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Speculative dynamics of prices and volume[☆]

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ABSTRACT

Using data on 50 million home sales from the last U.S. housing cycle, we document that much of the variation in volume came from the rise and fall in speculation. Cities with larger speculative booms have larger price booms, sharper increases in unsold listings as the market turns, and more severe busts. We present a model in which predictable price increases endogenously attract short-term buyers more than long-term buyers. Short-term buyers amplify volume by selling faster and destabilize prices through positive feedback. Our model matches key aggregate patterns, including the lead–lag price–volume relation and a sharp rise in inventories.

The housing market in the United States underwent a tumultuous cycle between 2000 and 2011. The rise and fall in house prices caused several problems for the U.S. economy. During the boom, a surge in housing investment drew resources into construction from other sectors (Charles et al., 2018) and contributed to a capital overhang that slowed the economic recovery (Rognlie et al., 2017). During the bust, millions of households lost their homes in foreclosure, and falling house prices led many others to cut consumption (Mayer et al., 2009; Mian et al., 2013; 2015; Guren and McQuade, 2020). Large real estate cycles are not unique to the U.S. (Mayer, 2011) or to this time period (Case, 2008; Glaeser, 2013). Given the economic costs of these recurring episodes, understanding their cause is critical.

This paper presents evidence that speculation was a key driver of this real estate cycle.[1] Three stylized facts from the cycle guide our analysis. First, prices and volume jointly rise and fall throughout the cycle. Second, volume falls before prices, resulting in a pronounced lead–lag relation between prices and volume. Third, the period during which prices continue to rise despite falling volume coincides with rapidly accumulating unsold listings. We refer to this period as the *quiet*, which is preceded by the

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[1] Harrison and Kreps (1978, p. 323) define speculation as follows: "Investors exhibit speculative behavior if the right to resell a stock makes them willing to pay more for it than they would pay if obliged to hold it forever."

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boom and followed by the *bust*. These stylized facts hold on average across cities and are especially pronounced in cities with larger cycles. They suggest that focusing on who was most active during each phase of the cycle can provide insight on the underlying mechanisms.

We study the behavior of speculative homebuyers during each of these three phases of the housing cycle using transaction-level data from CoreLogic on 50 million home sales between 1995 and 2014. We measure speculative buying and selling across 115 metropolitan statistical areas (MSAs), which represent 48% of the U.S. housing stock. We pursue two complementary approaches to identify speculative activity. First, following Bayer et al. (2020), we classify transactions based on their realized holding periods, denoting those buyers who resell the property within three years as short-term buyers. Second, following Chinco and Mayer (2015), we classify transactions based on the inferred occupancy status of the property, denoting buyers who list a mailing address distinct from the property address as non-occupant buyers. We supplement our transaction data with a separate CoreLogic data set on homes listed for sale, sourced from a consortium of local multiple listing service (MLS) boards. We link these data to transaction records to study the role of speculative buyers for inventory dynamics across MSAs.

The data reveal a strong relation between the differential entry of speculative buyers and the size of the cycle. While overall volume increases substantially during the boom of 2000–2005, both short-term and non-occupant volume rise dramatically more. In an accounting sense, growth in speculative volume explains 40% to 50% of total volume growth. This relation is also strong in the cross-section, as speculative volume growth can account for 30% to 50% of total volume growth across MSAs. Cities with stronger speculative volume booms also experience larger house price booms: MSAs with a one standard deviation larger short-volume and non-occupant boom see 25 and 15 percentage point larger cumulative price increases, respectively.

As the volume boom ends, price growth slows but remains positive, and unsold listings accumulate. Across MSAs, these patterns are more pronounced in cities with larger speculative volume booms. Our linked listing-transaction data further reveal that short-term buyers disproportionately contribute to the surge in aggregate inventories. MSAs with larger speculative volume booms also see substantially larger price busts, volume busts, and total foreclosures in the final phase of the cycle. We find that speculative volume is larger when house price growth over the past year is greater, which suggests that extrapolation–the belief that prices continue to rise after recent gains–draws speculators into the housing market. Consistent with our interpretation of the data, a National Association of Realtors survey reveals wide variation in expected holding times, shorter expected holding times among investors, and increases in the short-term buyer share following recent price gains.

In the second part of the paper, we provide a quantitative model to match these novel facts about the housing market. Our approach adapts core insights from Cutler et al. (1990), De Long et al. (1990), and Hong and Stein (1999) to study the housing market. As in these papers, extrapolation causes a predictable boom and bust in prices after a positive demand shock. In contrast, we relax the assumption of Walrasian market clearing, so that homes listed for sale may not sell immediately. To do so, we microfound extrapolation using the approach in Glaeser and Nathanson (2017) and then extend their framework to a non-Walrasian setting.

In our model, a mover attempts to sell her house by posting a list price. A potential buyer arrives and decides whether to purchase the house at that price. Potential buyers differ in the benefits they derive from owning a house; non-occupants benefit less than occupants. Buyers also differ in the expected amount of time until becoming a mover; short-term buyers have shorter horizons ex ante. The average flow benefit of potential buyers fluctuates randomly over time. Agents cannot observe this demand process, but they observe the history of price growth and the share of listings that sell each period. Using these market data, agents infer the current level and growth rate of the demand process and optimally make decisions in light of these beliefs–the choice of list price for movers, and whether or not to purchase for potential buyers. As in Glaeser and Nathanson (2017), agents mistakenly believe that potential buyers neglect time variation in the growth rate when deciding whether to buy.

We study how our housing market responds to a large, unexpected increase to the growth rate of the demand process. The model matches key facts from our empirical work, including the lead–lag relation between prices and volume, the excess growth of short-term and non-occupant volume during the boom, and a growth in listings during the quiet coming disproportionately from short-holding-period sales. In the model, the quiet occurs when agents overestimate demand and believe it continues to grow, which causes movers to increase their list prices despite falling transaction volume.

We then use this setting to evaluate the effect of speculation on the housing cycle. When we shut down speculation by imposing rational expectations, almost all of the salient aspects of the housing cycle disappear or become quantitatively insignificant. We find similar patterns when we remove short-term and non-occupant buyers from the model. Therefore, speculators amplify the effects of non-rational expectations on prices and quantities over the housing cycle. Motivated by this result, we study transaction taxes on non-occupant buyers as well as on all buyers, as governments have used such taxes in attempts to curb speculation (Chi et al., 2021). Taxing all buyers attenuates the housing cycle, but even a large 5% tax on non-occupants has only a small effect on the price boom, price bust, and volume boom.

Previous and contemporaneous empirical work examines short-term buyers (Adelino et al., 2016; Bayer et al., 2021) and non-occupant buyers (Haughwout et al., 2011; Bhutta, 2015; Chinco and Mayer, 2015) in the housing market, as well as the importance of speculation for volume or prices (Gao et al., 2020; Bayer et al., 2020; Mian and Sufi, 2022). Our paper is the first to focus on the joint dynamics of volumes, prices, and inventories, along with speculative activity. We present stylized facts that any model of this episode should be able to match. Our focus on joint dynamics emphasizes the connection between speculation and the lead-lag relationship between prices and volume, a pattern which receives less attention and has not been linked to speculation in past work. Beyond this, our data expands on past work through including more MSAs, non-mortgage sales, new microdata on homes listed for sale linked to prior transactions, and multiple measures of speculation.

Three strands of the literature theoretically explain the comovement of prices and volume in housing and other markets. In the first, investors disagree about asset values due to overconfidence (Daniel et al., 1998; 2001; Scheinkman and Xiong, 2003). The second exploits features specific to the housing market, such as credit constraints (Stein, 1995; Ortalo-Magné and Rady, 2006) or search and matching frictions (Wheaton, 1990; Díaz and Jerez, 2013; Head et al., 2014; Hedlund, 2016; Ngai and Sheedy, 2020; Anenberg and Bayer, 2020). The final strand incorporates psychology into models with extrapolative expectations to generate trade (Barberis et al., 2018; Liao and Peng, 2018). Some papers straddle multiple categories (Guren, 2014; Piazzesi and Schneider, 2009; Burnside et al., 2016). Relative to these studies, our model's contribution is to simultaneously generate three key patterns from our empirical work: the existence of the quiet, the disproportionate growth in short-term volume during the boom and quiet, and the excess growth in non-occupant purchases during the boom. In addition, our model illustrates a mechanism for how speculation amplifies the housing cycle, allows us to disentangle the relative importance of short-term and non-occupant buyers, and provides a framework to evaluate the effects of transaction taxes on the housing market.

1. Data

In this section, we describe the data we use to establish the core motivating facts for our model and how we identify speculative buyers in that data. Further information regarding the data is in Online Appendix A.

1.1. Data sources and sample selection

Our main data come from CoreLogic, a private vendor that collects and standardizes publicly available tax assessments and deeds records from across the U.S., and include observations from 115 MSAs. In analyses that require us to identify an owner's occupancy status, we use a subset of 102 MSAs for which we can be sure that there were no major changes in the way that mailing addresses were coded during our sample period. In Online Appendix A, we describe how we select these MSAs. Our analysis of the housing cycle covers the time period 2000 through 2011 because measuring realized holding periods requires observing consecutive transactions.

We include all arms-length transactions of single-family homes, condos, or duplexes that occur at a non-zero price. We then drop a small number of duplicate transactions where the same property is observed selling multiple times at the same price on the same day or where multiple transactions occur between the same buyer and seller at the same price on the same day. In Online Appendix A, we give the steps we follow to arrive at a final sample of 51,580,408 transactions. Given the geographic coverage of these data and their source in administrative records, our sample serves as a proxy for the population of transactions in the U.S. during the sample period.

Our listings data on individual homeowners is also provided by CoreLogic and is sourced from a consortium of local MLS boards throughout the country. For each listing, we observe the date the home was originally offered for sale, an indicator for whether the listing ever sold, and the date of sale for those that did. We link these data to the deeds data using the assessor's parcel number (APN) for the property. When analyzing listings, we focus our attention on a subset of the 115 MSAs for which we can be relatively certain that the listings data are representative of the majority of owner-occupied home sales in the area. In Online Appendix A, we describe the approach we use to select these MSAs, leaving us with a final sample of 57 MSAs for our listings analysis.

We supplement these transaction- and listing-level data with national and MSA-level housing stock counts from the U.S. Census, national counts of sales and listings of existing homes from the National Association of Realtors (NAR), and national and MSA-level nominal house-price indices from CoreLogic. We also use survey data to study heterogeneity in expected holding horizons in the cross-section and over time. Each March, as part of the Investment and Vacation Home Buyers Survey, the NAR surveys a nationally representative sample of around 2000 individuals who purchased a home in the previous year. The survey asks respondents to report the type of home purchased (investment property, primary residence, or vacation property) as well as the "length of time [the] buyer plans to own [the] property." Data on expected holding times and the share of purchases of each type are available between 2008 and 2015.

1.2. Identifying speculators

We identify speculators in our transaction-level data using two complementary approaches, each of which has been used in prior work. In the first approach, we categorize transactions based on their realized holding periods. We denote transactions held for less than three years as "short-term" sales and track the evolution of these sales over time. This approach follows Bayer et al. (2020), who classify speculators as those likely holding homes for short time periods for investment purposes. We similarly denote listings as short-term when the homeowner lists the house less than three years after buying it.

In the second approach, we classify homebuyers based on their occupancy status. Those who purchase a home without the intent to occupy it immediately are more speculative in the sense that a larger portion of their overall expected return is derived from capital gains rather than from the consumption value of living in the home. To identify these buyers, we follow Chinco and Mayer (2015) and mark buyers as non-occupants when the transaction lists the buyer's mailing address as distinct from the property address. While this proxy may

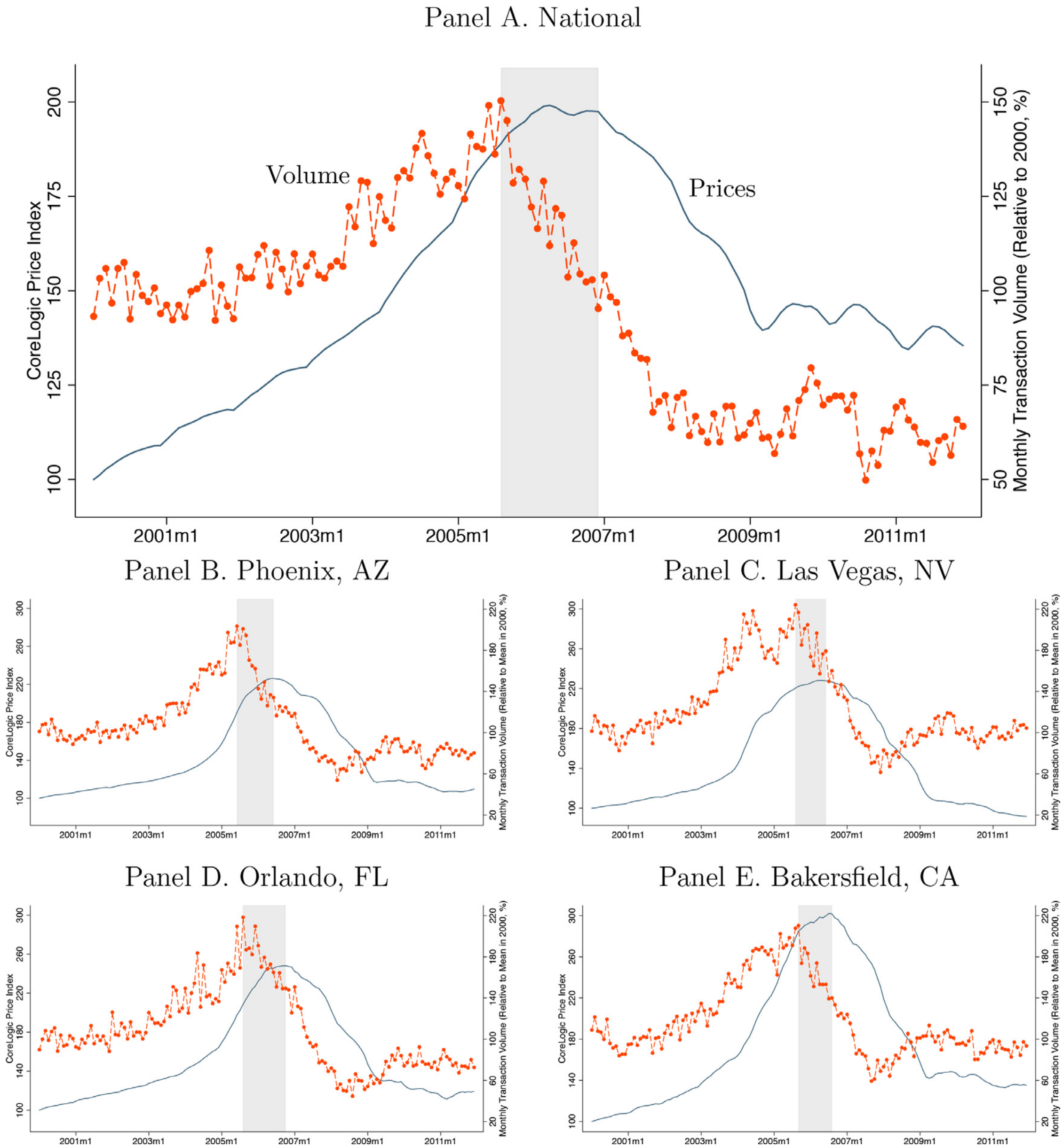


Fig. 1. The dynamics of prices and volume. This figure displays the dynamic relation between prices and volume in the U.S. housing market between 2000 and 2011. Panel A shows monthly prices and sales volume at the aggregate level. Panels B–E show analogous series for a set of cities that represent regions with the largest boom–bust cycles during this time: Phoenix, AZ; Las Vegas, NV; Orlando, FL; and Bakersfield, CA. Monthly price index information comes from CoreLogic and monthly sales volume is based on aggregated transaction data from CoreLogic for 115 MSAs representing 48% of the U.S. housing stock. We apply a calendar-month seasonal adjustment for volume. Shaded regions denote the quiet, defined as the period between the peak of volume and the last peak of prices before their pronounced decline.

misclassify some non-occupants as living in the home if they choose to list the property's address for property-tax-collection purposes, we believe it to be a useful gauge of the level of non-occupant purchases.

One advantage of both methods is that they are based on the full sample of housing transactions. Other work has identified speculators based on the presence of multiple first-lien mortgage records in credit reporting data or self-reported occupancy status on loan applications (Haughwout et al., 2011; Gao et al., 2020; Mian and Sufi, 2022). While based on similar ideas, such approaches may omit a substantial fraction of speculative activity.

2. Dynamics of prices, volume, and inventory

In this section, we document the three phases of the housing cycle we mention above: boom, quiet, and bust. In Panel A of Fig. 1, we plot aggregate trends in prices and volume between 2000 and 2011. In Panels B–E, we plot analogous series for four cities that represent regions with the largest boom–bust cycles during this time: Phoenix,

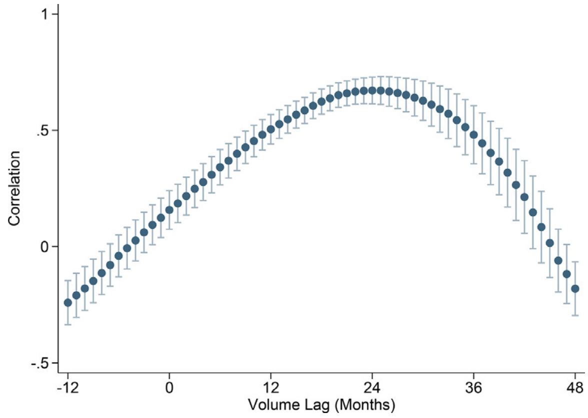


Fig. 2. The lead–lag relation between prices and volume. This figure shows that the correlation between prices and lagged volume is robust across MSAs and maximized at a positive lag of 24 months. We regress the demeaned log of prices on seasonally adjusted lagged volume divided by the 2000 housing stock following Eq. (1) for each lag from -12 months to 48 months and plot the implied correlation and its 95% confidence interval calculated using standard errors that are clustered by month. The implied correlation equals $\beta_k\,\mathrm{std}(v_{i,t-k})/\,\mathrm{std}(p_{i,t})$, where $v_{i,t-k}$ and $p_{i,t}$ are the demeaned regressors.

AZ; Las Vegas, NV; Orlando, FL; and Bakersfield, CA. During the housing cycle, volume peaks before prices, and there is a sustained period during which volume is falling rapidly on high prices. This dynamic holds consistently across regions that experienced large price cycles. At the aggregate level, volume rises to 150% of its level in 2000 and then falls back to this level before prices fall. In the four cities in Panels B–E, volume more than doubles during the boom. Prices subsequently peak between 200% and 300% of their 2000 levels.

Figure 2 shows that this lead–lag relation between prices and volume also holds on average across all MSAs in our sample from 2000 to 2011. We estimate correlations between prices and lagged volume by running regressions of the form:

$$p_{i,t} = \beta_k v_{i,t-k} + \eta_{i,t}, \tag{1}$$

where p is log price demeaned at the MSA level, v is volume normalized by the MSA's 2000 housing stock and demeaned at the MSA–calendar month level, i indexes MSAs, and time is measured in months. Figure 2 plots the correlations implied by each β_k coefficient for up to four years of lags ($k = 48$) and one year of leads ($k = -12$). The correlation is positive at most leads and lags but reaches its maximum at a positive lag of 24 months. Thus, changes in volume generally lead changes in prices by about two years.

In Panel A of Fig. 3, we plot aggregate trends in prices and inventories of homes listed for sale between 2000 and 2011. In Panels B–E, we plot analogous series for four cities that represent the same regions as in Fig. 1. Because Las Vegas and Orlando are not in our listings data, we replace them with the nearby MSAs of Reno and Daytona Beach. During the period when the relation between volume and prices reverses, aggregate inventories rise dramatically to nearly double their level from earlier in the cycle. This pattern also characterizes the joint dynamic of prices and inventories across cities in Panels B–E. In Phoenix, Reno, and Bakersfield, inventories rise during the quiet to between double and triple their earlier levels. In Daytona Beach, inventories rise to 450% of their pre-quiet levels.[2]

These stylized facts suggest that focusing on the dynamic of quantities–both volume and inventories–can provide insight on the drivers of the cycle. In particular, determining who was most heavily participating in the housing market during each phase may help us differentiate between various explanations for that cycle.

3. Speculators during the cycle

This section explores the role of speculators throughout the housing cycle and their correlation with the aggregate dynamics of prices, volume, and inventory.

3.1. Quantities and prices in the boom

Figure 4 presents a simple illustration of the quantitative importance of speculation during the cycle. The figure shows monthly aggregate time series for total transaction volume (with and without new construction), short-holding-period volume, and non-occupant volume calculated using our deeds data. Each series is normalized relative to its average value in 2000 and seasonally adjusted by removing calendar-month fixed effects. For reference, we also report the raw counts of each type of transaction in 2000, 2005, and 2010. To abstract from the effect of foreclosures on speculative volume during the bust, we drop lender acquisitions and dispositions of foreclosed properties when constructing the series in this figure.

While overall volume increased by 40% during the boom years of 2000–2005, speculative volume increased dramatically more. Both short-term sales and purchases by non-occupants approximately doubled between 2000 and 2005. Not only did these speculative components of volume increase more rapidly, but their increase also accounted for a non-trivial portion of the overall increase in volume. For example, total volume increased from 2.73 million transactions in 2000 to 3.82 million in 2005. During the same time period, short-holding-period volume increased from 510 to 940 thousand transactions, which implies that volume growth in this category alone can account for 39% of the total volume increase during the boom.[3] A similar calculation for non-occupant volume (in the 102 MSAs with reliable non-occupant data) implies that this measure of speculative activity can account for 53% of the volume increase during the boom. If we exclude new construction from the total volume statistics–because

[2] We repeat the analyses for Figs. 1–3 for MSAs outside the sand states. The results in Figures IA1, IA2, and IA3 of the online appendix reveal that the patterns we document are not exclusive to these states.

[3] Part of the increase in short-term volume during the boom happens mechanically because total volume is increasing. In Online Appendix B.1, we use conditional selling hazards by buyer cohort to quantify the contribution of an overall increase in total volume to the share of late-boom volume coming from short-term sales. Approximately 90% of the rise in short-term volume comes from the changing composition of buyers, rather than mechanical forces.

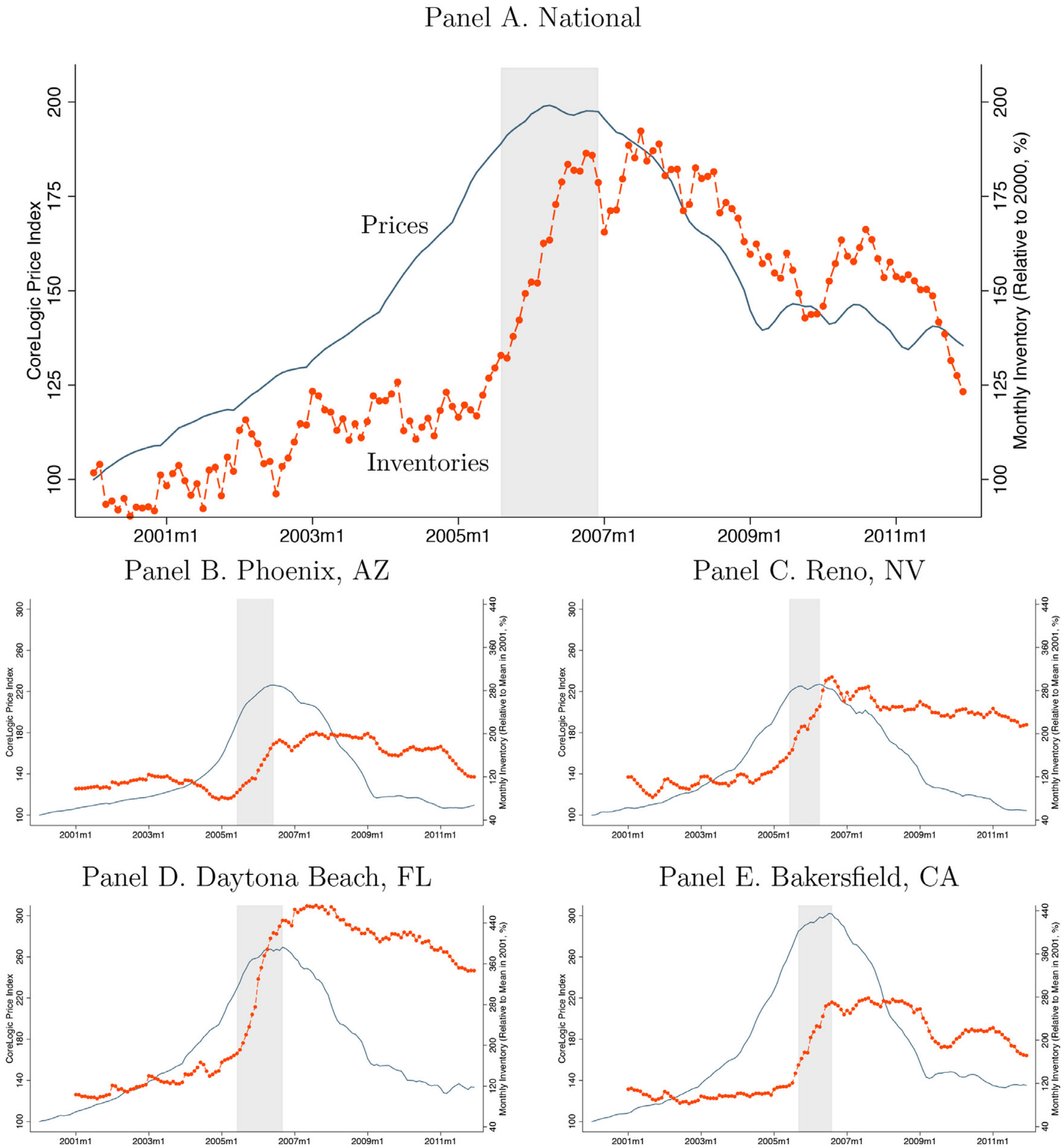
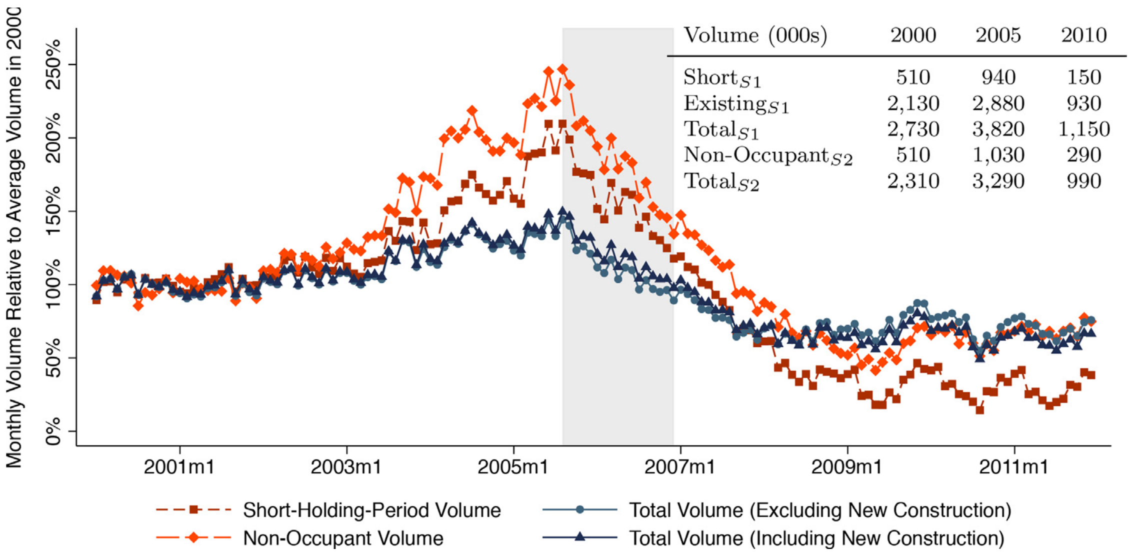


Fig. 3. The dynamics of prices and inventories. This figure displays the dynamic relation between prices and inventory in the U.S. housing market between 2000 and 2011. Panel A shows monthly prices and the inventory of listings at the aggregate level. Panels B–E show analogous series for a set of cities that represent regions with the largest boom–bust cycles during this time: Phoenix, AZ; Reno, NV; Daytona Beach, FL; and Bakersfield, CA. Aggregate inventory information comes from the National Association of Realtors and is available starting in 2000. Our MSA-level inventory data are available for these cities starting in 2001. Monthly price index information comes from CoreLogic and monthly inventory by MSA is based on aggregated data from CoreLogic for 57 of the 115 MSAs in our main sample for which listings data are available. We apply a calendar-month seasonal adjustment for inventories. Shaded regions denote the quiet, defined as the period between the peak of volume and the last peak of prices before their pronounced decline.

short-term sales can only involve homes previously sold–short-term volume accounts for 57% of the aggregate increase in existing home sales. These calculations illustrate that speculators were, in an accounting sense, a key driver of the volume boom.

The shift in the composition of volume toward speculative buyers also correlates highly with changes in total volume across local markets. This correlation can be seen in the top two panels of Fig. 5. Panel A presents scatter plots of the percentage change in total volume at the MSA level from 2000 to 2005 versus the percentage change in volume for short holding periods and long holding periods separately. Not only does the growth in volume of short-holding-period transactions correlate strongly with the increase in total volume across MSAs, but the magnitude of this relation is also much stronger for short holding peri-



Volume (000s)	2000	2005	2010
Short_{S1}	510	940	150
Existing_{S1}	2,130	2,880	930
Total_{S1}	2,730	3,820	1,150
Non-Occupant_{S2}	510	1,030	290
Total_{S2}	2,310	3,290	990

Fig. 4. Normalized aggregate volume by transaction type. This figure shows monthly aggregate time series for total transaction volume (navy triangles), total volume excluding new construction (blue circles), short-holding-period volume (red squares), and non-occupant volume (orange diamonds) between 2000 and 2011. All series exclude lender acquisitions and dispositions of foreclosed properties to remove the mechanical increase in short-term spells driven by forced sales during the bust. The non-occupant volume series only includes observations from the 102 MSAs for which we can consistently identify these transactions; the other series include observations for all 115 MSAs. Each series is separately normalized relative to its average value in the year 2000 and seasonally adjusted by removing calendar-month fixed effects. The raw counts of each type of transaction in the years 2000, 2005, and 2010 are reported in the upper right corner of the figure. In the table, *S*1 refers to the short-holding-period sample of 115 MSAs and *S*2 refers to the non-occupant sample of 102 MSAs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ods relative to long holding periods.[4] A similar conclusion arises from Panel B, which presents analogous scatter plots grouping transactions according to the occupancy status of the buyer rather than the holding period of the seller. The relation between total volume growth and non-occupant volume growth across MSAs is strong, positive, and larger in magnitude than the corresponding relation with growth in sales to owner-occupants.

Panels C and D further show that cross-MSA differences in speculative volume growth explain much of the differences in total volume growth. For each MSA, we plot the change in either short-holding-period volume (Panel C) or non-occupant volume (Panel D) divided by initial total volume on the y-axis against the percentage change in total volume on the x-axis. The slope provides an estimate of how much of a given increase in total volume during this period came in the form of short-holding-period or non-occupant volume. For short-holding-period volume, the answer is 30% (or 36% excluding new construction). For non-occupant volume, the slope is even larger and implies that, for the average MSA in our sample, 54% of the increase in total volume between 2000 and 2005 came from non-occupant purchases. Thus, shifts in the composition of volume toward speculative buyers are a major determinant of changes in total volume during the boom.

Table 2 shows how speculative volume relates to the size of the price and quantity cycles in the cross-section of MSAs (Table 1 shows summary statistics).[5] We estimate the correlation between growth in each speculative measure and various housing market outcomes by separately regressing these outcomes on each measure of speculation. To aid interpretation, we scale the change in outcomes for all quantity measures relative to total volume in 2003.

In Panel A, the first two columns show that house price booms are strongly related to the size of speculative volume booms across cities. Cities with a one standard deviation larger short-volume boom (12.9%) see a 24.9 percentage point larger cumulative price increase during the boom. Cities with a one standard deviation larger non-occupant boom (27.1%) see a 15.4 percentage point larger cumulative price increase during the boom. On average across cities, prices rise by 97% during the boom and quiet.

[4] One concern with our short-term speculation measure is that it is based on realized rather than expected holding periods. This way of measuring short-term speculation may complicate the interpretation of our results if buyers' intended holding periods endogenously respond to changes in economic conditions during the boom. Online Appendix B.2 presents instrumental variable regressions that predict short-term volume using pre-cycle demographics. The change in realized short-term volume is quantitatively important for overall volume growth and the size of the price cycle, even when using only the portion of short-term volume growth predicted by ex-ante buyer characteristics.

[5] We focus our empirical analysis on MSA-level outcomes for two reasons. First, the variation across cities is likely more informative for the aggregate housing cycle. Second, and related to the first, spatial correlation across ZIP Codes within cities hinders interpretation of cross-sectional results for some housing market outcomes. For example, MSA fixed effects account for 86% of the variation in house price booms across ZIP Codes. This fact is likely due to data limitations in house price index estimation, with local price indices often derived from spatial interpolation, and helps explain differences in results in cross-MSA analyses, as in our paper, and cross-ZIP Code, within-MSA analyses, as in Griffin et al. (2020).

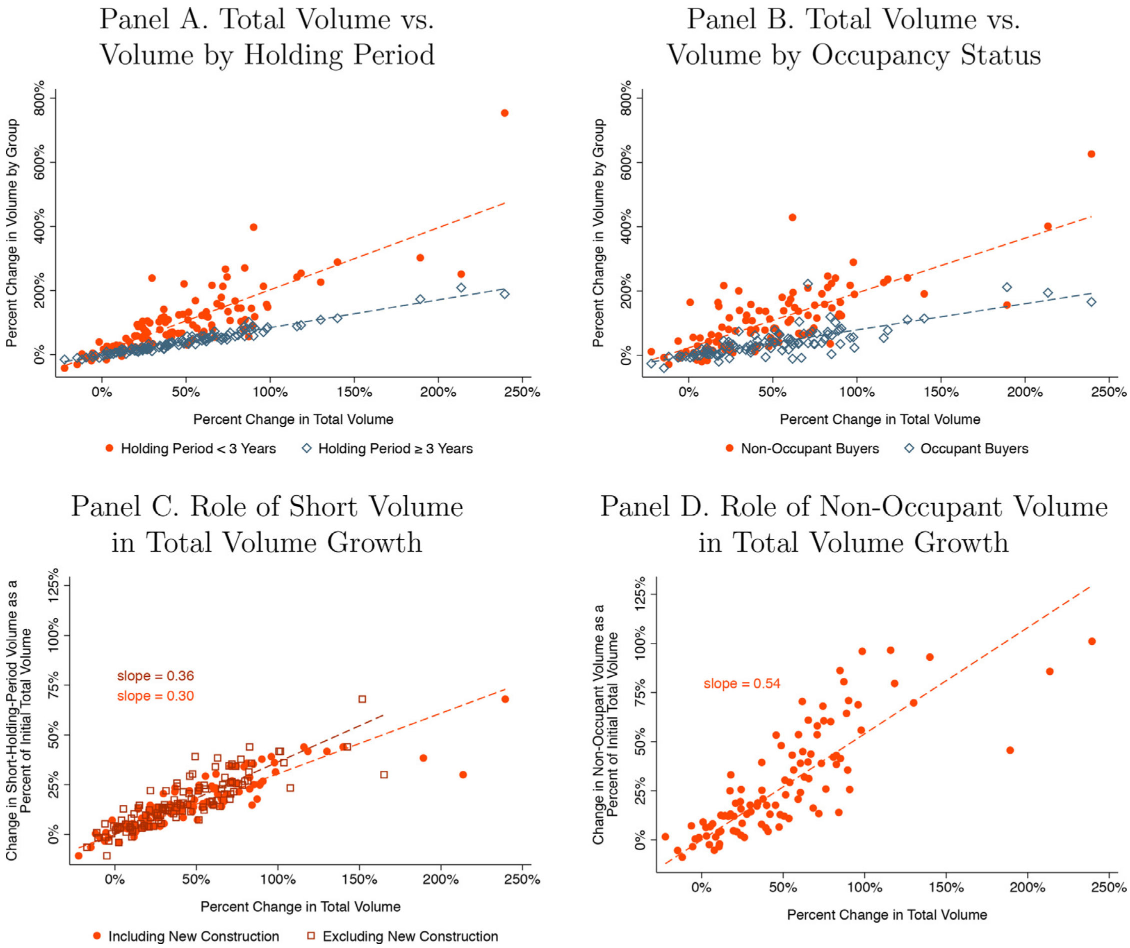


Fig. 5. Short-holding-period, non-occupant, and total volume growth across MSAs. This figure illustrates the quantitative importance of short-holding-period and non-occupant volume in accounting for the increase in total volume across MSAs between 2000 and 2005. The top two panels present MSA-level scatter plots of the percentage change in total volume from 2000 to 2005 versus the percentage change in volume for short and long holding periods (Panel A) and the percent change in volume for occupant and non-occupant buyers (Panel B). The bottom two panels show that the growth in short-holding-period and non-occupant volume were quantitatively important components of the growth in total volume across MSAs. For each MSA, we plot the change in short-holding-period volume (Panel C) and non-occupant volume (Panel D) divided by initial total volume on the y-axis against the percentage change in total volume on the x-axis. Because short-holding-period volume is based on the holding period of the seller and therefore cannot, by definition, include sales of newly constructed homes, Panel C also includes a version of the scatter plot that excludes new construction from total volume.

Thus, the relation between speculative volume and prices is economically large in the cross-section of MSAs.

Consistent with the aggregate evidence in Fig. 3, which shows a modest increase in listings during the boom, we find a small, statistically insignificant relation across MSAs between speculative booms and the change in listings during the boom (Panel B, columns 1–2). Given the strong relation between the short-term and total volume booms, this suggests that the increase in demand during the boom was sufficient to absorb the rising flow of listings from short-term buyers.

3.2. Quantities and prices in the quiet and bust

As discussed in Section 2, there is a quiet period in the housing cycle during which prices rise, transaction volumes rapidly fall, and there is a large increase in unsold listings. In Panel B of Table 2, columns 3 and 4 show that the rise in listings during the quiet correlates strongly with the run-up of speculative volume during the boom across MSAs. Cities with a one standard deviation larger short-volume boom (12.9%) see a larger cumulative increase in listings during the quiet of 76.9 percentage points relative to the total volume in 2003. Cities with a one standard deviation larger non-occupant boom (27.1%) see a cumulative increase in listings during the quiet of 71.7 percentage points relative to the total volume in 2003. Across cities, the mean increase in inventories during the quiet is 178% of 2003 total volume with a standard deviation of 144%. Thus, the relation between speculative booms and the rise of listings is quantitatively important in accounting for the cross-section of inventories.[6]

[6] Table 2 reports the change in the inventory of unsold listings. In the online appendix, Table IA6 reports analogous results using the change in the flow of new listings and shows qualitatively similar results. The rise in

Table 1

Speculators and housing market outcomes (summary statistics). This table reports summary statistics for MSA-level variables in different samples of MSAs. Δ Volume Quiet + Bust is defined as the change in total volume from 2005 through 2011. Δ Listings Boom is defined as the change in total listings from 2003 through 2005. Δ Listings Quiet is defined as the change in total listings from 2005 through 2007. Foreclosures Bust is defined as total foreclosures from 2007 through 2011. Price Boom is defined as the change in prices from 2000 through 2006. Price Bust is defined as the change in prices from 2006 through 2011. To aid interpretation of these relations, we scale the change in outcomes for all quantity measures relative to total volume in 2003 and multiply by 100. Total volume in 2003 has mean 28,061 and standard deviation 43,708 in the Short Volume Sample and mean 25,167 and standard deviation 35,967 in the Short Volume Sample with Listings.

Variable	Mean	Standard Deviation	Observations
Panel A. Short-Volume Sample			
Short-Volume Boom	15.97	12.93	115
Price Boom	97.06	47.88	115
Price Bust	-27.9	13.64	115
Δ Volume Quiet + Bust	-62.96	18.87	115
Foreclosures Bust	82.84	55.96	115
Panel B. Non-Occupant Volume Sample			
Non-Occupant Volume Boom	29.29	27.05	102
Short-Volume Boom	16.88	13.36	102
Price Boom	100.57	49.27	102
Price Bust	-28.99	13.97	102
Δ Volume Quiet + Bust	-63.32	19.47	102
Foreclosures Bust	86.57	58.08	102
Panel C. Short-Volume Sample with Listings			
Short-Volume Boom	14.64	12.33	57
Δ Listings Boom	91.67	94.93	57
Δ Listings Quiet	178.39	143.86	57
Panel D. Non-Occupant Volume Sample with Listings			
Non-Occupant Volume Boom	27.81	27.32	48
Short-Volume Boom	15.84	12.88	48
Δ Listings Boom	82.11	93.67	48
Δ Listings Quiet	171.74	151.29	48

In Fig. 6, we supplement this cross-MSA evidence by showing that short-term listings account for the majority of the increase in new listings from 2003 to 2007. We plot monthly series for total and short-term new listings, normalizing each series relative to its 2003 average and seasonally adjusting by removing calendar-month effects. These data only include a home listed for sale the first time it appears during a listing spell to avoid double-counting unsold listings. While total new listings rise to 150% of their 2003 average at the quiet's peak, short-term listings rise to 250% of their 2003 average and remain above 200% well into the bust. Short-term listings rise from 280 to 590 thousand, accounting for 55% of the rise in total new listings from 1.17 million to 1.73 million. In later stages of the bust, short-holding-period listings fall well below the 2003 level, consistent with the idea that purchases in the quiet and early bust are more likely to include fundamental buyers and longer-term investors.[7] This evidence suggests that attempted sales by speculators who bought during the boom explain much of the increase in listings during the quiet, and that the reduced entry of speculators during the quiet contributes to the eventual decline in total volume.

Larger speculative booms also predict stronger contractions in total volume and prices during the end of the cycle. Panel C of Table 2 shows that cities with a one standard deviation larger short-volume boom and non-occupant boom respectively see cumulative declines in total volume (relative to 2003 volume) that are 13.5 and 13.9 percentage points larger. The analogous results for prices, shown in columns 3 and 4 of Panel A, imply 7.4 and 4.5 percentage point larger declines during the bust. Thus, speculative booms explain much of the 63% average decline in volume during the quiet and bust (relative to 2003 volume) and 28% decline in prices during the bust. These cross-MSA results are consistent with the aggregate pattern in Fig. 4, in which speculative volume declines more sharply during the quiet and bust than does total volume. Turning points in both short-holding-period

unsold listings during the quiet is driven both by an increase in the rate at which homes were listed for sale and a reduction in the probability of sale conditional on listing. In the online appendix, we repeat the analysis for Tables 2 and IA6, while including an indicator for whether the MSA is in a sand state. The results in Tables IA7 and IA8 are similar, though somewhat weaker for the non-occupant volume boom.

[7] This evidence complements Genesove and Mayer (1997, 2001), who document the role of home equity and loss aversion, respectively, in preventing list prices from adjusting downward during a market downturn in Boston. Short-holding-period buyers are more likely to maintain high list prices because–in the home equity view–they will have paid down less of their mortgages when they turn to sell and because–in the loss aversion view–they will have paid higher initial prices than long-holding-period buyers. In our model, extrapolation creates another force causing recent buyers to set overly optimistic list prices, the same force that helps explain their initial entry into the market.

Table 2
Speculative booms and housing market outcomes. This table reports estimates of the relation between speculative volume and housing cycle measures at the MSA level. Δ Volume Quiet + Bust is defined as the change in total volume from 2005 through 2011. Δ Listings Boom is defined as the change in total listings from 2003 through 2005. Δ Listings Quiet is defined as the change in total listings from 2005 through 2007. Foreclosures Bust is defined as total foreclosures from 2007 through 2011. Price Boom is defined as the change in prices from 2000 through 2006. Price Bust is defined as the change in prices from 2006 through 2011. To aid interpretation of these relations, we scale the change in outcomes for all quantity measures relative to total volume in 2003 and multiply by 100. Table 1 presents summary statistics for each sample. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively. Standard errors appear in parentheses.

Panel A. MSA-Level Prices				
	Price Boom		Price Bust	
Short-Volume Boom	1.930***		−0.571***	
	(0.297)		(0.083)	
Non-Occupant Volume Boom		0.570***		−0.166***
		(0.173)		(0.049)
Number of Observations	115	102	115	102
R-squared	0.272	0.098	0.293	0.103
Panel B. MSA-Level Inventories				
	Δ Listings Boom		Δ Listings Quiet	
Short-Volume Boom	−1.133		5.961***	
	(1.027)		(1.353)	
Non-Occupant Volume Boom		−0.070		2.645***
		(0.505)		(0.718)
Number of Observations	57	48	57	48
R-squared	0.022	0.000	0.261	0.228
Panel C. MSA-Level Volume Quiet and Bust				
	Δ Volume Quiet + Bust		Foreclosures Bust	
Short-Volume Boom	−1.047***		0.895**	
	(0.096)		(0.398)	
Non-Occupant Volume Boom		−0.512***		−0.060
		(0.051)		(0.215)
Number of Observations	115	102	115	102
R-squared	0.515	0.505	0.043	0.001

Fig. 6. The flow of listings for short-holding-period buyers. In this figure, we illustrate the time variation in propensities to list among recent buyers versus all buyers between 2000 and 2011 in the U.S. We link listings micro data to transaction data at the property level to identify short-holding-period listings. We plot monthly aggregate time series for total listings (blue circles) and short-holding-period listings (red squares), defined as a listing where the previous sale occurred within the past three years. The series include observations for the 57 MSAs in our listings sample. Each series is separately normalized relative to its average value in the year 2003 and seasonally adjusted by removing calendar-month fixed effects. The raw counts of each type of listing in the years 2003, 2007, and 2010 are also reported in the upper right corner of the figure. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and non-occupant volume exactly coincide with the turning point in aggregate volume, the sharp rise in listings during the quiet, and the decline in price growth before its reversal.

Finally, we find that cities with larger short-term speculative booms experienced more severe foreclosure crises. The estimate in column 3 of Panel C implies that a one standard deviation increase in the short-volume boom is associated with 11.5 percentage points more foreclosures (relative to 2003 volume) in the bust, equal to 370 thousand more foreclosures. This effect is large relative to the 2.68 million foreclosures across the 115 MSAs in our data. In contrast, the relation between foreclosures and the non-occupant boom is insignificant (column 4 of Panel C).

3.3. Summary of main empirical results

Our results show strong relations between speculative purchases during the boom and the amplitude of the housing cycle. Across cities, a larger speculative boom predicts sharper increases in prices and volume during the boom, a greater boom and bust in prices, a larger surge in listings during the quiet, and a more pronounced fall in volume during the quiet and bust. Time series evidence also indicates that speculation accounts for much of the increase in volume during the boom and listings during the quiet.

These results suggest the following narrative linking short-term speculators to the housing cycle. As prices increase in the boom, short-term speculators buy houses in anticipation of capital gains, and this buying activity pushes up prices further. As price growth eventually slows, speculative volume slows, contributing disproportionately to the decrease in total volume. At the same time, speculative buyers from the recent past–who are now looking to sell–continue to generate a new flow of listings. Because smaller expected capital gains attract fewer new speculative buyers to the market, many of these new listings fail to sell. Prices rise as volume falls, which suggests sellers are still posting higher prices. The result is a quiet period with falling volume, rising inventories, and slowing price growth. Accumulating inventories and falling demand eventually result in negative price growth, which creates a lead–lag pattern between the drops in volume and prices. The goal of our model is to illustrate this causal narrative theoretically.

4. Characterizing speculative buyers

In this section, we use our microdata and other data to provide additional insight on speculative purchases. These facts motivate how we model speculation.

4.1. Extrapolation among speculators

Using multiple measures of speculation, we examine whether house price growth can predict subsequent speculative purchases and beliefs in the housing market. Our first measures use our deeds dataset. For each MSA and year from 2000 to 2011, we count total non-occupant purchases and divide by the equivalent count from 1999 as a normalization. We do the same for short-term purchases, defined here as those for which we observe another sale on the same property in the next three years. Panels A and B of Fig. 7 present binned scatter plots of normalized speculative purchases against house price growth in the past year. Both non-occupant and short-term purchases are much higher in the years and MSAs that witness higher house price appreciation in the last year.[8]

The second measure of speculation uses responses from the NAR's Investment and Vacation Home Buyers Survey. For each year of the survey, we calculate the fraction of respondents (except those reporting “don't know”) who report an expected holding time of less than three years or had already sold their home by the time of the survey. This measure captures the intention of buyers at the time of purchase. Thus, it complements our transaction-based metric that relies on realizations of short horizons after the fact. In Panel C of Fig. 7, we plot this measure of speculation against annual house price growth at the national level. A gain of 10% in house prices over the past year is associated with an 8.2 percentage point larger short-term buyer share.

Our final measures of speculation use responses from the 2014–2017 waves of the Federal Reserve Bank of New York's Survey of Consumer Expectations.[9] This survey asks respondents' views on housing as an investment as well as their probability of buying a non-primary home in the next three years. Thus, the survey directly queries non-occupant housing demand, complementing the measure of non-occupant purchases in our deeds data. Panels D and E of Fig. 7 present binned scatter plots of the survey measures against appreciation in the Zillow house price index over the past five years in the respondent's ZIP Code. The share of respondents saying that housing is a very good investment rises with local house price appreciation; the opposite is true for those calling housing a bad or very bad investment. The reported probability of buying a non-primary home also rises with lagged house price growth.

In summary, house price growth predicts increased speculative purchases in three different datasets. These results complement survey evidence showing that expected future house price growth rises with realized past house price growth (Case et al., 2012; Armona et al., 2019). We incorporate extrapolative beliefs into our model in such a way that speculative purchases and posted list prices respond strongly to recent price growth. This modeling choice builds on prior studies that use extrapolative expectations to understand other aspects of the housing market (Glaeser et al., 2008; Guren, 2014; Glaeser and Nathanson, 2017).

4.2. Overlap between short-term and non-occupant buyers

In this section, we examine overlap between short-term and non-occupant buyers. Data from the NAR's Investor

[8] In Online Appendix B.3, we estimate higher-frequency panel VAR specifications of speculative volume and lagged house price appreciation, in the style of Chinco and Mayer (2015). The positive relation between prices and speculative purchases continues to hold.

[9] The data come from the replication files of Armona et al. (2019). We thank Andreas Fuster for sharing this evidence with us.

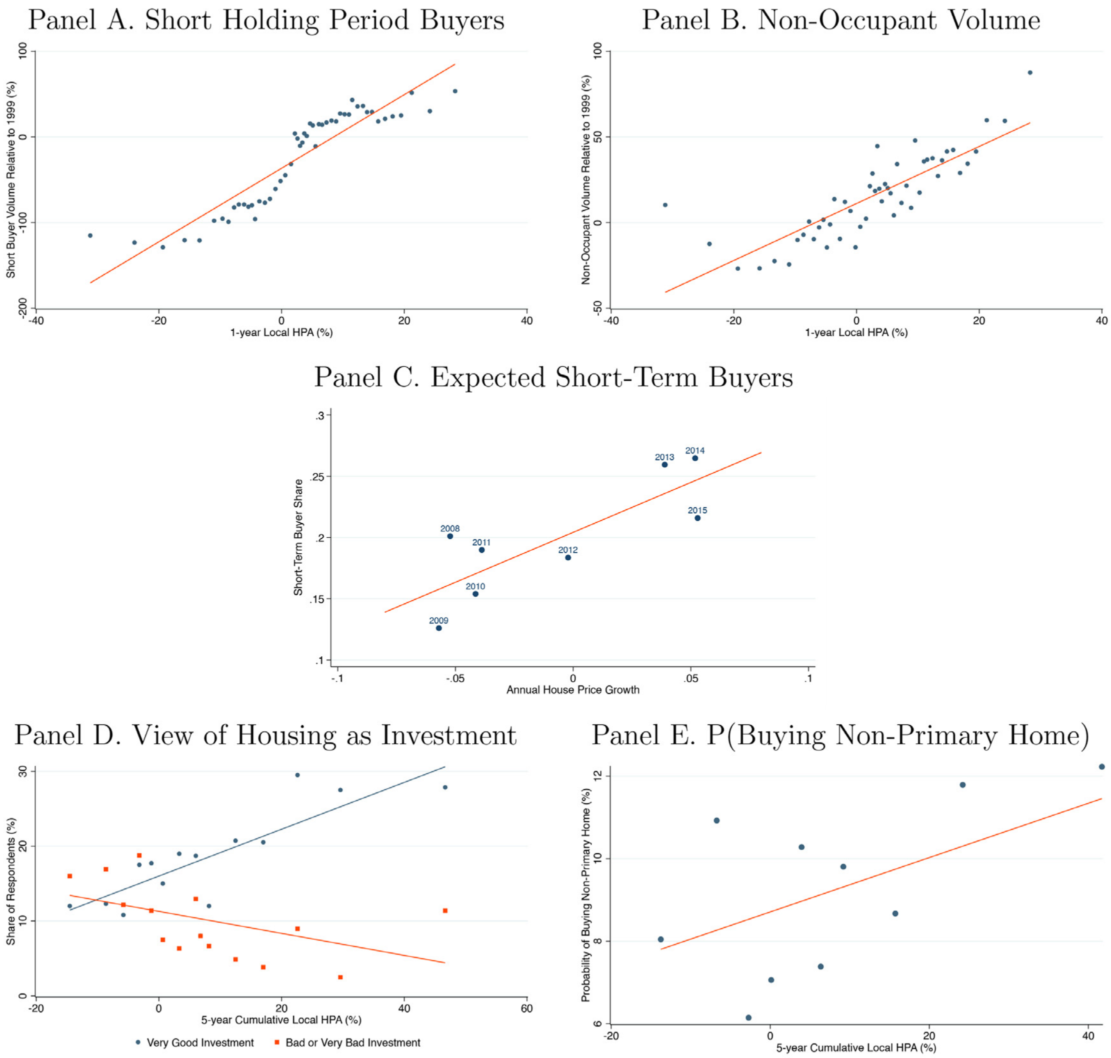


Fig. 7. Speculative homebuying and recent house price appreciation. Panels A and B use CoreLogic data to show the relation between short holding period volume and non-occupant volume at the MSA level, respectively, and the past year's house price appreciation. Volume measures are scaled relative to their level in 1999. Short-holding-period volume in Panel A is forward-looking, i.e., it is based on whether the buyer sells within three years. Panel C uses data from the NAR Investment and Vacation Home Buyers Survey; "annual house price growth" equals the average across that year's four quarters of the log change in the all-transactions FHFA U.S. house price index from four quarters ago, and "short-term buyer share" equals the share of respondents other than those reporting "don't know" who report an expected horizon of less than three years. We use the FHFA index here because it covers the 2015–2016 period. Panels D and E use data from the Federal Reserve Survey of Consumer Expectations and Armona et al. (2019) to study the relation between recent house price growth and the probability of buying a non-primary home. In these data, local house price appreciation is computed at the ZIP Code-level from Zillow.

and Vacation Home Buyers Survey report expected holding times separately for investor and non-investor buyers. As Fig. 8 shows, about 20% of investor buyers report expected holding periods of under three years, larger than the corresponding share among non-investor buyers. Therefore, these data provide direct evidence of overlap between short-term and non-occupant buyers.

To focus on speculators who entered during the 2000–2005 boom, we also measure this overlap in our CoreLogic data. We find that 27% of 2000–2005 short-term volume came from non-occupant buyers, while 41% of the increase in short-term volume over this time came from non-occupants (see Online Appendix C.1 for details). Therefore, non-occupants account for an excess share of the growth in short-term buyers.

The evidence in this section indicates that there is substantial overlap between short-term and non-occupant buyers. In light of this evidence, we allow for such overlap in our model.

4.3. Credit utilization

To examine the role credit plays in enabling speculative volume, we present in Table 3 summary statistics on the proportion of all-cash purchases in our data. Column 1 shows that 29% of short-term buyers and 38% of non-

Table 3
All-cash buyer shares. This table presents statistics on the share of buyers of various types who purchased their homes without the use of a mortgage (all-cash buyers). In column 1, the all-cash buyer share is measured at the transaction level and includes all transactions recorded between January 2000 and December 2011 from the CoreLogic deeds records described in Section 1.1. The first row includes only transactions by homebuyers who are observed to have sold the home within three years of purchase. The second row includes only non-occupant buyers. The third row includes all buyers. In columns 2–5, all-cash buyer shares are first calculated at the MSA-by-month level and then averaged across MSA-months within a given time period. The standard deviation of these MSA-month means is reported in parentheses for reference. Column 2 includes all MSA-months between January 2000 and December 2011. Column 3 includes only MSA-months between January 2000 and August 2005. Column 4 includes only MSA-months between August 2005 and December 2006. Column 5 includes only MSA-months between December 2006 and December 2011. All statistics are calculated in the full sample of 115 MSAs with the exception of those for non-occupants, which are calculated in the sample of 102 MSAs with valid non-occupancy data.

	Transaction-Level	MSA-Level			
	All Months	All Months	Boom	Quiet	Bust
Short Buyers	0.29	0.38	0.29	0.28	0.52
		(0.21)	(0.16)	(0.17)	(0.20)
Non-Occupant Buyers	0.38	0.41	0.36	0.32	0.50
		(0.18)	(0.15)	(0.14)	(0.18)
All Buyers	0.20	0.25	0.22	0.20	0.30
		(0.16)	(0.15)	(0.14)	(0.16)

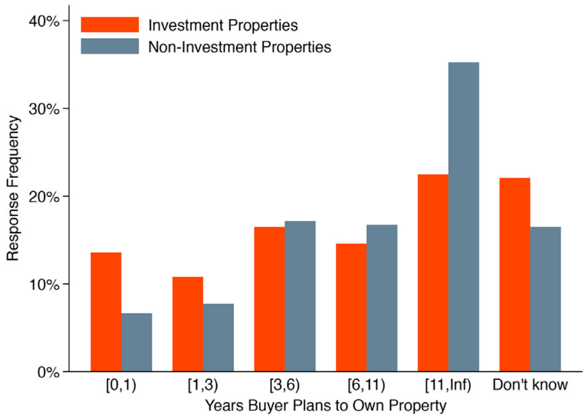


Fig. 8. Expected holding times of homebuyers, 2008–2015. This figure presents evidence on heterogeneity in expected holding times among recent homebuyers from the NAR Investment and Vacation Home Buyers Survey. We plot the response frequency averaged equally over each survey year from 2008 to 2015. We reclassify buyers who have already sold their properties by the time of the survey as having an expected holding time in [0,1).

occupant buyers do not use a mortgage. These shares exceed the all-cash share among all buyers, which is 20%. The remaining columns of the table report averages at the MSA-by-month level and show that all-cash transactions among speculators remain high at all points of the housing cycle. Thus, while credit may have enabled speculation, there is a disproportionately large group of speculators who do not use credit at all. The behavior of these buyers goes unobserved in any analysis of speculative activity based on mortgage data alone.[10]

In Online Appendix C.2, we study the relation between leverage and short-term volume growth. We find that short-term sales increase most strongly among sellers whose LTV when purchasing the home was between 60% and 85%. This evidence is consistent with prior work documenting credit growth among speculators during the boom (Haughwout et al., 2011; Bhutta, 2015; Mian and Sufi, 2022). However, it also suggests that very high credit utilization (LTV $\geq$ 85%) does not account for most of the rise in speculative buying.

Motivated by these findings, we omit credit constraints from our model of housing market speculation. We stress that, although we omit credit from the model, our findings are compatible with stories in which credit enables speculative entry during the cycle.

4.4. Buyer scale and experience

Next, we examine whether short-term buyers are individuals buying a few houses or firms buying many houses. In Online Appendix C.3, we present a methodology for classifying buyers as real estate developers, experienced investors holding three or more homes, or inexperienced buyers owning one or two homes. Of the short-term sales in 2000–2005, 15% of the initial purchases are from developers, 24% are from experienced investors, and 61% are from inexperienced buyers. This evidence is consistent with Bayer et al. (2020, 2021) who also find an important role for inexperienced short-term investors during this episode. In light of the large share of inexperienced buyers among short-term sellers, we allow buyers to own only one house in our model.

Finally, we explore whether short-term sellers remain within the MSA by buying another house nearby. We link transactions within MSA in our data by comparing names of buyers and sellers. As we describe in Online Appendix C.3, 69% of short-term sellers do not buy in the MSA within a quarter of the sale. To match the high share of such sellers, we assume in our model that homeowners exit the local housing market upon selling their house.

5. The model

The goal of our model is to match the joint dynamics of prices, volume, and listings. Additionally, the model

[10] The correlations between the speculative booms in Table 2 and their analogous counterparts that exclude cash transactions are approximately 0.9. Thus, while excluding all-cash transactions would understate the importance of speculators in the aggregate, the cross-sectional relationships in Table 2 are robust to excluding these transactions.

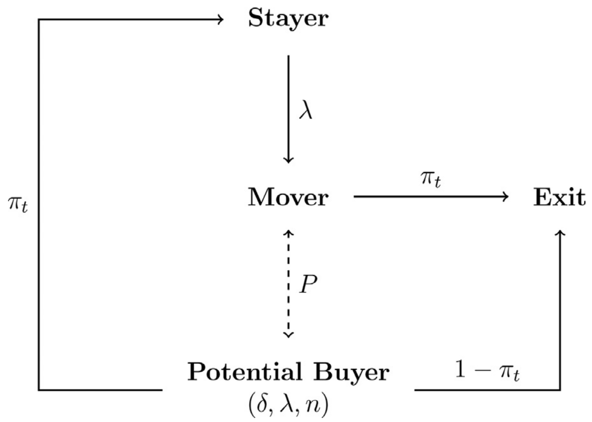


Fig. 9. Model flowchart. This figure illustrates how agents in the model transition between different types. At each time period, t, all movers list their homes for sale and are matched to potential buyers. Potential buyers decide whether to purchase at the mover's listed price P. If a potential buyer purchases, she becomes a stayer and receives a constant per-period housing utility e^{δ} during each period that she remains a stayer. If she does not purchase, she exits the market and consumes her terminal wealth. A stayer transitions into being mover with probability λ each period. The log of the housing utility, δ, that potential buyers who purchase will receive as stayers is the sum of a time-varying aggregate demand shifter, d_t, which is common to all potential buyers matched at time t, and an idiosyncratic term, a, which varies across potential buyers within a given cohort. The idiosyncratic term a is distributed $\mathcal{N}(\mu_n, \sigma_a)$ and depends on the potential buyer's type, n, which can be either occupant $(n = 1)$ or non-occupant $(n = 0)$. The mover hazard λ also differs across potential buyers and follows a discrete distribution given by $\Pr(\lambda = \lambda_j) = \beta_{n,j}$, for $j \in \{1, \ldots, J\}$. Potential buyers are aware of both δ and λ at the time they decide to purchase. Movers receive zero housing flow utility during the time when they are attempting to sell. Those who do not sell remain movers in the next period and those who do sell exit the market and consume their terminal wealth. We denote the probability of a sale by π_t.

should explain the disproportionate role of non-occupants and short-term sales in generating these dynamics.[11] In doing so, the model complements our empirical analysis by permitting stronger causal statements about the role of speculation and allowing us to conduct counterfactual explorations of model assumptions and policy design.

5.1. Environment and preferences

We present a discrete-time model of a city with a fixed amount of perfectly durable housing, normalized to have measure 1. There are three types of agents in the model: movers, stayers, and potential buyers. Movers are city homeowners who are trying to sell their homes. Stayers are city homeowners who do not list their homes for sale. Potential buyers are people from outside the city who get a one-time chance to buy a house from a mover. In Fig. 9, we illustrate how agents transition between these three types.

All agents are risk-neutral and can borrow or lend across periods at an interest rate of r. They maximize their expectation of the discounted present value of their per-period utility, which is the sum of two components: housing utility and non-housing consumption, whose price we normalize to 1.

Each period, a mover lists her house for sale by posting a list price, P. She then matches randomly to a potential buyer from outside the city, who decides whether to purchase at the listed price.[12] In the event of a sale, the mover exits the market and consumes her terminal wealth. Movers who fail to sell remain movers next period. We denote the share of listings that sell at time t by π_t. Movers receive 0 housing utility while listing their homes. They are impatient and discount time at rate $r_m \geq r$.

Potential buyers who decide to buy become stayers at the beginning of the next period. Those who do not buy exit the market and consume their terminal wealth. Stayers receive housing utility e^{δ} at the beginning of each period, but cannot sell their house. With probability λ each period, a stayer transitions to being a mover, at which point she lists her home for sale. Housing utility e^{δ} and the mover hazard λ remain constant for a given stayer over time but may vary across stayers. All stayers discount time at rate r.[13]

At time t, each potential buyer knows the housing utility she would receive while being a stayer if she chooses to purchase and the probability λ that she would transition into becoming a mover each period. For each potential buyer within a given cohort, the log of her housing utility, δ, is the sum of a time-varying aggregate demand shifter, d_t, and an idiosyncratic term, a, that varies across potential buyers at a point in time:

$$\delta = d_t + a. \tag{2}$$

Potential buyers observe their own value of δ but do not separately observe d_t and a. That is, they cannot determine what fraction of their personal valuation is common to all potential buyers in their cohort.

The demand shifter d_t affects the distribution of housing utility across different cohorts of potential buyers over time. We model it as a difference-stationary process with a persistent growth rate:

$$\begin{aligned} d_t &= d_{t-1} + g_t + \epsilon_t^d \\ g_t &= (1-\rho)\mu_g + \rho g_{t-1} + \epsilon_t^g, \end{aligned}$$

where $0 \leq \rho < 1$, and ϵ_t^d and ϵ_t^g are mean-zero independent normals. We denote $\sigma_d^2 = \mathrm{Var}(\Delta d_t)$ and $\gamma = \mathrm{Var}(g_t)/\mathrm{Var}(\Delta d_t)$, which implies that the variances of ϵ_t^d and ϵ_t^g are $(1-\gamma)\sigma_d^2$ and $\gamma(1-\rho^2)\sigma_d^2$, respectively. As with d_t, the growth rate g_t is unobservable to all agents in the model.

The idiosyncratic term a generates within-cohort heterogeneity in housing utility. We assume that there are two types of potential buyers, indexed by n: non-occupants $(n = 0)$ and occupants $(n = 1)$. To capture the idea that non-occupants generally receive smaller flow benefits from their homes than occupants, we allow the distribution of a

[11] In Online Appendix D, we discuss the relation between our model and prior work in detail.

[12] In other models, some movers fail to match to a potential buyer due to search frictions (Head et al., 2014; Guren, 2018). We abstract from this possibility.

[13] We assume that r is large enough to rule out rational bubbles and provide the precise condition for this in Online Appendix E.1.

to vary across these two groups. Specifically, the distribution of a across potential buyers of type n at each time t is $\mathcal{N}(\mu_n, \sigma_a^2)$. Each potential buyer knows whether she is a non-occupant or an occupant.

Finally, to capture heterogeneity in expected holding periods, we allow λ to vary across potential buyers within each cohort. We assume that λ follows a discrete distribution with possible values $\lambda \in \{\lambda_1, \ldots, \lambda_J\}$ and denote the joint probability that a potential buyer is of occupancy-type n and has mover hazard λ_j to be $\beta_{n,j}$. Thus, the distribution of expected investment horizons can also differ across non-occupants and occupants.

5.2. Inference about demand

To forecast the price at which they will eventually sell their house, agents must estimate the current level of the demand shifter, d_t, and its growth rate, g_t. Agents use historical data on city house prices to estimate these latent variables. We focus on equilibria in which all movers at a given time post the same list price, which we denote P_t (conditions for this outcome are below). Agents at time t observe the full history of price changes, $P_{t'}/P_{t'-1}$ for $t' < t$. They deduce any past price level, $P_{t'}$, by inflating the list price they observed as a potential buyer by cumulative price growth between the time of their purchase and t'. Agents also observe the history of the shares of listings that sell, $\pi_{t'}$ for $t' < t$.

To infer d_t and g_t from historical market data correctly, an agent needs to know how past potential buyers used market data to decide whether to buy a house. Following Glaeser and Nathanson (2017), we depart from rationality and propose that agents instead adopt a simplified model of how other agents decide to buy a house. Specifically, agents believe that other agents decide to buy a house if and only if:

$$e^{\delta} \geq \overline{\kappa} P, \tag{3}$$

where P is the list price of the house and $\overline{\kappa}$ is a time-invariant constant that is common across all potential buyers. As we discuss in Section 6.3, this is the key behavioral assumption that generates positive feedback and bubble-like dynamics within our theoretical framework. In employing this mental model, agents neglect the fact that the beliefs, and therefore the decision rule, of potential buyers could vary over time based on the changing history of market data.[14] However, conditional on the beliefs implied by this simplified model, agents make decisions optimally.

Given Eq. (2) and the decision rule in (3), agents believe that other agents buy if and only if:

$$a \geq \log P + \log \overline{\kappa} - d_t.$$

Therefore, according to agents' simplified model, the share of potential buyers at time t who would purchase at list price P is:

$$1 - F(\log P + \log \overline{\kappa} - d_t) \equiv \tilde{\pi}(P, d_t), \tag{4}$$

where $F(a) = \sum_{n=0}^{1} \sum_{j=1}^{J} \beta_{n,j} \Phi(a - \mu_n)$ is the CDF of a across both non-occupants and occupants, and $\Phi(\cdot)$ is the CDF of a normal random variable with mean 0 and variance σ_a^2.

Given market data on historical prices $P_{t'}$ and sales shares $\pi_{t'}$, agents at time t use Eq. (4) to infer past values of the demand shifter. In particular, by equating $\pi_{t'}$ to $\tilde{\pi}(P_{t'}, d_{t'})$, they infer that:

$$\tilde{d}_{t'} = \log P_{t'} - F^{-1}(1 - \pi_{t'}) + \log \overline{\kappa}, \tag{5}$$

where $\tilde{d}_{t'}$ denotes an agent's belief about the true value of the demand shifter $d_{t'}$. Given this inferred history of the demand shifter, agents employ a standard Kalman filter to arrive at posterior estimates of its current value, d_t, and its growth rate, g_t. Lemma 1 characterizes these posteriors (all proofs are in Online Appendix E).

Lemma 1. Conditional on house prices and sale probabilities before t, the posterior distributions of d_t and g_t are $\mathcal{N}(\hat{d}_t, \hat{\sigma}_d^2)$ and $\mathcal{N}(\hat{g}_t, \hat{\sigma}_g^2)$, where:

$$\hat{d}_t = \tilde{d}_{t-1} + \hat{g}_t$$

$$\hat{g}_t = \mu_g + (1-\alpha)\rho \sum_{k=1}^{\infty} (\alpha\rho)^{k-1} \left(\Delta\tilde{d}_{t-k} - \mu_g\right),$$

and $\hat{\sigma}_d$, $\hat{\sigma}_g$, and $\alpha \in (0,1)$ are constants depending on σ_d, γ, and ρ.

Together with Eq. (5), Lemma 1 shows that agents estimate the current level of the demand shifter, d_t, and its growth rate, g_t, from historical market data in a straightforward manner. In particular, differencing Eq. (5) yields:

$$\Delta\tilde{d}_{t-k} = \Delta \log P_{t-k} - \Delta F^{-1}(1 - \pi_{t-k}),$$

which implies that the expected growth rate, $\hat{g}_t$, is a weighted average of past price growth adjusted downward each period to reflect any increase in the share of unsold listings. The expected demand shifter, $\hat{d}_t$, equals this expected growth rate plus agents' belief about last period's demand shifter.

5.3. Mover problem

The mover's problem is to select a list price that maximizes the expected present value of utility conditional on beliefs about the demand shifter and its growth rate. We write the problem recursively as:

$$V^m(\hat{d}_t, \hat{g}_t) = \sup_P E\Big(\tilde{\pi}(P, d_t)P + (1 + r_m)^{-1}(1 - \tilde{\pi}(P, d_t)) \\ V^m(\hat{d}_{t+1}, \hat{g}_{t+1})\Big), \tag{6}$$

where the expectation is over $d_t \sim \mathcal{N}(\hat{d}_t, \hat{\sigma}_d^2)$. If the potential buyer who matches to the mover buys, the mover receives P and exits the city. The first term, $\tilde{\pi}(P, d_t)P$, gives the mover's perceived probability of this event times the payoff. The second term gives the discounted value of continuing as a mover next period times the probability of that event.

All movers at time t post the same list price when a unique P maximizes the right side of Eq. (6). We verify the

[14] This simplified model of other agents' willingness to pay is the same as the "cap rate error" that Glaeser and Nathanson (2017) introduce. That paper motivates this error by showing that common knowledge of rationality is not robust to small mistakes and involves unintuitive decision rules as a function of past prices.

existence of such a price at each point of the state space in our quantitative exercise. Lemma 2 clarifies how this price depends on mover beliefs, $\hat{d}_t$ and $\hat{g}_t$.

Lemma 2. The optimal list price takes the form $P_t = e^{\hat{d}_t} p(\hat{g}_t)$ *for some function* $p(\cdot)$.

The log list price scales one-for-one with the current belief about the level of the demand shifter, $\hat{d}_t$. It also depends on the belief about the growth rate, $\hat{g}_t$, because the option of selling next period becomes more valuable when movers expect faster demand growth.

Because $\hat{d}_t$ and $\hat{g}_t$ depend on historical market data, we can also characterize price posting as a function of past prices and sales shares. To provide intuition about price posting, Lemma 3 shows that when r_m is large, movers set prices in a simple extrapolative fashion.

Lemma 3. In the limit as $r_m \to \infty$*, agents' expectation of house price growth over the next period conditional on house prices and sale probabilities before t is:*

$$E\Delta\log P_{t+1} = \mu_g + (1-\alpha)\rho\sum_{k=1}^{\infty}\left(\frac{\rho}{1+(1-\alpha)\rho}\right)^k \times (\Delta\log P_{t-k} - \mu_g).$$

Given this expectation, movers at time $t+1$ *set prices according to the rule:*

$$\Delta\log P_{t+1} = E\Delta\log P_{t+1} + (1+(1-\alpha)\rho)\big(\log(\overline{\kappa}\,\overline{p}) - F^{-1}(1-\pi_t)\big),$$

for some constant $\overline{p}$.

In this limit, price growth expectations are a simple weighted average of past price changes, as in the reduced form extrapolation formulas that Barberis et al. (2015, 2018) and Liao and Peng (2018) assume. Similarly, price setting closely resembles the "backward-looking rule of thumb" that Guren (2018) assumes, except that movers here decrease list prices when they observe a high share of unsold listings in the prior period. Therefore, the bounded rationality of movers in our model endogenously leads to extrapolative expectations and price posting when movers are impatient.

5.4. Potential buyer problem

The potential buyer's problem is to decide whether to purchase or not, taking as given the price that movers post. At the end of time t, the expected utility for a potential buyer from purchasing a house is:

$$V^b(\hat{d}_t,\hat{g}_t;\lambda,\delta,n) = (1+r)^{-1}E\Big(e^{\delta} + \lambda V^m(\hat{d}_{t+1},\hat{g}_{t+1}) + (1-\lambda)V^s(\hat{d}_{t+1},\hat{g}_{t+1};\lambda,\delta)\Big), \quad (7)$$

where the expectation is over $d_t \sim \mathcal{N}\left(\frac{\sigma_a^2\hat{d}_t+\hat{\sigma}_d^2(\delta-\mu_n)}{\sigma_a^2+\hat{\sigma}_d^2}, \frac{\sigma_a^2\hat{\sigma}_d^2}{\sigma_a^2+\hat{\sigma}_d^2}\right)$.[15] A potential buyer who purchases becomes a stayer and receives housing utility e^{δ} at the beginning of the next period. With probability λ, she then becomes a mover, the value of which is equal to $V^m(\hat{d}_{t+1},\hat{g}_{t+1})$ and given by Eq. (6). With probability $1-\lambda$, she continues on as a stayer, the value of which we denote by $V^s(\hat{d}_{t+1},\hat{g}_{t+1};\lambda,\delta)$. At any time t, the stayer value function can be written recursively as:

$$V^s(\hat{d}_t,\hat{g}_t;\lambda,\delta) = (1+r)^{-1}E\Big(e^{\delta} + \lambda V^m(\hat{d}_{t+1},\hat{g}_{t+1}) + (1-\lambda)V^s(\hat{d}_{t+1},\hat{g}_{t+1};\lambda,\delta)\Big), \quad (8)$$

where the expectation is over $d_t \sim \mathcal{N}(\hat{d}_t,\hat{\sigma}_d^2)$.

A potential buyer decides to buy when the value of doing so is at least as large as the price: $V^b(\hat{d}_t,\hat{g}_t;\lambda,\delta,n) \geq P$. Lemma 4 recasts this decision rule in terms of the minimum housing utility at which a potential buyer decides to buy.

Lemma 4. A potential buyer at time t with housing utility e^{δ} *and occupancy type n and for whom* $\lambda = \lambda_j$ *decides to purchase a home with list price P if and only if:*

$$e^{\delta} \geq \kappa_{n,j}(\hat{g}_t)P,$$

for some function $\kappa_{n,j}(\cdot)$.

The potential buyer's decision rule is similar to the one in Eq. (3) that other agents believe she is using. She purchases if the per-period housing utility she would receive exceeds some fraction of the list price. The key distinction is that the fraction she actually uses depends on both the history of market data she observes and her type. In particular, because the potential buyer anticipates selling in the future, this fraction depends on $\hat{g}_t$, the expected growth rate of the demand shifter, and on λ, which determines the amount of time she expects until becoming a mover.

The cutoff rule in Lemma 4 determines both the share of listings that sell and the fraction of all purchases made by buyers of each of the $2J$ types. Specifically, a purchase occurs when:

$$a \geq \log P + \log\kappa_{n,j}(\hat{g}_t) - d_t,$$

which implies that the share of potential buyers of type n and λ_j who buy at time t is $1-\Phi(\log P + \log\kappa_{n,j}(\hat{g}_t) - d_t - \mu_n)$. Substituting the expression for list prices from Lemma 2 and averaging these shares over all potential buyer types gives the share of all listings that sell:

$$\pi_t = 1 - \sum_{n=0}^{1}\sum_{j=1}^{J}\beta_{n,j}\Phi\Big(\log p(\hat{g}_t) + \log\kappa_{n,j}(\hat{g}_t) + \hat{d}_t - d_t - \mu_n\Big). \quad (9)$$

[15] The posterior on d_t is different for potential buyers than for movers and stayers. A potential buyer's log housing utility, δ, conveys information about the current demand shifter, d_t, due to Eq. (2). Therefore, her posterior on d_t combines the posterior based on housing data, $\mathcal{N}(\hat{d}_t,\hat{\sigma}_d^2)$, with her prior based on her housing utility, $\mathcal{N}(\delta-\mu_n,\sigma_a^2)$. Movers and stayers, however, do not use their own δ to estimate d_t because it is a noisy observation of a past value of the shifter, $d_{t'}$, which they believe they infer directly as $\tilde{d}_{t'}$.

The share of sales at time t going to buyers of type n and λ_j, which we denote $b_{n,j,t}$, equals:

$$b_{n,j,t} = \pi_t^{-1}\beta_{n,j}\left(1 - \Phi\left(\log p(\hat{g}_t) + \log \kappa_{n,j}(\hat{g}_t) + \hat{d}_t - d_t - \mu_n\right)\right). \tag{10}$$

The share of listings that sell, π_t, and the share of sales going to each of the $2J$ types, $b_{n,j,t}$, determine the dynamics of all the aggregate quantity variables in the model.

5.5. Quantities

The model has three aggregate quantities of interest: transaction volume, Q_t, inventory available for sale, I_t, and new listings, L_t. The following accounting identities characterize the evolution of these aggregates as a function of sales probabilities, π_t, and the composition of buyers, $b_{n,j,t}$:

$$Q_t = \pi_t I_t,$$
$$I_t = (1 - \pi_{t-1})I_{t-1} + L_t,$$
$$L_t = \sum_{j=1}^{J} \lambda_j S_{j,t-1},$$

where $S_{j,t}$ measures the share of housing owned by stayers of type $\lambda = \lambda_j$ at the end of time t. This share evolves according to the following law of motion:

$$S_{j,t} = (1 - \lambda_j)S_{j,t-1} + (b_{0,j,t} + b_{1,j,t})Q_t.$$

As these equations make clear, the current composition of buyers affects the composition of stayers, thereby altering future listings and volume. Volume rises when there are more listings or when the selling probability is higher.

In addition to these aggregates, the model generates dynamic patterns in quantities that vary across both realized holding periods and buyer occupancy types. For instance, one variable we track in the data is new listings of homes purchased within the last three years. In the model, new listings at time t of homes purchased within the last K periods equals:

$$L_t^K = \sum_{k=1}^{K}\sum_{j=1}^{J} \lambda_j(1 - \lambda_j)^{k-1}(b_{0,j,t-k} + b_{1,j,t-k})Q_{t-k}.$$

Similarly, our empirical analysis decomposes volume according to the occupancy type of the buyer and the realized holding period of the seller. In the model, the decomposition by occupancy is straightforward: volume to buyers of occupancy type n equals $\sum_{j=1}^{J} b_{n,j,t}Q_t$. Decomposing volume by realized holding period is more complicated. The sales volume at time t of houses purchased within the last K periods equals $\sum_{k=1}^{K} \pi_t I_t^k$, where I_t^k denotes the inventory of listings at time t of homes purchased at time $t - k$. This quantity satisfies the recursion:

$$I_t^k = (1 - \pi_{t-1})I_{t-1}^{k-1} + \sum_{j=1}^{J} \lambda_j(1 - \lambda_j)^{k-1}(b_{0,j,t-k} + b_{1,j,t-k})Q_{t-k}$$

for $k > 0$, with initial condition $I_t^0 = 0$.

6. Model results

6.1. Simulation and calibration methodology

We perform a series of simulations to analyze the baseline properties of our model and to study impulse responses to a shock. Each simulation corresponds to 148 sequential realizations of the two stochastic shocks, ϵ_t^d and ϵ_t^g. The first 100 periods burn in the simulation, leaving 48 analysis periods. Each period represents a quarter, so our analysis spans 12 years. We draw a control sample of 1,000 independent simulations to analyze the model's baseline properties. To analyze the impulse response to a shock, we draw a treatment sample of 1,000 additional simulations identical to the control except in periods 101–104 during which the growth rate shocks ϵ_t^g are two standard deviations higher, representing a large but plausible increase in demand. Impulse responses are average differences between treatment and control outcomes.

Solving the model at any point in time requires evaluating both the function that movers use to set prices, $p(\hat{g}_t)$, and the function that potential buyers use to decide whether to purchase, $\kappa_{n,j}(\hat{g}_t)$. To do so, we discretize $\hat{g}_t$ using the Rouwenhorst (1995) method and then calculate the function values at these discrete points. To evaluate the functions outside these points, we use cubic splines between mesh points and linear splines beyond the boundaries.

We set $r = 0.012$ and $\rho = 0.880$, corresponding to annual values of 5% and 0.51 in Guren (2018) and Glaeser and Nathanson (2017), respectively. We normalize $\mu_0 = 0$, so that μ_1 gives the average log difference in housing utility between occupants and non-occupants. We set $\mu_g = -\sigma_d^2/2$, which implies that the unconditional expected growth rate of e^{d_t} is 0, so that the average growth rate of housing utility across cohorts of potential buyers is the same as that for stayers already living in the city. We choose $\overline{\kappa}$ so that the average value of $d_t - \hat{d}_t$ in the control simulations equals 0. This choice ensures that agents' simplified model in Eq. (3) leads to inferences about the level of the demand shifter that are correct on average.

We select values of the remaining parameters so that moments from our simulation match the empirical counterparts in Table 4. The composition of buyers and the volatility of demand growth determine $\beta_{n,j}$ and σ_d, respectively, and the selling hazard disciplines r_m, as more patient movers take longer to sell by setting higher prices. We target three features of the national U.S. housing cycle: the ratio of price boom to bust, the volume boom relative to the price boom, and the degree to which the non-occupant volume boom exceeds the occupant boom. Intuitively, these moments determine γ, σ_a, and μ_1 through quantifying extrapolation, the elasticity of demand, and the excess sensitivity of non-occupants.

6.2. Parameter estimates

Table 5 reports parameter values that match the moments in Panels B and C of Table 4. Non-occupant housing utility is 0.9% less than occupant housing utility on average, corresponding to less than a standard deviation

Table 4
Inputs into model calibration. This table reports parameters that we assume in the calibration, as well as targets we use to determine the remaining parameters. In the model, we target the mean buyer shares, quarterly selling hazard, and demand error across all analysis periods in control simulations. We theoretically derive the annual volatility of demand growth as well as the mean demand growth as functions of parameters. Price overshoot is the ratio of log price growth from the beginning to peak to log price growth from the beginning to the trough after the peak. Volume boom/price boom is the ratio of log existing volume growth from the beginning to the peak of volume (2000 to 2005, using numbers from Fig. 4) to aforementioned log price growth. Non-occupant boom/occupant boom is the ratio of each category of log volume growth from 2000 to 2005 in the sample of MSAs we use for non-occupant analysis. In the model, we use quarterly minimums and maximums instead of aggregating at the year level. We match all targets to within rounding. GN (2017) denotes Glaeser and Nathanson (2017).

Parameter or target	Value	Source
Panel A: Assumed parameters		
r (non-mover discount rate)	0.012	Guren (2018)
Potential λ values	$\{0.50, 0.17, 0.05, 0.03, 0.01\}$	Fig. 8
ρ (demand growth persistence)	0.880	GN (2017)
Panel B: Steady-state targets		
Occupant buyer shares	(0.06,0.07,0.16,0.16,0.34)	Fig. 8
Non-occupant buyer shares	(0.04,0.03,0.04,0.04,0.06)	Fig. 8
Annual volatility of demand growth	0.023	GN (2017)
Quarterly selling hazard	0.75	Guren (2018)
Mean demand error	0	Model
Mean demand growth	0	Model
Panel C: Cycle targets		
Price overshoot	2.3	Fig. 1
Volume boom/price boom	0.4	Fig. 1
Non-occupant boom/occupant boom	3.1	Fig. 4

Table 5
Outputs from model calibration. See text for definitions of parameters in Panel A. We find these values by searching for parameters such that moments from the model match targets in Table 4. Panel B reports regression coefficients of annualized price growth in the next year and between 2 and 5 years from now on last year's price growth. We run these regressions across control simulations at the beginning of the analysis period.

Parameter or outcome	Interpretation	Value
Panel A: Derived parameters		
σ_a	Flow utility dispersion	0.066
μ_1	Occupant premium	0.009
γ	g variance share	0.070
$\overline{\kappa}$	Assumed buying cutoff	0.029
σ_d	Demand volatility	0.011
μ_g	Mean demand growth	−0.000
r_m	Mover discount rate	0.141
$\beta_{0,j}$	Non-occupant shares	(0.143,0.022,0.030,0.030,0.045)
$\beta_{1,j}$	Occupant shares	(0.185,0.052,0.119,0.119,0.254)
Panel B: Steady-state outcomes		
1-year extrapolation	–	0.127
2–5-year extrapolation	–	0.042

in each group's distribution. The mover discount rate is 14%. To map this number into a flow cost of moving, we calculate how much higher the mover value function would be if the mover discount rate were equal to r for a single period. The average difference is 3.7% of the list price, in line with the typical costs of selling a house (Han and Strange, 2015) and smaller than the estimate in Guren (2018) of 2.1% per month.

Relative to occupant potential buyers, a much larger fraction of non-occupant potential buyers have short horizons. According to the estimates for $\beta_{n,j}$, over half of non-occupant potential buyers expect to become movers six months after buying a house; the equivalent share of occupant potential buyers is 25%. These estimates come from targeting the data in Fig. 8, which show that a relatively large share of buyers of investment properties intend to own for less than one year. They imply significant overlap between non-occupant and short-term potential buyers within the model.

Lemma 3 shows that when $r_m \to \infty$, price growth expectations are a weighted average of past price changes. Here, r_m is finite, but nonetheless large enough to generate extrapolation. To measure extrapolation, we follow Armona et al. (2019) by focusing on the relation between

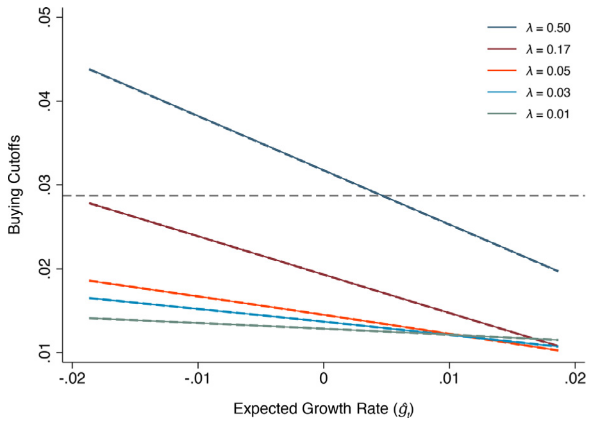


Fig. 10. Buying cutoffs for different expected growth rates. The buying cutoff, $\kappa_{n,j}(\hat{g}_t)$, determines how large a potential buyer's housing utility must be relative to the price of a house for her to decide to buy. It depends on the potential buyer's occupancy type, n, her quarterly moving hazard, λ_j, and the current expected quarterly growth rate of the demand shifter, $\hat{g}_t$. We plot values of these functions for the λ values in our calibration, which appear in the legend. Solid lines correspond to occupants ($n = 1$); dashed lines correspond to non-occupants ($n = 0$). The horizontal grey dashed line gives $\overline{\kappa}$, which agents mistakenly believe is the time-invariant buying cutoff for other potential buyers.

realized price growth over the last year and expectations of annualized price growth over the next 1 and 2–5 years. We measure this relation by regressing movers' 1- and 2–5-year expectations in period 105 of the control simulations against price growth in the prior four periods. The coefficients from these regressions of 0.127 and 0.042 are similar to though somewhat smaller than the corresponding values of 0.226 and 0.047 that Armona et al. (2019) find in survey data (see their Table 5).

6.3. Buyer cutoff rules

Agents in the model are fully rational except that they ignore the influence of historical market data on the home purchasing decisions of other agents. The effect of this departure from rationality on the model's dynamics depends on the extent to which the cutoffs that agents actually use when deciding to buy, $\kappa_{n,j}(\hat{g}_t)$, differ from the constant cutoff other agents assume they use, $\overline{\kappa}$. In Fig. 10, we plot these cutoffs. Four features of this figure are relevant for understanding the dynamics of our model.

First, the true buyer cutoffs, $\kappa_{n,j}(\hat{g}_t)$, decrease in the expected growth rate of the demand shifter, $\hat{g}_t$. Intuitively, potential buyers expect larger capital gains when the expected growth rate is high and are therefore willing to purchase at higher prices. Therefore, the expected growth rate of the demand shifter, $\hat{g}_t$, along with the demand shifter itself, d_t, both increase housing demand.

Second, when $\hat{g}_t$ is high, the cutoffs buyers actually use are less than the constant cutoff that other agents believe they use. This error causes agents in the next period to misattribute the speculative behavior of this period's buyers—who are purchasing due to high anticipated growth—to an increase in the level of the demand shifter, d_t, instead. As a result, when expected growth is high at time t, subsequent agents overestimate what the level of demand must have been at that time, i.e., $\tilde{d}_t > d_t$. Because the demand process is persistent, this error raises the expectations of next period's agents about the demand shifter, $\hat{d}_{t+1}$, and its growth rate, $\hat{g}_{t+1}$, leading movers to list their homes at a higher price. Thus, speculative buying raises subsequent house prices, causes overestimation of the demand shifter, and ignites positive feedback by raising the expected growth rate of next period's potential buyers.

Third, the slopes of the buyer cutoff functions, $\kappa_{n,j}(\hat{g}_t)$, are steeper for higher values of λ_j. Intuitively, potential buyers with shorter horizons expect to sell sooner, so their demand is more sensitive to expected capital gains. As a result, short-term buyers disproportionately drive the positive feedback through which speculative buying today stimulates such buying next period.

Finally, the buyer cutoffs for a given mover hazard are nearly identical for occupants and non-occupants.[16] Quantitatively, the threshold of housing utility at which a purchase occurs does not depend on occupancy status. The only difference in housing demand between occupants and non-occupants with the same horizon is that the distribution of housing utility for the non-occupants is shifted to the left of that of the occupants. As a result, because the non-occupants use the same cutoff as the occupants, a smaller share of them end up buying a house. For a given mover hazard, non-occupants' demand is therefore more elastic than occupants' with respect to the demand shifter, d_t, and its expected growth rate, $\hat{g}_t$.

6.4. Impulse responses

In Fig. 11, we plot the impulse responses. As with the national U.S. cycle in Figs. 1 and 3, the cycle in the model progresses through a boom, quiet, and bust (Panels A and B).[17] We use grey shading to mark the transition points between these phases, defined as the peaks of volume and prices. The quiet lasts eight quarters, close to the duration in Fig. 1 and the correlation-maximizing lag in Fig. 2.

In the boom, demand rises because the demand shifter, d_t, is higher and because the expected growth rate, $\hat{g}_t$, rises in response to price growth. Together, these channels differentially stimulate buying from potential buyers with higher λ (Panel C) and non-occupants (Panel D). The overall increase in housing demand pushes up the share of listings that sell, π_t (Panel E). Short-term buyers re-list their houses quickly, increasing the flow of listings during the boom (Panel F). Prices and volume increase as a result. Tempering the volume boom is the decline in inven-

[16] The cutoffs depend on occupancy type only because a potential buyer's housing utility, δ, conveys information about the contemporaneous demand shifter, d_t. Quantitatively, this channel is irrelevant because $\sigma_a = 0.066$ is much larger than $\hat{\sigma}_d = 0.011$.

[17] The price boom in our model is smaller than the national boom shown in Fig. 1. Potentially, the shocks that generated the national boom are stronger than the one year of two standard deviation shocks we feed into our model. Another possibility is that our assumed value of 0.023 for the annual volatility of demand growth (see Table 4) is too low. Finally, new construction and credit, which our model omits, may have amplified the national boom (Favilukis et al., 2017; Nathanson and Zwick, 2018). To ease comparison with the national cycle, we analyze outcomes in our model relative to the price boom it generates.

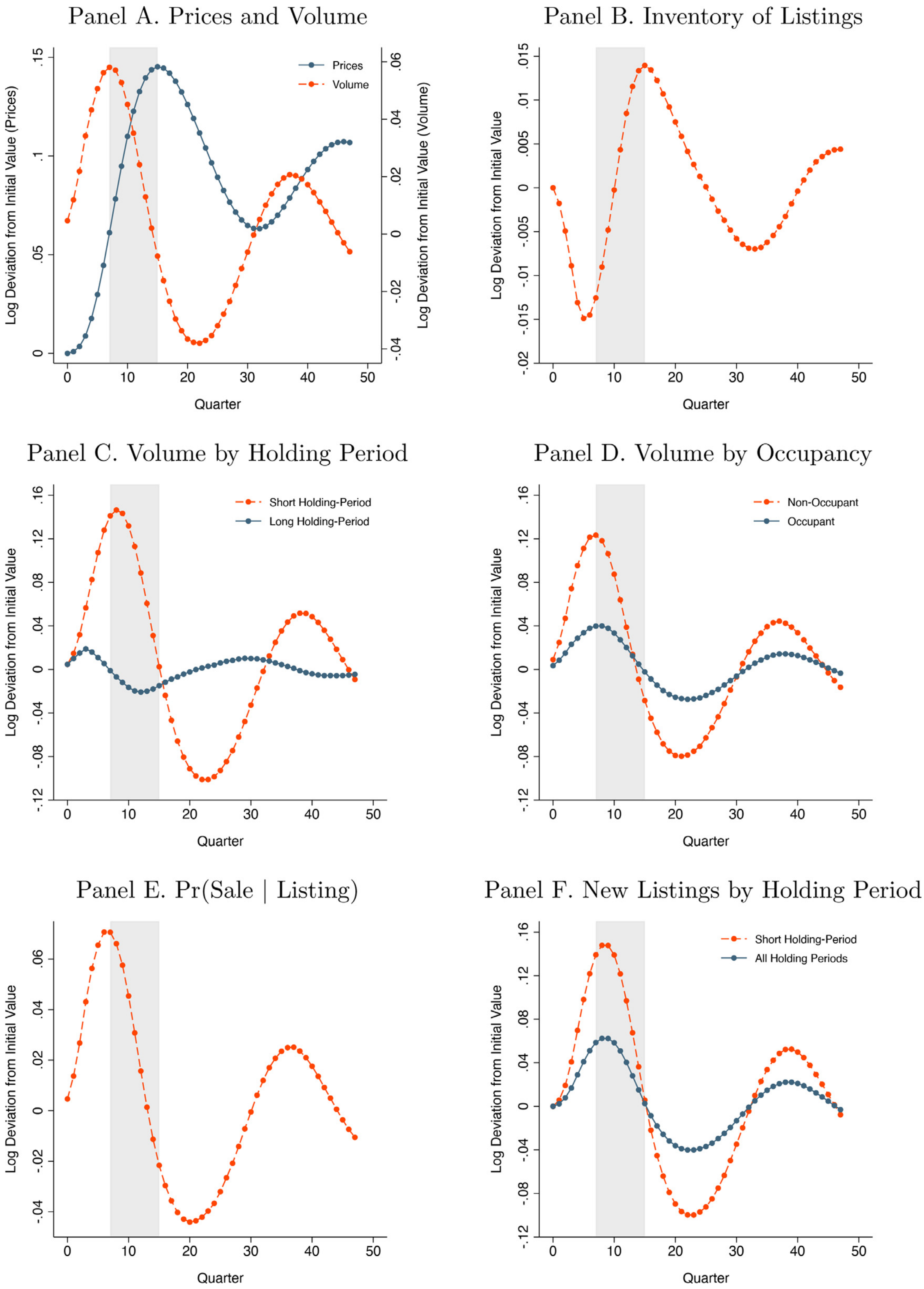


Fig. 11. Impulse responses. Impulse responses are average differences between log outcomes in control simulations and treatment simulations, in which a 2-standard-deviation shock to ϵ_t^g (the demand growth innovation) occurs in quarters 0 through 3. The shaded grey area denotes the beginning and end of the quiet. A short holding period is defined as less than or equal to 12 quarters and a long holding period is defined as greater than 12 quarters.

tory (Panel B), which occurs as the stock of unsold listings diminishes.

The qualitative behavior of volume, inventories, and sale probabilities during the boom is similar in search and matching models, such as Guren (2014). The key difference is the increasing flow of listings coming differentially from short-term buyers (Panel F). This flow limits the decline in inventories to 1.5 log points, amplifying and sustaining the rise in volume. Relative to the price boom, this decline in inventories is an order of magnitude smaller than in Guren (2014). Furthermore, the differential flow of short-term listings leads to the short-term volume boom shown in Panel C, which matches Fig. 4. The disproportionate increase in demand from non-occupants, together with the overall rise in volume, produces the strong non-occupant volume boom shown in Panel D that also matches Fig. 4.

In the quiet, demand begins to fall because the price level has risen so high. Because they neglect time-variation in the cutoff rule that other potential buyers are using, agents misattribute demand growth during the boom entirely to d_t, though much of it comes from $\hat{g}_t$, the expected capital gains channel. Eventually, agents over-estimate the demand level so much and post prices that are so high that sale probabilities start to fall (Panel E). Nonetheless, movers increase their list prices throughout the quiet because they continue to revise upward their estimate of the demand shifter for two reasons. First, because of past price growth, the expected growth rate, $\hat{g}_t$, remains high, which mechanically causes upward revisions to the expected level of demand. Second, the sale probability, π_t, remains high even though it is falling, and these high realizations constitute positive surprises about demand that cause movers to increase their beliefs. Eventually, π_t falls below its pre-shock average, ending these upward revisions and the concomitant increase in list prices.

One of the distinguishing features of the quiet in both the model and the data is the sharp rise in unsold inventories. At their peak, unsold listings are 1.4% above their pre-shock level. The two causes of the excess inventories are the fall in selling probabilities (Panel E) and the elevated flow of short-term listings continuing throughout the quiet (Panel F), which matches the data in Fig. 6. This second cause is novel to our model and may explain why inventories rise above their pre-shock level here whereas they fail to do so in models lacking this channel, such as Guren (2014).[18]

The bust begins as movers cut list prices. Agents revise down their expectations of the growth rate, which further depresses demand and sale probabilities. However, because they continue to believe that potential buyer demand is independent of the expected growth rate, movers do not cut prices enough to restore demand, and the bust continues over several periods. Volume falls below its pre-shock level, as in Fig. 1. The decline in $\hat{g}_t$ leads to a smaller share of short-term buyers, depressing the flow of new listings (Panel F), which allows inventories to recover (Panel B).

The model generates a second boom in prices, volume, and listings in the last five years of the simulation. This second boom occurs because prices overshoot on the way down, as is common in models with extrapolative expectations (Hong and Stein, 1999; Glaeser and Nathanson, 2017). Underpricing occurs when agents think that demand is lower than its true value. In this case, sale probabilities rise, and volume increases. This increase in demand disproportionately affects short-term buyers, so short-term volume and listings also rise during the second boom.

6.5. Counterfactuals

Many features of the impulse responses discussed above closely match the patterns observed in the data. However, the fact that our model matches these patterns does not directly speak to the role that speculation plays in generating those patterns. To quantify the contribution of speculation to the housing cycle, we rerun the simulation under three counterfactuals, each of which shuts down a different aspect of our baseline model. Impulse responses corresponding to Panels A–D of Fig. 11 are in Fig. 12; those corresponding to Panels E and F of Fig. 11 are in Figure IA4 of the online appendix.

6.5.1. Rational expectations

In the fully rational counterfactual, agents no longer use the simplified model for potential buyer behavior in Eq. (3). Instead, they correctly understand the problem that potential buyers are solving. As a result, they believe that the share of potential buyers at time t who would purchase at list price P is:

$$1-\sum_{n=0}^{1}\sum_{j=1}^{J}\beta_{n,j}\Phi\Big(\log P+\log\kappa_{n,j}(\hat{g}_t)-d_t-\mu_n\Big)\equiv\pi(P,d_t,\hat{g}_t).$$

Using this function, agents at time t correctly infer the past values of the demand shifter by equating $\pi_{t'}$ to $\pi(P_{t'},d_{t'},\hat{g}_{t'})$ and solving for $d_{t'}$. They calculate $\hat{d}_t$ and $\hat{g}_t$ using the Kalman filter in Lemma 1. The mover value function becomes:

$$V^m(\hat{d}_t,\hat{g}_t)=\sup_P E\bigg(\pi(P,d_t,\hat{g}_t)P+(1+r_m)^{-1}\times(1-\pi(P,d_t,\hat{g}_t))V^m(\hat{d}_{t+1},\hat{g}_{t+1})\bigg),$$

where the expectation is over $d_t\sim\mathcal{N}(\hat{d}_t,\hat{\sigma}_d^2)$. By an argument analogous to the proofs of Lemmas 2 and 4, the optimal price takes the form $e^{\hat{d}_t}p(\hat{g}_t)$, and a potential buyer buys when $e^{\delta}\geq\kappa_{n,j}(\hat{g}_t)P$, although $p(\cdot)$ and $\kappa_{n,j}(\cdot)$ may differ from the corresponding functions in those lemmas.

We compute impulse responses using the same parameters and sequence of shocks in the baseline model. Results appear in Panels A–D of Fig. 12. When expectations are rational, prices no longer overshoot, inventories never rise above their pre-shock value, and the volume

[18] Our model understates the rise in listings during the quiet because of our simplifying assumption that each mover matches to a potential buyer regardless of the number of contemporaneous movers. With a more realistic matching function, such as the one in Guren (2014), our model might also hit the peak of listings (relative to price growth) that appears in Fig. 3.

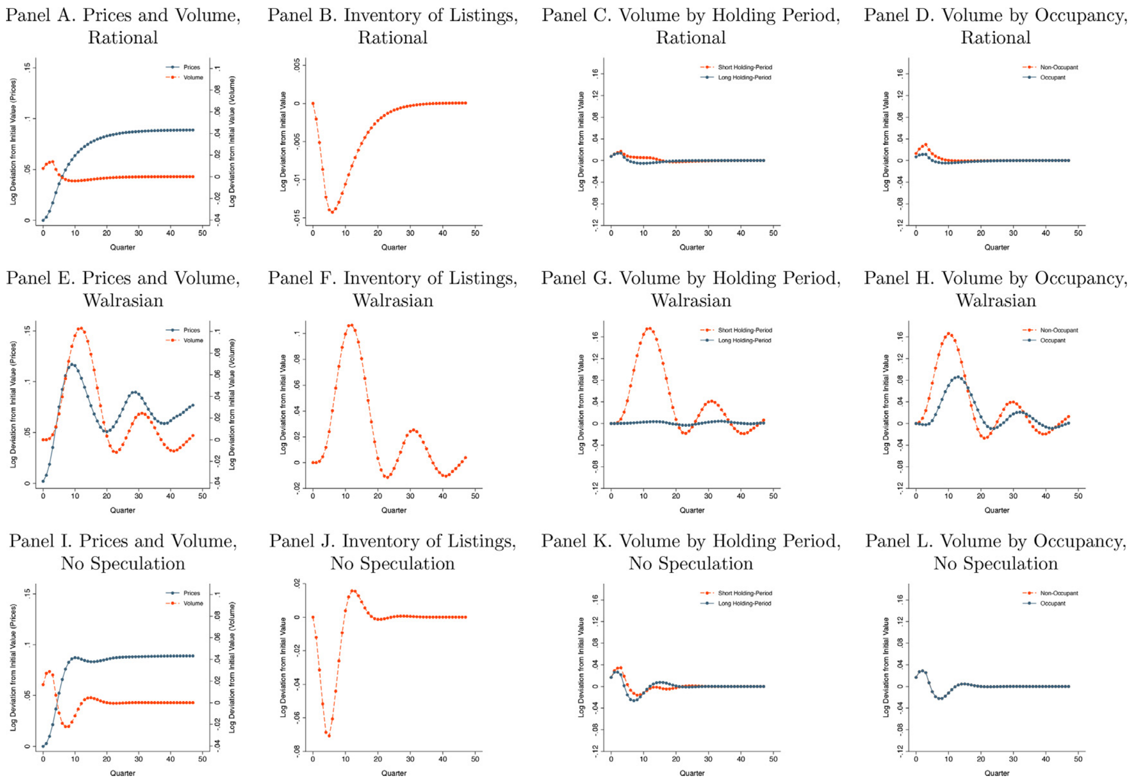


Fig. 12. Impulse responses in counterfactuals. Impulse responses are average differences between log outcomes in control simulations and treatment simulations, in which a 2-standard-deviation shock to ϵ_t^g (the demand growth innovation) occurs in quarters 0 through 3. A short holding period is defined as less than or equal to 12 quarters and a long holding period is defined as greater than 12 quarters.

boom lasts only four quarters and is only about one quarter of its size in the baseline model. The short- and long-horizon volume booms are nearly identical in size. In contrast, non-occupant volume continues to rise much more than occupant volume, because non-occupant demand is more elastic with respect to the demand shifter, d_t. Therefore, even when potential buyers have rational expectations, non-occupants react more strongly to the demand shock underlying the impulse response, but this reaction does not generate any positive feedback.

In summary, the price bust and the rise in listings above their initial value–two salient features of the data in Fig. 3–depend on departing from rational expectations. These features appear in the baseline model but not the rational version. Quantitatively, a large volume boom, and one that is disproportionately short-term, likewise depend on departing from rationality. An excess non-occupant volume boom does not.

6.5.2. Walrasian market clearing

In Online Appendix F.1, we solve a Walrasian version of our model in which a mechanism selects a price P_t each period so that the number of potential buyers willing to buy at that price equals the number of movers willing to sell. We also describe technical changes to the model setup and parameters that aid comparison to the baseline model.

We find that the equilibrium price is $P_t = e^{d_t} p(\hat{g}_t)$, where $p(\cdot)$ is a function. In contrast to the baseline model, the demand shifter, not its expected value, directly affects prices. Here, demand from buyers directly pins down the price; in the baseline model, movers choose the price and demand pins down the share of listings that sell. As a result, prices incorporate changes to demand more quickly with Walrasian market clearing. In the Walrasian model, agents believe that the equilibrium house price is $P_t = e^{d_t} \tilde{p}$, where $\tilde{p}$ is a constant. Therefore, when $\hat{g}_t$ is high, equilibrium prices exceed what agents expect, which leads them to think mistakenly that d_t is high. This force in turn pushes up $\hat{g}_{t+1}$, which increases P_{t+1}. This positive feedback mechanism is similar to the one in the baseline model.

The results are in Panels E–H of Fig. 12. Prices and volume both go through a large boom and bust cycle in the Walrasian model, as in the baseline model. However, volume now peaks after prices, so there is no longer a quiet. The price boom is faster, with prices reaching their peak nine quarters after the shock instead of 15. Under Walrasian market clearing, prices react more quickly to new information, explaining the absence of the quiet and the shorter duration of the price boom. Listings rise in the Walrasian model, but listings and volume coincide due to Walrasian market clearing, so these two variables never diverge as in the baseline model. Finally, short-term and non-occupant volume continue to rise in a large and disproportionate fashion in the Walrasian model.

In summary, many of the features of the baseline impulse response do not require departing from Walrasian market clearing, as they continue to appear in the Walrasian extension. These features include large price and volume cycles, high levels of listings while prices fall, and disproportionate volume booms from short-term sales and non-occupant purchases. However, the existence of the quiet—a period right after the boom in which volume falls while prices and listings rise–does require departing from Walrasian market clearing.

6.5.3. Absence of speculative buyers

The last counterfactual shuts down speculation by adjusting the distribution of potential buyer types while leaving the framework of the model unchanged. In particular, we set $\beta_{n,j} = 0$ for all n and j except for $n = 1$ and the j for which $\lambda_j = 0.03$. All potential buyers are occupants with a horizon of about eight years, which is close to the average horizon among potential buyers in the baseline model. By assigning all potential buyers the same (low) value of λ, this counterfactual removes both short-term buyers and the heterogeneity in holding periods that generates variation in the composition of buyers. We update $\overline{\kappa}$ so that the demand error is still zero and keep other parameters unchanged.

Panels I–L of Fig. 12 display the results. Prices and volume still go through a cycle, but the volume boom is three times smaller, and the price overshoot almost disappears. Listings fall 7%, much more than the decline of 1.5% in the baseline model. There is a quiet during which listings rise, but they reach a smaller value of 0.4% (versus the 1.4% in the baseline model) at the end of this period. Short-term volume rises slightly more than long-term volume because of the mechanical channel discussed in Online Appendix B.1, but by far less than the 7.8-fold relative increase in the baseline model. Finally, non-occupant volume equals zero by assumption.

In Online Appendix F.2, we explore the distinct roles of short-term and non-occupant potential buyers in amplifying the housing cycle. Removing either group attenuates the housing cycle, but there is substantial overlap between the two groups. If we eliminate short-term buyers while holding constant the share of non-occupants, the housing cycle becomes small, but if we eliminate non-occupants while keeping constant the share of short-term buyers, the housing cycle remains strong. These results suggest that short horizons are the key amplifying force in the model, as opposed to non-occupancy.

While these counterfactuals suggest that removing short-term potential buyers dramatically reduces the magnitude of the cycle, they may overstate this effect because we conduct the counterfactuals using parameter values calibrated in the baseline model under the assumption of exogenous trading horizons. During the 2000–2005 housing boom, it is possible that homeowners who originally expected to stay in their homes for many years decided instead to sell early to exploit rising house prices. We rule out this possibility in our model by assuming that homeowners only list their homes after receiving an exogenous moving shock. To match the 2000–2005 volume boom, our calibration compensates for this omission by assigning excess weight to the shares of potential buyers with high values of λ. Therefore, removing this large group of short-term buyers from the model may have an outsized effect relative to removing the likely smaller group of such buyers who exist in reality. Nonetheless, our counterfactual demonstrates that removing speculators qualitatively attenuates the price bust and volume cycle and amplifies the decline in inventories during the boom.

6.6. Transaction taxes

In this section, we use our model to study an ad valorem tax that buyers must pay at the time of purchase. The tax rate can depend on the buyer's occupancy type n, so that a buyer pays a tax $\tau_n P$ when purchasing a home at price P. We denote the vector of tax rates by $\tau = (\tau_0, \tau_1)$. Analyzing capital gains taxes would complicate our model significantly, because contemporaneous movers who bought at different past prices would face different optimality problems and hence choose different list prices, so we leave that analysis to future work.

Holding prices constant, the share of potential buyers who complete a purchase is lower in the presence of this tax. As a result, $\overline{\kappa}$ must go up, as we select this constant so that the average value of $d_t - \hat{d}_t$ equals zero. Intuitively, the threshold $\overline{\kappa}$ rises to reflect the decrease in housing demand from the new tax. We denote this new value $\overline{\kappa}^{\tau}$. By analyzing the mover value function, it is straightforward to show that the new optimal price is $P_t = e^{\hat{d}_t} p(\hat{g}_t)\overline{\kappa}/\overline{\kappa}^{\tau}$, where $p(\cdot)$ is the same function that is in Lemma 2. That is, prices scale down by a constant amount that reflects the reduced demand due to the tax.

The reduction in housing demand operates through the cutoff functions, $\kappa_{n,j}(\cdot)$. Due to the proportional nature of the tax, Lemma 4 continues to hold, but now these cutoff functions depend on the tax. We denote them as $\kappa^{\tau}_{n,j}(\hat{g}_t)$. A potential buyer of occupancy type n and for whom $\lambda = \lambda_j$ buys at time t if:

$$a \geq \log p(\hat{g}_t) + \log\left(\frac{\overline{\kappa}\kappa^{\tau}_{n,j}(\hat{g}_t)}{\overline{\kappa}^{\tau}}\right) + \hat{d}_t - d_t.$$

We explore a tax that binds equally on all buyers, so that $\tau_0 = \tau_1$, and a tax that affects only non-occupant buyers, so that $\tau_1 = 0$. We consider taxes of 0.5%, 1%, and 5%, which span the tax rates in many large cities (Chi et al., 2021).

Table 6 reports a 5% tax on all buyers significantly attenuates the price cycle, reducing the bust from 8.2% to 1.1%. It also reduces the volume boom, but this reduction is smaller than the corresponding one for prices. Smaller taxes of 0.5% and 1% also reduce the cycle amplitude, but these effects are much smaller.

The last three columns of Table 6 report results for the tax on non-occupant buyers. This tax is a weaker instrument for attenuating the house price cycle: the 5% tax reduces the price bust only to 5.8%, and the lower taxes have a smaller effect. The 5% tax nearly eliminates the non-occupant volume boom, reducing it to 0.1% from 12.3%. Therefore, targeting the tax to non-occupants limits its efficacy in reducing the house price cycle, as even a tax that nearly eliminates the non-occupant volume boom still leaves much of the house price cycle.

To understand the mechanism behind these results, in Figure IA5 in the online appendix, we plot the ad-

Table 6
Outcomes for different tax regimes. We report 100 times changes in log outcomes between treatment and control simulations. We define the end of the quiet as the first local maximum in the impulse response of log prices, and we measure the following outcomes at that time: price boom and listings end of quiet. We define the end of the boom as the first local maximum in the impulse response of log volume before the end of the quiet, and we measure the following outcomes at that time: volume boom, listings end of boom, short volume boom, non-occupant volume boom, and sale probability boom. The price bust is the change from the end of the quiet to the first local minimum of the impulse response of log prices after the end of the quiet. The tax is relative to the purchase price, payable at time of sale. We alter $\overline{\kappa}$ in each column to maintain a zero demand error while keeping other parameters the same. The baseline values correspond to Fig. 11.

		Tax on all buyers			Tax on non-occupant buyers		
Outcome	Baseline	0.5%	1%	5%	0.5%	1%	5%
Price boom	14.5	13.1	12.2	9.7	13.5	12.8	12.6
Price bust	−8.2	−6.4	−5.1	−1.1	−7.0	−6.0	−5.8
Volume boom	5.8	5.5	5.2	4.1	5.3	4.8	4.5
Listings, end of boom	−1.3	−1.2	−1.1	−1.0	−0.8	−0.8	−0.6
Listings, end of quiet	1.4	1.3	1.2	0.6	1.2	0.9	0.9
Short volume boom	14.1	13.7	13.2	10.3	13.5	11.8	11.4
Non-occupant volume boom	12.3	11.7	11.1	8.9	7.5	2.3	0.1
Sale probability boom	7.1	6.7	6.3	5.1	6.2	5.5	5.0

justed buying cutoffs, $\overline{\kappa}\kappa^{\tau}_{n,j}(\hat{g}_t)/\overline{\kappa}^{\tau}$, for both 5% tax scenarios. Comparing this figure to Fig. 10 shows how each tax changes housing demand. The 5% tax on all buyers raises the cutoffs for the $\lambda = 0.5$ group by about half a standard deviation (σ_a), which makes the $\lambda = 0.17$ group more marginal than before. Therefore, the tax effectively skews the composition of buyers towards those with longer horizons. The tax on non-occupants similarly raises the cutoffs, but only for non-occupants. As a result, both the $\lambda = 0.5$ occupants and the $\lambda = 0.17$ non-occupants are marginal. Therefore, many of the buyers with the shortest horizons are still active in the market, which provides an explanation for why this tax has a weaker effect.

7. Conclusion

In this paper, we present evidence that speculators in general and short-term speculators in particular play a crucial role in the housing cycle. This evidence raises additional lines of inquiry.

First, do the expansions in credit that typically accompany housing booms appeal disproportionately to short-term investors? Barlevy and Fisher (2011) document a strong correlation across U.S. metropolitan areas between the size of the 2000s house price boom and the take-up of interest-only mortgages. These mortgages back-load payments by deferring principal repayment for some amount of time and thus might appeal to buyers who expect to resell quickly. The targeting of credit expansions to short-term buyers might explain the amplification effects of credit availability on real estate booms documented by Favara and Imbs (2015), Di Maggio and Kermani (2017), and Rajan and Ramcharan (2015). Mian and Sufi (2022) explore this channel in contemporaneous work.

A second line of inquiry concerns tax policy. While we analyze a fixed transactions tax in this paper, in the spirit of Tobin (1978), Stiglitz (1989), Summers and Summers (1989), and Dávila (2015), natural alternatives such as a short-term capital gains tax might discourage housing speculation by lowering expected after-tax capital gains. However, such taxes discourage productive residential investment as well. Is this tax optimal, and if not, what type of tax policy would be better? It is also unclear empirically whether transaction and capital gains taxes would particularly discourage short-term investors, given that the incidence of this tax might fall more on buyers than sellers.

A third research question involves new construction, which is absent from our model. In a static model, Nathanson and Zwick (2018) predict that undeveloped land amplifies house price booms by facilitating speculation by developers. Developers have short investment horizons because the time from land purchase to home sale ranges from a few months to a few years. Moreover, because developers do not receive housing utility, their payoffs resemble those of the non-occupants in our model. Adding construction to the model in this paper might further clarify the role of land markets and new construction in housing cycles.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2022.07.002.

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