I see (observed quality) rather than being independent of true quality $q_{h\ell t}$. This is known as Berkson measurement error, and it cannot be solved through traditional IV methods.[4] This manifests itself in the first stage of the IV estimation:

$$\begin{aligned} p_{h\ell t} - \tilde{p}_{h\ell t} &= f(z_{h\ell t}) + \zeta_{h\ell t} \\ &= f(z_{h\ell t}) + \xi_{\ell t} + \beta X_{h\ell t} + u_{h\ell t} + \zeta_{h\ell t}. \end{aligned}$$

The residual now has two components: $u_{h\ell t}$, which is part of $\tilde{p}_{h\ell t}$, and $\zeta_{h\ell t}$, which is not. One thus cannot identify $p_{h\ell t} - \tilde{p}_{h\ell t}$ as it is observed with measurement error.

To assess whether the assumption that $\zeta_{h\ell t} = 0$ may generate spurious concavity, I perform Monte Carlo simulations that relax the assumptions in the main lemma. To do so, for each house in IV sample 1 (results are similar across the two samples) I simulate $d_{h\ell t}$ using an assumed true $g(\cdot)$, which is either the baseline cubic fit to the data in Figure 2 in the text or a linear fit to the data, and an assumed measurement error distribution $\zeta_{h\ell t}$. I simulate $d_{h\ell t}$ using:

$$d_{h\ell t} = g(p_{h\ell t} - \tilde{p}_{h\ell t}) + \psi_{\ell t} + \varepsilon_{h\ell t}.$$

However, rather than assuming $p_{h\ell t} - \tilde{p}_{h\ell t} = f(z_{h\ell t})$, I let $p_{h\ell t} - \tilde{p}_{h\ell t} = f(z_{h\ell t}) + \zeta_{h\ell t}$ and report results for different parameterizations for the other sources of relative markup variation $\zeta_{h\ell t}$.

Specifically, I follow a five step procedure 1,000 times and report the average values:

1. Based on first stage, calculate $p_{h\ell t} - \tilde{p}_{h\ell t} = f(z_{h\ell t})$. In doing so, I drop the 1st and 99th percentile, which remain dropped throughout the exercise so sample sizes are consistent.

2. Estimate $\psi_{\ell t}$ given assumed $g(\cdot)$.

3. Draw $\zeta_{h\ell t}$ from assumed distribution. Using the assumed $g(\cdot)$, calculate $g(f(z_{h\ell t}) + \zeta_{h\ell t}) + \psi_{\ell t}$.

4. $d_{h\ell t}$ is drawn from a Bernoulli distribution in which the house sells with probability $g(f(z_{h\ell t}) + \zeta_{h\ell t}) + \psi_{\ell t}$.

5. Run the estimator of interest on the simulated $d_{h\ell t}$s.

[4] There are two main ways to address Berkson measurement error in a nonlinear setting. First, one can have an additional outcome variable, which can be used as an instrument. I do not have such a variable here. Second, one can use higher-order conditional moments (e.g. $E[Y^2|X]$ in addition to $E[Y|X]$) to identify the distribution of Berkson error. Unfortunately, this does not work either as a I have a binary outcome variable and so the higher-order conditional moments do not provide any additional information. I have used this technique on alternate outcomes such as weeks on the market conditional on a transaction, and my finding of concavity is unchanged.

Table A19: Monte Carlo Simulations: Adding Independent Noise to Concave and Linear True Demand Curve

Panel A: $\zeta_{h\ell t}$ Added to Concave Assumed True Demand Curve			
Quadratic Polynomial Coef Estimates	SD of $\zeta_{h\ell t}$ 0	0.02	0.04
Constant	0.4789	0.464	0.422
	(0.002)	(0.002)	(0.002)
Linear	-2.218	-1.812	-0.820
	(0.077)	(0.077)	(0.077)
Quadratic	-41.572	-41.756	-35.524
	(4.508)	(4.662)	(4.411)
Quadratic 95% CI	[-49.754,-32.349]	[-50.934,-32.372]	[-44.065,-26.622]

Panel B: $\zeta_{h\ell t}$ Added to Linear Assumed True Demand Curve			
Quadratic Polynomial Coef Estimates	SD of $\zeta_{h\ell t}$ 0	0.02	0.04
Constant	0.463	0.463	0.464
	(0.002)	(.002)	(.002)
Linear	-2.319	-2.317	-2.295
	(0.083)	(0.079)	(0.077)
Quadratic	3.291	3.207	3.148
	(4.513)	(4.488)	(4.39)
Quadratic 95% CI	[-5.673,11.947]	[-5.362,11.746]	[-5.427,11.722]

Notes: Each column shows the mean and standard deviation over 1,000 Monte Carlo simulations of the point estimates of a quadratic polynomial for g(·) as in the main text. The simulated data is the actual data for all parameters except for whether the house sold within 13 months, which is created as simulated data using an assumed value for g(·), here a cubic estimate, and then adding noise to the first stage relative markup that is independent of the instrument and normally distributed with mean zero and the indicated standard deviation. The simulation procedure is described in detail in the Appendix text and uses IV sample 1.

Table A19 shows results with a normally distributed $\zeta_{h\ell t}$ that is independent of $f(z_{h\ell t})$. In panel A, the assumed true $g(\cdot)$ is the third-order polynomial estimate of $g(\cdot)$ shown in Figure 2 in the main text. In panel B, the assumed true $g(\cdot)$ is a linear fit to the data, identical to Figure 2 in the main text but with a linear fit instead of a cubic fit. Panel A shows that increasing the standard deviation of $\zeta_{h\ell t}$ leads to a $g(\cdot)$ that is steeper and more linear than the baseline estimates, reflecting bias if the true $g(\cdot)$ is not a polynomial. Panel B shows that adding noise to a linear true $g(\cdot)$ does not create spurious concavity. Other sources of variation in the relative markup that are independent of the instrument would thus likely lead to an under-estimate of the true degree of concavity, if anything, and would not generate spurious concavity.

Spurious concavity is, however, a possibility if the variance of $\zeta_{h\ell t}$ were correlated with $z_{h\ell t}$. Specifically, consider the case where the instrument captures most of the variation in the relative markup for sellers with low appreciation since purchase but little of the variation with high appreciation since purchase. Then the observed probability of sale at low $p_{h\ell t} - \tilde{p}_{h\ell t}$ would be an average of the probabilities of sale at true $p_{h\ell t} - \tilde{p}_{h\ell t}$s that are scrambled, yielding an attenuated slope for low $p_{h\ell t} - \tilde{p}_{h\ell t}$. However, at high $p_{h\ell t} - \tilde{p}_{h\ell t}$, the observed $p_{h\ell t} - \tilde{p}_{h\ell t}$ would be close to the true $p_{h\ell t} - \tilde{p}_{h\ell t}$, yielding the true slope.

Table A20 illustrates that this type of bias could create spurious concavity. However, generating the amount of concavity I observe in the data would require an extreme amount of unobserved vari-

Table A20: Monte Carlo Simulations: Other Sources of Markup Variation Corr With Instrument

SD $f(z) < .01$	0	0.10	0.20	0.50	0.20	0.40
SD $f(z) \geq .01$	0	0	0	0	0.10	0.10
Constant	0.463	0.466	0.473	0.484	0.474	0.482
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(.002)
Linear	-2.316	-2.273	-2.154	-1.973	-1.993	-1.847
	(0.078)	(0.081)	(0.082)	(0.082)	(0.082)	(0.081)
Quadratic	3.184	-2.434	-15.990	-37.090	-10.929	-27.476
	(4.480)	(4.523)	(4.659)	(4.682)	(4.728)	(4.652)
Quadratic 95% CI	[-5.893,11.690]	[-11.253,5.992]	[-25.000,-7.128]	[-46.687,-27.727]	[-20.048,-1.858]	[-36.481,-18.358]

Notes: Each column shows the mean and standard deviation over 1,000 Monte Carlo simulations of the point estimates of a three-part spline in g(·) as in the main text. The simulated data is the actual data for all parameters except for whether the house sold within 13 months, which is created as simulated data using an assumed value for g(·), here a cubic estimate, and then adding noise to the first stage relative markup. Here the variance of the noise depends on $f(z_{h\ell t})$ (the estimated log relative markup) and thus the instrument. Specifically, the noise is normally distributed with a standard deviation equal to the first row if $f(z_{h\ell t}) < .01$ and the second row if $f(z_{h\ell t}) \geq .01$. This makes the noise larger for homes with more appreciation since purchase, creating the potential spurious concavity from heteroskedasticity described in the text. The simulation procedure is described in detail in the Appendix text and uses IV sample 1.

ation in the relative markup at low levels of appreciation since purchase and virtually no unobserved variation in the relative markup at high levels of appreciation. To show this, I assume the true $g(\cdot)$ is linear and let the standard deviation of $\zeta_{h\ell t}$ depend on $f(z_{h\ell t})$ in a piecewise manner as indicated in the first two rows of the table. This piecewise formulation is a particularly extreme dependence of $\zeta_{h\ell t}$ on $f(z_{h\ell t})$. The first column shows estimates with no noise, which are approximately linear. To generate statistically-significant spurious concavity, the standard deviation of other sources of variation in the relative markup must be near 0.2 log points for high appreciation since purchase and zero for low appreciation since purchase. However, the lower bound of the 95 percent confidence interval in this case still falls well short of the point estimates of the quadratic term in in the baseline IV specification for sample 1 shown in Table 2. To match the point estimate on the quadratic term requires the relative markup be near 0.5 log points for high appreciation since purchase and zero for low appreciation since purchase. This is an extreme amount of measurement error for high appreciation since purchase relative to low appreciation since purchase: at high appreciation since purchase the measurement error must have roughly 20 times the variation induced by the instrument and must account for nearly the entire amount of variation in list and transaction prices in the raw data. This is implausible as unobserved quality is almost certain to account for some of the variation in list and transaction prices for all levels of appreciation since purchase, which bounds the variance of the measurement error distribution below what is necessary to generate significant spurious concavity. The last two columns show that one can obtain significant concavity with slightly less extreme assumptions, but still to get a point estimate near what I observe in the data, one would need a standard deviation of 0.1 log points for high appreciation since purchase and 0.4 log points for high appreciation since purchase, which again seems implausibly large.

D Facts About House List Prices

This appendix provides facts about house list prices that motivate some of the assumptions made in the model

Figure A12: Histogram of the Difference Between Log Transaction Price and Log Final List Price

Notes: The figure shows a histogram of the difference between log transaction price at the time of sale and log final list price for all homes in the San Francisco Bay, Los Angeles, and San Diego areas that were listed between April 2008 and February 2013 that are matched to a transaction and have a previous observed listing. The 1st and 99th percentiles are dropped from the histogram. N = 470,655.

D.1 List Prices Relative to Transaction Prices

As mentioned in the main text, the modal house sells at its list price at the time of sale and the average and median house sell within 0.016 log points of their list price. To illustrate this, Figure A12 shows a histogram of the difference between the log final list price at sale and the log transaction price in the Altos-DataQuick merged data after extreme outliers likely due to typos in the list or transaction price have been dropped. 9.17 percent of transactions occur exactly at the final list price, and 22.63 percent occur within one percent of the final list price. The mean of the difference between the log final list price and the log first list price is -0.016 log points, and the median is -0.010 log points.

Table A21 reinforces these findings by showing mean and median log difference for each of the three MSAs in each year. The mean does not fluctuate by more than 0.03 log points across years and MSAs.

Note that the stability of the difference between list price and transaction price across years and markets does not hold for the *initial* list price. This is because most houses are listed high and then the list price is lowered over time. Consequently, the difference between the log first list price and the transaction price is -0.060 log points, 0.044 log points below the difference between the log final list price and the transaction price. This varies over time and across markets because the number of markdowns varies as time to sale varies with market conditions. While this feature of the data

Table A21: Difference Between Log Transaction Price and Log Final List Price

	Mean			Median		
	SF Bay	Los Angeles	San Diego	SF Bay	Los Angeles	San Diego
2008	-0.021	-0.008	-0.023	-0.013	-0.017	-0.011
2009	0.001	-0.028	-0.010	0.000	0.000	-0.003
2010	-0.011	-0.008	-0.026	-0.007	-0.013	-0.019
2011	-0.015	-0.021	-0.031	-0.011	-0.018	-0.023
2012-3	0.008	-0.026	-0.009	0.000	-0.005	-0.002

Notes: Each cell shows the mean difference between the log transaction price and log final list price in the indicated MSA-year cell. To reduce the influence of outliers, the 1st and 99th percentiles have bin dropped. N = 470,655.

is abstracted from in the model, the model does allow for list prices to change as market conditions change, and thus it does allow for there to be differences between the initial and final list price. The key assumption is that houses sell at their *final* list price.

It is, however, possible that the difference between list and transaction prices varies systematically based on whether a house is listed above or below average. This would be problematic because I assume that the house sells at its list price regardless of whether it is overpriced or not.

To address this concern, I replicate the IV approach in the main text, but replace the indicator variable for whether the house was sold within 13 months with the difference between the log list price and the log transaction price, using both the first and final log list price. The IV control for unobserved quality is essential here, as in OLS it is unclear whether a house is being listed high because it is of high unobserved quality or because the seller has chosen a high list price. By instrumenting for unobserved quality, I isolate the effect of listing high relative to a house's quality on whether the house sells above or below its list price.

Figure A13 shows the results. The left column shows IV sample 1, while the right column shows IV sample 2. The top row shows binned scatter plots where the dependent variable is the log transaction price minus the log first list price, while the bottom row shows binned scatter plots where the dependent variable is the log transaction price minus the log final list price. In none of them is there a pronounced pattern. If anything, the difference between the log transaction price and log first list price shows a slight inverse-U pattern, suggesting that sellers have to cut their price less on average if they set their price at the "correct" initial price, but this effect is small and insignificant. The difference between the log transaction price and log final list price shows no clear pattern.

These results suggest that for empirically-relevant forms of *ex-post* bargaining, the list price is the best predictor of the transaction price. Due to linear utility in the model, this will not substantially alter the seller's incentive to set a list price close to the market average. In particular, if the demand curve $d\left(p_t^{list}, \Omega_t, \tilde{\theta}_t\right)$ is concave in list price but the sale price is $p_t = p_t^{list} + \upsilon$ where υ is mean-zero error, then the seller's problem will be:

$$\max_{p_t^{list}} E_\upsilon \left[d\left(p_t^{list}, \Omega_t, \tilde{\theta}_t\right) \left(p_t^{list} + \upsilon - s - \beta V_{t+1}^s\right)\right]$$

which reduces to

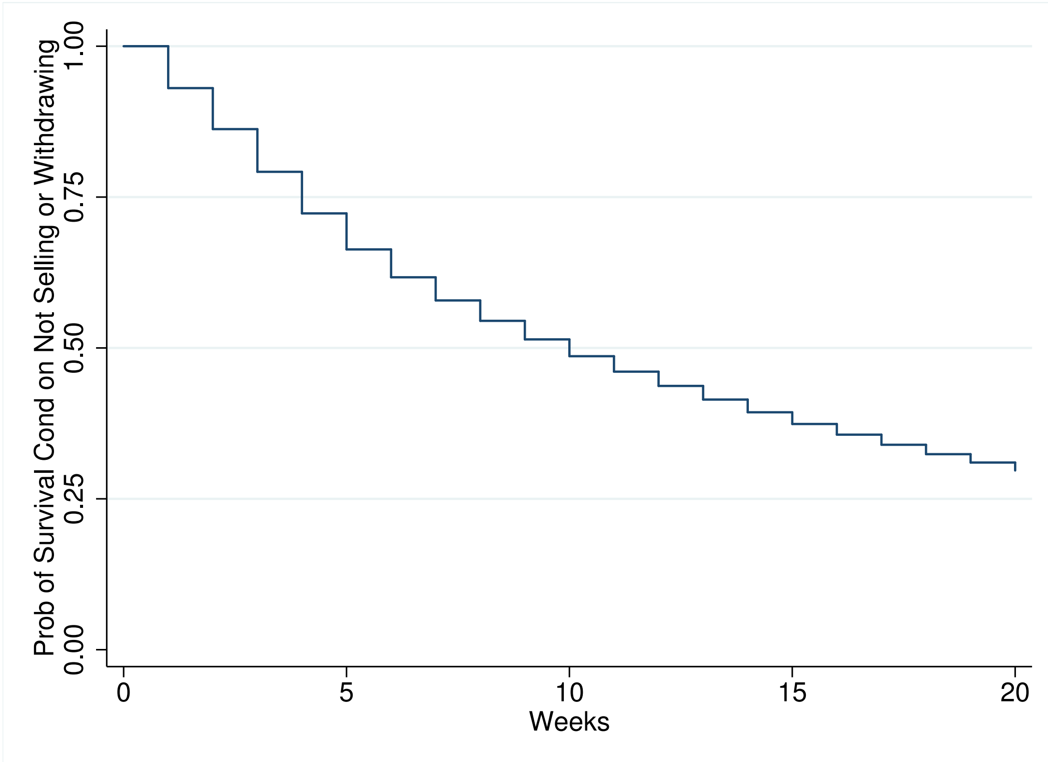
$$\max_{p_t^{list}} d\left(p_t^{list}, \Omega_t, \tilde{\theta}_t\right) \left(p_t^{list} - s - \beta V_{t+1}^s\right)$$

which is the same seller problem as my model with no *ex-post* bargaining.

Figure A13: IV Specification: Difference Between Log Transaction Price and Log List Price vs. Log Relative Markup

Notes: Each panel shows a binned scatter plot of the difference between the transaction price and the indicated log list price for the set of houses that transact net of ZIP × first quarter of listing fixed effects (with the average probability of sale within 13 weeks added in) against the estimated log relative markup $p - \tilde{p}$. To create the figure, a first stage regression of the log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and repeat sales and hedonic log predicted prices, as in (6), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup. The figure splits the data into 25 equally-sized bins of this estimated relative markup and plots the mean of the estimated relative markup against the mean of the difference between the log transaction and log list price net of fixed effects for each bin, as detailed in Appendix C. Before binning, the top and bottom 0.5 percent of the log sale price residual and any observations fully absorbed by fixed effects are dropped. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. IV sample 1 drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. The sample is the sample of houses that transact in each IV sample. N = 96,400 observations for IV sample 1 and 86,033 observations for IV sample 2 prior to dropping unique zip-quarter cells and winsorizing.

Figure A14: Kaplan-Meier Survival Curve For List Prices



Notes: The figure shows the Kaplan-Meier survival curve for list price in the Altos-DataQuick data, where sales and withdrawals are treated as censored observations and a price change is treated as a failure. The curve thus corresponds to the probability of a list price surviving for a given number of weeks conditional on the property not having sold. The sample is made up of 885,836 listings with 1,849,398 list prices and 15,104,588 week-listings of homes in the San Francisco Bay, Los Angeles, and San Diego areas. Any match between Altos and DataQuick is included in this sample. To help the reader observe price change hazards in the first several weeks of listing, the survival curve is only shown through 20 weeks.

D.2 Frequency of Price Changes in Microdata

To assess the frequency of price changes in the microdata, I use the Altos-DataQuick matched data. I create a dataset where each observation is a week-listing, with listings consolidated together so that de-listings and re-listings within 13 weeks without an intervening foreclosure are counted as a single listing (this is why I use only Altos listings that are matched to a DataQuick property). For the three MSAs, this gives me 885,836 listings with 1,849,398 unique price-listings and 15,104,588 week-listings.

Figure A14 shows the Kaplan-Meier survival curve for list prices, which plots the probability that a price survives for a given number of weeks conditional on the house not selling or being withdrawn from the market. The median price lasts 9 weeks (week 1 to week 10), or approximately two months. This is used to motivate a two-month fixed price in the staggered pricing model.

E Model

For simplicity of exposition, I define everything for the rule of thumb model and then describe how the staggered pricing model differs rather than juggling the two simultaneously.

E.1 Lemma 2: Optimal Price Setting

From the definition of V_t^s, sellers solve:

$$\max_{p_t} d\left(p_t, \Omega_t, \tilde{\theta}_t\right)\left[p_t - s - \beta V_{t+1}^s\right],$$

with first order condition:

$$\begin{aligned} 0 &= \frac{\partial d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{\partial p_t}\left[p_t - s - \beta V_{t+1}^s\right] + d\left(p_t, \Omega_t, \tilde{\theta}_t\right) \\ p_t &= s + \beta V_{t+1}^s + \frac{d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{-\frac{\partial d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{\partial p_t}}. \end{aligned}$$

Using the definitions of d^f and d^d:

$$\frac{\partial d^f\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{\partial p_t} = d^f\left(p_t, \Omega_t, \tilde{\theta}_t\right)\left[\frac{-f(\cdot)}{1-F(\cdot)} + \frac{-g(\cdot)}{1-G(\cdot)}\right],$$

and

$$\frac{\partial d^d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{\partial p} = d^d\left(p_t, \Omega_t, \tilde{\theta}_t\right)\left[\frac{g(\cdot)}{G(\cdot)} + \frac{-f(\cdot)}{1-F(\cdot)}\right].$$

So that the markup is (suppressing arguments for parsimony):

$$\begin{aligned} \frac{d_t}{-\frac{\partial d_t}{\partial p_t}} &= \frac{d^f + d^d}{d^f\left[\frac{f}{1-F} + \frac{g}{1-G}\right] + d^d\left[\frac{f}{1-F} - \frac{g}{G}\right]} \\ &= \frac{d^f + d^d}{d\frac{f}{1-F} + d^f\left[\frac{g}{1-G}\right] - d^d\left[\frac{1-G}{G}\frac{g}{1-G}\right]} \\ &= \frac{d^f + d^d}{d\frac{f}{1-F} + d\frac{g}{1-G} - \frac{g}{1-G}\frac{1}{G}d^d} \\ &= \frac{1}{\frac{f}{1-F} + \frac{g}{1-G}\left(1 - \frac{1}{G}\frac{d^d}{d}\right)}. \end{aligned}$$

This optimal price is unique on the concave region of the demand curve by standard arguments. However, the problem may not be globally concave if $\bar{\varepsilon}$ is past the point where $G(\cdot)$ begins to flatten, and sellers may have an incentive to deviate. If they do, they would always choose $\bar{\varepsilon}$, as the demand curve is very inelastic in the non-concave region, pushing the markup to the highest possible level. I describe tests for whether the seller would like to deviate to post $\bar{\varepsilon}$ in Section E.4.

E.2 F(·) Distribution, Full Equilibrium System, and Simulation Details

The $F(\cdot)$ distribution is parameterized as a uniform distribution with a mass point of weight χ at $\bar{\varepsilon}$. The density for $\varepsilon < \bar{\varepsilon}$ is defined by:

$$\int_{\underline{\varepsilon}}^{\bar{\varepsilon}} f(\varepsilon)\, d\varepsilon = 1 - \chi,$$

where $f(\varepsilon)$ is a constant f. Thus,

$$\int_{\underline{\varepsilon}}^{\bar{\varepsilon}} f d\varepsilon = 1 - \chi \Rightarrow f(\bar{\varepsilon} - \underline{\varepsilon}) = 1 - \chi \Rightarrow f = \frac{1-\chi}{\bar{\varepsilon} - \underline{\varepsilon}}.$$

The survivor function is:

$$\begin{aligned} 1 - F(\varepsilon) &= \int_{\varepsilon}^{\bar{\varepsilon}} f(\varepsilon)\, d\varepsilon + \chi = \frac{(\bar{\varepsilon} - \varepsilon)(1-\chi)}{\bar{\varepsilon} - \underline{\varepsilon}} + \chi \\ &= \frac{(\bar{\varepsilon} - \varepsilon)(1-\chi) + \chi(\bar{\varepsilon} - \underline{\varepsilon})}{\bar{\varepsilon} - \underline{\varepsilon}} \\ &= \frac{\bar{\varepsilon} - \varepsilon + \chi(\varepsilon - \underline{\varepsilon})}{\bar{\varepsilon} - \underline{\varepsilon}}. \end{aligned}$$

The hazard function is:

$$h(\varepsilon) = \frac{f(\varepsilon)}{1 - F(\varepsilon)} = \frac{\frac{1-\chi}{\bar{\varepsilon}-\underline{\varepsilon}}}{\frac{(\bar{\varepsilon}-\varepsilon)(1-\chi)}{\bar{\varepsilon}-\underline{\varepsilon}} + \chi} = \frac{1}{(\bar{\varepsilon} - \varepsilon) + \frac{\chi}{1-\chi}(\bar{\varepsilon} - \underline{\varepsilon})}.$$

The upper-tail conditional expectation is:

$$\begin{aligned} E[\varepsilon | \varepsilon > \varepsilon^*] &= \frac{\int_{\varepsilon^*}^{\bar{\varepsilon}} \varepsilon f(\varepsilon)\, d\varepsilon}{1 - F(\varepsilon^*)} = \frac{\chi\bar{\varepsilon} + \frac{1-\chi}{\bar{\varepsilon}-\underline{\varepsilon}} \int_{\varepsilon^*}^{\bar{\varepsilon}} \varepsilon d\varepsilon}{\frac{(\bar{\varepsilon}-\varepsilon)(1-\chi)}{\bar{\varepsilon}-\underline{\varepsilon}} + \chi} = \frac{\chi\bar{\varepsilon} + \frac{1-\chi}{\bar{\varepsilon}-\underline{\varepsilon}} \int_{\varepsilon^*}^{\bar{\varepsilon}} \varepsilon d\varepsilon}{\frac{(\bar{\varepsilon}-\varepsilon)(1-\chi)}{\bar{\varepsilon}-\underline{\varepsilon}} + \chi} = \frac{\chi\bar{\varepsilon} + \frac{1-\chi}{\bar{\varepsilon}-\underline{\varepsilon}} \frac{\bar{\varepsilon}^2 - {\varepsilon^*}^2}{2}}{\frac{(\bar{\varepsilon}-\varepsilon)(1-\chi)}{\bar{\varepsilon}-\underline{\varepsilon}} + \chi} \\ &= \frac{\chi\bar{\varepsilon} + \frac{1-\chi}{\bar{\varepsilon}-\underline{\varepsilon}} \frac{(\bar{\varepsilon}+\varepsilon^*)(\bar{\varepsilon}-\varepsilon^*)}{2}}{\frac{(\bar{\varepsilon}-\varepsilon)(1-\chi)}{\bar{\varepsilon}-\underline{\varepsilon}} + \chi} \\ &= \frac{\chi\bar{\varepsilon}(\bar{\varepsilon} - \underline{\varepsilon}) + \frac{1-\chi}{2}(\bar{\varepsilon} + \varepsilon^*)(\bar{\varepsilon} - \varepsilon^*)}{\bar{\varepsilon} - \varepsilon^* + \chi(\varepsilon^* - \underline{\varepsilon})}. \end{aligned}$$

The mean excess function is thus:

$$E[\varepsilon - \varepsilon^* | \varepsilon > \varepsilon^*] = \frac{\chi\bar{\varepsilon}(\bar{\varepsilon} - \underline{\varepsilon}) + \frac{1-\chi}{2}(\bar{\varepsilon} + \varepsilon^*)(\bar{\varepsilon} - \varepsilon^*)}{\bar{\varepsilon} - \varepsilon^* + \chi(\varepsilon^* - \underline{\varepsilon})} - \varepsilon^*.$$

The $G(\cdot)$ distribution is a type 1 generalized normal. The PDF is:

$$g(x) = \frac{\zeta}{2\sigma\Gamma(1/\zeta)} e^{-(|x-\mu|/\sigma)^\zeta},$$

and the CDF is:

$$G(x)=\frac{1}{2}+sgn(x-\mu)\frac{\gamma\left[\frac{1}{\zeta},\left(\frac{|x-\mu|}{\sigma}\right)^{\zeta}\right]}{2\Gamma(1/\zeta)}.$$

This implies a hazard function of:

$$\frac{g}{1-G}=\frac{\frac{\zeta}{\sigma}exp\left(-\left(|x-\mu|/\sigma\right)^{\zeta}\right)}{\Gamma(1/\zeta)-sgn(x-\mu)\gamma\left[\frac{1}{\zeta},\left(\frac{|x-\mu|}{\sigma}\right)^{\zeta}\right]}.$$

Note that the CDF is piecewise. However, in all calibrations $\mu \gg 0$, so $sgn(x-\mu)<0$. I thus perturb the equilibrium assuming that the equilibrium is on the upper-portion of the CDF. To assess the quality of the log-quadratic approximation I make sure that the dynamic model stay son the upper portion of the CDF and also compare the IRFs obtained from perturbation to IRFs obtained from one-time shocks in a deterministic model. Appendix G shows they are nearly identical, so this assumption is not crucial.

The markup is then:

$$\begin{aligned}Markup_t &= \frac{1}{\frac{f}{1-F}+\frac{g}{1-G}\left(1-\frac{1}{G}\frac{d^d}{d}\right)}\\ &= \frac{1}{\frac{1}{(\bar{\varepsilon}-\varepsilon)+\frac{\chi}{1-\chi}(\bar{\varepsilon}-\underline{\varepsilon})}+\frac{\frac{\zeta}{\sigma}exp\left(-\left(|p_t-E_\Omega[p_t]-\mu|/\sigma\right)^{\zeta}\right)}{\Gamma(1/\zeta)-sgn(p_t-E_\Omega[p_t]-\mu)\gamma\left[\frac{1}{\zeta},\left(\frac{|p_t-E_\Omega[p_t]-\mu|}{\sigma}\right)^{\zeta}\right]}\times\left(1-\frac{2\Gamma(1/\zeta)}{\Gamma(1/\zeta)+sgn(p_t-E_\Omega[p_t]-\mu)\gamma\left[\frac{1}{\zeta},\left(\frac{|p_t-E_\Omega[p_t]-\mu|}{\sigma}\right)^{\zeta}\right]}\frac{d^d}{d}\right)}\end{aligned}$$

It is worth simplifying several conditions with expectations over the set of list prices Ω. Note that there are two list prices: p_t^E with mass α and p_t^R with mass $1-\alpha$, so $E_{\Omega_t}[X]=\alpha X^E+(1-\alpha)X^R$. Consequently,

$$\begin{aligned}E_{\Omega_t}[p_t] &= \alpha p_t^E+(1-\alpha)p_t^R\\ E_{\Omega_t}[d_t] &= \alpha d_t^E+(1-\alpha)d_t^R.\end{aligned}$$

To simplify notation, let:

$$\begin{aligned}
G_t^E &= G\left(p_t^E - E_{\Omega_t}[p_t] - \mu\right) = \frac{1}{2} + sgn\left(p_t^E - E_{\Omega_t}[p_t] - \mu\right)\frac{\gamma\left[\frac{1}{\beta}, \left(\frac{\left|p_t^E - E_{\Omega_t}[p_t] - \mu\right|}{\sigma}\right)^{\zeta}\right]}{2\Gamma(1/\zeta)} \\
G_t^R &= G\left(p_t^R - E_{\Omega_t}[p_t] - \mu\right) = \frac{1}{2} + sgn\left(p_t^R - E_{\Omega_t}[p_t] - \mu\right)\frac{\gamma\left[\frac{1}{\beta}, \left(\frac{\left|p_t^R - E_{\Omega_t}[p_t] - \mu\right|}{\sigma}\right)^{\zeta}\right]}{2\Gamma(1/\zeta)} \\
M_t^E &= E\left[\varepsilon - \varepsilon_t^{*,E} | \varepsilon > \varepsilon_t^{*,E}\right] = \frac{\chi\bar{\varepsilon}\left(\bar{\varepsilon} - \underline{\varepsilon}\right) + \frac{1-\chi}{2}\left(\bar{\varepsilon} + \varepsilon_t^{*,E}\right)\left(\bar{\varepsilon} - \varepsilon_t^{*,E}\right)}{\bar{\varepsilon} - \varepsilon_t^{*,E} + \chi\left(\varepsilon_t^{*,E} - \underline{\varepsilon}\right)} - \varepsilon_t^{*,E} \\
M_t^R &= E\left[\varepsilon - \varepsilon_t^{*,R} | \varepsilon > \varepsilon_t^{*,R}\right] = \frac{\chi\bar{\varepsilon}\left(\bar{\varepsilon} - \underline{\varepsilon}\right) + \frac{1-\chi}{2}\left(\bar{\varepsilon} + \varepsilon_t^{*,R}\right)\left(\bar{\varepsilon} - \varepsilon_t^{*,R}\right)}{\bar{\varepsilon} - \varepsilon_t^{*,R} + \chi\left(\varepsilon_t^{*,R} - \underline{\varepsilon}\right)} - \varepsilon_t^{*,R}.
\end{aligned}$$

Then the market tightnesses are then:

$$\begin{aligned}
\theta_t^f &= \frac{B_t\phi_t}{S_t E_\Omega\left[1 - G\left(p_t - E_\Omega[p_t] - \mu\right)\right]} = \frac{B_t\phi_t}{S_t\left[\alpha\left(1 - G_t^E\right) + (1-\alpha)\left(1 - G_t^R\right)\right]} \\
\theta_t^d &= \frac{B_t(1-\phi_t)}{S_t E_\Omega\left[G\left(p_t - E_\Omega[p_t] - \mu\right)\right]} = \frac{B_t(1-\phi_t)}{S_t\left[\alpha G_t^E + (1-\alpha) G_t^R\right]}.
\end{aligned}$$

The buyer value function is:

$$V_t^b = b + \beta E_t V_{t+1}^b + \frac{1}{\phi_t\theta_t}\left[\alpha d_t^{E,f} M_t^E + (1-\alpha) d_t^{R,f} M_t^R\right].$$

Finally, the indifference condition is:

$$\frac{\alpha d_t^{E,f} M_t^E + (1-\alpha) d_t^{R,f} M_t^R}{\alpha d_t^{E,d} M_t^E + (1-\alpha) d_t^{R,d} M_t^R} = \frac{\phi_t}{1-\phi_t}.$$

The system is made up of G_t^E, G_t^R, M_t^E, and M_t^R,

$$
\begin{aligned}
d_t^R &= d_t^{R,f} + d_t^{R,d} \\
d_t^E &= d_t^{E,f} + d_t^{E,d} \\
d_t^{R,f} &= \xi^f \left(\frac{B_t \phi_t}{S_t \left[\alpha \left(1 - G_t^E\right) + (1-\alpha)\left(1 - G_t^R\right)\right]} \right)^\gamma \left(1 - G_t^R\right) \frac{\bar{\varepsilon} - \varepsilon_t^{*,R} + \chi\left(\varepsilon_t^{*,R} - \underline{\varepsilon}\right)}{\bar{\varepsilon} - \underline{\varepsilon}} \\
d_t^{R,d} &= \xi^d \left(\frac{B_t (1-\phi_t)}{S_t \left[\alpha G_t^E + (1-\alpha) G_t^R\right]} \right)^\gamma G_t^R \frac{\bar{\varepsilon} - \varepsilon_t^{*,R} + \chi\left(\varepsilon_t^{*,R} - \underline{\varepsilon}\right)}{\bar{\varepsilon} - \underline{\varepsilon}} \\
d_t^{E,f} &= \xi^f \left(\frac{B_t \phi_t}{S_t \left[\alpha \left(1 - G_t^E\right) + (1-\alpha)\left(1 - G_t^R\right)\right]} \right)^\gamma \left(1 - G_t^E\right) \frac{\bar{\varepsilon} - \varepsilon_t^{*,E} + \chi\left(\varepsilon_t^{*,E} - \underline{\varepsilon}\right)}{\bar{\varepsilon} - \underline{\varepsilon}} \\
d_t^{E,d} &= \xi^d \left(\frac{B_t (1-\phi_t)}{S_t \left[\alpha G_t^E + (1-\alpha) G_t^R\right]} \right)^\gamma G_t^E \frac{\bar{\varepsilon} - \varepsilon_t^{*,E} + \chi\left(\varepsilon_t^{*,E} - \underline{\varepsilon}\right)}{\bar{\varepsilon} - \underline{\varepsilon}} \\
H_t &= 1 - S_t \\
R_t &= N - B_t - H_t \\
B_t &= \left(1 - \frac{1}{\theta_{t-1}}\left[\alpha d_{t-1}^E + (1-\alpha) d_{t-1}^R\right]\right) B_{t-1} + \lambda_{t-1}^r R_{t-1} + (1-L)\lambda^h H_{t-1} \\
S_t &= \left(1 - \left[\alpha d_{t-1}^E + (1-\alpha) d_{t-1}^R\right]\right) S_{t-1} + \lambda^h H_{t-1} \\
V_t^h &= h + \beta E_t \left[\lambda^h \left[V_{t+1}^s + LV^0 + (1-L) V_{t+1}^b\right] + \left(1 - \lambda^h\right) V_{t+1}^h\right] \\
V_t^b &= b + \beta E_t V_{t+1}^b + \frac{1}{\phi_t \theta_t}\left[\alpha d_t^{f,E} M_t^E + (1-\alpha) d_t^{f,R} M_t^R\right] \\
V_t^s &= s + \beta E_t V_{t+1}^s + d_t^R \left[p_t^R - s - \beta V_{t+1}^s\right] \\
\varepsilon_t^{*R} &= p_t^R + b + \beta V_{t+1}^b - V_t^h \\
\varepsilon_t^{*E} &= p_t^E + b + \beta V_{t+1}^b - V_t^h \\
p_t^R &= s + \beta E_t V_{t+1}^s + Markup_t \\
p_t^E &= \frac{p_{t-2} + p_{t-3} + p_{t-4}}{3} + \psi \left(\frac{p_{t-2} + p_{t-3} + p_{t-4}}{3} - \frac{p_{t-5} + p_{t-6} + p_{t-7}}{3} \right) \\
p_t &= \frac{\alpha d_t^E p_t^E + (1-\alpha) d_t^R p_t^R}{\alpha d_t^E + (1-\alpha) d_t^R} \\
\lambda_t^r &= \bar{\lambda}^r + \rho\left(\lambda_t^r - \bar{\lambda}^r\right) + \eta \text{ with } \eta \sim N\left(0, \sigma_\eta^2\right)
\end{aligned}
$$

and,

$$
\frac{\alpha d_t^{E,f} M_t^E + (1-\alpha) d_t^{R,f} M_t^R}{\alpha d_t^{E,d} M_t^E + (1-\alpha) d_t^{R,d} M_t^R} = \frac{\phi_t}{1 - \phi_t}.
$$

I simulate this system with a log-quadratic approximation using Dynare as described in the main text. In Section E.4 I provide a test to show that the mass point at $\bar{\varepsilon}$ does not preclude the use of perturbation methods since it is essentially never reached.

For the impulse response functions, I use Dynare to compute the impulse response as the average difference between two sets of 100 simulations that use the same sequence of random shocks except for one period in which an additional standard deviation shock is added.

E.3 Steady State

The steady state that can be found by equating the value of the endogenous variables across time periods. Steady state values are denoted without t subscripts. Note that in steady state, $p_t^E = p_t^R$, so there is no price variation and all prices are equal to p_t. Consequently, there is no heterogeneity. I thus drop all $i = \{E, R\}$ superscripts.

Begin with the laws of motion, recalling that we have mass one of houses and mass N of agents. From (14) and (15),

$$H = \frac{d}{d + \lambda^h} \text{ and } S = \frac{\lambda^h}{d + \lambda^h}.$$

The law of motion for R_t, which is redundant but needed to solve for the steady state, is

$$R_t = \left(1 - \lambda_{t-1}^r\right) R_{t-1} + L\lambda^h H_{t-1}$$

so in steady state,

$$R = \frac{L\lambda^h}{\bar{\lambda}^r} H.$$

From (13) and (16) and the steady state expression for R:

$$\begin{aligned} B &= \frac{\lambda^h \theta}{d} H \\ N &= \left(1 + \frac{\lambda^h}{\frac{d}{\theta}} + \frac{L\lambda^h}{\bar{\lambda}^r}\right) \frac{d}{d + \lambda^h}. \end{aligned}$$

The steady state value functions are:

$$\begin{aligned} V^h &= \frac{h + \beta\lambda^h \left[V^s + LV^0 + (1 - L) V^b\right]}{1 - \beta\left(1 - \lambda^h\right)} \\ V^b &= \frac{b + \frac{1}{\phi\theta} d^f M}{1 - \beta} \\ V^s &= \frac{s + d\left[p - s - \beta V^s\right]}{1 - \beta} = \frac{s + d \frac{1}{\frac{1}{(\bar{\varepsilon} - \varepsilon)\left(1 + \frac{\chi}{1 - \chi}\right)} + \frac{1}{\sigma} \frac{1}{1 + exp\left(\frac{\mu}{\sigma}\right)} - \frac{1}{\sigma} \frac{d^d}{d}}}{1 - \beta}, \end{aligned}$$

where

$$M = \frac{\chi\bar{\varepsilon}\left(\bar{\varepsilon} - \underline{\varepsilon}\right) + \frac{1 - \chi}{2}\left(\bar{\varepsilon} + \varepsilon^*\right)\left(\bar{\varepsilon} - \varepsilon^*\right)}{\bar{\varepsilon} - \varepsilon^* + \chi\left(\varepsilon^* - \underline{\varepsilon}\right)} - \varepsilon^*.$$

With $\mu > 0$ as we find in the calibration and $p = E_\Omega[p]$ in steady state,

$$Markup = \frac{1}{\frac{1}{(\bar{\varepsilon} - \varepsilon) + \frac{\chi}{1 - \chi}(\bar{\varepsilon} - \underline{\varepsilon})} + \frac{\frac{\zeta}{\sigma} exp\left(-(\mu/\sigma)^\zeta\right)}{\Gamma(1/\zeta) + \gamma\left[\frac{1}{\zeta}, \left(\frac{\mu}{\sigma}\right)^\zeta\right]} \left(1 - \frac{2\Gamma(1/\zeta)}{\Gamma(1/\zeta) - \gamma\left[\frac{1}{\zeta}, \left(\frac{\mu}{\sigma}\right)^\zeta\right]} \frac{d^d}{d}\right)}$$

so,

$$
\begin{aligned}
\varepsilon^* &= b + \beta V^b + p - V^h \\
p &= s + \beta V^s + Markup \\
d &= d^f + d^d \\
d^f &= \xi^f \theta_f^\gamma \left(1 - G\left(-\mu\right)\right) \frac{\bar{\varepsilon} - \varepsilon^* + \chi\left(\varepsilon^* - \underline{\varepsilon}\right)}{\bar{\varepsilon} - \underline{\varepsilon}} \\
d^d &= \xi^d \theta_d^\gamma \left(1 - G\left(-\mu\right)\right) \frac{\bar{\varepsilon} - \varepsilon^* + \chi\left(\varepsilon^* - \underline{\varepsilon}\right)}{\bar{\varepsilon} - \underline{\varepsilon}} \\
\frac{d^f}{d^d} &= \frac{\phi}{1 - \phi}.
\end{aligned}
$$

Note that given θ^*, and ε^*, one can solve for d^d and d^f and hence ϕ and d. One can then solve for p, V^b, V^h, V^s, H, R, B, and S. Thus the steady state system can be reduced to a two equation system with two unknowns, θ^*, and ε^*:

$$
\begin{aligned}
N &= \left(1 + \frac{\lambda^h}{\frac{d}{\theta}} + \frac{L\lambda^h}{\bar{\lambda}^r}\right) \frac{d}{d + \lambda^h} \\
\varepsilon^* &= b + \beta V^b + p - V^h.
\end{aligned}
$$

This steady state can be solved numerically and has a unique solution.

E.4 Specification Checks

I run three different sets of checks on the model to make sure several assumptions I make in solving it are not problematic in practice.

First, I check that $\varepsilon_t^{*,R}$ and $\varepsilon_t^{*,E}$ do not go above $\bar{\varepsilon}$. In 200 simulations of 500 years each, $\varepsilon_t^{*,R}$ almost never goes above $\bar{\varepsilon}$ and $\varepsilon_t^{*,E}$ goes above $\bar{\varepsilon}$ less than 0.1 percent of the time. Using a perturbation method is thus not problematic despite the kink at $\bar{\varepsilon}$ because this kink is virtually never reached.

Second, I check that my assumption that sellers do not have an incentive to deviate from their interior optimum is correct. I do so by simulating for the seller's objective function in their optimization problem $d\left(p_t, \Omega_t, \tilde{\theta}_t\right)\left(p_t - s - \beta V_{t+1}^s\right)$ if the seller posts the interior optimum p_t or if the seller alternately sets their price so $\varepsilon_t^*\left(p_t\right) = \bar{\varepsilon}$, which delivers the highest price for the seller in the region of the demand curve where the house is almost certain to end up in the "do not follow" market and hence the probability of sale is roughly constant. Setting this price thus has the highest expected profit. In 200 simulations of 500 years each, I find that sellers would never have an incentive to deviate from the interior optimum. This is because the mass point in the idiosyncratic taste distribution occurs before the signal distribution $G\left(\cdot\right)$ begins to flatten.

Third, I calculate the dollar loss that backward-looking sellers experience by failing to optimize. To do so, I simulate the value of a backward-looking seller using,

$$
V_t^{s,E} = s + \beta V_{t+1}^{s,E} + d\left(p_t^E, \Omega_t, \tilde{\theta}_t\right)\left(p_t^E - s - \beta V_{t+1}^{s,E}\right),
$$

which calculates a value function similar to that of a rational seller but using the probability of sale and price of a backward-looking seller. The average and mean of this value is below half of one percent.

E.5 Staggered Pricing Model

E.5.1 Lemma 3: Optimal Staggered Price Setting

The price-setting seller's value function is:

$$V_t^{s,0} = \max_{p_t^0} \left\{ s + \beta V_{t+1}^{s,1}\left(p_t^0\right) + d\left(p_t^0, \Omega_t, \tilde{\theta}_t\right)\left(p - s - \beta V_{t+1}^{s,1}\left(p_t^0\right)\right)\right\}, \tag{A9}$$

where

$$V_t^{s,\tau}\left(p\right) = s + \beta V_{t+1}^{s,\tau+1}\left(p\right) + d\left(p, \Omega_t, \tilde{\theta}_t\right)\left(p - s - \beta V_{t+1}^{s,\tau+1}\left(p\right)\right), \tag{A10}$$

and $V_t^N = V_t^0$. The first order condition is:

$$\beta\left(1 - d\left(p_t^0, \Omega_t, \tilde{\theta}_t\right)\right) E_t \frac{\partial V_{t+1}^{s,1}}{\partial p_t^0} + d\left(p_t^0, \Omega_t, \tilde{\theta}_t\right) E_t \left[1 + \frac{\frac{\partial d\left(p_t^0, \Omega_t, \tilde{\theta}_t\right)}{\partial p_t^0}}{d\left(p_t^0, \Omega_t, \tilde{\theta}_t\right)}\left(p_t^0 - s - \beta V_{t+1}^{s,1}\left(p\right)\right)\right] = 0,$$

where for $\tau < N-1$,

$$E_t \frac{\partial V_t^{s,\tau}\left(p\right)}{\partial p} = \beta\left(1 - d\left(p, \Omega_t, \tilde{\theta}_t\right)\right) E_t \frac{\partial V_{t+1}^{s,\tau+1}\left(p\right)}{\partial p} + d\left(p, \Omega_t, \tilde{\theta}_t\right) E_t \left[1 + \frac{\frac{\partial d\left(p, \Omega_t, \tilde{\theta}_t\right)}{\partial p}}{d\left(p, \Omega_t, \tilde{\theta}_t\right)}\left(p - s - \beta V_{t+1}^{s,\tau+1}\left(p\right)\right)\right],$$

and,

$$E_t \frac{\partial V_t^{s,N-1}\left(p\right)}{\partial p} = d\left(p, \Omega_t, \tilde{\theta}_t\right) E_t \left[1 + \frac{\frac{\partial d\left(p, \Omega_t, \tilde{\theta}_t\right)}{\partial p}}{d\left(p, \Omega_t, \tilde{\theta}_t\right)}\left(p - s - \beta V_{t+1}^{s,0}\right)\right].$$

Defining $D_t^j\left(p\right) = E_t\left[\prod_{\tau=0}^{j-1}\left(1 - d^\tau\left(p, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)\right)\right] d\left(p, \Omega_{t+j}, \tilde{\theta}_{t+j}\right)$ and substituting $\frac{\partial V_{t+1}^{s,1}}{\partial p}, ..., \frac{\partial V_{t+N-1}^{s,N-1}}{\partial p}$ into the first order condition gives:

$$\sum_{\tau=0}^{N-1} \beta^\tau D_t^\tau\left(p\right) E_t \left[1 + \frac{\frac{\partial d\left(p, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)}{\partial p}}{d\left(p, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)}\left(p - s - \beta V_{t+\tau+1}^{s,\tau+1}\right)\right] = 0.$$

Rearranging gives:

$$p_t^0 = \frac{\sum_{\tau=0}^{N-1} \beta^\tau D_t^\tau\left(p\right) E_t\left[1 + \frac{-\frac{\partial d\left(p, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)}{\partial p}}{d\left(p, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)}\left(s + \beta V_{t+\tau+1}^{s,\tau+1}\right)\right]}{\sum_{\tau=0}^{N-1} \beta^\tau D_t^\tau\left(p\right) E_t\left[\frac{-\frac{\partial d\left(p, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)}{\partial p}}{d\left(p, \Omega_{t+\tau}, \tilde{\theta}_{t+\tau}\right)}\right]},$$

which, defining $\Psi_t^\tau = E_t \left[\frac{-\frac{\partial d(p_t,\Omega_{t+\tau},\tilde{\theta}_{t+\tau})}{\partial p_t}}{d(p_t,\Omega_{t+\tau},\tilde{\theta}_{t+\tau})} \right]$ and $\varphi_t^\tau = s + E_t V_{t+\tau+1}^{s,\tau+1} + \frac{1}{\Psi_t^\tau}$, simplifies to,

$$p_t^0 = \frac{\sum_{\tau=0}^{N-1} \beta^\tau D_t^\tau (p) \Psi_t^\tau \varphi_t^\tau}{\sum_{\tau=0}^{N-1} \beta^\tau D_t^\tau (p) \Psi_t^\tau}.$$

E.5.2 Altered Laws of Motion With Staggered Pricing

The laws of motion for sellers also need to be altered. Specifically, for all old vintages with $\tau > 0$, there are no new entrants and so the number laws of motion are:

$$S_t^\tau = \left(1 - d\left(p_{t-1}^{\tau-1}, \Omega_{t-1}, \tilde{\theta}_{t-1}\right)\right) S_{t-1}^{\tau-1} \ \forall \tau > 0 \tag{A11}$$

By contrast, new price setting sellers is equal to inflows plus those in the $N-1$th vintage that have yet to sell:

$$S_t^0 = \left(1 - d\left(p_{t-1}^{N-1}, \Omega_{t-1}, \tilde{\theta}_{t-1}\right)\right) S_{t-1}^{N-1} + \lambda^h H_{t-1}. \tag{A12}$$

There is also an adding up constraint that $S_t = \sum_{\tau=0}^{N-1} S_t^\tau$.

E.5.3 Full Staggered Pricing Model

An equilibrium of the staggered pricing model can be defined as:

Definition 2. Equilibrium with a fraction α of backward-looking sellers is a set of prices p_t^i, demands $d\left(p_t^i, \Omega_t, \tilde{\theta}_t\right)$, and purchase cutoffs $\varepsilon_t^{*,i}$ for each type of seller $i \in \{E, R\}$, a transaction-weighted average price p_t, rational seller, buyer, homeowner, and renter value functions V_t^s, V_t^b, and V_t^h, a probability that buyers follow the signal ϕ_t, entry cutoffs c_t^* and k_t^*, stocks of each type of agent B_t, S_t, H_t, and R_t, and a shock to the flow utility of renting x_t satisfying:

1. Optimal pricing for price resetters (25) for whom $\tau = 0$ and $p_t^\tau = p_{t-1}^{\tau-1}$ for $\tau > 0$.
2. Optimal purchasing decisions by buyers: $\varepsilon_t^{*,\tau} = p_t^\tau + b + \beta V_{t+1}^b - V_t^h$;
3. The demand curve for each vintage of seller $\tau = \{0, ..., N-1\}$ in the f submarket (10), the d submarket, (11), and the aggregate (12), all of which result from buyer search behavior;
4. The value functions for buyers (20), homeowners (9), and for price resetting sellers (A9) and each vintage of non-resetting sellers (A10).
5. The laws of motion for buyers (13) and each vintage of sellers (A11) and (A12) and the closed system conditions for homes (15) and people (16) that implicitly define the laws of motion for homeowners and renters;
6. Buyers are indifferent across markets (19);
7. All agents have rational expectations that λ_t^r evolves according to the AR(1) process (26).

The steady state is identical to the steady state in the backward-looking model because prices are constant so all groups set the same price.

Given this equilibrium, I now develop the full dynamic system that is put into Dynare as with the backward-looking model. I do so for $N = 2$ both for simplicity of exposition and to match my simulations.

There are two list prices: p_t^0 with mass $\frac{S_t^0}{S_t}$ and p_t^1 with mass $\frac{S_t^1}{S_t}$, so:

$$\begin{aligned} E_{\Omega_t}\left[p_t\right] &= \frac{S_t^0}{S_t} p_t^0 + \frac{S_t^1}{S_t} p_t^1 \\ E_{\Omega_t}\left[d_t\right] &= \frac{S_t^0}{S_t} d_t^0 + \frac{S_t^1}{S_t} d_t^1. \end{aligned}$$

To simplify notation, let:

$$\begin{aligned} G_t^0 &= G\left(p_t^0 - E_{\Omega_t}\left[p_t\right] - \mu\right) = \frac{1}{2} + sgn\left(p_t^0 - E_{\Omega_t}\left[p_t\right] - \mu\right) \frac{\gamma\left[\frac{1}{\beta}, \left(\frac{\left|p_t^0 - E_{\Omega_t}\left[p_t\right] - \mu\right|}{\sigma}\right)^{\zeta}\right]}{2\Gamma\left(1/\zeta\right)} \\ G_t^1 &= G\left(p_t^1 - E_{\Omega_t}\left[p_t\right] - \mu\right) = \frac{1}{2} + sgn\left(p_t^1 - E_{\Omega_t}\left[p_t\right] - \mu\right) \frac{\gamma\left[\frac{1}{\beta}, \left(\frac{\left|p_t^1 - E_{\Omega_t}\left[p_t\right] - \mu\right|}{\sigma}\right)^{\zeta}\right]}{2\Gamma\left(1/\zeta\right)} \\ M_t^0 &= E\left[\varepsilon - \varepsilon_t^{*,0} | \varepsilon > \varepsilon_t^{*,0}\right] = \frac{\chi\bar{\varepsilon}\left(\bar{\varepsilon} - \underline{\varepsilon}\right) + \frac{1-\chi}{2}\left(\bar{\varepsilon} + \varepsilon_t^{*,0}\right)\left(\bar{\varepsilon} - \varepsilon_t^{*,0}\right)}{\bar{\varepsilon} - \varepsilon_t^{*,0} + \chi\left(\varepsilon_t^{*,0} - \underline{\varepsilon}\right)} - \varepsilon_t^{*,0} \\ M_t^R &= E\left[\varepsilon - \varepsilon_t^{*,1} | \varepsilon > \varepsilon_t^{*,1}\right] = \frac{\chi\bar{\varepsilon}\left(\bar{\varepsilon} - \underline{\varepsilon}\right) + \frac{1-\chi}{2}\left(\bar{\varepsilon} + \varepsilon_t^{*,1}\right)\left(\bar{\varepsilon} - \varepsilon_t^{*,1}\right)}{\bar{\varepsilon} - \varepsilon_t^{*,1} + \chi\left(\varepsilon_t^{*,1} - \underline{\varepsilon}\right)} - \varepsilon_t^{*,1}. \end{aligned}$$

As before,

$$\begin{aligned} \theta_t^f &= \frac{B_t \phi_t}{S_t E_\Omega\left[1 - G\left(p_t - E_\Omega\left[p_t\right] - \mu\right)\right]} = \frac{B_t \phi_t}{S_t\left[\alpha\left(1 - G_t^E\right) + \left(1 - \alpha\right)\left(1 - G_t^R\right)\right]} \\ \theta_t^d &= \frac{B_t\left(1 - \phi_t\right)}{S_t E_\Omega\left[G\left(p_t - E_\Omega\left[p_t\right] - \mu\right)\right]} = \frac{B_t\left(1 - \phi_t\right)}{S_t\left[\alpha G_t^E + \left(1 - \alpha\right) G_t^R\right]}. \end{aligned}$$

The buyer value function is:

$$V_t^b = b + \beta E_t V_{t+1}^b + \frac{1}{\phi_t \theta_t}\left[\frac{S_t^0}{S_t} d_t^{0,f} M_t^0 + \frac{S_t^1}{S_t} d_t^{1,f} M_t^1\right].$$

Finally, the indifference condition is:

$$\frac{\frac{S_t^0}{S_t} d_t^{0,f} M_t^0 + \frac{S_t^1}{S_t} d_t^{1,f} M_t^1}{\frac{S_t^0}{S_t} d_t^{0,d} M_t^0 + \frac{S_t^1}{S_t} d_t^{1,d} M_t^1} = \frac{\phi_t}{1 - \phi_t}.$$

The system is made up of G_t^0, G_t^1, M_t^0, and M_t^1,

$$\begin{aligned}
d_t^0 &= d_t^{0,f}+d_t^{0,d}\\
d_t^1 &= d_t^{1,f}+d_t^{1,d}\\
d_t^{0,f} &= \xi^f\left(\frac{B_t\phi_t}{S_t\left[\frac{S_t^0}{S_t}\left(1-G_t^0\right)+\frac{S_t^1}{S_t}\left(1-G_t^1\right)\right]}\right)^\gamma\left(1-G_t^0\right)\frac{\bar{\varepsilon}-\varepsilon_t^{*,0}+\chi\left(\varepsilon_t^{*,0}-\underline{\varepsilon}\right)}{\bar{\varepsilon}-\underline{\varepsilon}}\\
d_t^{0,d} &= \xi^d\left(\frac{B_t\left(1-\phi_t\right)}{S_t\left[\frac{S_t^0}{S_t}\left(1-G_t^0\right)+\frac{S_t^1}{S_t}\left(1-G_t^1\right)\right]}\right)^\gamma G_t^0\frac{\bar{\varepsilon}-\varepsilon_t^{*,0}+\chi\left(\varepsilon_t^{*,0}-\underline{\varepsilon}\right)}{\bar{\varepsilon}-\underline{\varepsilon}}\\
d_t^{0,f} &= \xi^f\left(\frac{B_t\phi_t}{S_t\left[\frac{S_t^0}{S_t}\left(1-G_t^0\right)+\frac{S_t^1}{S_t}\left(1-G_t^1\right)\right]}\right)^\gamma\left(1-G_t^1\right)\frac{\bar{\varepsilon}-\varepsilon_t^{*,1}+\chi\left(\varepsilon_t^{*,1}-\underline{\varepsilon}\right)}{\bar{\varepsilon}-\underline{\varepsilon}}\\
d_t^{1,d} &= \xi^d\left(\frac{B_t\left(1-\phi_t\right)}{S_t\left[\frac{S_t^0}{S_t}\left(1-G_t^0\right)+\frac{S_t^1}{S_t}\left(1-G_t^1\right)\right]}\right)^\gamma G_t^1\frac{\bar{\varepsilon}-\varepsilon_t^{*,1}+\chi\left(\varepsilon_t^{*,1}-\underline{\varepsilon}\right)}{\bar{\varepsilon}-\underline{\varepsilon}}\\
H_t &= 1-S_t\\
R_t &= N-B_t-H_t\\
B_t &= \left(1-\frac{1}{\theta_{t-1}}\left[\frac{S_{t-1}^0}{S_{t-1}}d_{t-1}^0+\frac{S_{t-1}^1}{S_{t-1}}d_{t-1}^1\right]\right)B_{t-1}+\lambda_{t-1}^r R_{t-1}+\left(1-L\right)\lambda_t^h H_{t-1}\\
S_t^0 &= \left(1-d\left(p_{t-1}^1,\Omega_{t-1},\tilde{\theta}_{t-1}\right)\right)S_{t-1}^1+\varsigma\\
S_t^1 &= \left(1-d\left(p_{t-1}^0,\Omega_{t-1},\tilde{\theta}_{t-1}\right)\right)S_{t-1}^0\\
S_t &= S_t^0+S_t^1\\
V_t^h &= h+\beta E_t\left[\lambda^h\left[V_{t+1}^s+LV^0+\left(1-L\right)V_{t+1}^b\right]+\left(1-\lambda^h\right)V_{t+1}^h\right]\\
V_t^b &= b+\beta E_t V_{t+1}^b+\frac{1}{\phi_t\theta_t}\left[\frac{S_t^0}{S_t}d_t^{f,0}M_t^0+\frac{S_t^1}{S_t}d_t^{f,1}M_t^1\right]\\
V_t^{s,0} &= s+\beta E_t V_{t+1}^{s,1}+d_t^0\left[p_t^0-s-\beta V_{t+1}^{s,1}\right]\\
V_t^{s,1} &= s+\beta E_t V_{t+1}^{s,0}+d_t^1\left[p_t^1-s-\beta V_{t+1}^{s,0}\right]\\
\varepsilon_t^{*0} &= p_t^0+b+\beta V_{t+1}^0-V_t^h\\
\varepsilon_t^{*1} &= p_t^1+b+\beta V_{t+1}^b-V_t^h\\
p_t^1 &= p_{t-1}^0\\
\lambda_t^r &= \bar{\lambda}^r+\rho\left(\lambda_t^r-\bar{\lambda}^r\right)+\eta \text{ with } \eta\sim N\left(0,\sigma_\eta^2\right)
\end{aligned}$$

and,

$$\frac{\frac{S_t^0}{S_t}d_t^{0,f}M_t^0+\frac{S_t^1}{S_t}d_t^{1,f}M_t^1}{\frac{S_t^0}{S_t}d_t^{0,d}M_t^0+\frac{S_t^1}{S_t}d_t^{1,d}M_t^1}=\frac{\phi_t}{1-\phi_t},$$

plus the pricing rule. Since

$$\Psi_t^0 = \frac{f_t^0}{1-F_t^0} + \frac{g_t^0}{1-G_t^0}\left(1 - \frac{1}{G_t^0}\frac{d_t^{0,d}}{d_t^0}\right)$$
$$\Psi_t^1 = \frac{f_{t+1}^1}{1-F_{t+1}^1} + \frac{g_{t+1}^1}{1-G_{t+1}^1}\left(1 - \frac{1}{G_t^1}\frac{d_{t+1}^{1,d}}{d_{t+1}^1}\right)$$

and

$$\varphi_t^0 = s + E_t V_{t+1}^{s,1} + \frac{1}{\frac{f_t^0}{1-F_t^0} + \frac{g_t^0}{1-G_t^0}\left(1 - \frac{1}{G_t^0}\frac{d_t^{0,d}}{d_t^0}\right)}$$
$$\varphi_t^1 = s + E_t V_{t+2}^{s,0} + \frac{1}{\frac{f_{t+1}^1}{1-F_{t+1}^1} + \frac{g_{t+1}^1}{1-G_{t+1}^1}\left(1 - \frac{1}{G_t^1}\frac{d_{t+1}^{1,d}}{d_{t+1}^1}\right)}$$

the pricing rule (25) is:

$$p_t^0 = \frac{\left(\begin{array}{c} d_t^0\left(\frac{f_t^0}{1-F_t^0} + \frac{g_t^0}{1-G_t^0} - \frac{1}{\sigma}\frac{d_t^{0,d}}{d_t^0}\right)\left(s + E_t V_{t+1}^{s,1} + \frac{1}{\frac{f_t^0}{1-F_t^0} + \frac{g_t^0}{1-G_t^0}\left(1-\frac{1}{G_t^0}\frac{d_t^{0,d}}{d_t^0}\right)}\right) + \\ \beta\left(1-d_t^0\right)E_t\left[d_{t+1}^1\left(\frac{f_{t+1}^1}{1-F_{t+1}^1} + \frac{g_{t+1}^1}{1-G_{t+1}^1}\left(1-\frac{1}{G_t^1}\frac{d_{t+1}^{1,d}}{d_{t+1}^1}\right)\right)\left(s + V_{t+2}^{s,0} + \frac{1}{\frac{f_{t+1}^1}{1-F_{t+1}^1} + \frac{g_{t+1}^1}{1-G_{t+1}^1}\left(1-\frac{1}{G_t^1}\frac{d_{t+1}^{1,d}}{d_{t+1}^1}\right)}\right)\right] \end{array}\right)}{d_t^0\left(\frac{f_t^0}{1-F_t^0} + \frac{g_t^0}{1-G_t^0}\left(1-\frac{1}{G_t^0}\frac{d_t^{0,d}}{d_t^0}\right)\right) + \beta\left(1-d_t^0\right)E_t\left[d_{t+1}^1\left(\frac{f_{t+1}^1}{1-F_{t+1}^1} + \frac{g_{t+1}^1}{1-G_{t+1}^1}\left(1-\frac{1}{G_t^1}\frac{d_{t+1}^{1,d}}{d_{t+1}^1}\right)\right)\right]}$$

E.6 Non-Concave Model

For the non-concave model, I use a demand curve that uses the same distributional assumptions but has a slope equal to the slope of the demand curve with concavity at the average price and thus the same steady state markup as before. I set $G(\cdot) = 1$ to eliminate concavity which implies $\phi = 1$, and I keep ε^* the same as my previous calibration, I set $\chi = 0$ to get as much room for ε^* to fluctuate as possible,[5] and choose $\underline{\varepsilon}$ and $\bar{\varepsilon}$ to satisfy:

$$\begin{aligned}
\left(\bar{\varepsilon}^{nc} - \varepsilon_t^{*nc}\right) + \frac{\chi}{1-\chi}\left(\bar{\varepsilon}^{nc} - \underline{\varepsilon}^{nc}\right) &= Markup \\
\frac{\bar{\varepsilon}^{nc} - \varepsilon^{*nc} + \chi\left(\varepsilon^{*nc} - \underline{\varepsilon}^{nc}\right)}{\bar{\varepsilon}^{nc} - \underline{\varepsilon}^{nc}} &= Pr\left[Sell\right],
\end{aligned}$$

where $Markup$ and $Pr\left[Sell\right]$ are the markup and probability of sale in the baseline calibration. The other parameters are left unchanged.

[5] This does not affect the results. It does, however, make it so that perturbation methods are usable as $\bar{\varepsilon}$ is virtually never reached.

The full system is then:

$$\begin{aligned}
d_t^R &= \xi^f \left(\frac{B_t}{S_t}\right)^\gamma \frac{\bar{\varepsilon} - \varepsilon_t^{*,R}}{\bar{\varepsilon} - \underline{\varepsilon}} \\
d_t^E &= \xi^f \left(\frac{B_t}{S_t}\right)^\gamma \frac{\bar{\varepsilon} - \varepsilon_t^{*,E}}{\bar{\varepsilon} - \underline{\varepsilon}} \\
H_t &= 1 - S_t \\
R_t &= N - B_t - H_t \\
B_t &= \left(1 - \frac{1}{\theta_{t-1}} \left[\alpha d_{t-1}^E + (1-\alpha) d_{t-1}^R\right]\right) B_{t-1} + \lambda_{t-1}^r R_{t-1} + (1-L)\,\lambda_t^h H_{t-1} \\
S_t &= \left(1 - \left[\alpha d_{t-1}^E + (1-\alpha) d_{t-1}^R\right]\right) S_{t-1} + \lambda^h H_{t-1} \\
V_t^h &= h + \beta E_t \left[\lambda^h \left[V_{t+1}^s + L V^0 + (1-L) V_{t+1}^b\right] + \left(1 - \lambda_{t+1}^h\right) V^h\right] \\
V_t^b &= b + \beta E_t V_{t+1}^b + \frac{1}{\theta_t}\left[\alpha d_t^E \frac{\left(\bar{\varepsilon} - \varepsilon_t^{*,E}\right)}{2} + (1-\alpha) d_t^R \frac{\left(\bar{\varepsilon} - \varepsilon_t^{*,R}\right)}{2}\right] \\
V_t^s &= s + \beta E_t V_{t+1}^s + d_t^R \left[p_t^R - s - \beta V_{t+1}^s\right] \\
\varepsilon_t^{*R} &= p_t^R + b + \beta V_{t+1}^b - V_t^h \\
\varepsilon_t^{*E} &= p_t^E + b + \beta V_{t+1}^b - V_t^h \\
p_t^R &= s + \beta E_t V_{t+1}^s + \left(\bar{\varepsilon} - \varepsilon_t^{*R}\right) \\
p_t^E &= \frac{p_{t-2} + p_{t-3} + p_{t-4}}{3} + \psi \left(\frac{p_{t-2} + p_{t-3} + p_{t-4}}{3} - \frac{p_{t-5} + p_{t-6} + p_{t-7}}{3}\right) \\
p_t &= \frac{\alpha d_t^E p_t^E + (1-\alpha) d_t^R p_t^R}{\alpha d_t^E + (1-\alpha) d_t^R} \\
x_t &= \rho x_{t-1} + \eta \text{ with } \eta \sim N\left(0, \sigma_\eta^2\right)
\end{aligned}$$

The non-concave model with staggered pricing is similar, except for the altered law of motion and optimal price setting for resetters. This follows the same formula as above, except the optimal price and $\frac{dd}{dp}$ are changed to be the same as in this section. Consequently,

$$p_t^0 = \frac{\frac{d_t^0}{\bar{\varepsilon} - \varepsilon_t^{*0}} \left(s + E_t V_{t+1}^{s,1} + \bar{\varepsilon} - \varepsilon_t^{*0}\right) + \beta \left(1 - d_t^0\right) E_t \left[\frac{d_{t+1}^1}{\bar{\varepsilon} - \varepsilon_{t+1}^{*1}} \left(s + V_{t+2}^{s,0} + \bar{\varepsilon} - \varepsilon_{t+1}^{*1}\right)\right]}{\frac{d_t^0}{\bar{\varepsilon} - \varepsilon_t^{*0}} + \beta \left(1 - d_t^0\right) E_t \left[\frac{d_{t+1}^1}{\bar{\varepsilon} - \varepsilon_{t+1}^{*1}}\right]}.$$

E.7 Microfoundation For Backward-Looking Sellers

This appendix presents a microfoundation for the Backward looking sellers' price setting equation (23).

The backward-looking sellers are near-rational sellers with limited information whose optimizing behavior produces a price-setting rule of thumb based on the recent price path. They are not fully rational in two ways. First, backward-looking sellers understand that a seller solves,

$$\max_{p_t} d\left(p_t, \Omega_t, \tilde{\theta}_t\right) p_t + \left(1 - d\left(p_t, \Omega_t, \tilde{\theta}_t\right)\right) \left(s + \beta V_{t+1}^s\right),$$

with first order condition,

$$p_t = s + \beta E_t V^s_{t+1} + E_t \left[\frac{-d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{\frac{\partial d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{\partial p_t}} \right]. \tag{A13}$$

However, they do not fully understand the laws of motion and how prices and the value of being a seller evolve. Instead, they think the world is a function of a single state variable, the average price $E[p_t]$, and can only make "simple" univariate forecasts that take the form of a first order approximation of (A13) in average price and relative price:

$$\begin{aligned} p_t &= s + \beta\left(\bar{V}^s_{t+1} + \pi_1 E[p_t]\right) + \bar{M} + \pi_2 E[p_t - E[p_t]] \\ &= s + \beta\left(\bar{V}^s_{t+1} + \pi_1 E[p_t]\right) + \bar{M}, \end{aligned} \tag{A14}$$

where $\bar{V}^s$, $\bar{M}$, π_1, and π_2 are constants.[6]

Second, they mistakenly assume that price follows a random walk with drift with both the innovations φ and the drift ζ drawn independently from mean zero normal distributions with variances σ^2_φ and σ^2_ζ. They also have limited information and only see the transaction-weighted average prices p_t of houses that transact between two to four months ago $\bar{p}_{t-3} = \frac{p_{t-2}+p_{t-3}+p_{t-4}}{3}$ and between five to seven months ago $\bar{p}_{t-6} = \frac{p_{t-5}+p_{t-6}+p_{t-7}}{3}$, corresponding to the lag with which reliable house price indices are released. Through a standard signal extraction problem, they expect that today's price will be normally distributed with mean $E[p_t] = \bar{p}_{t-3} + E[\zeta]$, where $E[\zeta] = \frac{\sigma^2_\zeta}{\sigma^2_\zeta + \sigma^2_\varphi}\left(\bar{p}_{t-3} - \bar{p}_{t-6}\right)$. Given this normal posterior, backward-looking sellers follow an AR(1) rule:

$$p^E_t = \frac{p_{t-2}+p_{t-3}+p_{t-4}}{3} + \psi\left(\frac{p_{t-2}+p_{t-3}+p_{t-4}}{3} - \frac{p_{t-5}+p_{t-6}+p_{t-7}}{3}\right), \tag{A15}$$

where everything is lagged because where $\psi = \frac{\sigma^2_\zeta}{\sigma^2_\zeta + \sigma^2_\varphi}$ and p_t is the transaction-weighted average price at time t:

$$p_t = \frac{\alpha d^E_t p^E_t + (1-\alpha) d^R_t p^R_t}{\alpha d^E_t + (1-\alpha) d^R_t}. \tag{A16}$$

F Calibration

F.1 Calibration Targets

The aggregate moments and parameters chosen from other papers are:

- A long-run homeownership rate of 65 percent. The homeownership hovered between 64 percent and 66 percent from the 1970s until the late 1990s before rising in the boom of the 2000s and falling afterwards.
- $\gamma = 0.8$ from the median specification of Genesove and Han (2012). Anenberg and Bayer (2015) find a similar number.
- $L = 0.7$ from the approximate average internal mover share for Los Angeles of 0.3 from Anenberg and Bayer (2015), which is also roughly consistent with Wheaton and Lee's (2009)

[6] The second line follows from the second assumption, which implies a symmetric posterior for p_t so $p_t = E[p_t]$.

analysis of the American Housing Survey and Table 3-10 of the American Housing survey, which shows that under half of owners rented their previous housing unit.

- A median tenure for owner occupants of approximately nine years from American Housing Survey 1997 to 2005 (Table 3-9).

- The approximately equal time for buyers and sellers is from National Association of Realtors surveys (Head et al., 2014; Genesove and Han, 2012). This implies that a normal market is defined by a buyer to seller ratio of $\theta = 1$. I assume a time to sale in a normal market of four months for both buyers and sellers. There is no definitive number for the time to sale, and in the literature it is calibrated between 2.5 and six months. The lower numbers are usually based on real estate agent surveys (*e.g.*, Genesove and Han, 2012), which have low response rates and are effectively marketing tools for real estate agents. The higher numbers are calibrated to match aggregate moments (Piazzesi and Schneider, 2009). I choose four months, which is slightly higher than the realtor surveys but approximately average for the literature.

- Price is equal to \$760,000, roughly the average transaction price in the IV samples. IV Sample 1 corresponds is \$758,803 and in IV sample 2 is \$781,091. The results are not sensitive to this calibration target.

- One in ten houses that are inspected are purchased. Genesove and Han (2012) show that in National Association of Realtors surveys of buyers the mean buyer visits 9.96 homes. This does lead to a $\xi > 1$, but this is standard for search models and not a practical issue for the model.

- A monthly buyer search cost of of 0.75 of the average price per month, so that the average buyer, who is in the market for four months, has total search costs equal to 3 percent of the average home's price as described in the main text. Since this target is somewhat speculative, I vary it in robustness checks.

- A five percent annual discount rate, as is standard in the literature.

- $\psi = 0.4$. ψ is the AR(1) coefficient in the backward-looking model and is set based evidence from Case et al. (2012). Using surveys of home buyers, Case et al. (2012) show that regressing realized annual house price appreciation on households' *ex-ante* beliefs yields a regression coefficient of 2.34. I use this survey evidence to calibrate the beliefs of the backward-looking sellers by dividing the approximate regression coefficient one would obtain in quarterly simulated data (approximately 0.94) by their coefficient. Since this target is somewhat speculative, I vary it in robustness checks.

- h is set so that the present discounted value of the flow utility of living in a home is approximately 2/3 of its value in steady state, which implies $h =$ \$6.78k per month for a \$760,000 house. Since this target is somewhat speculative, I vary it in robustness checks to show it is effectively a normalization.

Two time series moments are used:

- The persistence of the shock $\rho = 0.95$ is chosen to match evidence on the persistence of population growth from the corrigendum of Head et al. (2014). They report that the autocorrelation of population growth is 0.62 at a one year horizon, 0.29 at a two year horizon, and 0.06 at a three-year horizon. These imply monthly autocorrelations of 0.961, 0.950, and 0.925. I choose the middle value. This moment controls when the shock begins to mean revert, and all that matters for the results is that the shock does not mean revert before three years.

- A standard deviation of annual log price changes of 0.065 for the real CoreLogic national house price index from 1976 to 2013. This is set to match the standard deviation of aggregate prices for homes that transact collapsed to the quarterly level in stochastic simulations.

The seller search cost is pinned down by the shape of the demand curve, the steady state probability of sale, and the target steady state price. This is the case because $p = s + \beta V^s + Markup$ and $V^s = \frac{s+dMarkup}{1-\beta}$ together imply that:

$$\frac{s}{p} = 1 - \beta - (\beta d + 1 - \beta) \frac{Markup}{p}.$$

In the baseline calibration, the monthly seller search cost is 2.1 percent of the sale price.

The seller search cost is important as it controls the degree of search frictions sellers face. Consequently, I introduce a procedure to adjust the binned scatter plot to match a target for the monthly seller search cost as a fraction of the price in steady state. This requires changing the demand curve so it is more elastic, which can either be done by shrinking the log relative markup axis or by stretching the probability of sale axis. The former would add concavity, while the later would reduce concavity. To err on the side of not adding concavity to the data, I use the former procedure. Specifically, the new probability of sale $probsell'$ is set according to $probsell' = stretch \times (probsell - median\,(probsell)) + median\,(probsell)$, and the $stretch$ parameter is selected to hit a target s/p. I report results that target target monthly seller search costs of 1.0 percent, 1.5 percent, and 2.5 percent.

F.2 Estimation and Calibration Procedure

As described in the text, the estimation and calibration procedure proceeds in two steps. First, I calibrate to the micro estimates. Then I match the aggregate and time series moments.

Approximation of $d\,(p)$ in Equation (27)

Note that $d\left(p_t, \Omega_t, \tilde{\theta}\right)$ can be written as:

$$\begin{aligned} d\,(p_t) &= q\left(\theta_t^f\right)(1 - G\,(p_t - E\,[p] - \mu))\,(1 - F\,(\varepsilon_t^*\,(p_t))) + q\left(\theta_t^d\right) G\,(p_t - E\,[p] - \mu)\,(1 - F\,(\varepsilon_t^*\,(p_t))) \\ &= \kappa_t\,(1 - F\,(\varepsilon^*\,(p_t))) \left[\begin{array}{c} \left(\frac{\phi_t}{E_{\Omega_t}\left[1 - G\left(p_t - E_{\Omega_t}[p_t] - \mu\right)\right]}\right)^\gamma [1 - G\,(p - E_{\Omega_t}\,[p_t] - \mu)] \\ + \frac{\xi^d}{\xi^f} \left(\frac{(1-\phi_t)}{E_{\Omega_t}\left[G\left(p_t - E_{\Omega_t}[p_t] - \mu\right)\right]}\right)^\gamma G\,(p - E_{\Omega_t}\,[p_t] - \mu) \end{array} \right], \end{aligned}$$

where $\kappa = \xi^f \left(\frac{B_t}{S_t}\right)^\gamma$. Given the distributional assumption on $F\,(\cdot)$,

$$1 - F\,(\varepsilon^*\,(p_t)) = \frac{\bar{\varepsilon} - \chi \underline{\varepsilon}}{\bar{\varepsilon} - \underline{\varepsilon}} + \frac{1 - \chi}{\bar{\varepsilon} - \underline{\varepsilon}} \varepsilon^*\,(p_t),$$

where $\varepsilon^*(p_t) = p_t + b + \beta V_{t+1}^b - V_t^h$ and so $\varepsilon_t^*(p_t) = p_t - E_{\Omega_t}[p_t] + \varepsilon_t^*(E_{\Omega_t}[p_t])$. Thus,

$$\begin{aligned}
1 - F(\varepsilon^*(p_t)) &= \frac{\bar{\varepsilon} - \chi\underline{\varepsilon}}{\bar{\varepsilon} - \underline{\varepsilon}} + \frac{1-\chi}{\bar{\varepsilon} - \underline{\varepsilon}}\left(p_t - E_{\Omega_t}[p_t] + \varepsilon_t^*(E_{\Omega_t}[p_t])\right) \\
&= \frac{\bar{\varepsilon} - \chi\underline{\varepsilon}}{\bar{\varepsilon} - \underline{\varepsilon}} + \frac{1-\chi}{\bar{\varepsilon} - \underline{\varepsilon}}\left(p_t - E_{\Omega_t}[p_t] + \varepsilon_{mean}^* - \varepsilon_{mean}^* + \varepsilon_t^*(E_{\Omega_t}[p_t])\right) \\
&= 1 - F\left(\varepsilon_{mean}^* + p_t - E_{\Omega_t}[p_t]\right) + \left(\varepsilon_t^*(E_{\Omega_t}[p_t]) - \varepsilon_{mean}^*\right)\frac{1-\chi}{\bar{\varepsilon} - \underline{\varepsilon}}.
\end{aligned}$$

Because the estimated density $\frac{1-\chi}{\bar{\varepsilon}-\underline{\varepsilon}}$ is 0.0001, the last term is close to zero. I thus approximate

$$1 - F(\varepsilon^*(p_t)) \approx 1 - F\left(\varepsilon_{mean}^* + p_t - E_{\Omega_t}[p_t]\right),$$

where the approximation error is small.

I also approximate $\phi_t = \phi_{mean}$. The approximation error is small here as well because fluctuations in ϕ over the cycle are relatively small. Finally, for simplicity I approximate ϕ_{mean} and ε_{mean}^* by their steady state values, which are close to the mean values over the cycle given the mean zero shocks and lack of a substantial asymmetry in the model.

Calculating $d(p_t)$ then takes two steps. First, I solve for ϕ in steady state. The steady state equilibrium condition is:

$$\frac{E_{\Omega_t}\left[d^f\left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^*\right]\right]}{E_{\Omega_t}\left[d^d\left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^*\right]\right]} = \frac{\phi_t}{1-\phi_t}.$$

I approximate ϕ by assuming that $E[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^*]$ is the same for all bins, which is roughly the case, and then solving for ϕ. Second, I calculate $d(p_t)$ from (27) using $\varepsilon^*(p) = \varepsilon^{*,mean} + p_t - E_\Omega[p]$.

Calibration To Micro Estimates

The procedure to calibrate to the micro estimates is largely described in the main text. I start with the IV binned scatter plot (p_b, d_b), which can be thought of as an approximation of the demand curve by 25 indicator functions after the top and bottom 2.5 percent of the price distribution is dropped. In Figure 2, the log relative markup p is in log deviations from the average, and I convert it to a dollar amount using the average price of \$760,000 in the IV sample. For each combination of σ, χ, and the density of $F(\cdot)$, I use equation (27) to calculate the mean of squared error:

$$\Sigma_b\left(d_b - d^{3\ month}(p_b)\right)/N_b.$$

Because the data is in terms of probability of sale within 13 weeks, $d^{3\ month}(p_b) = d(p_b) + (1 - d(p_b))\, d(p_b) + (1 - d(p_b))^2\, d(p_b)$ is the simulated probability a house sells within three months. I also need to set κ_t, the multiplicative constant. I do so by minimizing the same sum of squared errors for a given vector of the parameters $(\sigma, \mu, density)$.

ζ could also be chosen using this method, but doing so obtains a very large ζ that introduces numerical error into the dynamic model solution. Consequently, I choose $\zeta = 8$, which gives most of the improvement in mean squared error from choosing ζ optimally relative to using a normal distribution with $\zeta = 2$ while reducing numerical error. The results are not sensitive to this normalization.

Additionally, The seller search cost s is pinned down by the elasticity of demand at the zero point, and using the zero point estimated from the data leads to a very large s because the zero point is slightly on the inelastic side of the kink. Because the zero point corresponding to the average price is not precisely estimated and depends on the deadline used for a listing to count as a sale, I shifting the zero point by up to one percent to to obtain a more plausible seller search cost.

At each step of the optimization, for a given value of the density I find $\bar{\varepsilon}$, $\underline{\varepsilon}$, and χ to match targets for $1-F(\varepsilon^*) = \frac{\bar{\varepsilon}-\varepsilon^*+\chi(\varepsilon^*-\underline{\varepsilon})}{\bar{\varepsilon}-\underline{\varepsilon}}$ and $E[\varepsilon-\varepsilon^*|\varepsilon>\varepsilon^*] = \frac{\chi\bar{\varepsilon}(\bar{\varepsilon}-\underline{\varepsilon})+\frac{1-\chi}{2}(\bar{\varepsilon}+\varepsilon^*)(\bar{\varepsilon}-\varepsilon^*)}{\bar{\varepsilon}-\varepsilon^*+\chi(\varepsilon^*-\underline{\varepsilon})} - \varepsilon^*$. The target for $E[\varepsilon-\varepsilon^*_{mean}]$ is chosen to match a target value of b assuming $V^0 \approx V^h$. This is done by matching the aggregate targets below through the calibration system below and choosing $E[\varepsilon-\varepsilon^*|\varepsilon>\varepsilon^*]$ to match the target b.

Matching the Aggregate Targets

To match the aggregate targets in Table 4, I invert the steady state so that the remaining parameters can be solved for in terms of the target moments conditional on $\left(\sigma, \zeta, \mu, \bar{\varepsilon}, \underline{\varepsilon}, \chi, \xi^d/\xi^f, \text{ and } \varepsilon^*_{mean}\right)$. I solve this system, defined below, conditional on the steady-state targets described in Table 4 in the main text. I then select a value for the standard deviation of innovations to the AR(1) shock σ_η, run 25 random simulations on 500 years of data, and calculate the standard deviation of annual log price changes. I adjust the target value for σ_η and recalibrate the remainder of the moments until I match the two time series moments. I repeat this procedure altering α until the impulse response to the renter flow utility shock in the backward-looking model peaks after 36 months.

The Calibration System

Many variables can be found from just a few target values, and I reduce the unknowns to a four equation and four unknown system. The system is defined by:

- β, L, and γ, are set to their assumed monthly values.
- b and h are set to their assumed values.
- $\theta = 1$ from the equality of buyer and seller time on the market.
- $d = 1/4$ together with indifference in steady state imply:

$$\xi^f = \frac{d}{\theta \frac{d}{\theta^\gamma \phi^{\gamma-1}(1-G)^{1-\gamma}(1-F)}},$$

  where and $1-F(\varepsilon^*)$ $1-G(-\mu)^{1-\gamma}$ can be found from the first stage of the calibration.

- λ^h is set to match the frequency with which homeowners move.
- The homeownership rate in the model, $\frac{H}{H+B+R}$, is matched to the target moment. Plugging in steady-state values gives:

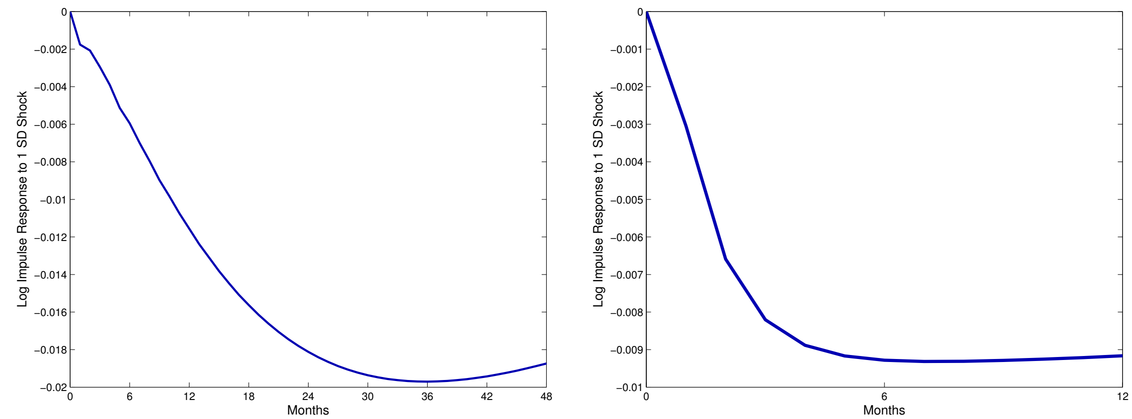
$$\text{Homeownership Rate} = \frac{1}{1+\frac{\lambda^h\theta}{d}+\frac{L\lambda^h}{\bar{\lambda}^r}}.$$

  This is solved for $\bar{\lambda}^r$:

$$\bar{\lambda}^r = \frac{HRRateL\lambda^h}{1-HRRate-HRRate\frac{\lambda^h\theta}{d}}$$

Figure A15: Impulse Response Functions: Downward Shock

A: Rule of Thumb Model B: Staggered Pricing Model



Notes: The left panel shows a downward shock in the rule of thumb model, while the right panel shows a downward shock in the staggered model.. Simulated impulse responses are calculated by differencing two simulations of the model from periods 100 to 150, both of which use identical random shocks except in period 101 in which a one standard deviation negative draw is added to the random sequence, and then computing the average difference over 100 simulations.

- The population N can then be solved for from $N = H + B + R$

$$N = \frac{d}{d+\lambda^h}\left(1 + \frac{\lambda^h \theta}{d} + \frac{L\lambda^h}{\bar{\lambda}^r}\right).$$

This leaves s and V^0, which are solved for jointly to match the target price and satisfy three equilibrium conditions for steady state:

$$\varepsilon^* = b + \beta V^b + p - V^h$$
$$p = s + \beta V^s + \frac{1}{\frac{1}{(\bar{\varepsilon}-\varepsilon^*)+\frac{\chi}{1-\chi}(\bar{\varepsilon}-\underline{\varepsilon})} + \frac{g}{1-G}\left(1 - \frac{1}{G}\frac{d^d}{d}\right)}.$$

G Additional Simulation Results

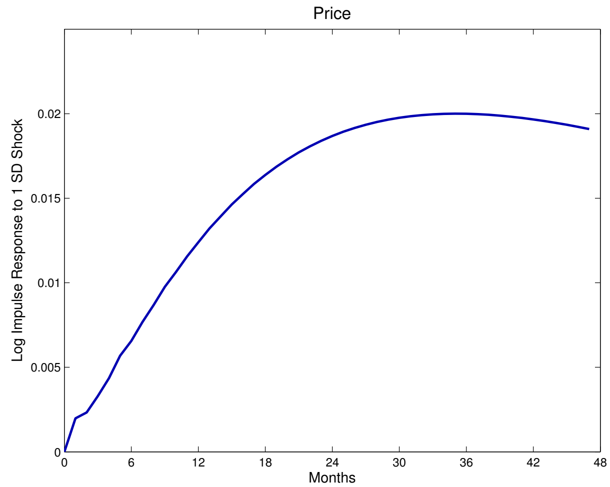
G.1 Downward Shocks

Figure A15 shows the impulse response to a downward shock directly analogous to Figure 5. As in the data, there is very little detectable asymmetry between an upward and downward shock because the semi-elasticity of demand is locally smooth. Across all 14 calibrations, the impulse response is 36 months for both a downward and upward shock. However, for a very large shock, downward may show slightly more concavity because the elasticity of demand rises sharply when relative price is extremely low.

G.2 Deterministic, Non approximated Shock

To ensure that the impulse response is not being driven by the third order perturbation solution method, I solve a deterministic version of the model by Newton's method. The model starts in steady state and at time zero is it with a surprise one-time shock to η of size σ_η and then deterministically

Figure A16: Impulse Response Functions: Deterministic Shock in Rule of Thumb Model



Notes: This figure shows impulse responses analogous to Panel A of Figure 5 with an exactly-solved deterministic model. The impulse responses are created by running a simulation with a surprise one-time shock to η of size σ_η at time zero.

returns to steady state as x_t reverts back to zero. I then plot deterministic impulse responses for a variable X as $\log(X_t/X_{ss})$ where X_{ss} is its steady state value. This results in the IRFs in Figure A16, which are comparable to Figure 5. Across all 14 calibrations, the maximum period of the deterministic one time shock IRF and the stochastic IRF are within one month of each other. The perturbation solution thus seems quite accurate.

G.3 Detailed Intuition For Staggered Pricing Model

The full dynamic intuition with staggered pricing is more nuanced than the static intuition presented above because the seller has to weigh the costs and benefits of perturbing price across multiple periods. The intuition is clearest when one considers why a seller does not find it optimal to deviate from a slowly-adjusting price path by listing his or her house at a level closer to the new long-run price after a one-time permanent shock to fundamentals.

After a positive shock to prices, if prices are rising slowly why do sellers not list at a high price, sell at that high price in the off chance that a buyer really likes their house, and otherwise wait until prices are higher? Search is costly, so sellers do not want to set a very high price and sit on the market for a very long time. Over a shorter time horizon, the probability of sale and profit are very sensitive to perturbing price when a house's price is relatively high but relatively insensitive to perturbing price when a house's price is relatively low. This is the case for two reasons. First, despite the fact that the probability of sale is lower when a house's price is relatively high, demand is much more elastic and so a seller weights that period's low optimal price more heavily. Second, on the equilibrium path, prices converge to steady state at a decreasing rate, so the sellers lose more buyers today by setting a high price than they gain when they have a relatively low price tomorrow. Consequently, in a rising market sellers care about not having too high of a price when their price is high and do not deviate by raising prices when others are stuck at lower prices.

After a negative shock to prices, if prices are falling slowly and search is costly, why do sellers not deviate and cut their price today to raise their probability of sale and avoid search costs if selling tomorrow means selling at a lower price? Although the fact that the elasticity of demand is higher when relative price is higher makes the seller care more about not having too high of a relative price when their price is higher, there is a stronger countervailing effect. Because prices converge to steady state at a decreasing rate on the equilibrium path, sellers setting their price today will undercut sellers with fixed prices more than the sellers are undercut in the future. They thus gain relatively fewer buyers by having a low price when their price is relatively high and leave a considerable amount of money on the table by having a low price when their price is relatively low. On net, sellers care about not having too low of a price when they have the lower price and do not deviate from a path with slowly falling prices.

Another way of putting these intuitions is that the model features a trade-off between leaving money on the table when a seller has the relatively low price and gaining more buyers when a seller has the relatively high price. On the upside, since price resetters raise prices more than future price setters and since they care more about states with more elastic demand, the loss from losing buyers when a resetters have the relatively high price is stronger. On the downside, since price resetters cut prices more than future price resetters, the money left on the table by having a lower price when their prices are relatively low is stronger.