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

Adam M. Guren \cdot April 16, 2018

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

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

A Facts About Momentum

A.1 Data

A.1.1 National and Regional Data

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

Other price a measures used include:

- A median sales price index for existing single-family homes. The data is monthly for the whole nation from January 1968 to January 2013 and available on request from the National Association of Realtors.
- The quarterly national "expanded purchase-only" HPIs that only includes purchases and supplements the FHFA's database from the GSEs with deeds data from DataQuick from Q1 1991 to Q4 2012. This is an interval-weighted geometric repeat-sales index.

- The monthly Case-Shiller Composite Ten from January 1987 to January 2013. This is an interval-weighted arithmetic repeat-sales index.
- A median sales price index for all sales (existing and new homes) from CoreLogic from January 1976 to August 2013.

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

A.1.2 City-Level Data

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

A.2 Facts on Momentum in the United States

House price momentum has consistently been found across cities, countries, time periods, and price index measurement methodologies (Cho, 1996; Titman et al., 2014). Figure A1 shows two nationwide measures of momentum for the CoreLogic repeat-sales house price index for 1976 to 2013 and a third measure for the same index across 103 cities. Panel A shows that autocorrelations are positive for 11 quarterly lags of the quarterly change in the price index adjusted for inflation and seasonality. Panel B shows an impulse response in log levels to an initial one percent price shock estimated from an AR(5). In response to the shock, prices gradually rise for two to three years before mean reverting. Finally, panel C shows a histogram of AR(1) coefficients estimated separately for 103 metropolitan area repeat-sales house price indices from CoreLogic using a regression of the annual change in log price on a one-year lag of itself as in Case and Shiller (1989):

$$\Delta_{t,t-4}\ln p = \beta_0 + \beta_1 \Delta_{t-4,t-8}\ln p + \varepsilon. \tag{A1}$$

 β_1 is positive for all 103 cities, and the median city has an annual AR1 coefficient of 0.60.

To assess the robustness of these facts about house price momentum, Table A2 shows several measures of momentum for five different national price indices. The indices are the CoreLogic National repeat-sales house price index discussed in the main text, the Case-Shiller Composite Ten, the FHFA expanded repeat-sales house price index, the National Association of Realtors' national median price for single-family homes, and CoreLogic's national median price for all transactions. The first column shows the coefficient on an AR(1) in log annual price change run at quarterly frequency as in equation (A1).¹ The next two columns show the one- and two-year lagged auto-correlations of the quarterly change in log price. The fourth column shows the quarterly lag in which the autocorrelation of the quarterly change in log price is first negative. The fifth column shows the quarter subsequent to a shock in which the impulse response from an estimated AR(5)

¹Case and Shiller (1989) worry that the same house selling twice may induce correlated errors that generate artificial momentum in regression (A1) and use $\Delta p_{t,t-4}$ from one half of their sample and $\Delta p_{t-4,t-8}$ from the other. I have found that this concern is minor with 25 years of administrative data by replicating their split sample approach with my own house price indices estimated from the DataQuick micro data.

CBSA Code	Main City Name	Start	End	32820	Memphis, TN	1984	2013
10420	Akron, OH	1978	2013	33124	Miami, FL	1976	2013
10580	Albany, NY	1992	2013	33340	Milwaukee, WI	1976	2013
10740	Albuquerque, NM	1992	2013	33460	Minneapolis, MN	1976	2013
10900	Allentown, PA	1976	2013	34980	Nashville, TN	1976	2013
12060	Atlanta, GA	1976	2013	35004	Nassau, NY	1976	2013
12420	Austin, TX	1976	2013	35084	Newark, NJ-PA	1976	2013
12540	Bakersfield, CA	1976	2013	35300	New Haven, CT	1985	2013
12580	Baltimore, MD	1976	2013	35380	New Orleans, LA	1976	2013
12940	Baton Rouge, LA	1992	2013	35644	New York, NY	1976	2013
13140	Beaumont, TX	1993	2013	36084	Oakland, CA	1976	2013
13644	Bethesda, MD	1976	2013	36420	Oklahoma City, OK	1976	2013
13820	Birmingham, AL	1976	2013	36540	Omaha, NE	1990	2013
14484	Boston, MA	1976	2013	36740	Orlando, FL	1976	2013
14860	Bridgeport, CT	1976	2013	37100	Ventura, CA	1976	2013
15380	Buffalo, NY	1991	2013	37764	Peabody, MA	1976	2013
15764	Cambridge, MA	1976	2013	37964	Philadelphia, PA	1976	2013
15804	Camden, NJ	1976	2013	38060	Phoenix, AZ	1976	2013
16700	Charleston, SC	1976	2013	38300	Pittsburgh, PA	1976	2013
16740	Charlotte, NC	1976	2013	38900	Portland, OB	1976	2013
16974	Chicago, IL	1976	2013	39100	Poughkeepsie, NY	1976	2013
17140	Cincinnati, OH	1976	2013	39300	Providence, BI	1976	2013
17460	Cleveland, OH	1976	2013	39580	Raleigh, NC	1976	2013
17820	Colorado Springs CO	1976	2013	40060	Bichmond VA	1976	2013
17900	Columbia SC	1977	2013	40140	Biverside CA	1976	2013
18140	Columbus, OH	1976	2013	40380	Rochester NY	1991	2013
19124	Dallas TX	1977	2013	40484	Bockingham County NH	1990	2013
19380	Davton OH	1976	2013	40900	Sacramento CA	1976	2013
19740	Denver, CO	1976	2013	41180	St. Louis, MO	1978	2013
19804	Detroit MI	1989	2013	41620	Salt Lake City UT	1992	2013
20764	Edison NJ	1976	2013	41700	San Antonio TX	1991	2013
21340	El Paso, TX	1977	2013	41740	San Diego, CA	1976	2013
22744	Fort Lauderdale FL	1976	2013	41884	San Francisco, CA	1976	2013
22144	Fort Worth TX	1984	2010	41940	San Jose CA	1976	2010
23420	Freeno CA	1076	2010	42044	Santa Ana CA	1976	2010
23420	Gary IN	1970	2013	42644	Seattle WA	1976	2013
24340	Grand Bapide MI	1002	2010	44140	Springfield MA	1976	2010
24540	Greensboro NC	1076	2013	44140	Stockton CA	1976	2013
24000	Greenville SC	1076	2013	45060	Surgeuse NV	1002	2013
24800	Hartford CT	1076	2013	45104	Tacoma WA	1992	2013
26180	Honolulu, HI	1970	2013	45300	Tampa FI	1977	2013
20180	Houston TY	1082	2013	45780	Talipa, FL	1970	2013
20420	Indianapolia IN	1962	2013	45760	Topoleo, OII	1970	2013
20900	Indianapolis, IN	1991	2013	45820	These AZ	1965	2013
27200	Jacksonvine, FL	1970	2015	40000	Tucson, AZ	1970	2013
2014U 28040	Knowville TN	1980 1077	2013	40140	Tuisa, UK Virginia Pooch VA	1981	2013
20940	Lako Countre II	1000	2013	47244	Womer MI	1970	2013
29404 20820	Lake County, IL	1982	2013	47044	Washington DC	1970	2013
29820	Las vegas, NV	1983	2013	47894	West Dalm Details E	1970	2013
30780	Little Rock, AR	1985	2013	48424	Wishita VC	1080	2013
31084	Los Angeles, UA	1007	2013	48020	Wilminster DE	1980	2013
31140	Louisville, KY	1987	2013	48864	Wilmington, DE	1976	2013
32580	McAllen, TX	1992	2013	49340	Worcester, MA	1976	2013

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

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

Table A2: The Robustness of Momentum Across Price Measures and Metrics

Notes: Each row shows six measures of momentum for each of the five house price indices. The first row shows the $AR(1 \text{ coefficient} \text{ for a regression of the annual change in log price on a on-year lag of itself estimated on quarterly data, as in equation (A1), with robust standard errors in parenthesis. The second and third columns show the one and two year lagged autocorrelations of the quarterly change in log price. The fourth column shows the quarterly lag in which the autocorrelation of the quarterly change in log price is first negative. The fifth column indicates the quarter in which the impulse response function estimated from an <math>AR(5)$, reaches its peak. Finally, the last column shows the quarterly lag for which the Lo-MacKinlay variance ratio computed as in equation (A2) reaches its peak.

Dependent Variable: Annual Change in Log Price Index at CBSA Level							
Specification	With Interaction	Without Interaction					
Coefficient on Year-Lagged Annual Change in Log Price Coefficient on Interaction With Positive Lagged Change	$\begin{array}{c} 0.614^{***} \\ (0.011) \end{array}$	$\begin{array}{c} 0.591^{***} \\ (0.020) \\ 0.045 \\ (0.031) \end{array}$					
CBSA Fixed Effects CBSAs	Yes 103	Yes 103					
Ν	13,188	13,188					

Table A3: Testing For Asymmetry in Momentum

Notes: *** p < 0.001. Each column shows a regression of the annual change in log price on a one-year lag of itself and CBSA fixed effects. In column two, the interaction between the lag of annual change in log price with an indicator for whether the lag of the annual change in log price is also included as in equation (A3). The regressions are estimated on the panel of 103 CBSAs repeat-sales price indices listed in TableA1. Robust standard errors are in parentheses.

Figure A1: Momentum in Housing Prices



Notes: Panel A and B show the autocorrelation function for quarterly real price changes and an impulse response of log real price levels estimated from an AR(5) model, respectively. The IRF has 95% confidence intervals shown in grey. An AR(5) was chosen using a number of lag selection criteria, and the results are robust to altering the number of lags. Both are estimated using the CoreLogic national repeat-sales house price index from 1976-2013 collapsed to a quarterly level, adjusted for inflation using the CPI, and seasonally adjusted. Panel C shows a histogram of annual AR(1) coefficients of annual house price changes as in regression (A1) estimated separately on 103 CBSA division repeat-sales house price indices provided by CoreLogic. The local HPIs are adjusted for inflation using the CPI. The 103 CBSAs and their time coverage, which ranges from 1976-2013 to 1995-2013, are listed in TableA1.

estimated in log levels reaches its peak value. Finally, the sixth column shows the quarterly lag in which the Lo-MacKinlay variance ratio statistic reaches its peak value. This statistic is equal to,

$$V(k) = \frac{var\left(\sum_{t=1}^{t-k+1} r_{t-k+1}\right)/k}{var(r_t)} = \frac{var\left(\log\left(p_t\right) - \log\left(p_{t-k}\right)\right)/k}{var\left(\log\left(p_t\right) - \log\left(p_{t-1}\right)\right)},\tag{A2}$$

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

Table A2 shows evidence of significant momentum for all price measures and all measures of momentum. The two median price series exhibit less momentum as the IRFs peak at just under two years and the two-year-lagged autocorrelation is much closer to zero.

Table A3 tests for asymmetry in momentum. Many papers describe prices as being primarily sticky on the downside (*e.g.*, Leamer, 2007; Case, 2008). To assess whether this is the case, I turn to the panel of 103 CBSA repeat-sales price indices described in Appendix B, which allows for a more powerful test of asymmetry than using a single national data series. I estimate a quarterly

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

Table A4: Momentum Across Countries

Notes: p < 0.05, p < 0.01, p < 0.01. Each row shows the AR(1) coefficient for a regression of the annual change in log price on an annual lag of itself, as in equation (A1), estimated on quarterly, non-inflation-adjusted data from the indicated country for the indicated time period. Robust standard errors are in parentheses, and N indicates the number of quarters in the sample. The BIS identifiers and series descriptions are listed for each country. Australia: Q:AU:4:3:0:1:0:0, residential property for all detached houses, eight cities. Belgium Q:BE:0:3:0:0:0, residential property all detached houses. Denmark: Q:DK:0:2:0:1:0:0, residential all single-family houses. France: Q:FR:0:1:1:6:0, residential property prices of existing dwellings. Great Britain: Q:GB:0:1:0:1:0:0, residential property prices all dwellings from the Office of National Statistics. Netherlands: Q:NL:0:2:1:1:6:0, residential existing houses. Norway: Q:NO:0:3:0:1:0:0, Residential detached houses. New Zealand: Q:NZ:0:1:0:3:0:0, residential all dwellings. Sweden: Q:SE:0:2:0:1:0:0, owner-occupied detached houses. Switzerland: Q:CH:0:2:0:2:0:2:0:0, owner-occupied single-family houses.

AR(1) regression of the form:

$$\Delta_{t,t-4} \ln p_c = \beta_0 + \beta_1 \Delta_{t-4,t-8} \ln p_c + \beta_2 \Delta_{t-4,t-8} \ln p_c \times 1 \left[\Delta_{t-4,t-8} \ln p_c > 0 \right] + \phi_c + \varepsilon, \quad (A3)$$

where c is a city. If momentum is stronger on the downside, the interaction coefficient β_2 should be negative. However, Table A3 shows that the coefficient is insignificant and positive. Thus momentum appears equally strong on the upside and downside when measured using a repeat-sales index.

A.3 House Price Momentum Across Countries

Table A4 shows annual AR(1) regressions as in equation (A1) run on quarterly non-inflationadjusted data for ten countries. The data come from the Bank for International Settlements, which compiles house price indices from central banks and national statistical agencies. The data and details can be found online at http://www.bis.org/statistics/pp.htm. I select ten countries from the BIS database that include at least 15 years of data and have a series for single-family detached homes or all homes. Countries with per-square-foot indices are excluded. With the exception of Norway, which shows no momentum, and the Netherlands, which shows anomalously high momentum, all of the AR(1) coefficients are significant and between 0.2 and 0.6. Price momentum thus holds across countries as well as within the United States and across U.S. metropolitan areas.

B Data

The matched listings-transactions micro data covers the San Francisco Bay, San Diego, and Los Angeles metropolitan areas. The San Francisco Bay sample includes Alameda, Contra Costa,

Marin, San Benito, San Francisco, San Mateo, and Santa Clara counties. The Los Angeles sample includes Los Angeles and Orange counties. The San Diego sample only includes San Diego County. The data from DataQuick run from January 1988 to August 2013. The Altos data run from October 2007 to May 2013. I limit my analysis to April 2008 to February 2013, as described in footnote 6.

B.1 DataQuick Characteristic and History Data Construction

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

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

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

Third, problematic observations are identified. In particular, transfers between family members are identified and dropped based on a DataQuick transfer flag and a comparison buyer and seller names. Sales with prices that are less than or equal to one dollar are also counted as transfers. Partial consideration sales, partial sales, group sales, and splits are also dropped, as are deed transfers that are part of the foreclosure process but not actually transactions. Transactions that appear to be corrections or with implausible origination loan to value ratios are also flagged and dropped. Properties with implausible characteristics (<10 square feet, < 1 bedroom, < 1/2 bathroom, implausible year built) have the implausible characteristic replaced as a missing value.

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

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

B.2 Altos Research Listings Data Construction and Match to DataQuick

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

After formatting the Altos data, I match the Altos data to the DataQuick property IDs. I first use the address hash, applying the matched property ID to every listing with the same MLS identifier (all listings with the same MLS ID are the same property, and if they do not all match

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

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

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

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

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

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

Figure A2 shows the fraction of all single-family transactions of existing homes for which my data accounts in each of the three metropolitan areas over time. Because the match rates start low in October 2007, I do not start my analysis until April 2008, except in San Diego where almost all listings have no listed address until August 2008. Besides that, the match rates are fairly stable, except for a small dip in San Diego in mid-2009 and early 2012 and a large fall off in the San Francisco Bay area after June 2012. I consequently end the analysis for the San Francisco Bay area

at June 2012. Figures A3, A4, and A5 show match rates by ZIP code. One can see that the match rate is consistently high in the core of each metropolitan area and falls off in the outlying areas, such as western San Diego county and Escondido in San Diego, Santa Clarita in Los Angeles, and Brentwood and Pleasanton in the San Francisco Bay area.

B.3 Construction of House Price Indices

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

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

$$p_{h\ell t} = \xi_{h\ell} + \phi_t + \varepsilon_{h\ell t},\tag{A4}$$

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

I follow Case and Shiller (1989) by using a GLS interval-weighted estimator to account for the fact that longer time intervals tend to have a larger variance in the error of (A4). This is typically implemented by regressing the square of the error term $\varepsilon_{h\ell t}^2$ on a linear (Case-Shiller index) or quadratic (FHFA) function of the time interval between the two sales. The regression coefficients are then used to construct weights corresponding to $\frac{1}{\sqrt{\tilde{\varepsilon}_{h\ell t}^2}}$ where $\hat{\varepsilon}_{h\ell t}^2$ is a predicted value from the interval regression. I find that the variance of the error of (A4) is non-monotonic: it is very high for sales that occur quickly, falls to its lowest level for sales that occur approximately three years after the first sale, and then rises slowly over time. This is likely due to flippers who upgrade a house and sell it without the upgrade showing up in the data. Consequently, I follow a non-parametric approach by binning the data into deciles of the time interval between the two sales, calculate the average $\varepsilon_{h\ell t}^2$ for the decile $\bar{\varepsilon}_{h\ell t}^2$, and weight by $\frac{1}{\sqrt{\tilde{\varepsilon}_{h\ell t}^2}}$. The results are nearly identical using a linear interval weighting.

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

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

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

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

$$p_{i\ell t} = \phi_t + \beta X_i + \varepsilon_{i\ell t},\tag{A5}$$

where X_i is a vector of third-order polynomials in four housing characteristics: age, bathrooms, bedrooms, and log (square feet), all of which are winsorized at the one percent level by county



Figure A2: Match Rates by Month of Transaction

Figure A3: Match Rates by ZIP Code: Bay Area





Figure A4: Match Rates by ZIP Code: Los Angeles

Figure A5: Match Rates by ZIP Code: San Diego



for all properties in a county, not just those that trade. Recall that these characteristics are all recorded as a single snapshot in 2013, so X_i is not time dependent. I do not include a characteristic if over 25 percent of the houses in a given geography are missing data for a particular characteristic. Again $\exp(\phi_t)$ is a house price index, which I smooth using a 3-month moving average. The log predicted price of a house is:

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

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

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

B.4 Construction of the Final Analysis Samples

I drop listings that satisfy one of several criteria:

- 1. If the list price is less than \$10,000;
- 2. If the assessed structure value is less than five percent of the assessed overall value;
- 3. If the data shows the property was built after the sale date or there has been "significant improvement" since the sale date;
- 4. If there was an implausibly large change in the house's value, indicating a typo or large renovation;
- 5. If there is a previous sale within 90 days.

Each observation is a listing, regardless of whether it is withdrawn or ends in a transaction. The outcome variable is sold within 13 weeks, where withdrawn listings are counted as not transacting. The price variable is the initial list price. The predicted prices are calculated for the week of first listing by interpolation from the monthly index values. The sample is summarized in Table 1 in the main text, and the fraction of the sample accounted for by each MSA and year are summarized in Table A5.

B.5 Estimation of Equity Positions at Date of Listing

I estimate the equity position of the seller at date of listing for each listing in the final sample using the DataQuick data on both transactions and mortgage liens together with the listing dates for each property. While the data on mortgages is rich—it contains every lien, and I am able to observe loan amounts, loan type (fixed or adjustable rate), and DataQuick's estimated mortgage interest rate—I do not have enough data to perfectly calculate equity for three reasons. First, I only observe new mortgage liens and cannot tell which mortgages have been prepaid or replaced. I thus cannot definitely know whether a new mortgage is a refinance, consolidation, or a second mortgage. Second, I do not observe some features of the mortgage, such as the frequency and time of reset, the margin over one-year LIBOR (or a similar index) to which an adjustable rate mortgage resets,

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

Table A5: Share of Sample Accounted For By Each MSA and Year

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

the interest rate path (e.g. teaser rates or balloon mortgages), whether the mortgage is interest only, and whether the borrower is current on their mortgage payments or has prepaid. Finally, if a mortgage is a home equity line of credit, I do not observe its draw down. There are also cases where loan type or interest rate are missing.

Because of these data limitations, I follow a procedure to estimate equity similar to DeFusco (2018) and make several assumptions that allow me to estimate the equity of each home. In particular I assume:

- 1. Assumptions about mortgages:
 - (a) All adjustable rate mortgages are 5/1 ARMs (among the most popular ARMs) that amortize over 30 years that reset to a 2.75% margin over one-year LIBOR on the date of reset, which according to the Freddie Mac Primary Mortgage Market Survey is roughly the average historical margin.
 - (b) All fixed rate mortgages and mortgages of unknown type are 30 year fixed rate mortgages.
 - (c) All mortgages with a missing DataQuick estimated interest rate (most are prior to 1995) are assigned an interest rate equal to the average interest rate on a 30-year fixed rate mortgage in the month of origination from the Freddie Mac Primary Mortgage Market Survey.
- 2. All borrowers are current on their mortgage, have not prepaid their mortgage unless they move or refinance, and all home equity lines of credit are drawn down immediately. Consequently, the mortgage balance at listing can be computed by amortizing all outstanding loans to the date of listing.
- 3. All houses can have at most two outstanding mortgages at one time (the DataQuick data includes up to three in a given history entry, and I choose the largest two). Mortgages are estimated to be a first or second mortgage according to several rules:
 - (a) Initial mortgage balances:
 - i. If a property has an observed prior transaction, the initial mortgage balance is the mortgage amount associated with that transaction (the mortgage balance used to estimate the cumulative loan to value ratio)

- ii. If the house has no observed prior transactions but there are observed mortgage liens, a new loan is counted as a first mortgage if it is greater than or equal to 50% of the hedonic value of the house (computed using the ZIP hedonic price index described above) at the time of purchase and a second mortgage if it is less than 50%.
- iii. If the house has no observed prior transactions and no observed new mortgage liens since 1988, there is no mortgage balance by 2008 when the sample starts. Since we are interested in screening out houses with negative equity, this is a harmless assumption as any homeowner with no new mortgage liens in 20 years has a very low mortgage balance and very high equity.
- (b) If a new lien record shows two mortgages simultaneously taken out, both outstanding mortgage "slots" are updated unless the two mortgages have the same value (a likely duplicate in the records) or both are very small (less than half of the outstanding mortgage balance together), in which case they are likely a second and third mortgage and only the larger of the two is counted as a second mortgage.
- (c) If a new lien record shows one new mortgage, then:
 - i. If the property has no mortgage, it is a first mortgage.
 - ii. If the property only has a second mortgage (only for homes with no observed prior transaction), the new mortgage is a first mortgage if it is over half of the hedonic estimated value and otherwise a second mortgage.
 - iii. If the property has no second mortgage, the new mortgage is a second mortgage if it is less than half the estimated first mortgage balance and otherwise the new mortgage is a refinancing of the first mortgage.
 - iv. If there is currently a second mortgage, there are two cases:
 - A. If the balance is greater than the total current combined mortgage balance minus \$10,000 (for error), this is a mortgage consolidation. Replace the first mortgage with the new mortgage and eliminate the second mortgage.
 - B. Otherwise, the loan for which the outstanding balance is closest to the new loan amount is replaced, unless the loan is closer to the second mortgage and under 25% of the second mortgage balance in which case it is a third mortgage and is dropped, as I assume that houses have up to two mortgages for simplicity.

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

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

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

C Micro Evidence For Concave Demand

C.1 Binned Scatter Plots

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

Recall that the econometric model is:

$$d_{h\ell t} = g \left(p_{h\ell t} - \tilde{p}_{h\ell t} \right) + \psi_{\ell t} + \varepsilon_{h\ell t}, \tag{A6}$$

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

$$p_{h\ell t} = f(z_{h\ell t}) + \beta X_{h\ell t} + \xi_{\ell t} + u_{h\ell t}.$$
(A7)

To create the IV binned scatter plots. I first estimate $f(z_{h\ell t})$ by (A7) and let $p_{h\ell t} - \tilde{p}_{h\ell t} = f(z_{h\ell t})$. I drop the top and bottom 0.5 percentiles of $p_{h\ell t} - \tilde{p}_{h\ell t}$ and ZIP-quarter cells with a single observation and create 25 indicator variables ζ_b corresponding to 25 bins q of $p_{h\ell t} - \tilde{p}_{h\ell t}$. I project sale within 13 weeks $d_{h\ell t}$ on fixed effects and the indicator variables:

$$d_{h\ell t} = \psi_{\ell t} + \zeta_b + \nu_{h\ell tq} \tag{A8}$$

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

C.2 Proof of Lemma 1

Recall that the Lemma assumes that:

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

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

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

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

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

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

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

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



Figure A6: Reduced-Form Relationship Between the Instrument and the Outcome Variable

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

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

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

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

For the quadratic case, I estimate

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

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

C.3 Instrumental Variable Robustness and Specification Tests

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



Figure A7: Instrumental Variable Estimates With Probability of Sale Axis in Logs

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

Figure A6 shows the reduced-form relationship between the instrument and outcome variable when both are residualized against fixed effects and the repeat-sales and hedonic predicted price. The estimates presented in the main text rescale the instrument axis into price (and in the process flip and shrink the x axis), but the basic concave relationship between probability of sale and appreciation since purchase is visible in the reduced form. The clear concave relationship in the reduced form is important because it ensures that nonlinearities in the first stage are not driving the overall concave relationship (although one could surmise this from the smooth and monotonic first stage).

Figure A7 shows IV binned scatter plots when the y-axis is rescaled to a logarithmic scale so that the slope represents the elasticity of demand. The demand curve is still robustly concave.

Figure A8 shows third-order polynomial fits varying the number of weeks that a listing needs



Figure A8: Instrumental Variable Estimates: Varying The Sell-By Date

Notes: For both samples, the figure shows third-order polynomial fits of equation (2) for the probability of sale by eleven different deadlines (6, 8, 10, 12, 14, 16, 18, 20, 22, 24, and 26 weeks) net of fixed effects (with the average probability of sale added in) against the estimated log relative markup. To create the figure, a first stage regression of the log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and repeat sales and hedonic log predicted prices, as in (5), is estimated by OLS. The predicted value of the polynomial of the instrument is used as the relative markup before equation (2) is run. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. IV sample 1 drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. IV sample 2 does away with the estimated equity requirement and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. N = 140,344 observations for IV sample 1 and 137,238 observations for IV sample 2 prior to dropping unique zip-quarter cells and winsorizing.

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

Figure A9 shows the IV binned scatter plot and a third-order polynomial fit when the sample is limited to transactions and transaction prices are used rather than initial list prices. Substantial concavity is still present, assuaging concerns that the concavity in list prices may not translate into a strategic complementarity in transaction prices. The upward slope in the middle of the figure is not statistically significant.

Figure A10 shows third-order polynomial fits for each ZIP-3 in the data set with over 2,000 observations, so that the cubic polynomial is estimated with some degree of confidence. These ZIP-3s form the core of my analysis sample. The pointwise standard errors on each line are fairly wide and are not shown, but one can see that almost all of the ZIP-3s there is substantial curvature.

Figure A11 provides some evidence on the exclusion restriction by showing how observed quality varies with time since purchase. In particular, it shows plots of six measures of observed quality residualized against zip by quarter of listing fixed effects (with the mean added back in) against the date of the previous transaction for both of the IV samples. For both samples, there is no clear relationship between bedrooms and bathrooms and original sale date. To the extent to



Figure A9: Instrumental Variable Estimates: Transaction Prices

Notes: For both samples, the figure shows a binned scatter plot of the probability of sale within 13 weeks net of ZIP \times first quarter of listing fixed effects (with the average probability of sale within 13 weeks added in) against the estimated log relative markup $p - \tilde{p}$ measured using transaction prices rather than list prices. It also shows an overlaid cubic fit of the relationship, as in equation (2). To create the figure, a first stage regression of the log transaction price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and repeat sales and hedonic log predicted prices, as in (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. N = 96,400 observations for IV sample 1 and 86,033 observations for IV sample 2 prior to dropping unique zip-quarter cells and winsorizing.

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

Tables A6, A8, A10, A12, A14, A16, and A18 present various robustness and specification tests of the main IV specification for IV sample 1 (column 3 of Table 2). Tables A7, A9, A11, A13, A15, A17, and A19 repeat the same robustness tests for IV sample 2 (column 5 of Table 2). For all



Figure A10: Instrumental Variable Estimates: Best Fit Polynomial By ZIP-3

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

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

Tables A6 and A7 evaluate the exclusion restriction that unobserved quality is independent of when a seller purchased by controlling for date of purchase (above the horizontal line) and time since purchase (below the horizontal line). The first specification adds a linear trend in date of purchase or time since purchase in $X_{h\ell t}$ along with the two predicted prices, thus accounting for any variation in unobserved quality that varies linearly in date of purchase or time since purchase. To the extent that unobserved quality varies with date of purchase in the same way that lot size, rooms, and age do in Figure A11, a linear time trend will help control for unobserved quality. If anything, adding a linear time trend strengthens the finding of concavity, with more negative point estimates on the quadratic term. The second specification adds a separate linear time trend for each MSA, and things look similar albeit with slightly wider confidence intervals. The third specification adds a separate linear time trend for each ZIP-3. The confidence interval widens in IV



Figure A11: Observed Quality (Residualized Against ZIP-Quarter FE) By Original Sale Date

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

sample 1 to the point that the quadratic bootstrapped 95 percent confidence interval includes zero, although zero remains slightly outside the confidence interval for IV sample 2. Importantly, as the confidence intervals widen, the point estimates stay stable, indicating that concavity is present and robust until the data is pushed to its statistical limit.

The next three rows of Tables A6 and A7 take an alternate, less parametric approach to controlling for when a seller purchased. Rather than using a linear time trend, the first two specifications include fixed effects for quintiles and deciles of time since purchase or date of purchase in $X_{h\ell t}$, where the quintile or decile are computed within ZIP codes. This controls for differences in unobserved quality within these bins. The concavity remains significant, although the point estimate is a bit less negative when only variation within deciles of date of or time since purchase are used. Finally, the last specification controls for quintile of date of purchase or time since purchase interacted with ZIP code. This controls for unobserved quality within a ZIP code and date of or time since purchase quintile. Concavity again remains significant, providing further reassurance that the results are not being driven by unobserved quality differing by when the seller purchase.

To address concerns that the results are being driven by unobserved quality differences among houses that were purchased during the peak of the boom and ensuing bust, Tables A8 and A9 limit the sample to houses purchased at different time periods. The first three rows limit the sample to homes purchased before the bust (before 2005), after 1994, and in a window from 1995 to 2004. The last two rows add linear time trends to the purchased before 2005 sample. In all cases, the bootstrapped 95 percent confidence intervals for the quadratic term continue to show significant concavity, and if anything the point estimate on the quadratic term are more negative.

Tables A10 and A11 show various specification checks. The first set of regressions limit the analysis to ZIP-quarter cells with at least 15 and 20 observations to evaluate whether small sample bias in the estimated fixed effect $\xi_{h\ell t}$ could be affecting the results. In both cases, the results appear similar to the full sample and the bootstrapped confidence interval shows a significantly negative quadratic term, which suggests that bias in the estimation of the fixed effects is not driving the results. The second set introduces $X_{h\ell t}$, the vector of house characteristics that includes the repeat-sales and hedonic predicted prices, as a quadratic, cubic, quartic, and quintic function instead of linearly. The assumed linearity of these characteristics is not driving the results. In particular, introducing $z_{h\ell t}$ nonlinearly and $\hat{p}_{h\ell t}^{repeat}$ linearly is not driving the results, as when $z_{h\ell t}$ and $\hat{p}_{h\ell t}^{repeat}$ are both introduced as fifth-order polynomials the results are virtually unchanged. Finally, the third set considers different specifications for the flexible function of the instrument $f(z_{h\ell t})$ in the first stage, which is quintic in the baseline specification. Again, the order of $f(\cdot)$ does not appear to alter the finding of significant concavity.

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

- House Characteristic Controls: This specification includes a third-order polynomial in age, log square feet, bedrooms, and bathrooms in $X_{h\ell t}$ along with the predicted prices.
- Alternate Time To Sale Definition: Instead of measuring time to sale as first listing to the filing of the deed transfer request, this specification measures time to sale as first listing to the first of the deed transfer request or the last listing.
- 18 and 10 Weeks to Sale: This specification varies sell-by deadline for the binary y-variable from 13 weeks to 10 and 18 weeks, respectively.
- No Weights: This specification does not weight observations by the inverse standard deviation of the repeat-sales house price index prediction error at the ZIP level.

Dependent Var: Sell Within 13 Weeks							
Specification	Quadratic	Polynomial	Coefficients	Quadratic Coefficient			
(Details In Text)	Constant	Linear	Quadratic	Bootstrapped 95% CI	Obs		
Linear Trend in	0.476***	-3.360***	-64.978*	[-141.455, -28.643]	140,344		
Date of Purchase	(0.008)	(0.660)	(27.420)				
Separate Lin Trend by MSA	0.475^{***}	-3.384***	-65.263*	[-132.992, -23.934]	$140,\!344$		
in Date of Purchase	(0.008)	(0.602)	(27.196)				
Separate Lin Trend by ZIP3	0.472^{***}	-3.846***	-67.074	$\left[-209.563, 31.991 ight]$	$140,\!344$		
in Date of Purchase	(0.009)	(0.790)	(58.677)				
FE For Quintile by ZIP5	0.484^{***}	-2.768^{***}	-59.616^{**}	[-119.857, -119.857]	$140,\!344$		
of Date of Purchase by ZIP5	(0.008)	(0.511)	(21.200)				
FE For Decile by ZIP5	0.483^{***}	-2.117^{***}	-38.520**	[-73.311, -23.815]	$140,\!344$		
of Date of Purchase	(0.008)	(0.399)	(12.798)				
FE For Quintile of	0.489^{***}	-1.832^{***}	-45.086^{**}	[-89.831, -29.013]	$140,\!344$		
Date of Purchase by ZIP5	(0.008)	(0.339)	(14.389)				
Linear Trend in	0.476***	-3.381***	-65.428*	[-143.701, -28.427]	140,344		
Time Since Purchase	(0.008)	(0.671)	(27.992)				
Separate Lin Trend by MSA	0.475^{***}	-3.405***	-65.711*	[-135.552, -23.315]	$140,\!344$		
in Time Since Purchase	(0.008)	(0.613)	(27.805)				
Separate Lin Trend by ZIP3	0.472^{***}	-3.877***	-66.861	[-211.542, 34.073]	$140,\!344$		
in Time Since Purchase	(0.009)	(0.804)	(59.931)				
FE For Quintile by ZIP5	0.484^{***}	-2.767^{***}	-59.616^{**}	[-119.918, -37.027]	$140,\!344$		
of Time Sincef Purchase by ZIP5	(0.008)	(0.511)	(21.203)				
FE For Decile by ZIP5	0.483^{***}	-2.117^{***}	-38.520**	[-73.168, -23.829]	$140,\!344$		
of Time Since Purchase	(0.008)	(0.399)	(12.792)				
FE For Quintile of	0.489^{***}	-1.832^{***}	-45.086^{**}	[-89.831, -29.013]	$140,\!344$		
Time Since of Purchase by ZIP5	(0.008)	(0.339)	(14.385)				

Table A6: IV Sample 1 Robustness 1: Controls for When a Seller Purchased

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when $g(\cdot)$ in equation (2) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (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. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

- No Possibly Problematic Observations: A small number of listings are matched to multiple property IDs and I use an algorithm described in Appendix B to guess of which is the relevant property ID. Additionally, there are spikes in the number of listings in the Altos data for a few dates, which I have largely eliminated by dropping listings that do not match to a DataQuick property ID. Despite the fact that these two issues affect a very small number of observations, this specification drops both types of potentially problematic observations to show that they do not affect results.
- By Time Period: This specification splits the data into two time periods, February 2008 to June 2010 and July 2010 to February 2013.

Dependent Var: Sell Within 13 Weeks							
Specification	Quadratic	Polynomial	Coefficients	Quadratic Coefficient			
(Details In Text)	Constant	Linear	Quadratic	Bootstrapped $95\%~{\rm CI}$	Obs		
Linear Trend in	0.458***	-2.673***	-42.695*	[-91.13,-21.18]	137,238		
Date of Purchase	(0.009)	(0.532)	(18.076)				
Separate Lin Trend by MSA	0.457^{***}	-2.698^{***}	-43.123^{*}	[-87.811, -19.434]	$137,\!238$		
in Date of Purchase	(0.009)	(0.485)	(17.723)				
Separate Lin Trend by ZIP3	0.455^{***}	-2.928^{***}	-43.085	[-134.888, -4.592]	$137,\!238$		
in Date of Purchase	(0.010)	(0.640)	(32.826)				
FE For Quintile by ZIP5	0.463^{***}	-2.481^{***}	-45.042*	[-95.238, -26.751]	$137,\!238$		
of Date of Purchase by ZIP5	(0.009)	(0.547)	(17.575)				
FE For Decile by ZIP5	0.464^{***}	-2.000***	-32.312^{*}	[-68.555, -19.295]	$137,\!238$		
of Date of Purchase	(0.010)	(0.461)	(13.160)				
FE For Quintile of	0.465^{***}	-1.600***	-29.582*	[-61.786, -19.183]	$137,\!238$		
Date of Purchase by ZIP5	(0.009)	(0.307)	(11.512)				
Linear Trend in	0.458***	-2.684***	-42.910*	[-92.536, -21.014]	137,238		
Time Since Purchase	(0.009)	(0.538)	(18.339)				
Separate Lin Trend by MSA	0.457^{***}	-2.709^{***}	-43.336*	[-89.129, -19.319]	$137,\!238$		
in Time Since Purchase	(0.009)	(0.491)	(18.011)				
Separate Lin Trend by ZIP3	0.455^{***}	-2.942^{***}	-43.110	[-137.981, -4.543]	$137,\!238$		
in Time Since Purchase	(0.010)	(0.647)	(33.263)				
FE For Quintile by ZIP5	0.463^{***}	-2.481^{***}	-45.051*	[-95.247, -26.694]	$137,\!238$		
of Time Sincef Purchase by ZIP5	(0.009)	(0.547)	(17.575)				
FE For Decile by ZIP5	0.464^{***}	-2.000***	-32.308*	[-68.579, -19.333]	$137,\!238$		
of Time Since Purchase	(0.010)	(0.461)	(13.155)	-			
FE For Quintile of	0.465^{***}	-1.600^{***}	-29.582*	[-61.779, -19.183]	$137,\!238$		
Time Since of Purchase by ZIP5	(0.009)	(0.307)	(11.511)	-			

Table A7: IV Sample 2 Robustness 1: Controls for When a Seller Purchased

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

• By MSA: This specification runs separate regressions for the San Francisco Bay, Los Angeles, and San Diego areas.

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

Table A14 and A15 show various robustness checks. These include:

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

Table A8: IV Sample 1 Robustness 2: Sample Restrictions For Date of Purchase

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when $g(\cdot)$ in equation (2) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (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. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

- Beta varies by MSA-Year or MSA-Quarter: In this specification, β , the control for observables in the first stage relationship which is assumed fixed across MSAs and years in the baseline specification, is estimated separately for each MSA-year or MSA-quarter rather than in a pooled regression. This accounts for potentially differential sorting between households and homes across space and time.
- Only Low All Cash Share ZIPs: This specification limits the sample to ZIP codes where less than 10 percent of buyers buy in all cash (a hallmark of investors).
- Uniqueness Controls: This specification drops households that appear to be unique in their ZIP code in an effort to get a more homogenous sample. Uniqueness is defined three ways. First, if beds, baths, square feet, lot size, rooms, or year built is more than 2 standard deviations from the mean value (e.g. unique on one dimension). Second, the same metric with a threshold of 1.5 standard deviations. Third, if the average squared value of a house's Z score for these characteristics is above 2. Note that if a characteristic is missing for a house, it is not counted as having a high Z score.
- Tier Controls: This specification uses a ZIP code level repeat sales house price index as in the main estimation to estimate the value of all homes based on their most recent transaction. It then splits each ZIP code into two or four tiers based on the estimated value of the house and makes the fixed effects $\xi_{\ell t}$ and $\psi_{\ell t}$ to be ZIP-quarter-tier level instead of the ZIP-quarter level in the baseline specification.

The results show that the concavity is not affected by any of the above controls, although confidence

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

Table A9: IV Sample 2 Robustness 2: Sample Restrictions For Date of Purchase

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

intervals do widen when fewer observations are used (only low all cash share ZIPs) or when more fixed effects are added.

The top section of Tables A16 and A17 show results for the subset of homes that transact for three different outcome variables. First, it shows the main sale within 13 weeks outcome, for which the concavity is still significant. The second two specifications show results using weeks on the market as the outcome variable, for which concavity is indicated by a positive quadratic term rather than a negative term when probability of sale is the dependent variable. For both the baseline and alternate weeks on the market definitions, there is significant concavity.

The bottom section of Tables A16 and A17 show results for different sample restrictions. The top row includes investors who previously purchased with all cash. The concavity is somewhat weakened, which is not surprising as these sellers, who have had low appreciation since purchase, likely upgrade the house in unobservable ways, which should make these low appreciation (and by the instrument, high list price) houses sell faster, reducing the concavity.

For IV sample 1, the next four rows of Table A16 show results when the estimated equity threshold for inclusion in the sample is changed, while the last two rows show results when short sales and houses subsequently foreclosed upon are excluded and when houses with negative appreciation since purchase are excluded.² While the results are robust, they are weaker when we condition on a higher equity requirement. This is the case both because shrinking sample sizes expand confidence intervals and because the point estimate on the quadratic term drops a bit as the lowest appreciation

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

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

Table A10: IV Sample 1 Robustness 3: Specification Checks

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when $g(\cdot)$ in equation (2) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (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. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

since purchase borrowers have non-zero equity and are less sensitive to the instrument. Nonetheless, the results are either significantly concave or just barely insignificant at the 95 percent confidence level, making clear that the finding of concavity is not being driven by the sample selection criteria.

For IV sample 2, the bottom three rows of table A17 impose an estimated equity requirement of varying levels on IV sample 2. Again, the results are a bit weaker for higher equity requirements but are still significant.

Finally Tables A18 and A19 show results controlling for the number of nearby foreclosures (within 1 and 0.25 miles) over the entire downturn and over the past year. The results are very stable, indicating that the concavity cannot be explained by nearby foreclosure sales. These results are largely unchanged if one looks at other distance thresholds.

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

Table A11: IV Sample 2 Robustness 3: Specification Checks

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

C.4 Ordinary Least Squares

OLS assumes that there is no unobserved quality and thus no need for an instrument. This ordinary least squares approach implies that:

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

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

$$p_{h\ell t} = \xi_{\ell t} + \beta X_{h\ell t} + \eta_{h\ell t},\tag{A9}$$

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

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

This section provides additional OLS results to show that the findings in Figure 1 and columns one, two, and four of Table 2 are robust.

Dependent Var: Sell Within 13 Weeks Unless Otherwise Indicated						
Specification	Quadratic	Polynomial	Coefficients	Quadratic Coefficient		
(Details In Text)	Constant	Linear	Quadratic	Bootstrapped 95% CI	Obs	
House Characteristic	0.481***	-2.514***	-50.595***	[-80.123, -33.569]	133,671	
Controls	(0.008)	(0.366)	(12.066)			
Alternate Time	0.511^{***}	-2.140***	-36.433***	[-59.576, -25.285]	$140,\!344$	
to Sale Defn	(0.010)	(0.320)	(9.014)			
Dep Var: 18 Weeks	0.547^{***}	-2.205***	-40.078***	[-65.127, -27.644]	$140,\!344$	
	(0.007)	(0.340)	(9.607)			
Dep Var: 10 Weeks	0.425^{***}	-2.132***	-41.778***	[-71.622, -29.343]	$140,\!344$	
	(0.007)	(0.321)	(11.095)			
No Weights	0.466^{***}	-1.868***	-34.965***	[-58.351, -23.906]	$140,\!344$	
	(0.008)	(0.312)	(8.778)			
No Poss Problematic Obs	0.485^{***}	-2.231***	-40.822***	[-68.327, -29.289]	$135,\!858$	
	(0.007)	(0.340)	(9.944)			
No Short Interval Between	0.481^{***}	-2.278***	-41.368***	[-69.123, -28.903]	139,580	
Prev Trans and Listing	(0.008)	(0.356)	(10.562)			
First Listed 2008-7/2010	0.453***	-2.190***	-30.295**	[-55.285,-10.604]	69,240	
,	(0.012)	(0.346)	(11.216)			
First Listed 7/2010-2013	0.502^{***}	-2.248***	-44.960^{*}	[-94.677, -26.093]	71,104	
,	(0.008)	(0.372)	(18.294)			
Bay Area	0.511***	-2.609***	-36.537**	[-70.887,-19.171]	39,550	
v	(0.016)	(0.633)	(13.883)		,	
Los Angeles	0.463***	-1.940***	-47.637**	[-85.803, -24.353]	82,803	
0	(0.008)	(0.415)	(15.634)	. , ,	,	
San Diego	0.494***	-4.374***	-100.529	[-100.529, 483.072]	17,991	
<u> </u>	(0.018)	(0.451)	(132.245)	. , 1		

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

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when $g(\cdot)$ in equation (2) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (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. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

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

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

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

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

Table A14: IV Sample 1 Robustness 5: Miscellaneous Robustness Tests II

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when $g(\cdot)$ in equation (2) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (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. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

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

Table A15: IV Sample 2 Robustness 5: Miscellaneous Robustness Tests II

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

Quadratic Constant	c Polynomial Linear	l Coefficients Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
0.680***	-1.991***	-56.791**	[-102.866, -35.732]	96,400
(0.007)	(0.325)	(17.277)		
12.959^{***}	69.766^{***}	$2,008.614^{***}$	$\left[1333.398,\!3282.778 ight]$	96,400
(0.217)	(9.739)	(492.627)		
11.130^{***}	57.628^{***}	$1,758.968^{***}$	[1149.601, 2919.092]	96,400
(0.407)	(7.678)	(436.691)		
0.480***	-1.553***	-21.995*	[-45.709,-12.182]	169,147
(0.007)	(0.272)	(8.594)		
0.451^{***}	-3.215^{***}	-49.967***	[-89.533, -31.677]	$158,\!217$
(0.008)	(0.477)	(15.030)		
0.464^{***}	-3.054^{***}	-54.223***	[-95.958, -36.222]	150,932
(0.008)	(0.450)	(15.497)		
0.498^{***}	-1.410***	-22.902**	[-39.058, -1.223]	113,717
(0.009)	(0.266)	(8.845)		
0.512^{***}	-1.001***	-15.918*	[-26.834, 2.268]	$99,\!640$
(0.009)	(0.216)	(6.893)		
0.499^{***}	-1.360^{***}	-23.190^{**}	[-39.136, -5.792]	$107,\!896$
(0.010)	(0.236)	(8.128)		
0.475^{***}	-1.132^{***}	-29.955^{**}	[-55.902, -16.12]	$102,\!342$
(0.010)	(0.300)	(10.174)		
	Quadratic Constant 0.680^{***} (0.007) 12.959^{***} (0.217) 11.130^{***} (0.407) 0.480^{***} (0.007) 0.451^{***} (0.008) 0.464^{***} (0.008) 0.498^{***} (0.009) 0.512^{***} (0.009) 0.499^{***} (0.010) 0.475^{***} (0.010)	$\begin{array}{c cccc} \mbox{Quadratic Polynomial}\\ \mbox{Constant Linear}\\ \hline \begin{tabular}{lllllllllllllllllllllllllllllllllll$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

Table A16: IV Sample 1 Robustness 6: Transactions Only and Relaxing Sample Restrictions

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when $g(\cdot)$ in equation (2) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (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. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing. The rows with a † indicate that rather than excluding households who had less than negative 20 percent appreciation since purchase from the sample, households with less than negative 10 percent appreciation since purchase have been excluded. This is done so that the stricter equity requirement does not make it so that the houses with the lowest appreciation since purchase have essentially all sellers who previously purchased with abnormally high down payments.

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

Table A17: IV Sample 2 Robustness 6: Transactions Only and Relaxing Sample Restrictions

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

Dependent Variable (Details In Text)	Quadratic Constant	Polynomial Linear	Coefficients Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs
Control For Foreclosures Within .25 Miles Over Entire Downturn Control For Foreclosures Within 1 Mile Over Entire Downturn	$(0.008) \\ 0.479^{***} \\ (0.008) \\ 0.479^{***}$	(0.339) -2.301*** (0.358) 2.308***	(12.415) -41.762** (13.021) 41.484**	[-78.965,-30.086]	140,344
Control For Forcelogung	(0.008)	-2.308	(10.220)	[-18.431,-29.18]	140,344
Within .25 Miles in Past Year Control For Foreclosures	(0.008) 0.479^{***} (0.008)	(0.342) -2.293*** (0.359)	(12.338) -41.415** (13.025)	[-78.461,-29.906]	140,344
Within 1 Mile in Past Year	0.479^{***} (0.008)	-2.303^{***} (0.357)	-41.487^{**} (12.944)	[-78.618,-29.784]	140,344

Table A18: IV Sample 1 Robustness 7: Controls for Nearby Foreclosures

Notes: * p <0.05, ** p<0.01, *** p<0.001. Each row shows regression coefficients when $g(\cdot)$ in equation (2) is approximated using a quadratic polynomial for a different robustness test described in the first column and detailed in the appendix text. A first stage regression of log list price on a fifth-order polynomial in the instrument, fixed effects at the ZIP x first quarter of listing level, and log predicted price using both a repeat-sales and a hedonic methodology, as in (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. The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The sample, IV sample 1, drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. The number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

Table A19:	IV Samp	le 2 Robustness	3 7:	Controls	for	Nearby	Foreclosures
------------	---------	-----------------	------	----------	-----	--------	--------------

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

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

Dependent Var: Weeks on Market							
Specification (Details In Text)	Quadratic Constant	Polynomial Linear	Coefficients Quadratic	Quadratic Coefficient Bootstrapped 95% CI	Obs		
House Characteristic	0.460^{***}	-0.184***	-0.612***	[-0.769, -0.506]	399,423		
Controls	(0.005)	(0.010)	(0.068)				
Alternate Time	0.514^{***}	-0.222***	-0.530***	[-0.703, -0.402]	$416,\!373$		
to Sale Defn	(0.013)	(0.014)	(0.080)				
Dep Var: 18 Weeks	0.542^{***}	-0.180***	-0.595***	[-0.773, -0.467]	$416,\!373$		
	(0.005)	(0.015)	(0.080)				
Dep Var: 10 Weeks	0.393***	-0.218***	-0.467***	[-0.633, -0.352]	$416,\!373$		
	(0.004)	(0.012)	(0.074)				
Hedonic Predicted	0.470***	-0.176***	-0.391***	[-0.578, -0.236]	663,976		
Price Only	(0.006)	(0.012)	(0.091)				
Low REO ZIPs	0.470^{***}	-0.331***	-0.382^{*}	[-0.752, -0.147]	$134,\!666$		
	(0.013)	(0.026)	(0.174)				
Low Short Sale ZIPs	0.476^{***}	-0.325***	-0.433*	[-0.765, -0.146]	109,249		
For Predicted Price	(0.016)	(0.022)	(0.172)				
Only FE Cells With	0.460***	-0.250***	-0.481***	[-0.7150.336]	251,945		
At Least 20 Obs	(0.008)	(0.014)	(0.099)		,		
Predicted Prices	0.459^{***}	-0.212***	-0.596***	[-0.725, -0.495]	416,373		
Introduced as Cubic	(0.004)	(0.011)	(0.059)		,		
Beta Varies By MSA-Year	0.458^{***}	-0.199***	-0.543***	[-0.704, -0.437]	416,373		
·	(0.005)	(0.012)	(0.070)				
First Listed 2008-7/2010	0.451***	-0.289***	-0.452***	[-0.637,-0.31]	223,429		
	(0.008)	(0.013)	(0.084)	[,]	-) -		
First Listed 7/2010-2013	0.465***	-0.106***	-0.595***	[-0.757, -0.499]	192,944		
,	(0.005)	(0.018)	(0.069)		,		
Bay Area	0.478***	-0.213***	-0.573***	[-0.7280.414]	110.719		
2007 11100	(0.010)	(0.015)	(0.081)	[0=0, 0]			
Los Angeles	0.446***	-0.199***	-0.495***	[-0.7550.336]	247.818		
	(0.005)	(0.019)	(0.110)	[,		
San Diego	0.473***	-0.196***	-0.718***	[-0.759, -0.677]	57.836		
0	(0.008)	(0.030)	(0.025)	L / J	, -		
	· /	· /	· /				

Table A20: Ordinary Least Squares Robustness

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. 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. The fixed effects at the quarter of initial listing x ZIP x distress status level. Distress status corresponds to three groups: normal sales, REOs (sales of foreclosed homes and foreclosure auctions), and short sales (cases where the transaction was less than the amount outstanding on the loan and withdrawals that are subsequently foreclosed on in the next two years). The entire procedure is weighted by the reciprocal of the standard deviation of the prediction error in the repeat-sales house price index in the observation's ZIP code from 1988 to 2013. Before running the second-stage regression, 0.5 percent of the sample is winsorized on each end of the distribution of the relative markup, and any observations fully absorbed by fixed effects are dropped. Standard errors and the 95 percent confidence interval for the quadratic term are computed by block bootstrapping the entire procedure on 35 ZIP-3 clusters. The number of observations listed is prior to dropping observations that are unique to a ZIP-quarter cell and winsorizing. The appendix text details each specification.



Figure A12: The Effect of List Price on Probability of Sale: Ordinary Least Squares

Notes: Each panel shows a binned scatter plot of the probability of sale within 13 weeks against the log relative markup. The OLS methodology assumes no unobserved quality. To create each figure, a first stage regression of log list price on fixed effects at the ZIP x first quarter of listing level x seller distress status level and repeat sales and hedonic log predicted prices, as in (A9), 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. Panel A uses all listings with a prior observed sale N=416,373. Panel B uses listings with a prior observed sale that lead to transactions N = 310,758. Panel C uses IV sample 1, which drops sales of foreclosures, sales of homes with less than negative 20 percent appreciation since purchase, sales by investors who previously purchased with all cash, and homes with under -10 percent estimated equity. For panel C, N=140,344. Panel D uses IV sample 2 does away with the estimated equity requirement in IV sample 1 and instead drops DataQuick determined short sales and withdrawn listings that are foreclosed upon in the subsequent year. For panel D, N=137,2387. In all cases, he number of observations listed is prior to dropping unique zip-quarter cells and winsorizing.

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

First, Figure A12 shows binned scatter plots for OLS for all listings, transactions only, and each of the IV samples. In each, a clear pattern of concavity is visible, but as discussed in the main text, the upward slope on the left indicates the presence of substantial unobserved quality—particularly among homes that do not sell—and thus the need for an instrument.³ The concavity is only slightly stronger in the IV samples, assuaging concerns about sample selection. Importantly, most of the differences occur in the extremely low log relative markup quantiles, which do not look like outliers in the IV binned scatter plot, assuaging concerns about sample selection driving some of the findings of concavity.

Table A20 shows a number of robustness and specification checks. Those different from the IV specification checks described previously are:

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

All specifications show significant concavity.

C.5 Measurement Error and Robustness to Other Sources of Markup Variation

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

Recall that I want estimate the non-linear effect of the relative markup $p_{h\ell t} - \tilde{p}_{h\ell t}$ on the probability of sale $d_{h\ell t}$. The reference price is $\tilde{p}_{h\ell t} = \xi_{\ell t} + q_{h\ell t}$, where $\xi_{\ell t}$ is the average price in

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

location ℓ at time t. $q_{h\ell t}$ is quality defined as $q_{h\ell t} = \beta X_{h\ell t} + u_{h\ell t}$ where $u_{h\ell t}$ is unobserved quality and $X_{h\ell t}$ are observable measures of quality. Unobserved quality affects $q_{h\ell t}$, which in turn affects $\tilde{p}_{h\ell t}$.

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

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

= $f(z_{h\ell t}) + \xi_{\ell t} + \beta X_{h\ell t} + u_{h\ell t} + \zeta_{h\ell t}.$

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

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

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

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

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

- 1. Based on first stage, calculate $p_{h\ell t} \tilde{p}_{h\ell t} = f(z_{h\ell t})$. In doing so, I drop the 1st and 99th percentile, which remain dropped throughout the exercise so sample sizes are consistent.
- 2. Estimate $\psi_{\ell t}$ given assumed $g(\cdot)$.
- 3. Draw $\zeta_{h\ell t}$ from assumed distribution. Using the assumed $g(\cdot)$, calculate $g(f(z_{h\ell t}) + \zeta_{h\ell t}) + \psi_{\ell t}$.
- 4. $d_{h\ell t}$ is drawn from a Bernoulli distribution in which the house sells with probability $g(f(z_{h\ell t}) + \zeta_{h\ell t}) + \psi_{\ell t}$.
- 5. Run the estimator of interest on the simulated $d_{h\ell t}$ s.

Table A21 shows results with a normally distributed $\zeta_{h\ell t}$ that is independent of $f(z_{h\ell t})$. In panel A, the assumed true $g(\cdot)$ is the third-order polynomial estimate of $g(\cdot)$ shown in Figure 2

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

Panel A: $\zeta_{h\ell t}$ Ad	ded to Concave A	Assumed True Der	nand Curve
Quadratic Polynomial		SD of $\zeta_{h\ell t}$	
Coef Estimates	0	0.02	0.04
Constant	0.4789	0.464	0.422
	(0.002)	(0.002)	(0.002)
Linear	-2.218	-1.812	-0.820
	(0.077)	(0.077)	(0.077)
Quadratic	-41.572	-41.756	-35.524
	(4.508)	(4.662)	(4.411)
Quadratic	[-49.754, -32.349]	[-50.934, -32.372]	[-44.065, -26.622]
95% CI			
Panel B: $\zeta_{h\ell t}$ Ac	ded to Linear As	ssumed True Dem	and Curve
Quadratic Polynomial		SD of $\zeta_{h\ell t}$	
Coef Estimates	0	0.02	0.04
Constant	0.463	0.463	0.464
	(0.002)	(.002)	(.002)
Linear	-2.319	-2.317	-2.295
	(0.083)	(0.079)	(0.077)
Quadratic	3.291	3.207	3.148
	(4.513)	(4.488)	(4.39)
Quadratic 95% CI	[-5.673, 11.947]	[-5.362, 11.746]	[-5.427, 11.722]

Table A21: Monte Carlo Simulations: Adding Independent Noise to Concave and Linear True Demand Curve

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

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

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

Table A22 illustrates that this type of bias could create spurious concavity. However, generating the amount of concavity I observe in the data would require an extreme amount of unobserved variation in the relative markup at low levels of appreciation since purchase and virtually no unobserved variation in the relative markup at high levels of appreciation. To show this, I assume

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

Table A22: Monte Carlo Simulations: Other Sources of Markup Variation Corr With Instrument

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

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

D Facts About House List Prices

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



Figure A13: Histogram of the Difference Between Log Transaction Price and Log Final List Price

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

D.1 List Prices Relative to Transaction Prices

As mentioned in the main text, the modal house sells at its list price at the time of sale and the average and median house sell within 0.016 log points of their list price. To illustrate this, Figure A13 shows a histogram of the difference between the log final list price at sale and the log transaction price in the Altos-DataQuick merged data after extreme outliers likely due to typos in the list or transaction price have been dropped. 9.17 percent of transactions occur exactly at the final list price, and 22.63 percent occur within one percent of the final list price. The mean of the difference between the log final list price and the log first list price is -0.016 log points, and the median is -0.010 log points.

Table A23 reinforces these findings by showing mean and median log difference for each of the three MSAs in each year. The mean does not fluctuate by more than 0.03 log points across years and MSAs.

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

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

Table A23: Difference Between Log Transaction Price and Log Final List Price

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

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

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

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

Figure A14 shows the results. The left column shows IV sample 1, while the right column shows IV sample 2. The top row shows binned scatter plots where the dependent variable is the log first list price, while the bottom row shows binned scatter plots where the dependent variable is the log transaction price minus the log final list price. In none of them is there a pronounced pattern. If anything, the difference between the log transaction price and log first list price shows a slight inverse-U pattern, suggesting that sellers have to cut their price less on average if they set their price at the "correct" initial price, but this effect is small and insignificant. The difference between the log transaction price and log final list price shows no clear pattern.

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

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

which reduces to

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

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

Figure A14: IV Specification: Difference Between Log Transaction Price and Log List Price vs. Log Relative Markup



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



Figure A15: Kaplan-Meier Survival Curve For List Prices

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

D.2 Frequency of Price Changes in Microdata

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

Figure A15 shows the Kaplan-Meier survival curve for list prices, which plots the probability that a price survives for a given number of weeks conditional on the house not selling or being withdrawn from the market. The median price lasts 9 weeks (week 1 to week 10), or approximately two months. This is used to motivate a two-month fixed price in the staggered pricing model.

E Model

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

E.1 Market Tightness in Each Submarket and the Probabilities of Purchase and Sale

The mass of sellers in the f submarket is S_t times the weighted average probability that any given seller is in the f submarket $E_{\Omega} [1 - G(\cdot)]$, and the mass of sellers in the d submarket is similarly $S_t E_{\Omega} [G(\cdot)]$. Consequently, the market market tightness in the f and d submarkets is:

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

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

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

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

$$d^{f}\left(p_{t},\Omega_{t},\tilde{\theta}_{t}\right) = q^{f}\left(q_{t}^{f}\right)\left(1 - G\left(p_{t} - E_{\Omega_{t}}\left[p_{t}\right] - \mu\right)\right)\left(1 - F\left(\varepsilon_{t}^{*}\left(p_{t}\right)\right)\right)$$

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

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

where,

$$d^{d}\left(p_{t},\Omega_{t},\tilde{\theta}_{t}\right) = q^{d}\left(\theta_{t}^{d}\right)G\left(p_{t}-E_{\Omega_{t}}\left[p_{t}\right]-\mu\right)\left(1-F\left(\varepsilon_{t}^{*}\left(p_{t}\right)\right)\right),$$

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

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

$$\begin{aligned} d\left(p_{t},\Omega_{t},\tilde{\theta}_{t}\right) &= Pr\left[Good\ Signal\right]Pr\left[Sell|Good\ Signal\right] + Pr\left[Bad\ Signal\right]Pr\left[Sell|Bad\ Signal\right]\\ &= d^{f}\left(p_{t},\Omega_{t},\tilde{\theta}_{t}\right) + d^{d}\left(p_{t},\Omega_{t},\tilde{\theta}_{t}\right). \end{aligned}$$

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

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

The value function of a buyer who follows, $V_t^{b,f}$, a buyer who does not follow $V_t^{b,d}$, and a buyer prior to choosing a submarket V_t^b , are then:

$$V_t^{b,f} = b + \beta E_t V_{t+1}^b + \frac{1}{\phi_t \theta_t} E_{\Omega_t} \left[d^f \left(p_t, \Omega_t, \tilde{\theta}_t \right) E \left[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^* \right] \right]$$
(A10)

$$V_t^{b,d} = b + \beta E_t V_{t+1}^b + \frac{1}{(1 - \phi_t) \theta_t} E_{\Omega_t} \left[d^d \left(p_t, \Omega_t, \tilde{\theta}_t \right) E \left[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^* \right] \right]$$
(A11)
$$V_t^b = \max \left\{ V_t^{b,f}, V_t^{b,d} \right\}.$$

E.2 Lemma 2: Optimal Price Setting

From the definition of V_t^s , sellers solve:

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

with first order condition:

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

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

$$\frac{\partial d^{f}\left(p_{t},\Omega_{t},\tilde{\theta}_{t}\right)}{\partial p_{t}}=d^{f}\left(p_{t},\Omega_{t},\tilde{\theta}_{t}\right)\left[\frac{-f\left(\cdot\right)}{1-F\left(\cdot\right)}+\frac{-g\left(\cdot\right)}{1-G\left(\cdot\right)}\right],$$

and

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

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

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

This optimal price is unique on the concave region of the demand curve by standard arguments. However, the problem may not be globally concave if $\bar{\varepsilon}$ is past the point where $G(\cdot)$ begins to flatten, and sellers may have an incentive to deviate. If they do, they would always choose $\bar{\varepsilon}$, as the demand curve is very inelastic in the non-concave region, pushing the markup to the highest possible level. I describe tests for whether the seller would like to deviate to post $\bar{\varepsilon}$ in Section E.5.

E.3 $F(\cdot)$ Distribution, Full Equilibrium System, and Simulation Details

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

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

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

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

The survivor function is:

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

The hazard function is:

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

The upper-tail conditional expectation is:

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

The mean excess function is thus:

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

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

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

and the CDF is:

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

This implies a hazard function of:

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

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

The markup is then:

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

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

$$E_{\Omega_t} [p_t] = \alpha p_t^E + (1 - \alpha) p_t^R$$

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

To simplify notation, let:

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

Then the market tightnesses are then:

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

The buyer value function is:

$$V_{t}^{b} = b + \beta E_{t} V_{t+1}^{b} + \frac{1}{\phi_{t} \theta_{t}} \left[\alpha d_{t}^{E,f} M_{t}^{E} + (1 - \alpha) d_{t}^{R,f} M_{t}^{R} \right].$$

Finally, the indifference condition is:

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

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

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

and,

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

I simulate this system with a log-quadratic approximation using Dynare as described in the main text. In Section E.5 I provide a test to show that the mass point at $\bar{\varepsilon}$ does not preclude the use of perturbation methods since it is essentially never reached.

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

E.4 Steady State

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

Begin with the laws of motion, recalling that we have mass one of houses and mass N of agents. From (13) and (14),

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

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

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

so in steady state,

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

From (12) and (15) and the steady state expression for R:

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

The steady state value functions are:

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

where

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

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

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

so,

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

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

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

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

E.5 Specification Checks

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

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

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

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

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

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

Staggered Pricing Model E.6

E.6.1 Lemma 3: Optimal Staggered Price Setting

The price-setting seller's value function is:

$$V_t^{s,0} = \max_{p_t^0} \left\{ s + \beta V_{t+1}^{s,1} \left(p_t^0 \right) + d \left(p_t^0, \Omega_t, \tilde{\theta}_t \right) \left(p - s - \beta V_{t+1}^{s,1} \left(p_t^0 \right) \right) \right\},\tag{A12}$$

where

$$V_t^{s,\tau}(p) = s + \beta V_{t+1}^{s,\tau+1}(p) + d\left(p,\Omega_t,\tilde{\theta}_t\right) \left(p - s - \beta V_{t+1}^{s,\tau+1}(p)\right),$$
(A13)

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

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

where for $\tau < M - 1$,

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

and,

into

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

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

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

Rearranging gives:

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

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

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

E.6.2 Altered Laws of Motion With Staggered Pricing

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

$$S_{t}^{\tau} = \left(1 - d\left(p_{t-1}^{\tau-1}, \Omega_{t-1}, \tilde{\theta}_{t-1}\right)\right) S_{t-1}^{\tau-1} \ \forall \tau > 0$$
(A14)

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

$$S_t^0 = \left(1 - d\left(p_{t-1}^{M-1}, \Omega_{t-1}, \tilde{\theta}_{t-1}\right)\right) S_{t-1}^{M-1} + \lambda^h H_{t-1}.$$
(A15)

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

E.6.3 Full Staggered Pricing Model

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

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

- 1. Optimal pricing for price resetters (22) for whom $\tau = 0$ and $p_t^{\tau} = p_{t-1}^{\tau-1}$ for $\tau > 0$.
- 2. Optimal purchasing decisions by buyers: $\varepsilon_t^{*,\tau} = p_t^{\tau} + b + \beta V_{t+1}^b V_t^h;$
- 3. The demand curve for each vintage of seller $\tau = \{0, ..., M 1\}$ 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), homeowners (8), and for price resetting sellers (A12) and each vintage of non-resetting sellers (A13).
- 5. The laws of motion for buyers (12) and each vintage of sellers (A14) and (A15) and the closed system conditions for homes (14) and people (15) that implicitly define the laws of motion for homeowners and renters;
- 6. Buyers are indifferent across markets (16);
- 7. All agents have rational expectations that λ_t^r evolves according to the AR(1) process (23).

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

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

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

$$E_{\Omega_{t}}[p_{t}] = \frac{S_{t}^{0}}{S_{t}}p_{t}^{0} + \frac{S_{t}^{1}}{S_{t}}p_{t}^{1}$$
$$E_{\Omega_{t}}[d_{t}] = \frac{S_{t}^{0}}{S_{t}}d_{t}^{0} + \frac{S_{t}^{1}}{S_{t}}d_{t}^{1}.$$

To simplify notation, let:

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

As before,

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

The buyer value function is:

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

Finally, the indifference condition is:

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

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

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

and,

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

plus the pricing rule. Since

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

and

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

the pricing rule (22) is:

$$p_{t}^{0} = \frac{\left(\begin{array}{c} d_{t}^{0} \left(\frac{f_{t}^{0}}{1 - F_{t}^{0}} + \frac{g_{t}^{0}}{1 - G_{t}^{0}} - \frac{1}{\sigma} \frac{d_{t}^{0,d}}{d_{t}^{0}} \right) \left(s + E_{t} V_{t+1}^{s,1} + \frac{1}{\frac{f_{t}^{0}}{1 - F_{t}^{0}} + \frac{g_{t}^{0}}{1 - G_{t}^{0}} \left(1 - \frac{1}{G_{t}^{0}} \frac{d_{t}^{0,d}}{d_{t}^{0}} \right) \right) + \left(\beta \left(1 - d_{t}^{0} \right) E_{t} \left[d_{t+1}^{1} \left(\frac{f_{t+1}^{1}}{1 - F_{t+1}^{1}} + \frac{g_{t+1}^{1}}{1 - G_{t+1}^{1}} \left(1 - \frac{1}{G_{t}^{1}} \frac{d_{t+1}^{1,d}}{d_{t+1}^{1}} \right) \right) \left(s + V_{t+2}^{s,0} + \frac{1}{\frac{f_{t+1}^{1}}{1 - F_{t+1}^{1}} + \frac{g_{t+1}^{1,d}}{1 - G_{t+1}^{1}} \left(1 - \frac{1}{G_{t}^{1}} \frac{d_{t+1}^{1,d}}{d_{t+1}^{1}} \right) \right) \right] \right) \\ \frac{d_{t}^{0} \left(\frac{f_{t}^{0}}{1 - F_{t}^{0}} + \frac{g_{t}^{0}}{1 - G_{t}^{0}} \left(1 - \frac{1}{G_{t}^{0}} \frac{d_{t}^{0,d}}{d_{t}^{0}} \right) \right) + \beta \left(1 - d_{t}^{0} \right) E_{t} \left[d_{t+1}^{1} \left(\frac{f_{t+1}^{1}}{1 - F_{t+1}^{1}} + \frac{g_{t+1}^{1}}{1 - G_{t+1}^{1}} \left(1 - \frac{1}{G_{t}^{1}} \frac{d_{t+1}^{1,d}}{d_{t+1}^{1}} \right) \right) \right] \right)$$

E.7 Non-Concave Model

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

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

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

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

The full system is then:

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

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

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

E.8 Microfoundation For Backward-Looking Sellers

This appendix presents a microfoundation for the Backward looking sellers' price setting equation (20).

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

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

with first order condition,

$$p_t = s + \beta E_t V_{t+1}^s + E_t \left[\frac{-d \left(p_t, \Omega_t, \tilde{\theta}_t \right)}{\frac{\partial d \left(p_t, \Omega_t, \tilde{\theta}_t \right)}{\partial p_t}} \right].$$
(A16)

However, they do not fully understand the laws of motion and how prices and the value of being a seller evolve. Instead, they think the world is a function of a single state variable, the average price $E[p_t]$, and can only make "simple" univariate forecasts that take the form of a first order approximation of (A16) in average price and relative price:

$$p_{t} = s + \beta \left(\bar{V}_{t+1}^{s} + \pi_{1} E[p_{t}] \right) + \bar{M} + \pi_{2} E[p_{t} - E[p_{t}]]$$

$$= s + \beta \left(\bar{V}_{t+1}^{s} + \pi_{1} E[p_{t}] \right) + \bar{M},$$
(A17)

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

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

$$p_t^E = \frac{p_{t-2} + p_{t-3} + p_{t-4}}{3} + \psi \left(\frac{p_{t-2} + p_{t-3} + p_{t-4}}{3} - \frac{p_{t-5} + p_{t-6} + p_{t-7}}{3} \right),$$
(A18)

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

$$p_t = \frac{\alpha d_t^E p_t^E + (1 - \alpha) d_t^R p_t^R}{\alpha d_t^E + (1 - \alpha) d_t^R}.$$
 (A19)

F Calibration

F.1 Calibration Targets

The aggregate moments and parameters chosen from other papers are:

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

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

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

- A median tenure for owner occupants of approximately nine years from American Housing Survey 1997 to 2005 (Table 3-9).
- The approximately equal time for buyers and sellers is from National Association of Realtors surveys (Head et al., 2014; Genesove and Han, 2012). This implies that a normal market is defined by a buyer to seller ratio of $\theta = 1$. I assume a time to sale in a normal market of four months for both buyers and sellers. There is no definitive number for the time to sale, and in the literature it is calibrated between 2.5 and six months. The lower numbers are usually based on real estate agent surveys (*e.g.*, Genesove and Han, 2012), which have low response rates and are effectively marketing tools for real estate agents. The higher numbers are calibrated to match aggregate moments (Piazzesi and Schneider, 2009). I choose four months, which is slightly higher than the realtor surveys but approximately average for the literature.
- Price is equal to \$760,000, roughly the average transaction price in the IV samples. IV Sample 1 corresponds is \$758,803 and in IV sample 2 is \$781,091. The results are not sensitive to this calibration target.
- One in ten houses that are inspected are purchased. Genesove and Han (2012) show that in National Association of Realtors surveys of buyers the mean buyer visits 9.96 homes. This does lead to a $\xi > 1$, but this is standard for search models and not a practical issue for the model.
- A monthly buyer search cost of 0.75 of the average price per month, so that the average buyer, who is in the market for four months, has total search costs equal to 3 percent of the average home's price as described in the main text. Since this target is somewhat speculative, I vary it in robustness checks.
- A five percent annual discount rate, as is standard in the literature.
- $\psi = 0.4$. ψ is the AR(1) coefficient in the backward-looking model and is set based evidence from Case et al. (2012). Using surveys of home buyers, Case et al. (2012) show that regressing realized annual house price appreciation on households' *ex-ante* beliefs yields a regression coefficient of 2.34. I use this survey evidence to calibrate the beliefs of the backward-looking sellers by dividing the approximate regression coefficient one would obtain in quarterly simulated data (approximately 0.94) by their coefficient. Since this target is somewhat speculative, I vary it in robustness checks.
- h is set so that the present discounted value of the flow utility of living in a home is approximately 2/3 of its value in steady state, which implies h = \$6.78k per month for a \$760,000 house. Since this target is somewhat speculative, I vary it in robustness checks to show it is effectively a normalization.

Two time series moments are used:

• The persistence of the shock $\rho = 0.95$ is chosen to match evidence on the persistence of population growth from the corrigendum of Head et al. (2014). They report that the auto-correlation of population growth is 0.62 at a one year horizon, 0.29 at a two year horizon, and

0.06 at a three-year horizon. These imply monthly autocorrelations of 0.961, 0.950, and 0.925. I choose the middle value. This moment controls when the shock begins to mean revert, and all that matters for the results is that the shock does not mean revert before three years.

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

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

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

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

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

F.2 Estimation and Calibration Procedure

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

Approximation of d(p) in Equation (24)

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

$$\begin{split} d\left(p_{t}\right) &= q\left(\theta_{t}^{f}\right)\left(1 - G\left(p_{t} - E\left[p\right] - \mu\right)\right)\left(1 - F\left(\varepsilon_{t}^{*}\left(p_{t}\right)\right)\right) + q\left(\theta_{t}^{d}\right)G\left(p_{t} - E\left[p\right] - \mu\right)\left(1 - F\left(\varepsilon_{t}^{*}\left(p_{t}\right)\right)\right) \\ &= \kappa_{t}\left(1 - F\left(\varepsilon^{*}\left(p_{t}\right)\right)\right)\left[\left(\frac{\phi_{t}}{E_{\Omega_{t}}\left[1 - G\left(p_{t} - E_{\Omega_{t}}\left[p_{t}\right] - \mu\right)\right]}\right)^{\gamma}\left[1 - G\left(p - E_{\Omega_{t}}\left[p_{t}\right] - \mu\right)\right] \\ &+ \frac{\xi^{d}}{\xi^{f}}\left(\frac{(1 - \phi_{t})}{E_{\Omega_{t}}\left[G\left(p_{t} - E_{\Omega_{t}}\left[p_{t}\right] - \mu\right)\right]}\right)^{\gamma}G\left(p - E_{\Omega_{t}}\left[p_{t}\right] - \mu\right)\right], \end{split}$$

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

$$1 - F\left(\varepsilon^{*}\left(p_{t}\right)\right) = \frac{\overline{\varepsilon} - \chi \underline{\varepsilon}}{\overline{\varepsilon} - \underline{\varepsilon}} + \frac{1 - \chi}{\overline{\varepsilon} - \underline{\varepsilon}}\varepsilon^{*}\left(p_{t}\right),$$

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

$$1 - F\left(\varepsilon^{*}\left(p_{t}\right)\right) = \frac{\overline{\varepsilon} - \chi \underline{\varepsilon}}{\overline{\varepsilon} - \underline{\varepsilon}} + \frac{1 - \chi}{\overline{\varepsilon} - \underline{\varepsilon}}\left(p_{t} - E_{\Omega_{t}}\left[p_{t}\right] + \varepsilon^{*}_{t}\left(E_{\Omega_{t}}\left[p_{t}\right]\right)\right)$$
$$= \frac{\overline{\varepsilon} - \chi \underline{\varepsilon}}{\overline{\varepsilon} - \underline{\varepsilon}} + \frac{1 - \chi}{\overline{\varepsilon} - \underline{\varepsilon}}\left(p_{t} - E_{\Omega_{t}}\left[p_{t}\right] + \varepsilon^{*}_{mean} - \varepsilon^{*}_{mean} + \varepsilon^{*}_{t}\left(E_{\Omega_{t}}\left[p_{t}\right]\right)\right)$$
$$= 1 - F\left(\varepsilon^{*}_{mean} + p_{t} - E_{\Omega_{t}}\left[p_{t}\right]\right) + \left(\varepsilon^{*}_{t}\left(E_{\Omega_{t}}\left[p_{t}\right]\right) - \varepsilon^{*}_{mean}\right)\frac{1 - \chi}{\overline{\varepsilon} - \underline{\varepsilon}}.$$

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

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

where the approximation error is small.

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

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

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

I approximate ϕ by assuming that $E[\varepsilon - \varepsilon_t^* | \varepsilon > \varepsilon_t^*]$ is the same for all bins, which is roughly the case, and then solving for ϕ . Second, I calculate $d(p_t)$ from (24) using $\varepsilon^*(p) = \varepsilon^{*,mean} + p_t - E_{\Omega}[p]$.

Calibration To Micro Estimates

The procedure to calibrate to the micro estimates is largely described in the main text. I start with the IV binned scatter plot (p_b, d_b) , which can be thought of as an approximation of the demand curve by 25 indicator functions after the top and bottom 2.5 percent of the price distribution is dropped. In Figure 2, the log relative markup p is in log deviations from the average, and I convert it to a dollar amount using the average price of \$760,000 in the IV sample. For each combination of σ , χ , and the density of $F(\cdot)$, I use equation (24) to calculate the mean of squared error:

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

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

 ζ could also be chosen using this method, but doing so obtains a very large ζ that introduces numerical error into the dynamic model solution. Consequently, I choose $\zeta = 8$, which gives most of the improvement in mean squared error from choosing ζ optimally relative to using a normal distribution with $\zeta = 2$ while reducing numerical error. The results are not sensitive to this normalization. Additionally, The seller search cost s is pinned down by the elasticity of demand at the zero point, and using the zero point estimated from the data leads to a very large s because the zero point is slightly on the inelastic side of the kink. Because the zero point corresponding to the average price is not precisely estimated and depends on the deadline used for a listing to count as a sale, I shifting the zero point by up to one percent to to obtain a more plausible seller search cost.

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

Matching the Aggregate Targets

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

The Calibration System

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

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

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

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

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

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

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

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



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

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

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

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

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

G Additional Simulation Results

G.1 Downward Shocks

Figure A16 shows the impulse response to a downward shock directly analogous to Figure 5. As in the data, there is very little detectable asymmetry between an upward and downward shock because the semi-elasticity of demand is locally smooth. Across all 14 calibrations, the impulse response is 36 months for both a downward and upward shock. However, for a very large shock, downward may show slightly more concavity because the elasticity of demand rises sharply when relative price is extremely low.

G.2 Deterministic, Non approximated Shock

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





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

deterministically returns to steady state as x_t reverts back to zero. I then plot deterministic impulse responses for a variable X as $\log (X_t/X_{ss})$ where X_{ss} is its steady state value. This results in the IRFs in Figure A17, which are comparable to Figure 5. Across all 14 calibrations, the maximum period of the deterministic one time shock IRF and the stochastic IRF are within one month of each other. The perturbation solution thus seems quite accurate.

G.3 Detailed Intuition For Staggered Pricing Model

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

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

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

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