Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

Price-Segmented Beliefs and the U.S. Housing Boom

Margaret M. Jacobson

2026-022

Please cite this paper as:
Jacobson, Margaret M. (2026). "Price-Segmented Beliefs and the U.S. Housing Boom," Finance and Economics Discussion Series 2026-022. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2026.022.

Price-Segmented Beliefs and the U.S. Housing Boom

By Margaret M. Jacobson*
April 23, 2026
Federal Reserve Board

Abstract

This paper shows that expected capital gains in several MSAs were higher for relatively lower-priced, rather than higher-priced, houses during the U.S. boom of the 2000s. Because buyers of lower-priced houses tend to be more sensitive to credit conditions than buyers of higher-priced houses, this paper documents patterns that are consistent with an interaction of beliefs and credit conditions in a time period where direct evidence on house price beliefs is scarce. Documenting this interaction is important for unifying beliefs and credit conditions as joint, instead of competing, explanations for the U.S. housing boom of the 2000s.

Keywords: housing booms, beliefs, transaction data.
JEL: D14, D91, R21, R31

*This material reflects the views of the author and not those of the Federal Reserve Board of Governors. This note was previously included as a section of an earlier draft of the author's paper "Beliefs, Aggregate Risk, and the U.S. Housing Boom." Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX) and distributed through Inter-University Consortium for Political and Social Research. More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group. I thank the Bureau of Economic Analysis, specifically Scott Wentland and Ben Bridgeman, for access to and help with ZTRAX. I thank Aditya Aladangady, Eirik Brandsaas, and Raven Molloy for helpful comments. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant NO. 2015174787. Contact: Margaret.M.Jacobson@frb.gov

1 Introduction

Optimistic beliefs and looser credit conditions are two highly studied drivers of the U.S. housing boom of the 2000s.[1] While these drivers are often studied in isolation, which allows for clean interpretation of mechanisms, studying them as complementary can allow for propagation dynamics arising from their interaction.[2] However, studying their interaction is challenging due to limited data on beliefs prior to 2007.[3]

This paper finds that beliefs were higher in relatively lower-priced, rather than higher-priced, houses in the 2000s for all locations studied. Since buyers of lower-priced houses are more sensitive to credit conditions (Fidelman and Tapak, 2026), this paper's evidence of higher expected capital gains in the lower-priced housing segment points to an interaction of beliefs and credit conditions.[4] Interpreted more broadly, this evidence suggests that beliefs and credit conditions were complementary, rather than competing, drivers of the U.S. housing boom of the 2000s.

To investigate how beliefs vary across housing price segments, this paper estimates a statistical model of price changes developed by Landvoigt et al. (2015) using Zillow (2026) ZTRAX transaction data on repeat housing sales. Transaction-level data provides repeat sales prices of the same property, which, in turn, allows for the estimation of a common component of expected capital gains and a cross-sectional dispersion component across types of houses segmented by price. This model assumes a one-dimensional quality index so that the sale price of a house fully reflects its quality. Consequently, as explained by Landvoigt et al. (2015), any statistical model of price changes can give rise to an expected price change and thus expected capital gains, which can, in turn, be used to proxy for beliefs.

By expanding the analysis of Landvoigt et al. (2015) beyond San Diego, CA to include Phoenix, AZ and Cleveland, OH, this paper adds new evidence to the dearth of data on beliefs in the 2000s. Because the U.S. housing boom of the 2000s varied in timing and magnitude across metropolitan statistical areas (MSAs), as documented by Ferreira and Gyourko (2023), estimating beliefs for multiple MSAs is important for a more comprehensive

[1] Cox and Ludvigson (2021) empirically test optimistic beliefs and looser credit conditions and find evidence in favor of both explanations. Kaplan et al. (2020) find that beliefs are quantitatively more important in a state-of-the-art structural model. Duca et al. (2021) and Piazzesi and Schneider (2016) provide overviews of housing cycle drivers.

[2] Jacobson (2024), Johnson (2019), and Dong et al. (2022) provide evidence of propagation channels arising from the interaction of beliefs and credit conditions.

[3] See Kuchler et al. (2023, Table 2) for documentation of U.S. house price beliefs and their limited availability prior to 2007. Jacobson (2024) navigates limited data on beliefs by constructing an empirical proxy from the University of Michigan Survey of Consumers.

[4] Kaplan et al. (2020) find that renters purchased smaller (and hence less expensive) homes than homeowners in response to expanded access to credit.

account of the episode. For this reason, I study three MSAs that capture characteristics of different submarkets, but all show higher expected capital gains in relatively lower-priced houses. San Diego is typically characterized by authors like Saiz (2010) as having a low elasticity of housing supply such that it is difficult—because of geography—to build more houses in response to higher house prices. On the other hand, Phoenix and Cleveland are both characterized as having geography that lends to a higher elasticity of housing supply. However, their fundamentals differ; Phoenix in the 2000s faced rapid housing and population growth and Cleveland depopulation.[5]

Complementing these within-MSA findings, this paper also estimates substantial variation in expected capital gains over time and across the three MSAs studied, which corroborates the empirical evidence of Soo (2018).

2 Estimates of Expected Capital Gains

Transactions of repeat sales of single-family homes for the MSAs of Cleveland, OH; Phoenix, AZ; and San Diego, CA are obtained via Zillow (2026) ZTRAX assessment and transaction data accessed through the Bureau of Economic Analysis in 2019. Applying the cleaning steps detailed in Appendix A to arm's length, non-foreclosed sales of residential properties made by owner-occupiers results in over 280,000 transactions of houses that are sold at least once from 1998 to 2008.[6] Limiting the sample to repeat sales is essential because the statistical model estimates expected capital gains from the observed sales of the same property.

Expected capital gains of house i at time t in MSA j vary by their current log price $\log p_t^{i,j}$ where the idiosyncratic shocks $e_{t+1}^{i,j}$ have mean zero and are such that the law of large numbers holds in the cross section of houses. Because this paper assumes that there is a one-dimensional quality index, quality is reflected one-for-one in the house price at any given time t and there are no additional controls.[7]

The statistical model can be written as:

$$\log p_{t+1}^{i,j} - \log p_t^{i,j} = a_{t+1,t}^{j} + b_{t+1,t}^{j} \log p_t^{i,j} + e_{t+1,t}^{i,j} \tag{1}$$

Estimating the equation above would restrict the sample to houses that sold in successive years, such as a sale in 2000 and 2001, for example. To incorporate information from longer-dated sales, such as a house that sold in 2000 and again in 2003, for example, the above

[5] See Glaeser and Tobia (2007), Glaeser et al. (2008), and Glaeser and Gyourko (2005).

[6] Appendix A also compares estimates of San Diego to those of Landvoigt et al. (2015).

[7] See Case and Shiller (1987) for the advantages of repeat sales approaches like the one used in this paper relative to hedonic approaches that control for property characteristics.

equation is iterated forward to capture expected capital gains between years $t+k$ and t for each $t = 1998, ..., 2007$ and $k \in [1, 2008-t]$.

$$\log p^{i,j}_{t+k} - \log p^{i,j}_{t} = a^{j}_{t+k,t} + b^{j}_{t+k,t} \log p^{i,j}_{t} + \epsilon^{i,j}_{t+k,t}$$

For $k \geq 2$, the above equation can be written in terms of $a_{t+1,t}$ and $b_{t+1,t}$.

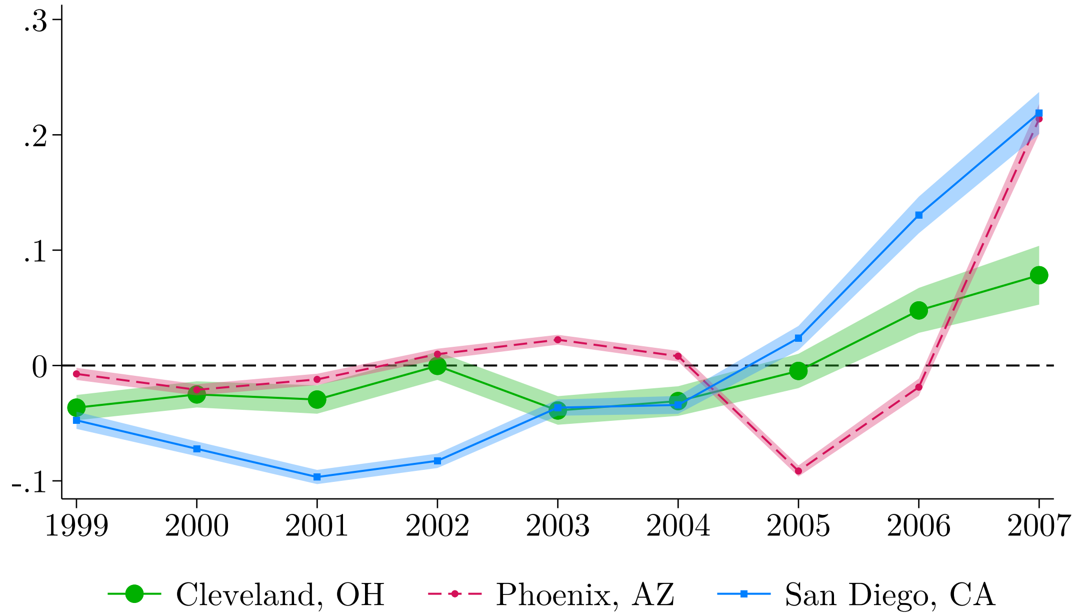
$$logp^{i,j}_{t+k} = a^{i,j}_{t+k,t+k-1} + \sum_{m=t+2}^{t+k} \prod_{\ell=m}^{t+k} (1 + b^{j}_{\ell,\ell-1}) a^{j}_{m-1,m-2} + \prod_{\ell=t+1}^{t+k} (1 + b_{\ell,\ell-1}) \log p^{i,j}_{t} \qquad (2)$$

Equations (1) and (2) are estimated separately for each MSA $j \in \{$Cleveland, Phoenix, San Diego$\}$. Estimation is for $t = 1998, ..., 2007$ via two-step GMM with a robust weight matrix. The first-step residuals are used to estimate the weighting matrix for the second step, which ensures that the estimator is robust to heteroskedasticity. Estimates $\hat{a}^{j}_{t+k,t}$ and $\hat{b}^{j}_{t+k,t}$ can be obtained by adding/multiplying $\hat{a}^{j}_{t+1,t}$ and $\hat{b}^{j}_{t+1,t}$, respectively.

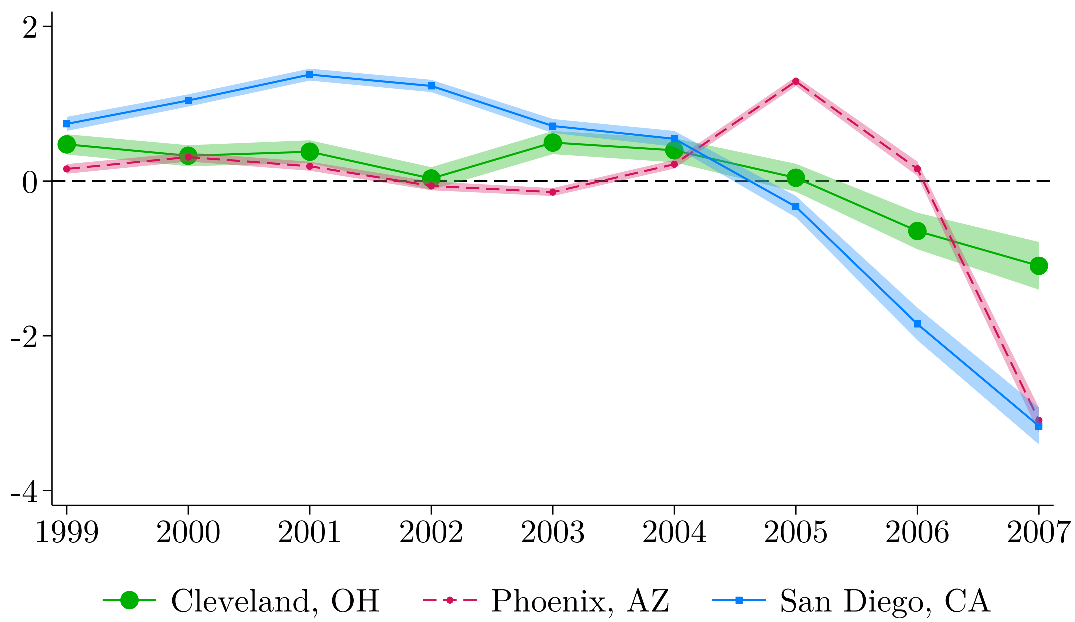
The slopes $b^{j}_{t+1,t}$ are the coefficients of interest and test for cross-sectional dispersion in expected capital gains across house-price segments for each MSA j for any given pair of years $t+1$ and t, conditional on the full sample of transactions between years $t+k$ and t. If $\hat{b}^{j}_{t+1,t} = 0$ then there is no cross-sectional dispersion and all houses in that MSA have the same expected capital gains regardless of their price. If $\hat{b}^{j}_{t+1,t} > 0$, then expected capital gains are relatively higher for more expensive houses in MSA j, which are those houses that have a higher sales price at year t. If $\hat{b}^{j}_{t+1,t} < 0$, relatively cheaper houses in MSA j have higher expected capital gains. Because Fidelman and Tapak (2026) find that households in lower-priced housing segments tend to be more sensitive to credit conditions, testing if $\hat{b}^{j}_{t+1,t} = 0$ can provide insights on the interaction of beliefs and credit conditions. The intercepts $a^{j}_{t+1,t}$ are the average expected capital gain.

Figure (1) shows the GMM estimates of the coefficients from equations (1) and (2) as the markers and 95% confidence intervals as the shaded bands for Cleveland, Phoenix and San Diego. Estimates shown are those from one year t to the next year $t+1$ such that $k = 1$. While these can be added/multiplied to obtain those that correspond to $k \geq 2$, those for $k = 1$ can be more readily compared to actual 12-month percentage change in house prices as shown in figure (2).[8]

[8] The estimates for 2007 and 2008 are shown for completeness even though the housing bust was largely unanticipated. If these years were not included in estimation, then $\hat{b}^{j}_{t+1,t}$ and $\hat{a}^{j}_{t+1,t}$ could be even larger than the values shown in figure (1).



(a) Cross-sectional Dispersion of Expected Capital Gains ($\hat{b}^j_{t+1,t}$), Percentage Points



(b) Average Expected Capital Gains ($\hat{a}^j_{t+1,t}$), Percentage Points

Figure 1: Estimated average and cross-sectional dispersion of expected capital gains, with 95% confidence bands, for repeat sales of single-family homes in Cleveland, OH; Phoenix, AZ; and San Diego, CA from the equations (1) and (2), $\log p^{i,j}_{t+1} - \log p^{i,j}_t = a^j_{t+1,t} + b^j_{t+1,t} \log p^{i,j}_t + \epsilon^{i,j}_{t+1,t}$ and $logp^{i,j}_{t+k} = a^{i,j}_{t+k,t+k-1} + \sum_{m=t+2}^{t+k} \prod_{\ell=m}^{t+k}(1+b^j_{\ell,\ell-1})a^j_{m-1,m-2} + \prod_{\ell=t+1}^{t+k}(1+b_{\ell,\ell-1}) \log p^{i,j}_t$, respectively, where $t = 1998, ..., 2007$ and $k \in [1, 2008-t]$. The data consist of 48,968 repeat sales in Cleveland, OH; 148,842 repeat sales in Phoenix, AZ; and 84,076 repeat sales in San Diego, CA via ZTRAX (Zillow, 2026).

The top panel (1a) shows that expected capital gains were relatively higher for lower-priced houses for all three MSAs shown until about 2005, as shown by the estimates of the cross-sectional dispersion of expected capital gains across house price segments $\hat{b}^j_{t+1,t}$. These estimates show that a 1 percent less expensive house (relative to the average house) was expected to have at most a 0.1 percentage point higher expected capital gain.

Comparing across MSAs shown, panel (1a) points to lower-priced houses having relatively higher expected capital gains in San Diego than in Phoenix or Cleveland, on average. Because the housing supply elasticity is lower in San Diego than in Phoenix or Cleveland (according to Saiz, 2010), increased demand for less expensive houses was more likely to result in relatively higher price increases, and thus capital gains.[9] Conversely, Phoenix's near-zero dispersion suggests relatively uniform expected capital gains across house-price segments. This can be attributed to, in part, a high share of speculative investors who—per Gao et al. (2020)—tended to be insensitive to credit conditions.[10]

By construction, the estimated average expected capital gains, $\hat{a}^j_{t+1,t}$ shown in the bottom panel (1b), closely track the 12-month percentage change in house prices shown in figure (2). This alignment helps validate that the estimated data generating process in equations (1) and (2) correctly reflects key attributes about regional house prices—specifically the early peak for San Diego, the later arriving rapid surge for Phoenix, and virtually no boom for Cleveland. Notably, expected capital gains in Phoenix and Cleveland were similar and remained below those of San Diego until 2003, which likely reflects lower buyer incomes in these regions, as noted by Ferreira and Gyourko (2023). However, after 2003, expected capital gains in Phoenix and Cleveland diverge sharply, which is likely due to the influx of housing investors in the former, but not the latter.

It is also worth noting that figure (1) shows substantial time variation in estimates of both average and cross-sectional expected capital gains for each MSA. By the start of the bust in 2007, the positive values of $\hat{b}^j_{t+1,t}$ for all MSAs shown indicate that relatively more expensive houses were holding their value than less expensive houses, while the negative value of $\hat{a}^j_{t+1,t}$ indicates that average expected capital gains were negative. This time variation is important for understanding the evolution of beliefs throughout various stages of a boom-bust cycle.

[9]For discussions of the limitations of the estimates of Saiz (2010) see Aastveit et al. (2023), Oh et al. (2025), and Louie et al. (2025).

[10]Other studies on the role of investors include Graham (2024), Chinco and Mayer (2016), Mian and Sufi (2022), Bayer et al. (2021), Albanesi et al. (2022). Because non-owner occupiers like housing investors are excluded from these estimates, and investors tended to be more optimistic than owner occupiers, these estimates shown are likely a lower bound on expected capital gains for Phoenix.

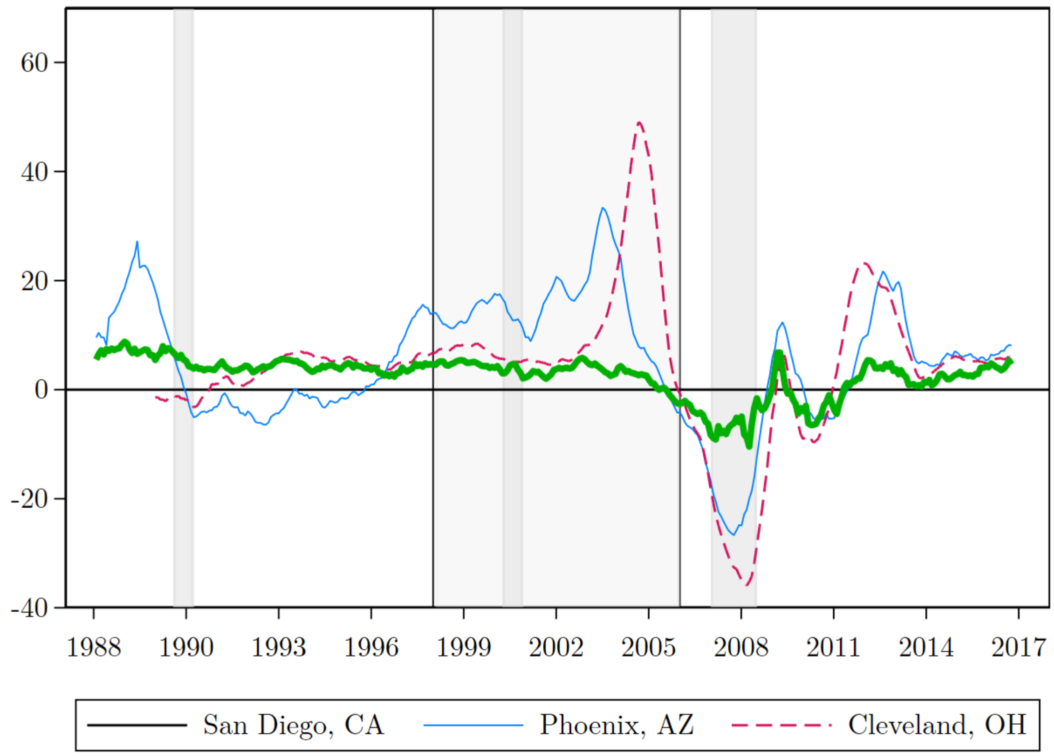


Figure 2: 12-month percentage change in house prices for select metropolitan statistical areas, percentage points. Dark shaded bands are NBER recessions and the light shaded banded between the two vertical lines is the U.S. housing boom period defined as 1998 to 2006 in this paper. Source: S&P Cotality Case-Shiller Home Price Indices, National Bureau of Economic Research.

3 Conclusion

The boom in national U.S. house prices is largely attributed to optimistic beliefs and looser credit conditions. Because data on beliefs prior to 2007 is limited, studying the interaction of beliefs and credit conditions is challenging. Estimating the statistical model of Landvoigt et al. (2015) on transaction-level housing data for the MSAs of Cleveland, OH; Phoenix, AZ; and San Diego, CA shows that lower-priced houses had higher expected capital gains than their higher-priced counterparts. Because buyers of lower-priced houses tend to be more sensitive to looser credit conditions (Fidelman and Tapak, 2026), and these houses had higher expected capital gains, this paper documents a pattern that supports an interaction of credit conditions and optimistic beliefs about future housing.

A Appendix: Data

This section gives detailed cleaning steps of the Zillow (2026) ZTRAX transaction and assessment data to obtain a sample similar to that of Landvoigt et al. (2015) for the MSAs of Cleveland, OH; Phoenix, AZ; and San Diego, CA. The Zillow (2026) ZTRAX data is a panel of housing transactions and the cleaning steps can be grouped by those related to deeds, characteristics, and outliers.

First, to obtain housing market transactions, deeds (`documenttype`) that are not arm's length transfers of homes are dropped as are other non-arm's length deeds such as those indicating a partial sale of a house. Following Landvoigt et al. (2015), I keep only grant deeds (`GRDE`), condo deeds (`CDDE`), corporate deeds (`CPDE`), and individual deeds (`IDDE`). Because the list of deeds denoting arm's length transactions is more exhaustive for Cleveland, OH and Phoenix, AZ, I delete entries for `documenttype` that are conservator's deed (`CVDE`), deed in lieu of foreclosure (`DELU`), gift deed (`GFDE`), intrafamily transfer (`INTR`), partnership deed (`PTDE`), personal representative's deed (`PRDE`), sheriff's deed (`SHDE`), trustee's deed (`TRFC`). Deeds that remain have values for `documenttype` that include administrator's deed (`ADDE`), agreement of sale (`AGSL`), bargain and sale deed (`BSDE`), condominium deed (`CPDE`), court order/action (`COCA`), corporation deed (`CPDE`), correction deed (`CRDE`), deed (`DEED`), fiduciary deed (`FDDE`), guardian's deed (`GDDE`), grant deed (`GRDE`), individual deed (`IDDE`), joint tenancy deed (`JTDE`), land contract (`LDCT`), other (`OTHR`), quitclaim deed (`QCDE`), re-recorded deed (`RRDE`), tax deed (`TXDE`), and warranty deed (`WRDE`).

Second, deeds are dropped based on buyer or house characteristics. Deeds without a latitude or longitude are dropped as are deeds that transfer multiple parcels as identified by the APN number. Second homes and trailers are dropped as are foreclosed properties. Buyers that are not a couple or single person are dropped eliminating buyers that are a corporation or partnership (`CO`,`PT`), a trust (`FT`,`IT`,`LV`,`RL`,`RT`,`TE`), or a beneficiary (`BF`).[11]

Single-family homes are denoted by the `propertylanduse` variable from the assessment data[12] and observations that are kept include single-family residences (`RR101`), condominiums (`RR106`)[13], cooperatives (`RR107`), row houses (`RR108`), planned unit developments (`RR109`),

[11] This is achieved by keeping observations with `buyercode` equal to domestic partners (`DP`), formerly known as (`FK`), her husband (`HH`), husband and wife (`HW`), individual (`ID`), married man (`MM`), minor (`MN`), married person (`MP`), married woman (`MW`), single man (`SM`), single person (`SP`), single woman (`SW`), unmarried man (`UM`), unmarried woman (`UW`), widowed (`WW`) and dropping those with `buyercode` equal to affiant (`AF`), borrower or trustor in default (`BR`), estate (`ES`), executor (`EX`), government (borough, city, village, etc.) (`GV`), surviving joint tenant (`SJ`), personal representative (`PR`), agent (`AG`), not provided (`NP`).

[12] The `propertylanduse` variable from the assessment data and `propertyusestndcode` variable from the transaction data are mostly but not always consistent. I use the assessment data as the main variable to denote property use because it has fewer blank observations and is more stable across time.

[13] Although it may be debatable as to whether or not condominiums should be included as single-family

bungalows (`RR113`), zero lot lines (`RR114`), manufactured, modular and prefabricated homes (`RR115`), patio homes (`RR116`), garden homes (`RR119`), landominiums (`RR120`), and inferred single-family homes (`RR999`). Dropped observations have a `propertylanduse` variable from the assessment data equal to rural residences including farms/productive land (`RR102`), mobile homes (`RR103`), residential common areas (`RR110`), time shares (`RR111`), seasonal, cabin, vacation residences (`RR112`), residential parking garages (`RR117`), and other improvements (`RR118`). Observations from the transaction data are also dropped such as those where the `propertyusestndcode` variable equals agricultural (`AG`), apartment (`AP`), commercial (`CM`), mobile homes (`MB`), mixed use (`MX`), unimproved (`UL`), multifamily (`MF`).

Lastly, to control for outliers, transactions with prices below $15,000, combined loan-to-value ratios (first plus second mortgage) above 120 percent, and annualized capital gains above 50% are dropped. To avoid the influence of house flipping, all pairs of sales that are less than 180 days apart are dropped. Some properties that were sold twice in the same year, but more than 180 days apart remain in the sample. If the property was sold more than once in the same year, then these transactions are dropped. If the property was sold in another year then the earlier sale date in the year is dropped. Given that house prices are rising throughout this period, keeping the later sale should bias capital gains downward. Given the high house price growth observed at the MSA-level in Phoenix, AZ, robustness checks were run to increase the annualized capital gain threshold from 50% to 60% and 70% with little change to the estimates. Similarly, second family homes were included in a separate robustness check with little alteration to the estimates.

Table (1) compares the estimates of average and cross-sectional capital gains for San Diego, CA to those of Landvoigt et al. (2015). Overall, the estimated coefficients from equations (1) and (2) resemble those of Landvoigt et al. (2015). A few minor discrepancies likely arise from the differences in source data used (Trulia vs. Zillow). My sample is larger than theirs with 84,076 repeat sales compared to their 70,315.

homes, dropping condominiums decreases the number of observations from 84,076 to 53,463 for San Diego, CA and the estimates of expected capital gains differ to a larger extent from those of Landvoigt et al. (2015) shown in table (1).

	2000	2001	2002	2003	2004	2005	2006	2007
$a_{t+1,t}^{LPS}$	1.29	1.41	1.30	0.87	0.60	-0.56	-1.09	-3.18
	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.07)	(0.10)	(0.12)
$b_{t+1,t}^{LPS}$	-0.093	-0.10	-0.09	-0.05	-0.04	0.04	0.07	0.22
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.01)	(0.01)	(0.01)
$a_{t+1,t}^{author}$	1.04	1.37	1.23	0.71	0.55	-0.33	-1.84	-3.16
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.10)	(0.12)
$b_{t+1,t}^{author}$	-0.07	-0.10	-0.08	-0.04	-0.03	0.02	0.13	0.21
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.008)	(0.009)

Table 1: Upper panel contains estimates from Landvoigt et al. (2015) (LPS) of 70,315 repeat sales in San Diego County during the years 1999-2008 using transaction data from Trulia. The lower panel contains a replication of their estimates using ZTRAX (Zillow, 2026) assessment and transaction data for 84,076 repeat sales in San Diego County. The numbers in parentheses are standard errors.

References

Aastveit, Knut Are, Bruno Albuquerque, and Andre K. Anundsen, "Changing Supply Elasticities and Regional Housing Booms," *Journal of Money, Credit and Banking*, 2023, *55* (7), 1749–1783.

Albanesi, Stefania, Giacomo DeGiorgi, and Jaromir Nosal, "Credit growth and the financial crisis: A new narrative," *Journal of Monetary Economics*, 2022, *132*, 118–139.

Bayer, Patrick, Kyle Mangum, and James W. Roberts, "Speculative Fever: Investor Contagion in the Housing Bubble," *American Economic Review*, February 2021, *111* (2), 609–51.

Case, Karl E. and Robert J. Shiller, "Prices of single-family homes since 1970: new indexes for four cities," 1987. New England Economic Review, September 1987, pages 45-56.

Chinco, Alex and Chris Mayer, "Misinformed Speculators and Mispricing in the Housing Market," *Review of Financial Studies*, 2016, *29* (2), 486–522.

Cox, Josue and Sydney C. Ludvigson, "Drivers of the great housing boom-bust: Credit conditions, beliefs, or both?," *Real Estate Economics*, 2021, *49* (3), 843–875.

Dong, Ding, Zheng Liu, Pengfei Wang, and Tao Zha, "A theory of housing demand shocks," *Journal of Economic Theory*, 2022, *203*, 105484.

Duca, John V., John Muellbauer, and Anthony Murphy, "What Drives House Price Cycles? International Experience and Policy Issues," *Journal of Economic Literature*, September 2021, *59* (3), 773–864.

Ferreira, Fernando and Joseph Gyourko, "Anatomy of the Beginning of the Housing Boom across U.S. Metropolitan Areas," *The Review of Economics and Statistics*, 11 2023, *105* (6), 1442–1447.

Fidelman, Tomer and Tomas Tapak, "Housing Markets and Macroeconomic Shocks," 2026. Working Paper.

Gao, Zhenyu, Michael Sockin, and Wei Xiong, "Economic Consequences of Housing Speculation," *The Review of Financial Studies*, 03 2020, *33* (11), 5248–5287.

Glaeser, Edward L. and Joseph Gyourko, "Urban Decline and Durable Housing," *Journal of Political Economy*, 2005, *113* (2), 345–375.

_ **and Kristina Tobia**, "The Rise of the Sunbelt," 2007. Taubman Center Policy Brief.

_ **, Joseph Gyourko, and Albert Saiz**, "Housing Supply and Housing Bubbles," *Journal of Urban Economics*, 2008, pp. 198–217.

Graham, James, "House Prices, Investors, and Credit in the Great Housing Bust," 2024. Working Paper.

Jacobson, Margaret M., "Beliefs, Aggregate Risk, and the U.S. Housing Boom," 2024. Manuscript.

Johnson, Stephanie, "Mortgage Leverage and House Prices," 2019. Working Paper.

Kaplan, Greg, Kurt Mitman, and Gianluca Violante, "The Housing Boom and Bust: Model Meets Evidence," *Journal of Political Economy*, 2020, *128* (9).

Kuchler, Theresa, Monika Piazzesi, and Johannes Stroebel, "Chapter 6 - Housing market expectations," 2023, pp. 163–191.

Landvoigt, Tim, Monika Piazzesi, and Martin Schneider, "The Housing Market(s) of San Diego," *American Economic Review*, 2015, *105* (4), 1371–1407.

Louie, Schuyler, John A. Mondragon, and Johannes Wieland, "Supply Constraints do not Explain House Price and Quantity Growth Across US Cities," 2025. Working paper.

Mian, Atif and Amir Sufi, "Credit Supply and Housing Speculation," *The Review of Financial Studies*, 03 2022, *35* (2), 680–719.

Oh, Hyunseung, Choongryul Yang, and Chamna Yoon, "Land Development and Frictions to Housing Supply Over the Business Cycle," 2025. Working Paper.

Piazzesi, Monika and Martin Schneider, "Housing and Macroeconomics," in John B. Taylor and Harald Uhlig, eds., *Handbook of Macroeconomics*, Vol. 2, North Holland, 2016, chapter 19.

Saiz, Albert, "The Geographic Determinants of Housing Supply," *The Quarterly Journal of Economics*, 2010, *125* (3), 1253–1296.

Soo, Cindy, "Quantifying Sentiment with News Media Across Local Housing Markets," *The Review of Financial Studies*, 2018, *31* (10), 3689–3719.

Zillow, "Zillow Transaction and Assessment Database (ZTRAX), United States, 1940-2020," 2026. Inter-university Consortium for Political and Social Research [distributor], 2026-01-27. https://doi.org/10.3886/ICPSR39652.v2.