# House Price Momentum and Strategic Complementarity

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**Abstract**

House prices exhibit substantially more momentum, positive autocorrelation in price changes over two to three years, than existing theories can explain. This paper introduces, empirically grounds, and quantitatively analyzes an amplification mechanism for momentum that can reconcile theory with the data. Sellers have an incentive not to set a unilaterally high or low list price because the demand curve they face is concave in relative price: increasing the list price of an above-averaged priced house rapidly reduces its probability of sale, while cutting the price of a below-average-priced home reduces revenue but only slightly improves its chance of selling. The resulting strategic complementarity amplifies frictions that generate sluggish price adjustment because sellers adjust their price gradually to stay near the average. I provide new micro-empirical evidence that the demand curve faced by sellers is concave and show using a search model calibrated to the micro evidence that concave demand amplifies 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 (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, a literature that explains momentum by introducing frictions including search (Head et al., 2014), Bayesian learning (Anenberg, 2014), extrapolative expectations (Case and Shiller, 1987; Glaeser and Nathanson, 2017), and the gradual spread of sentiment (Burnside et al., 2016) has been unable to quantitatively explain the degree of momentum in the data.

This paper introduces, empirically grounds, and quantitatively analyzes an amplification mechanism for a broad class of underlying frictions that can reconcile existing theories with the data. Intuitively, no seller wants to set a list price that "sticks out" from comparable houses on the market. If the list price is too high, the house may sit on the market; if it is too low, the house will not sell much more quickly but will garner a lower price. Momentum is amplified as prices adjust sluggishly to changes in fundamentals because sellers who cannot coordinate find it costly to move their price too far from the market average. This paper provides direct micro-empirical evidence for this mechanism and shows that it amplifies momentum by a factor of two to three.

Formally, the amplification works through a strategic complementarity whereby the optimal list price is increasing in the list price of other sellers (Cooper and John, 1988). The strategic complementarity arises because sellers face a demand curve that is concave in relative price: the probability a house sells is more sensitive to list price for houses priced above than below the market average. This concavity implies that raising a house's relative list price reduces the likelihood of sale and expected revenue dramatically, while lowering its relative price only increases the probability of sale slightly and leaves money on the table. This mechanism requires two key assumptions. First, in setting a list price, sellers face a demand curve that trades off price and probability of sale due to search frictions, which are an important feature of housing markets. Second, the tradeoff must be stronger for above-average priced houses.

I approach this second assumption as an empirical question, and turn to micro data on listings for the San Francisco Bay, Los Angeles, and San Diego metropolitan areas from 2008 to 2013 to assess the degree of concavity of the demand curve faced by sellers. As a first pass, I present a simple ordinary least squares (OLS) specification, which reveals a concave relationship. OLS is, however, unsuitable to quantitatively assess the degree of concavity because higher-priced houses are of higher unobserved quality, which biases the estimated demand curve to be too inelastic. To

[1] See also Cutler et al. (1991), Cho (1996), Titman et al. (2014), Head et al. (2014), and Glaeser et al. (2014). Cutler et al. (1991) and Moskowitz et al. (2012) describe how momentum differs across assets. Appendix A shows that momentum holds across metropolitan areas in the U.S., countries, time periods, and price index construction methodologies.

address this bias, I use an instrument that exploits variation in the incentives for individual sellers to set a high list price that is independent of unobserved quality. The instrumental variable (IV) estimates robustly show statistically and economically significant concavity.

In particular, I use variation induced by differences in when contemporaneous sellers purchased and instrument a house's relative list price with the amount of local price appreciation since the seller purchased. Sellers who have experienced 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 appreciation since purchase is low, the amount of equity a seller can extract is low. Because such sellers are likely to be 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, when sellers have more equity to extract, the down payment constraint is less likely to be binding. Because each dollar extracted is not leveraged to the same extent, 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. For both reasons, all else equal, sellers with less appreciation since purchase set higher prices.

Because I compare listings within a ZIP code and quarter, the supply-side variation induced by appreciation since purchase identifies the curvature of demand if unobserved quality is independent of when a seller purchased their home. I evaluate this assumption and find that concavity is robust to controls, sample restrictions, proxies for unobserved quality and date of purchase, and other sources of relative price variation that are independent of appreciation since purchase.

To assess the amount of amplification generated by concave demand quantitatively, I embed concave demand in a Diamond-Mortensen-Pissarides equilibrium search model of the housing market. 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, concave demand arises because at high relative prices, buyers are on the margin of whether they should even look at a house, which is sensitive to its list price. On the other hand, at low relative prices, they are mostly on the margin of whether they should purchase, which depends more on the buyer's idiosyncratic taste for the particular house than the list price.

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. In a rational expectations equilibrium with identical sellers, all sellers change their prices simultaneously and no gradual adjustment

[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.

arises from the incentive to be close to the mean. However, frictions that generate differential insensitivities of prices to changes in fundamentals cause protracted price adjustments because sellers optimally adjust their list price gradually so as to not stray too far from the market average. Importantly, this strategic complementarity amplifies *any* friction that generates heterogeneity in the speed of adjustment. This includes most frictions proposed by the literature, such as staggered pricing, backward-looking expectations, learning, and the gradual spread of sentiment.

While I am agnostic as to which particular friction is at work in practice, I introduce two different frictions from the literature into the model in order to evaluate the degree of amplification. 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 shape of the demand curve to match the micro empirical estimates. Across a range of calibrations, 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 momentum in the data with concavity relative to without concavity. I conclude that concave demand amplifies momentum by a factor of two and three.

My findings have implications beyond the housing market. Strategic complementarities arising from concave demand are frequently used in macroeconomic models,[3] but there is limited empirical evidence of their importance or strength.[4] I use the rich data available in the housing market to provide the first direct evidence for concave demand. While my findings do not imply that concave demand is important for price stickiness outside the housing market, I show that concave demand is not a theoretical curiosity and can substantially amplify price stickiness in practice.

The remainder of the paper proceeds as follows. Section 2 presents the micro data and a

[3]The concave demand curve is similar to "kinked" demand curves (Stiglitz, 1979) which, since Ball and Romer (1990) has been frequently cited as a potential source of real rigidities. An extension of Dixit-Stiglitz preferences proposed by Kimball (1995) that allows for concave demand is frequently used to tractably introduce real rigidities through strategic complementarity in price setting.

[4]The empirical literature has assessed the importance of concave demand largely by assessing whether the ramifications of strategic complementarities are borne out in micro data (Klenow and Willis, 2016) and by examining examining exchange-rate pass through for imported goods (*e.g.,* Gopinath and Itshoki, 2010; Nakamura and Zerom, 2010). The only other direct evidence for strategic complementarity is Amiti et al. (2017), who use exchange rate variation to separately identify the response of firms' pricing to their own costs and the prices of their competitors.

preliminary OLS analysis. Section 3 presents the preferred estimates of the concavity of demand that address bias in OLS using an instrument. Section 4 presents robustness checks for the empirical results. Section 5 presents the model. Section 6 calibrates the model to the micro estimates and assesses the degree to which strategic complementarity amplifies momentum. Section 7 concludes.

# 2 OLS Analysis of the Concavity of Housing Demand

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 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 unsold on the market (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 step-function demand—may be smoothed into a concave demand curve by uncertainty about a house's value.

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.[5] This section presents the data on home listings and transactions used in the analysis and a simple first pass OLS analysis of the shape of the demand curve. OLS is, however, unsuitable for a quantitative analysis of concave demand because it is biased by the conflation of price and unobserved quality, which I address in subsequent sections.

## 2.1 Data

I combine data on listings with data on housing characteristics and transactions. The details of data construction can be found in Appendix B. The listings data come from Altos Research, which every Friday records a snapshot of homes listed for sale on multiple listing services (MLS) from

[5]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 long time period.

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 homes in 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.[6] 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.

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. Table 1 provides summary statistics for the listings successful matched to a DataQuick property ID which constitute my analysis sample. It also provides summary statistics the two subsamples I use in my IV analysis, which are described in the next section.

### 2.2 Empirical Framework and Estimation

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. In robustness checks in the appendix, I vary the horizon and use time to sale for houses that sell. The data consist of homes, denoted with a subscript $h$, listed in markets defined by a location $\ell$ (a ZIP code in the data) and time period $t$ (a quarter in the data).

[6] 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 | 72.3% | 74.6% | 68.7% | 62.7% | 100% | 100% | 100% | 100% |
| Prior Transaction | 62.7% | 100% | 100% | 100% | 64.7% | 100% | 100% | 100% |
| REO | 22.4% | 27.8% | 0% | 0% | 28.7% | 35.6% | 0% | 0% |
| Short Sale or Subsequent Foreclosure | 19.4% | 23.6% | 13.50% | 0% | 19.8% | 24.3% | 15.9% | 0% |
| Estimated Equity < -10% | 30.9% | 49.3% | 100% | 88.4% | 31% | 47.9% | 100% | 94.2% |
| 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 | 44.3% | 42.9% | 44.8% | 42.9% | 61.2% | 57.5% | 65.2% | 68.5% |
| 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 | 2.310 | 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 B. 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 B, and a -10 percent threshold is chosen because the equity measure is noisy.

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 $\ell$ 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 $\ell$ at time $t$, represented by a fixed effect $\xi_{\ell t}$, and quality $q_{h\ell t}$:

$$\tilde{p}_{h\ell t} = \xi_{\ell t} + q_{h\ell t}. \tag{1}$$

In the main text, I assume that quality is a linear combination of observable measures of quality $\beta X_{h\ell t}$.

I model the probability of sale $d_{h\ell t}$ as being a potentially nonlinear function of $p_{h\ell t} - \tilde{p}_{h\ell t}$:

$$d_{h\ell t} = g\left(p_{h\ell t} - \tilde{p}_{h\ell t}\right) + \psi_{\ell t} + \varepsilon_{h\ell t}. \tag{2}$$

The demand curve in relative price $g\left(\cdot\right)$ 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 independent of $p_{h\ell t} - \tilde{p}_{h\ell t}$.[7] 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 $\ell$ at time $t$. $g(\cdot)$ can then be estimated by first estimating $p_{h\ell t} = \xi_{\ell t} + \beta X_{h\ell t} + \nu_{h\ell t}$ and plugging the estimated residual $\nu_{h\ell t} = p_{h\ell t} - \tilde{p}_{h\ell t}$ into (2).

I use a linear combination of two observed measures of quality for $X_{h\ell t}$. 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 $\tau$ 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 B. For the OLS analysis, the fixed effects $\xi_{\ell t}$ and $\psi_{\ell t}$ are at the ZIP $\times$ distress status level, where distress status is an indicator for whether the house is a non-distressed sale, a bank sale of a foreclosure, or a short sale in order to absorb differences in the average price by distress category.

### 2.3 OLS Results and Limitations

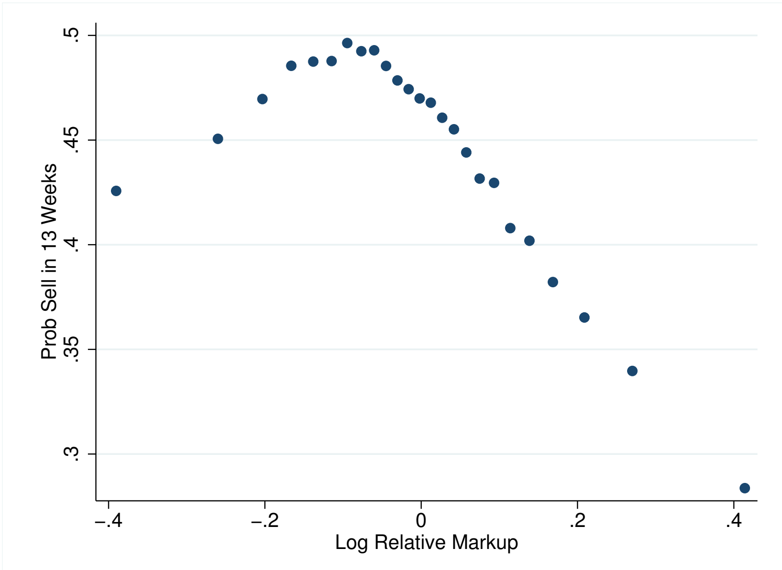
Figure 1 shows the OLS estimate of $g(\cdot)$ non-parametrically using a binned scatter plot that parameterizes $g(\cdot)$ using indicator variables for each of 25 quantiles of $p_{h\ell t} - \tilde{p}_{h\ell t}$ as detailed in Appendix C. The relationship is highly concave.

That being said, Figure 1 also highlights the limitations of OLS: quality unobserved to the econometrician is likely positively correlated with price, but OLS assumes that there is no unobserved quality. This biases the slope and potentially the shape of the demand curve. To assess the direction of the bias, it is useful to consider an extreme example in which all of the variation in price conditional on observed quality is due to unobserved quality. In this case, the estimated demand curve would slope upward because higher quality homes that are priced the same sell faster. Consequently, one would expect unobserved quality to lead to an estimated demand curve slope that is upwardly biased (less negative), or equivalently a demand curve that is too inelastic. Such bias is clearly evident in the upward slope at low relative prices in Figure 1. This same bias also explains why the demand curve is so inelastic, with a house priced 40 percent above average only having a 40 percent lower probability of sale.

The bias in the OLS estimates is important to address given that this paper's goal is to quantitatively assess the degree of amplification provided by concave demand. Furthermore, if unobserved quality varied systematically with list price, the shape of the demand curve could also be biased.

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

Figure 1: Ordinary Least Squares Estimate of the Effect of List Price on Probability of Sale




Notes: The figure 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 the figure, a first stage regression of log list price on fixed effects at the ZIP x first quarter of listing x seller distress status level and repeat sales and hedonic log predicted prices 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 (2), 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. The sample consists of all listings with a prior observed sale, with 416,373 observations prior to dropping unique zip-quarter cells and winsorizing.

# 3 Instrumental Variables Analysis of the Concavity of Demand

To estimate the concavity of demand in the presence of unobserved quality, this section uses a non-linear instrumental variables approach that traces out the demand curve using supply-side variation in seller pricing behavior that is independent of unobserved quality. I first present the econometric approach and the identification condition that an instrument must satisfy. I then present my instrument and results.

## 3.1 Instrumental Variables Empirical Framework and Estimation

I model quality as the sum of the same linear combination of observed quality $\beta X_{h\ell t}$ as in Section 2 and quality unobserved by the econometrician $u_{h\ell t}$:

$$q_{h\ell t} = \beta X_{h\ell t} + u_{h\ell t}. \tag{3}$$

Combining (1) and (3), the reference price $\tilde{p}_{h\ell t}$ can be written as:

$$\tilde{p}_{h\ell t} = \xi_{\ell t} + \beta X_{h\ell t} + u_{h\ell t}. \tag{4}$$

I identify $g(\cdot)$ in the presence of unobserved quality by introducing an instrumental variable $z_{h\ell t}$ that creates 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

$$p_{h\ell t} = f(z_{h\ell t}) + \tilde{p}_{h\ell t} = f(z_{h\ell t}) + \xi_{\ell t} + \beta X_{h\ell t} + u_{h\ell t}. \tag{5}$$

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 $u_{h\ell t}$. 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 a no measurement error assumption. I defer discussion of whether these assumptions hold in practice until after I introduce the instrument.

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 first estimates equation (5) by OLS using a flexible polynomial for $f(\cdot)$ and then uses the predicted $f(z_{h\ell t})$ as $p_{h\ell t} - \tilde{p}_{h\ell t}$ to estimate equation (2) by OLS.[8]

I assess the degree of concavity of $g(\cdot)$ 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 as in Section 2 and overlay a third-order polynomial fit with pointwise 95 percent confidence bands, again clustering by ZIP-3.

### 3.2 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

[8] All estimates 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 to account for the reduced precision of the predicted prices in areas with fewer transactions.

longer time on the market for an identical house. My instrument takes advantage of two sources of variation in the marginal utility of cash on hand that are independent of unobserved quality.

The first source of variation is that sellers with less equity to extract upon sale on average have a higher marginal utility of cash on hand. This is the case because many sellers use the equity they extract from sale for the down payment on their next home (Stein, 1995). Households with little equity to extract are more likely to be on a down payment constraint. Because each dollar of equity extracted is used towards the next down payment and leveraged, the marginal utility of cash on hand high. By contrast, sellers with significant equity to extract may have enough cash on hand that they no longer face a binding down payment constraint. Because they do not leverage each additional dollar of equity they extract, their marginal utility of cash on hand is lower. While the presence of a binding down payment constraint depends on an individual seller's liquid asset position and access to credit, 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.[9]

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. A subsequent literature has confirmed the importance of loss aversion in housing markets.

I use one instrument to capture the effect of both of these sources of variation: the log of appreciation in the ZIP code repeat-sales house price index since purchase $z_{h\ell t} = \log\left(\frac{\phi_{\ell t}}{\phi_{\ell \tau}}\right)$, where $\phi$ is the repeat-sales house price index, $t$ is the period of listing, and $\tau$ is the period of previous sale. In the case of equity extraction, financing and refinancing decisions make seller equity endogenous. $z_{h\ell t}$ isolates the exogenous component of equity as it is isomorphic to equity if all homeowners take out an identical mortgage and do not refinance. 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. 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 (5). 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.[10] 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

[9] See Head et al. (2018) for a model consistent with this story and Anenberg (2011) for empirical evidence on both sources of variation.

[10] In the first stage, 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 coefficients 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 due to the definition of a predicted price using a repeat sales house price index. $f(z_{h\ell t})$ 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 in Appendix C, and the results are virtually unchanged.

$d_{h\ell t}$, 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 in the context of my instrument as requiring that unobserved quality for sellers contemporaneously in the same market be independent of when the seller purchased. I test this assumption in Section 4.

### 3.3 Instrumental Variables Subsamples

I focus on sellers for whom the exogenous variation is cleanest and the exclusion restriction is most plausible and consequently exclude four groups from the main analysis sample. I relax these sample restrictions in robustness tests described in Section 4.

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, 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, 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 different proxies for equity, creating two different IV subsamples. First, I create a proxy for the equity of 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 of the payment schedule. Consequently, I follow DeFusco (2018) 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 B. 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 using an alternate proxy for equity 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.

Fourth, I drop sellers who experience extreme price drops since purchase (over 20 percent). Such sellers only have positive equity if they took out a very unusual initial mortgage.

The two IV samples are substantially smaller than the full sample of listings with an observed prior transaction because of the large number of REO sales and listings by negative equity sellers from 2008 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%. The second IV sample thus has 137,238 listings leading to 86,033 transactions. Table 1 provides summary statistics for these samples and compares them to the samples used in the OLS analysis. I defer discussion of concerns about sample selection to Section 4.

### 3.4 Instrumental Variables Results

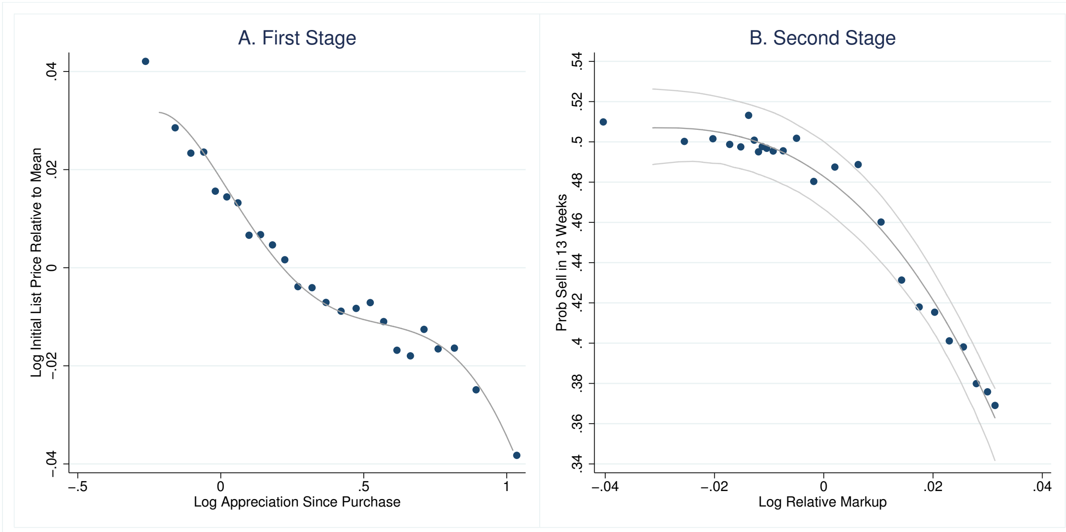
Figure 2 shows first and second stage binned scatter plots for both IV samples: IV sample one which excludes extreme negative equity sellers, and IV sample two which excludes short sales and withdrawals that are subsequently foreclosed upon. The results are similar. As shown in panel A, the first stage is strong, smooth, and monotonic, with a joint F statistic of 206 for IV sample one. The y-axis of this panel shows the variation induced by the instrument that identifies the shape of demand and makes up the x-axis of the second stage in panel B. Panel B shows the demand curve and is the IV analogue of Figure 1. Relative to Figure 1, the relative markups are compressed, which reflects that much of the OLS variation in the relative markup is due to unobserved quality. 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 displays 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.

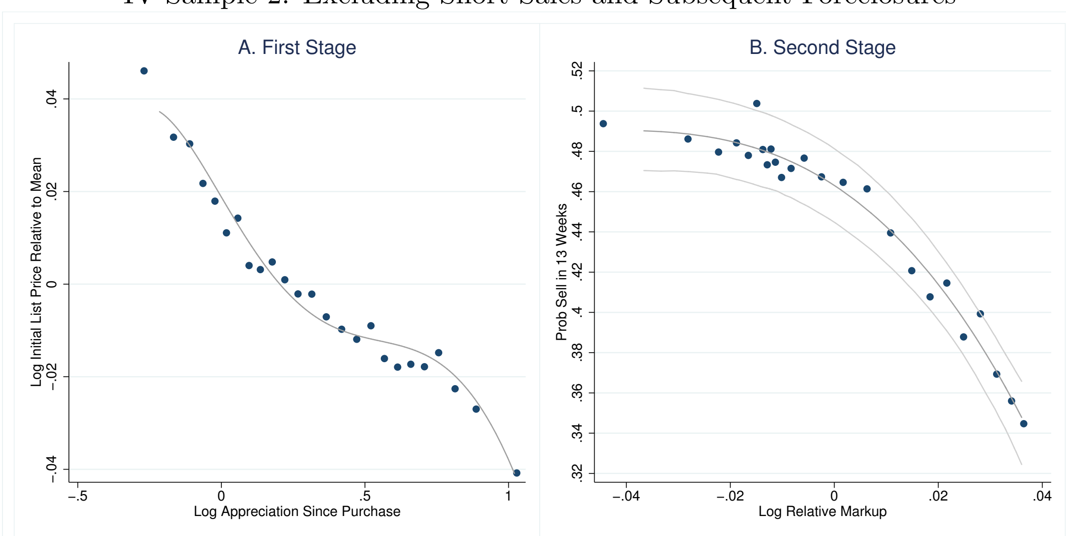
Relative to the OLS results in Figure 1, the bias is eliminated, and the elasticity of demand is far more plausible. At the mean price, the IV sample one estimates imply that raising the list price by one percent reduces the probability of sale within 13 weeks by approximately 2.7 percentage points. Given the base of 48 percentage points, this amounts to a reduction in the probability of sale within 13 weeks of 5.6 percent or equivalently an increase in time on the market of 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 concavity.

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 × 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 (2). 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 (5), 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 (5) 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: IV 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× 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 (2) 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 (5), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup in equation (2), 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 (2), 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.

# 4 Robustness of Instrumental Variables Results

This section describes tests that address the robustness of the results and concerns about the exclusion restriction and measurement error in Condition 1. For parsimony, most of the robustness tests are relegated to Appendix C.

## 4.1 Selection of the IV Samples

To assuage concerns about selection of the IV samples, Column 1 of Table 2 shows OLS results for the full set of listings with a observed prior transaction as in Figure 1 while columns 2 and 4 show OLS results for IV sample one and IV sample two. In all three samples, OLS displays clear and significant concavity and the 95 percent confidence intervals on the quadratic terms overlap. 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.

## 4.2 Exclusion Restriction

The exclusion restriction, which is part one of Condition 1, is that unobserved quality is independent of when a seller purchased. One potential concern is that sellers with higher appreciation since purchase improve their house in unobservable ways with their home equity. However, this implies a positive first stage relationship between price and appreciation since purchase while I find a strong negative relationship.[11] Beyond this, the exclusion restriction is difficult to test because I only have a few years of listings data. Flexibly controlling for when a seller bought weakens the effect of the instrument on price in equation (5) and widens the confidence intervals to the point that any curvature is not statistically significant.

Nonetheless, I evaluate the identification assumption that date of purchase is independent of unobserved quality as best I can in five sets of robustness tests in Appendix C. First, I include various additional observable measures of quality in $X_{h\ell t}$ and find the results do not substantially change. 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 controls for unobserved quality that varies linearly in date of purchase or in time since purchase by adding a linear time trend for the entire sample, at the MSA level, and at the ZIP-3 level to the quality index. Fourth, to control for unobservables correlated with date of purchase or time since purchase more non-parametrically, I include fixed effects for quintiles date of purchase and time since purchase for each ZIP code in $X_{h\ell t}$. Fifth, one might be concerned that households that purchased near the house price peak or in the bust

[11] My identification strategy would find extra concavity if sellers with high appreciation since purchase improve their house with their equity but sellers who have experienced low appreciation since purchase do not. This seems unlikely, as sellers with low appreciation since purchase are more likely to be liquidity constrained and improve their house if they gain equity. Furthermore, this effect would have to be extreme in order to generate significant concavity.

are different. To address this concern, I limit the sample to sellers who purchased prior to 2004 and again include a linear time trend. In all of these tests, concavity remains a robust finding, although the standard errors widen to the point that concavity is no longer significant—although importantly point estimates are little changed—when a separate linear time trend is used for each ZIP-3.

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.

### 4.3 Measurement Error

Beyond the positive relationship between unobserved quality and price, unobserved quality creates a second, more subtle econometric issue: measurement error in $\tilde{p}_{h\ell t}$ because the true $\tilde{p}_{h\ell t}$ is not observable. This can be seen in the second part of Condition 1, which 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, my 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.

The instrument does not address measurement error in this context because the measurement error is non-classical. In equation (5), 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. By contrast, for classical measurement error, the error is independent of the true $\tilde{p}_{h\ell t}$. 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. This is why an additional assumption is necessary.

I use two strategies to show that the bias created by other sources of markup variation that induce measurement error does not cause significant spurious concavity. First, I show 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 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 (2) and (4) and suppose that:*

$$z_{h\ell t}\perp\left(u_{h\ell t},\varepsilon_{h\ell t}\right), \tag{6}$$

$$p_{h\ell t}=f\left(z_{h\ell t}\right)+\zeta_{h\ell t}+\tilde{p}_{h\ell t}, \tag{7}$$

*$\zeta_{h\ell t} \perp f(z_{h\ell t})$, 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.

### 4.4 Other Robustness Tests

In both samples, the results are robust across geographies, time periods, and specifications, although in a handful of cases restricting to a smaller sample leads to insignificant results. In addition to the robustness checks described as tests of the exclusion restriction, the results are robust to controlling for nearby foreclosures, using different functional forms for $f(\cdot)$ and for the observables $X_{h\ell t}$, allowing for differential sorting by letting $\beta$ vary across time and space, accounting for the uniqueness of a house in its neighborhood, and accounting for different price tiers within ZIP codes. Using alternate measures of whether a house sells quickly does not alter the results, nor does relaxing the criteria for inclusion in each IV sample. Robust concavity remains if transaction prices are used rather than list prices, which assuages concerns that bargaining or price wars undo the concavity in list price. Finally, 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.

Overall, the instrumental variable results provide robust evidence of demand concave in relative price for these three MSAs from 2008 to 2013.[12]

[12] Aside from the tail end of my sample, this period was a depressed market. The similarity between my results and Carrillo's (2012) 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.

# 5 A Search Model of House Price Momentum

The remainder of the paper quantitatively assesses the extent to which the concavity in the micro-data amplifies frictions that cause momentum.

Momentum, which refers to autocorrelation in price changes, is a puzzle because forward-looking models have a strong arbitrage force that eliminates momentum, even with short sale constraints. Furthermore, momentum cannot be empirically explained by serially correlated changes in fundamentals (Case and Shiller, 1989; Capozza et al. 2004). Glaeser et al. (2014) conclude that in a frictionless model, "there is no reasonable parameter set" consistent with short-run momentum.

Five main types of frictions have been introduced to explain momentum. First, gradual learning about market conditions can create momentum. Anenberg (2014) structurally estimates Bayesian learning model and explains a quarter of the momentum in the data.[13] With a realistic frequency of observation, learning happens too quickly to fully explain momentum.

Second, Head et al. (2014) demonstrate that search frictions can generate momentum by making the adjustment of market tightness, and thus a house's liquidity, gradual in response to shocks to fundamentals. Their calibrated model explains 40 percent of the autocorrelation in price changes in the data over one year and no momentum over two years. Indeed, over 85 percent of the price impulse response occurs in the first quarter after a shock, while in the data analyzed in Appendix A, roughly 25 percent occurs in the first quarter.

Third, a behavioral finance literature hypothesizes that investors 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. Recently, Glaeser and Nathanson (2017) 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 quantitatively explain momentum when all agents follow their behavioral theory and observe prices with a six-month lag. However, their model can only explain a third of momentum when under half of sellers are rational, as suggested by recent experimental evidence (Kuchler and Zafar, 2017; Armona et al. 2018).

Fourth, Burnside et al. (2016) 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.[14]

Fifth and finally, standard nominal rigidities such as adjustment costs for list prices or staggered list price setting can cause a small amount of momentum.

Concave demand amplifies any source of momentum that creates heterogeneity in the speed of adjustment by inducing all sellers to not stray too far from the slowest adjusters. Instead of

[13]Anenberg finds an annual AR(1) coefficient of 0.165. By contrast, Appendix A reports a coefficients of 0.65 to 0.70 for repeat sales price indices and 0.45 to 0.50 for median price measures.

[14]In the Burnside et al. 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.

introducing a laundry list of frictions in this mold, my approach is to introduce two prominent and tractable frictions—extrapolative expectations and staggered pricing—and show that they are amplified by a similar amount.

Doing so requires a search model in which sellers have a tradeoff between price and time on the market. This section adapts a standard search model in the mold of Wheaton (1990), Krainer (2001), Novy-Marx (2009), Piazzesi and Schneider (2009), Genesove and Han (2012), Ngai and Tenreyro (2013), and Head et al. (2014) to include concave demand. I first introduce a model of a metropolitan area, describe the housing market, and show how sellers set list prices. I then add the two frictions and define equilibrium. Table 3 summarizes the notation.

## 5.1 Setting

Time is discrete and all agents are risk neutral. Agents have a discount factor of $\beta$. There is a fixed housing stock of mass one, no construction, and a fixed population of size $N$.[15]

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.

Each period with probability $\lambda^h$ and $\lambda_t^r$, respectively, homeowners and renters receive shocks that cause them to separate from their current house or apartment, as in Wheaton (1990). A renter who gets a shock enters the market as a homogenous buyer. Homeowners who get a shock leave the MSA with probability $L$, in which case they become a seller and receive a present discounted value of $V^0$ for leaving. With probability $1-L$, homeowners remain in the city and simultaneously become a buyer and a homogenous seller. Buyers and sellers 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 (2018). Because the population is constant, every time a seller leaves the city she is 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:

$$V_t^h = h + \beta E_t \left[ \lambda^h \left( V_{t+1}^s + LV^0 + (1-L) V_{t+1}^b \right) + \left(1-\lambda^h\right) V_{t+1}^h \right]. \tag{8}$$

## 5.2 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 that can be thought of as an initial impression as to whether a house is worth visiting.

[15] 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 | |
| $\lambda^h$ | Prob Homeowner Gets Shock | |
| $\lambda_t^r$ | Prob Renter Gets Shock | Exogenous Driving Process |
| | Other Fixed Parameters | |
| $\beta$ | Discount Factor | |
| $L$ | Probability Seller Leaves Metro Area | |
| $V^0$ | PDV of Exiting Metro Area | |
| | Utilities | |
| $\varepsilon$ | Match-Specific One-Time Utility Benefit | $\sim F(\varepsilon)$ |
| $\upsilon_h$ | Permanent House Quality | Mean Zero |
| | Stochastic Draws | |
| $\eta_{h,t}$ | Noise in $\upsilon_h$ in Binary Signal About Quality,<br>IID Common to All Buyers in Period $t$ | $\sim G(\eta)$ |
| | Parameters / Values | |
| $\theta_t^m$ | Market Tightness $= B/S$ in Submarket $m = \{f, d\}$ | Endogenous |
| $\tilde{\theta}_t$ | Vector of $\theta^m$ s | Endogenous |
| $q^m(\theta_t^m)$ | Prob. Seller Meets Buyer in $m$ (Matching Fn) | Endogenous |
| $\xi^m$ | Constant in Matching Function in $m$ | |
| $\gamma$ | Matching Function Elasticity in all $m$s | |
| $p_t$ | List Price Adjusted for Permanent Quality | Endogenous |
| $\Omega_t$ | Distribution of Prices | Endogenous |
| $\varepsilon_t^*$ | Threshold $\varepsilon$ for Purchase | Endogenous |
| $\mu$ | Threshold for Binary Signal | |
| | Distribution Parameters | |
| $\underline{\varepsilon}, \bar{\varepsilon}$ | Bounds of Dist of $F(\varepsilon)$, Uniform With Mass Point | |
| $\chi$ | Size of Mass Point of Uniform Dist at $\bar{\varepsilon}$ | |
| $\sigma$ | Generalized Normal Variance Parameter | |
| $\zeta$ | Generalized Normal Shape Parameter | |

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 $\varepsilon$, which is match-specific, drawn from $F(\varepsilon)$ at inspection, and realized as utility at purchase. They also observe the house's permanent quality $\upsilon_h$, 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,[16] or equivalently that risk neutral buyers and sellers expect that the average sale price will be an affine function of the list price.[17] 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 $1 - F(\varepsilon_t^*)$.

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 market average quality-adjusted price is above a threshold $\mu$. However, quality $\upsilon_h$ (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.[18] 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 $\Omega_t$ is the cumulative distribution function of list prices and $E_{\Omega_t}[\cdot]$ represents an expectation with respect to the distribution of prices $\Omega_t$ 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 sub-

[16]The assumption that houses sell at list price 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 price. Appendix D uses the IV procedure in Section 3 replacing $d_{h\ell t}$ with the difference between list and transaction prices and finds no strong relationship between list and transaction prices. 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.

[17]Most house list price changes are decreases. I abstract from such duration dependence to maintain a tractable state space.

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

market $f$ 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 $\phi_t$.

After choosing a submarket, buyers search randomly within that sub-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 $\theta_t^m$ is the ratio of buyers to sellers in submarket $m = \{f, d\}$, $\theta_t = B_t/S_t$ is aggregate market tightness, and $\tilde{\theta}_t = \left\{\theta_t^d, \theta_t^f, \theta_t\right\}$. 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 within a submarket. 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.

Appendix E derives the market tightness in each submarket, and *ex ante* probability of purchase conditional on following or not following the signal. It shows that the probability that a seller sells, which constitutes the demand curve she faces, can be written as:

$$d\left(p_t, \Omega_t, \tilde{\theta}_t\right) = d^f\left(p_t, \Omega_t, \tilde{\theta}_t\right) + d^d\left(p_t, \Omega_{t,} \tilde{\theta}_t\right), \tag{9}$$

where,

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

is the demand curve faced by a seller in the $f$ submarket and,

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

is the demand curve faced by a seller in the $d$ submarket. The appendix also shows that the probability a buyer buys given the $\phi_t$ randomization strategy is $\frac{1}{\theta_t} E_{\Omega_t}\left[d\left(p_t, \Omega_{t,} \tilde{\theta}_t\right)\right]$.

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. 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:

$$B_t = \left(1 - \frac{1}{\theta_{t-1}} E_{\Omega_{t-1}}\left[d\left(p_{t-1}, \Omega_{t-1}, \tilde{\theta}_{t-1}\right)\right]\right) B_{t-1} + \lambda_{t-1}^r R_{t-1} + (1 - L)\lambda^h H_{t-1} \tag{12}$$

$$S_t = \left(1 - E_{\Omega_{t-1}}\left[d\left(p_{t-1}, \Omega_{t-1}, \tilde{\theta}_{t-1}\right)\right]\right) S_{t-1} + \lambda^h H_{t-1}. \tag{13}$$

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:

$$1 = H_t + S_t \tag{14}$$

$$N = R_t + B_t + H_t. \tag{15}$$

When a buyer buys, she receives the expected surplus $E\left[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^*\right]$ where $\varepsilon_t^*$ is a function of $p_t$. The value function of a buyer who follows, $V_t^{b,f}$, and a buyer who does not follow, $V_t^{b,d}$, are defined in Appendix E, and the value of a buyer prior to choosing a submarket $V_t^b$ is $V_t^b = \max\left\{V_t^{b,f}, V_t^{b,d}\right\}$. In equilibrium, buyers are indifferent between $f$ and $d$ and can choose either submarket next period, so the ratio of expected surpluses in each market is equal to the ratio of the randomization probabilities:

$$\frac{E_{\Omega_t}\left[d^f\left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^*\right]\right]}{E_{\Omega_t}\left[d^d\left(p_t, \Omega_t, \tilde{\theta}_t\right) E\left[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^*\right]\right]} = \frac{\phi_t}{1-\phi_t}. \tag{16}$$

This pins down the fraction of buyers who go to submarket $f$, $\phi_t$. Because $V_t^{b,f} = V_t^{b,d}$ , $V_t^b$ can then be rewritten as the sum of the outside option of being a buyer next period and the expected surplus of following the signal:

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

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:

$$V_t^s = s + \beta E_t V_{t+1}^s + \max_{p_t}\left\{d\left(p_t, \Omega_t, \tilde{\theta}_t\right)\left[p_t - s - \beta E_t V_{t+1}^s\right]\right\}. \tag{18}$$

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

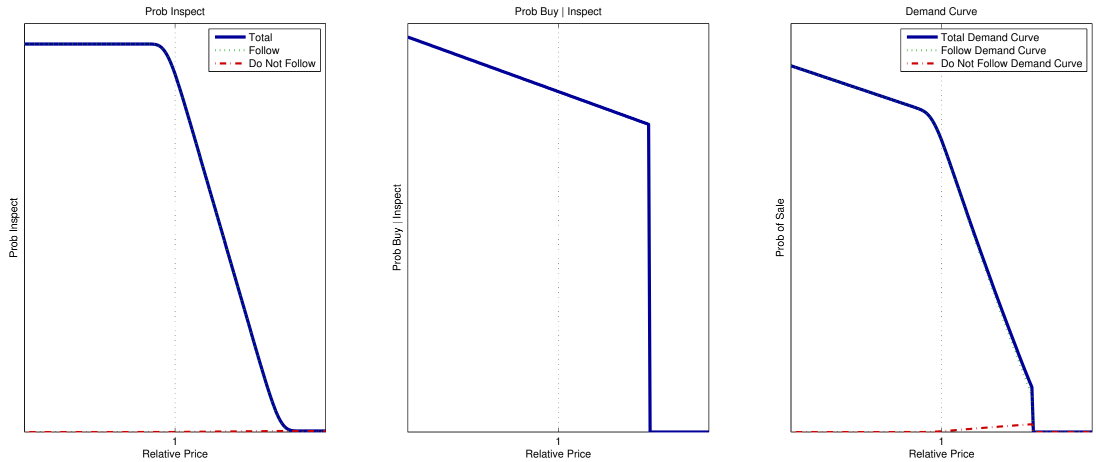
I parameterize the model by assuming flexible distributions for $F(\cdot)$, the distribution of idiosyncratic match quality, and $G(\cdot)$, the noise in the signal, that allow me to closely fit the microdata. I assume that $F(\varepsilon_m)$ is a uniform distribution on $[\underline{\varepsilon}, \bar{\varepsilon}]$ with a mass point of mass $\chi$ at $\bar{\varepsilon}$.[19] For $G(\cdot)$ I use a type 1 generalized normal distribution with mean $\mu$, variance parameter $\sigma$, and shape parameter $\zeta$, which has a probability density function (PDF) of $g(x) = \frac{\zeta}{2\sigma\Gamma(1/\zeta)} e^{-(|x-\mu|/\sigma)^\zeta}$.[20] 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.

The model generates a locally concave demand curve 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 $\varepsilon_m$ and price, so demand is less elastic. At above average prices, the demand curve is dominated by the fact that perturbing the

[19]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.

[20]This is the same as a normal if the shape parameter $\zeta$ is equal to two. When $\zeta > 2$, the PDF is more "flat topped" which results in a cumulative density function (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.

Figure 3: The Concave Demand Curve in the Model




Notes: The figures are generated using the baseline calibration described in Section 6. 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 the $d$ 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 2.

price affects whether the house gets a good signal, in which case it attracts a lot of buyers, or a bad signal, in which case it ends up in a market with few buyers. To illustrate how the demand curve is built up from its various components, Figure 3 shows the shapes of the probability of inspection $q\left(\theta_t^f\right)\left(1-G\left(p_t-E_{\Omega_t}\left[p_t\right]-\mu\right)\right)+q\left(\theta_t^d\right)G\left(p_t-E_{\Omega_t}\left[p_t\right]-\mu\right)$, the probability of purchase conditional on inspection $1-F\left(\varepsilon^*\left(p_t\right)\right)$, and their product, the overall demand curve faced by sellers $d\left(p_t,\Omega_t,\tilde{\theta}_t\right)$. The probability of inspection and overall demand curve are split into the $f$ and $d$ submarket components, revealing that the $d$ submarket has a negligible effect on the overall demand curve because it has few buyers in equilibrium. Note that the axes are switched from a standard Marshallian supply and demand diagram to be consistent with the empirical estimates.

### 5.3 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 (18) 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 $s+\beta V_{t+1}^s$. This 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 more gradually when fundamentals change: $s+\beta V_{t+1}^s$ 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.[21] 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:*

$$\begin{aligned} p_t &= s + \beta E_t V_{t+1}^s + E_t \left[ \frac{-d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{\frac{\partial d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{\partial p_t}} \right] \\ &= s + \beta E_t V_{t+1}^s + \frac{1}{\frac{f(\varepsilon_t^*)}{1-F(\varepsilon_t^*)} + \frac{g\left(p_t - E_{\Omega_t}[p_t]-\mu\right)}{1-G\left(p_t - E_{\Omega_t}[p_t]-\mu\right)} \left[1 - \frac{1}{G\left(p_t - E_{\Omega_t}[p_t]-\mu\right)} \frac{d^d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}{d\left(p_t, \Omega_t, \tilde{\theta}_t\right)}\right]}, \end{aligned} \tag{19}$$

*where $d^d$ is defined by (11) and $d$ is defined by (9).*

*Proof.* See Appendix E. □

In equation (19), the seller markup is 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 square brackets. 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.[22]

However, in a rational expectations equilibrium in which all sellers can set their price flexibly, all sellers choose the same list price, $p_t = E_{\Omega_t}[p_t]$, and there is no heterogeneity 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 separately introduce two two tractable and transparent frictions that generate some heterogeneity in the insensitivity of prices to fundamentals: a small fraction of rule-of-thumb sellers and staggered pricing. I call these the "rule of thumb model" and the "staggered pricing model" and define their equilibria separately.

[21] 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. This turns out not to be a concern as the mass point in the idiosyncratic taste distribution occurs before the probability of inspection curve flattens.

[22] Because few buyers are endogenously in the $d$ submarket, the term in square brackets is near unity.

### 5.4 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 recent evidence from surveys and experiments finds significant heterogeneity in the degree to which expectations are backward-looking. For instance, Kuchler and Zafar (2017) analyze survey expectations and find significant extrapolation by lower-educated households that make up 44 percent of the sample but minimal extrapolation by higher-educated households. Similarly, Armona et al. (2018) use an experiment to estimate that 41 percent of households are extrapolators. 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).

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 (19) but a fraction $\alpha$ 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:

$$p_t^E = \frac{p_{t-2}+p_{t-3}+p_{t-4}}{3} + \psi\left(\frac{p_{t-2}+p_{t-3}+p_{t-4}}{3} - \frac{p_{t-5}+p_{t-6}+p_{t-7}}{3}\right), \tag{20}$$

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

$$p_t = \frac{\alpha d_t^E p_t^E + (1-\alpha)\, d_t^R p_t^R}{\alpha d_t^E + (1-\alpha)\, d_t^R}. \tag{21}$$

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).[23] [24]

### 5.5 Source of Insensitivity 2: Staggered Price Setting

Prices in housing markets are adjusted only infrequently, with the median price lasting two months in the Altos listings data as shown in Appendix D. This is the case because it takes time to market a house and collect offers and because 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

[23] 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.

[24] I assume that regardless of whether rational or backward-looking sellers sell faster, inflows adjust so that $\alpha$ 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 (18), and the value function of a buyer remains (17), but there are now two prices $p_t^E$ and $p_t^R$.

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 $M$ groups of sellers that set prices every $M$ periods, typically using $M = 2$ in monthly simulations. Denote the prices $p_t$, value functions $V_t^s$, seller masses $S_t$, and purchase thresholds $\varepsilon_t$ of a vintage of sellers that set prices $\tau = \{0, ..., M-1\}$ periods ago by $\tau$ superscripts. Buyers receive the same signals, and the buyer's problem and value function remain the same. The seller's value function is as in (18), except the value function for $V_t^{s,\tau}$ has $V_{t+1}^s$ terms replaced by $V_{t+1}^{s,\tau+1}$ for $\tau = \{0, M-2\}$ and by $V_{t+1}^{s,0}$ for $\tau = M-1$.

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

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

$$p_t^0 = \frac{\sum_{\tau=0}^{M-1} \beta^\tau D_t^\tau \left(p_t^0\right) \Psi_t^\tau \varphi_t^\tau}{\sum_{\tau=0}^{M-1} \beta^\tau D_t^\tau \left(p_t^0\right) \Psi_t^\tau} \tag{22}$$

*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 exactly 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 $\tau$ 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 $\tau$ periods after the price is set, and $V_{t+M}^{s,M} = V_{t+M}^{s,0}$.*

*Proof.* See Appendix E. □

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.[25]

### 5.6 Equilibrium

I add stochastic shocks to the model by assuming that the entry rate of renters $\lambda_t^r$ follows an AR(1):

$$\lambda_t^r = \bar{\lambda}^r + \rho \left(\lambda_{t-1}^r - \bar{\lambda}^r\right) + u_t \text{ with } u_t \sim N\left(0, \sigma_\eta^2\right) \text{ and iid.} \tag{23}$$

A positive shock thus causes the entry of potential buyers into the market, which increases demand and pushes up prices.[26] The results do not depend qualitatively or quantitatively depend on this shock.

[25] In addition to the new price setting rule, the law of motion for sellers (13) needs to be altered to $M$ different laws of motion for each of the the $M$ groups of sellers each with separate prices. These modifications are relegated to Appendix E.

[26] 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

An equilibrium with a fraction $\alpha$ of backward-looking sellers is defined as:[27]

**Definition 1.** Equilibrium with a fraction $\alpha$ 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, and homeowner value functions $V_t^s$, $V_t^b$, $V_t^h$, a probability that buyers follow the signal $\phi_t$, stocks of each type of agent $B_t$, $S_t$, $H_t$, and $R_t$, and a process for the entry rate of renters $\lambda_t^r$ satisfying:

1. Optimal pricing for rational sellers (19) and the pricing rule (20) for backward-looking sellers, which depends on lagged transaction-weighted average prices (21);

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 (9), all of which result from buyer search behavior;

4. The value functions for buyers (17), rational sellers (18), and homeowners (8);

5. The laws of motion for buyers (12) and sellers (13) and the closed system conditions for homes (14) and agents (15) that implicitly define the laws of motion for homeowners and renters;

6. The indifference of buyers across markets (16);

7. Rational expectations that $\lambda_t^r$ evolves according the AR(1) process (23).

The model cannot be solved analytically, so I simulate it numerically in Dynare (Adjemian et al., 2013) 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 $u_t = 0 \ \forall \ t$.[28] 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.

# 6 Amplification of Momentum in the Calibrated Model

## 6.1 Calibration

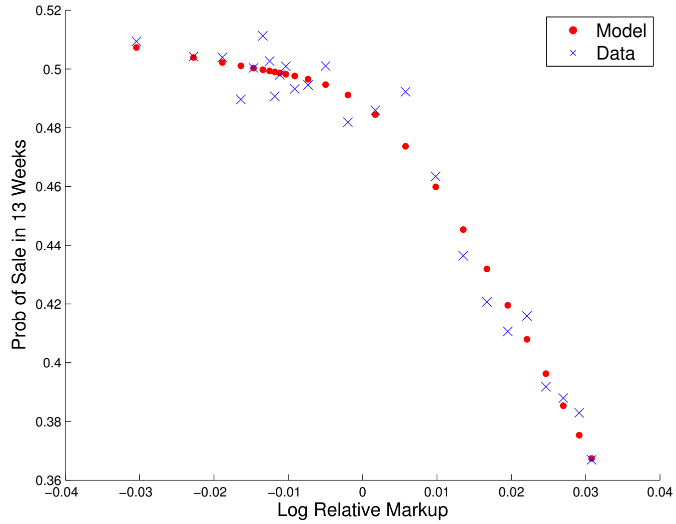
To assess the degree to which concave demand curves amplify house price momentum, this section calibrates the model to the empirical findings presented in Section 2 and aggregate moments.

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.

[27] An analogous equilibrium with $M$ groups of staggered sellers is defined in Appendix E. Aside from switching $i \in \{E, R\}$ for $\tau = \{0, ..., M-1\}$, it differs from the above definition of an equilibrium with backward-looking sellers in three key ways. First, prices are (22) for sellers that can reset their prices and fixed for sellers that 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.

[28] 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).

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 (24) and approximating $\phi_t$ by its steady state value using (16) as described in the text.

In order to simulate the model, 22 parameters listed in Table 5 must be set. This section describes the calibration procedure and targets, with details in Appendix F. Because a few parameters are based on limited data and subject to uncertainty, I use the baseline calibration for exposition and use an additional 13 alternate parameterizations to determine a plausible range for the degree of amplification.

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; $\sigma$ and $\zeta$, the variance and shape parameters of the signal distribution, control how much the elasticity of demand changes as relative price increases; and $\mu$, 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 Figure 2. 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 as in 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. Appendix E shows that the probability of sale at the time the list price is posted can be approximated as:

$$d\left(p_t - E_{\Omega_t}\left[p_t\right]\right) \approx \kappa_t \left(1 - F\left(\varepsilon^*_{mean} + p_t - E_{\Omega_t}\left[p_t\right]\right)\right) \times \left[\begin{array}{l} \left(\frac{\phi_{mean}}{E_{\Omega_t}\left[1-G\left(p_t - E_{\Omega_t}[p_t]-\mu\right)\right]}\right)^{\gamma}\left[1 - G\left(p_t - E_{\Omega_t}\left[p_t\right] - \mu\right)\right] \\ +\frac{\xi^d}{\xi^f}\left(\frac{(1-\phi_{mean})}{E_{\Omega_t}\left[G\left(p_t - E_{\Omega_t}[p_t]-\mu\right)\right]}\right)^{\gamma} G\left(p_t - E_{\Omega_t}\left[p_t\right] - \mu\right) \end{array}\right], \tag{24}$$

where $\kappa_t$ is a fixed effect and $\varepsilon^*_{mean}$ and $\phi_{mean}$ are the mean values of these variables over the cycle. For a given set of parameters, I solve for $\phi_{mean}$ using a steady-state version of (16) and use (24) to simulate the probability of sale in three months for each $p - E_{\Omega}\left[p_t\right]$. I then find the values of the density of $F(\cdot)$, $\mu$, and $\sigma$ that minimize the mean squared error between the simulated demand curve and the IV binned-scatter plot, with $\kappa_t$ chosen match the average probability of sale.[29] [30] [31]

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 parameters 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 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, and the average time on the market. The more speculative targets are varied in calibrations that I use to determine the plausible range for the degree of amplification.

The final step of the calibration is to choose both $\alpha$ and a driving shock process to match the time series features of house prices indicated in the bottom panel of Table 4. For the backward-looking model, I adjust $\alpha$ and recalibrate the model until the impulse response to the renter entry reaches its peak at 36 months to match an impulse response estimated from the CoreLogic national house price index in Appendix A.1. Table 5 summarizes the baseline calibrated parameter values

[29] Evaluating (24) requires values for $\frac{\xi^d}{\xi^f}$, $\varepsilon^*_{mean}$, and a parametrization of $F(\cdot)$ given its density. I describe the baseline values here. Because these calibration targets are uncertain, I alter these values in Table 6. I assume $\varepsilon^*_{mean} = \$100\text{k}$, which is a normalization that has no impact on the economics of the model. I assume $\xi^d/\xi^f = 1/2$. This has no analog in the data, and I show in robustness checks that it is of minimal importance for my quantitative results. If $\xi^d$ is high enough relative to $\xi^f$, sellers may have an incentive to deviate and set a price of $\bar{\varepsilon}$ when prices are rising and buyers visit rarely. I rule out a substantially higher $\xi^d/\xi^f$ because the stronger incentive to deviate would generate asymmetries in house prices not present in the data. To parameterize $F(\cdot)$, I introduce two additional moments that along with the assumed $\varepsilon^*_{mean}$ and density pin down $\underline{\varepsilon}$, $\bar{\varepsilon}$, and $\chi$: the average fraction of home inspections that lead to a purchase $1 - F\left(\varepsilon^*_{mean}\right)$ and the average mean excess function $E\left[\varepsilon - \varepsilon^*_{mean} | \varepsilon > \varepsilon^*_{mean}\right]$. The mean excess function is selected to match a reasonable target for the buyer search cost of 0.75 percent of the purchase cost of the house per month and varied in robustness tests.

[30] The optimal $\zeta$ is very large and leads to numerical error in simulations. Consequently, I set $\zeta = 8$, which gets nearly all the way to the improvement in mean squared error from the optimal $\zeta$ while reducing numerical error. The results are not sensitive to this choice of $\zeta$.

[31] Through equations (18) and (19), 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.

Table 4: Calibration Targets For Baseline Calibration

| Steady State Parameter or Moment | Value | Source / Justification |
|---|---|---|
| | Parameters | |
| $\gamma$ (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 Value From Flow Util (Normalization) |
| $\xi^d/\xi^f$ | 0.5 | Limited Incentive to "Fish" |
| $\varepsilon^*$ 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 |
| $\psi$ | 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 |
| $\rho$ (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 |
|---|---|---|---|---|---|
| $\beta$ | Monthly Discount Factor | 0.996 | -b/P | Flow Util of B (search cost)/Price | 0.75% |
| $\gamma$ | Matching Fn Elasticity | 0.8 | -s/P | Flow Util of S (search cost)/Price | 2.1% |
| $\xi^f$ | Matching Fn Efficiency, Follow | 2.540 | $\bar{\varepsilon}$ | Upper Bound of $F$ Dist | $ 161 k |
| $\xi^d$ | Matching Fn Efficiency, Defy | 1.270 | $\underline{\varepsilon}$ | Lower Bound of $F$ Dist | -$5,516 k |
| $\lambda^h$ | Monthly Prob H Moving Shock | 0.009 | $\chi$ | Weight of Mass Point at $\bar{\varepsilon}$ | 0.090 |
| $\bar{\lambda}^r$ | Ave Monthly Prob R Moving Shock | 0.013 | $\sigma$ | Variance Param in $G(\cdot)$ | 39.676 |
| $N$ | Population | 1.484 | $\zeta$ | Shape Param in $G(\cdot)$ | 8 |
| $L$ | Prob Leave MSA | 0.7 | $\mu$ | Threshold for Signal | 39.676 |
| $\psi$ | AR(1) Param in Rule of Thumb | 0.4 | $\sigma_\eta$ | SD of Innovations to AR(1) shock | 0.00004 |
| $V^0$ | PDV of Leaving MSA | $2,776 k | $\rho$ | Persistence of AR(1) shock | 0.950 |
| $h$ | Flow Util of H | $6.783 k | $\alpha$ | Fraction Backward Looking | 0.299 |

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

for the backwards-looking model. For the staggered pricing model, I use $M = 2$ groups in a monthly calibration to match a median price duration of 9 weeks in the Altos data as 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 report results that take out backward-looking sellers and add staggering.

### 6.2 Quantitative Results on Amplification

Figure 5 shows impulse response of prices to a shock to fundamentals in models with and without concavity under the baseline calibration.[32]

Panel A shows these impulse responses for the rule of thumb model. The solid line shows the model impulse response with 30 percent backward looking sellers, the $\alpha$ that generates a 36-month impulse response.[33] The dotted line shows an impulse response from an autoregression on the CoreLogic national repeat sales house price index described in Appendix A with the 95 percent confidence interval shown as thin grey lines. The two impulse responses match closely: 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 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. Generating a 36 month impulse response without concave demand requires 74 percent of sellers to be backward looking, indicating that concave demand more than doubles momentum in the baseline calibration.

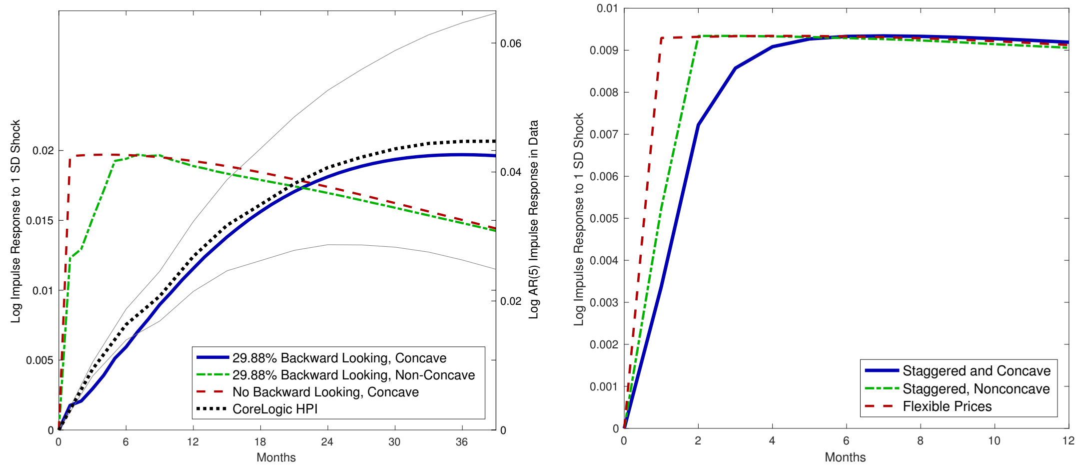
Far fewer backward-looking sellers are needed to match the data with concave demand in the rule-of-thumb model because the strategic complementarity creates a two-way feedback. When a shock occurs, the backward-looking sellers are not aware of it for several months, and the rational sellers only slightly 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

[32] 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. 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. Adding rule of thumb sellers increases the size of the impulse response to an identical shock. Rather than altering the shock in each case, the impulse responses for the nonconcave and flexible cases are scaled to have the same maximum value as the rule of thumb impulse response in panel A and the staggered and concave impulse response in panel B.

[33] 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 (2017) and Armona et al. (2018). 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.

Figure 5: Price Impulse Response Functions: Model and Data

A: Rule of Thumb Model B: Staggered Pricing Model




Notes: Panel A 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 nonconcave calibration maintains the steady state markup and probability of sale as described in Appendix E. The nonconcave and fully-flexible IRFs are scaled to have the same maximum value as the backward-looking and concave IRF. Also shown on the right vertical axis 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 described in Appendix A. The vertical axes of the model and AR(5) are different because the AR(5) shows the impulse response to a quarterly standard deviation shock, while the model impulse response is to a monthly standard deviation 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. The no staggering and no concavity IRFs are scaled to have the same maximum value as the staggered and concave IRF. Simulated IRFs 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.

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. The solid line shows the 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, although almost all of the autocorrelation is within the first five months. The baseline calibration of the staggered pricing model also reveals that concave demand amplifies frictions by a factor of 2.5.

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

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

| | Rule of Thumb Model | | | Staggered Pricing Model | | | |
|---|---|---|---|---|---|---|---|
| | $\alpha$ Concave | $\alpha$ 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 |
| $\varepsilon^* = \$50$k | 0.2988 | 0.7375 | 2.468 | 7 | 3.5 | 5 | 2.5 |
| $\varepsilon^* = \$150$k | 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 | | | | |
| $\psi = 0.5$ | 0.3457 | 0.7852 | 2.271 | | | | |

Notes: Each row shows a different robustness check. The entire model is recalibrated given the indicated parameter change. The first column shows $\alpha$, 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 $\alpha$ 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 third column shows the amplification, calculated as the ratio of the first to the second column. The fourth and sixth 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 fifth and seventh 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.

that last far beyond the point that all sellers have reset their price.[34]

To determine a plausible range for the amplification of momentum across a range of calibration assumptions, Table 6 shows summary statistics for the amplification of momentum under 14 different calibrations. For the rule of thumb model, amplification is measured as the ratio of the fraction of backward-looking sellers $\alpha$ without concavity to $\alpha$ with concavity. For the staggered pricing model, amplification is measured as the ratio of the maximum period of the impulse response with concavity to the maximum period without concavity, which 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

[34]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.

maximum.

Table 6 reveals that the degree of amplification in the baseline calibration discussed above is a robust finding. Across a broad range of calibrations and for both frictions, concave demand robustly amplifies momentum by a factor of two to three. Reassuringly, altering the parameters with somewhat speculative calibration targets has little to no effect on the factor of amplification.

The parameter that largest effect on 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 strategic complementarity that enters through the additive markup in equation (19) is weakened. 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 search cost may be considered high, I vary it in robustness tests.[35] 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.

### 6.3 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 assess in my model, 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 (2016) 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 rapidly 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. Anenberg (2014)

[35]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.

obtains about a quarter of the momentum in the data from first-order learning. When amplified by a factor of two to three, learning could come close to fully explaining momentum.

# 7 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 cannot quantitatively explain momentum. This paper introduces a mechanism that amplifies many proposed frictions into substantial momentum to fill the gap between theory and data. 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 pricing friction 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 often use a concave demand curve. This paper provides new evidence that a concave demand curve in relative price is more than a theoretical construct and can have a significant effect on market dynamics.

## References


Adjemian, S., H. Bastani, M. Juillard, K. Frederic, F. Mihoubi, G. Perendia, J. Pfeifer, M. Ratto, and S. Villemot (2011). Dynare: Reference Manual, Version 4.

Albrecht, J., P. A. Gautier, and S. Vroman (2016). Directed Search in the Housing Market. *Review of Economic Dynamics 19*, 218–231.

Amiti, M., O. Itskhoki, and J. Konings (2017). International Shocks and Domestic Prices: How Large Are Strategic Complementarities?

Anenberg, E. (2011). Loss aversion, equity constraints and seller behavior in the real estate market. *Regional Science and Urban Economics 41*(1), 67–76.

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

Anenberg, E. and P. Bayer (2015). Endogenous Sources of Volatility in Housing Markets: The Joint Buyer-Seller Problem.

Armona, L., A. Fuster, and B. Zafar (2018). Home Price Expectations and Behavior: Evidence From a Ranomized Information Experiment.

Ball, L. and D. Romer (1990). Real Rigidities and the Non-Neutrality of Money. *The Review of Economic Studies 57*(2), 183–203.

Barberis, N., A. Shleifer, and R. Vishny (1998). A Model of Investor Sentiment. *Journal of Financial Economics 49*, 307–343.

Berkovec, J. A. and J. L. Goodman (1996). Turnover as a Measure of Demand for Existing Homes. *Real Estate Economics 24*(4), 421–440.

Burnside, C., S. Rebelo, and M. Eichenbaum (2016). Understanding Booms and Busts in Housing Markets. *Journal of Political Economy 124*(4), 1088–1147.

Campbell, J. Y. and N. G. Mankiw (1989). Consumption, Income, and Interest Rates: Reinterpreting the Time Series Evidence. In O. J. Blanchard and S. Fischer (Eds.), *NBER Macroeconomics Annual 1989*, Volume 4, pp. 185–246. Cambridge, MA: MIT Press.

Capozza, D. R., P. H. Hendershott, and C. Mack (2004). An Anatomy of Price Dynamics in Illiquid Markets: Analysis and Evidence from Local Housing Markets. *Real Estate Economics 32*(1), 1–32.

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

Case, K. E. and R. J. Shiller (1987). Prices of Single-Family Homes Since 1970: New Indices for Four Cities. *New England Economic Review* (September), 45–56.

Case, K. E. and R. J. Shiller (1989). The Efficiency of the Market for Single-Family Homes. *American Economic Reiwew 79*(1), 125–137.

Case, K. E., R. J. Shiller, and A. K. Thompson (2012). What Have They Been Thinking? Homebuyer Behavior in Hot and Cold Markets. *Brookings Papers on Economic Activity* (Fall), 265–298.

Cho, M. (1996). House Price Dynamics: A Survey of Theoretical and Empirical Issues. *Journal of Housing Research 7*(2), 145–172.

Cooper, R. and A. John (1988). Coordinating Coordination Failures in Keynesian Models. *Quarterly Journal of Economics 103*(3), 441–463.

Cutler, D. M., J. M. Poterba, and L. H. Summers (1991). Speculative Dynamics. *Review of Economic Studies 58*(3), 529–546.

DeFusco, A. A. (2018). Homeowner Borrowing and Housing Colalteral: New Evidence from Expiring Price Controls. *Journal of Finance 73*(2), 523–573.

Fehr, E. and J.-R. Tyran (2005). Individual Irrationality and Aggregate Outcomes. *Journal of Economic Perspectives 19*(4), 43–66.

Frazzini, A. (2006). The Disposition Effect and Underreaction to News. *The Journal of Finance 61*(4), 2017–2046.

Fuster, A., D. Laibson, and B. Mendel (2010). Natural Expectations and Macroeconomic Fluctuations. *Journal of Economic Perspectives 24*(4), 67–84.

Gali, J. and M. Gertler (1999). Inflation Dynamics: A Structural Econometric Analysis. *Journal of Monetary Economics 44*, 195–222.

Genesove, D. and L. Han (2012). Search and Matching in the Housing Market. *Journal of Urban Economics 72*(1), 31–45.

Genesove, D. and C. Mayer (1997). Equity and Time to Sale in the Real Estate Market. *American Economic Reivew 87*(3), 255–269.

Genesove, D. and C. Mayer (2001). Loss Aversion and Seller Behavior: Evidence From the Housing Market. *Quarterly Journal of Economics 116*(4), 1233–1260.

Glaeser, E. L., J. Gyourko, E. Morales, and C. G. Nathanson (2014). Housing Dynamics: An Urban Approach. *Journal of Urban Economics 81*, 45–56.

Glaeser, E. L. and C. G. Nathanson (2017). An Extrapolative Model of House Price Dynamics. *Journal of Financial Economics 126*(1), 147–170.

Gopinath, G. and O. Itskhoki (2010). In Search of Real Rigidities. In D. Acemoglu and M. Woodford (Eds.), *NBER Macroeconomics Annual*, Volume 25, pp. 261–310. Chicago: University of Chicago Press.

Guren, A. (2015). The Causes and Consequences of House Price Momnetum.

Guren, A. and T. McQuade (2018). How Do Foreclosures Exacerbate Housing Downturns?

Haltiwanger, J. and M. Waldman (1989). Limited Rationality and Strategic Complements: the Implications for Macroeconomics. *The Quarterly Journal of Economics 104*(3), 463–483.

Han, L. and W. C. Strange (2016). What is the Role of the Asking Price for a House? *Journal of Urban Economics 93*, 115–130.

Hausman, J. A., H. Ichimura, W. K. Newey, and J. L. Powell (1991). Identification and Estimation of Polynomial Errors-In-Variables Models. *Journal of Econometrics 50*(3), 273–295.

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

Head, A., H. Lloyd-Ellis, and H. Sun (2016). Search, Liquidity, and the Dynamics of House Prices and Construction: Corrigendum. *American Economic Review 106*(4), 1214–1219.

Head, A., H. Sun, and C. Zhou (2018). Default, Mortgage Standards and Housing Liquidity.

Hong, H. and J. C. Stein (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *The Journal of Finance 54*(6), 2143–2184.

Kim, J., S. Kim, E. Schaumburg, and C. A. Sims (2008). Calculating and Using Second-Order Accurate Solutions of Discrete Time Dynamic Equilibrium Models. *Journal of Economic Dynamics and Control 32*(11), 3397–3414.

Kimball, M. (1995). The Quantitative Analytics of the Basic Neomonetarist Model. *Journal of Money, Credit and Banking 27*(4), 1241–1277.

Klenow, P. J. and J. L. Willis (2016). Real Rigidities and Nominal Price Changes. *Economica 83*, 443–472.

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

Kuchler, T. and B. Zafar (2017). Personal Experiences and Expectations About Aggregate Outcomes.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2012). Time Series Momentum. *Journal of Financial Economics 104*(2), 228–250.

Nakamura, E. and D. Zerom (2010). Accounting for Incomplete Pass-Through. *Review of Economic Studies 77*, 1192–1230.

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

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

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

Stein, J. C. (1995). Prices and Trading Volume in the Housing Market: A Model with Down-Payment Effects. *Quarterly Journal of Economics 110*(2), 379–406.

Stiglitz, J. (1979). Equilibrium in Product Markets with Imperfect Information. *American Economic Review 69*(2), 339–345.

Taylor, C. R. (1999). Time-on-the-Market as a Sign of Quality. *Review of Economic Studies 66*(3), 555–578.

Taylor, J. B. (1980). Aggregate Dynamics and Staggered Contracts. *Journal of Political Economy 88*(1), 1–23.

Titman, S., K. Wang, and J. Yang (2014). The Dynamics of Housing Prices. *Journal of Real Estate Research 36*(3), 283–317.

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