

SPECULATIVE DYNAMICS OF PRICES AND VOLUME*

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Abstract

We present a dynamic theory of prices and volume in asset bubbles. In our framework, predictable price increases endogenously attract short-term investors more strongly than long-term investors. Short-term investors amplify volume by selling more frequently, and they destabilize prices through positive feedback. Our model predicts a lead-lag relationship between volume and prices that we confirm in the 2000-2008 US housing bubble. Using data on 50 million home sales from this episode, we document that much of the variation in volume arose from the rise and fall in short-term investment.

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The role of speculation in driving asset prices has long been a topic of debate among economists (Keynes, 1936; Fama, 1970; Shiller, 1981; Black, 1986; Cochrane, 2011).¹ Modern empirical work on “speculative dynamics” begins with Cutler et al. (1991), who document short-run momentum and long-run reversals in the prices of many diverse assets. These patterns are especially strong during asset “bubbles,” which have drawn attention due to their frenzied activity and subsequent social costs (Kindleberger, 1978; Shiller, 2005; Glaeser, 2013). Uncovering the mechanisms responsible for such episodes is critical for guiding policy.

Several distinct theories have been offered to explain these asset pricing facts.² This paper sheds new light on this topic by exploring a less studied feature of asset market bubbles—the speculative dynamics of volume. Large movements in transaction volume frequently accompany price cycles (Genesove and Mayer, 2001; Hong and Stein, 2007), yet many theories of bubbles ignore implications for volume. Furthermore, the leading explanation of volume during bubbles—disagreement over asset values—is silent on the dynamic relationship between prices and volume, suggesting only that volume and mispricing should be correlated (Scheinkman and Xiong, 2003).

We present a model of the joint speculative dynamics of prices and volume during bubbles. Following past work (De Long et al., 1990; Barberis et al., 2015), the model features extrapolative expectations: investors expect prices to increase following past increases. The model departs from past work in two ways. First, instead of the standard dichotomy between feedback traders and rational arbitrageurs, investors differ only in their expected investment horizon. Some buyers plan to sell after one year, while others plan to hold for many years. The second departure is to specify a term structure for extrapolation. In particular, extrapolation declines with the forecast horizon, so that short-run expectations display more sensitivity than long-run expectations to past prices. When this term structure holds, past

¹Harrison and Kreps (1978, p. 323) define speculation in the following way: “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.”

²These theories include Cutler et al. (1990), De Long et al. (1990), Daniel et al. (1998), Barberis et al. (1998), Hong and Stein (1999), Abreu and Brunnermeier (2003), and Piazzesi and Schneider (2009).

price growth disproportionately attracts short-horizon investors, who in turn generate excess volume when they sell.

Section 1 presents empirical support for both of these departures. Prior work estimating extrapolative expectations finds that short-run future expectations display more sensitivity to past price movements than long-run future expectations (Graham and Harvey, 2003; Vissing-Jorgensen, 2004; Armona et al., 2016). In survey evidence from the National Association of Realtors, expected holding times vary considerably across buyers in the housing market. Furthermore, the share of respondents reporting an expected holding time less than 3 years commoves strongly with recent house price appreciation.

These facts motivate the model in Section 2, which studies a housing market populated by extrapolative investors with heterogeneous horizons. In the model, potential buyers arrive each instant and decide whether to buy a house. If they buy, they must hold the house for some period, after which they are free to sell. Both the expected duration of this period as well as the flow utility received during it vary across potential buyers. Potential buyers expect to sell immediately upon the period’s expiration at the prevailing price of housing. The price of housing reacts sluggishly to changes in the number of potential buyers who wish to buy. This “price stickiness” combines with extrapolative expectations to generate positive feedback between price growth and demand that causes bubbles.

Section 3 studies the joint dynamics of prices and volume by analytically characterizing the response of these variables to a one-time demand shock. Heterogeneity in expected holding periods interacts with extrapolative expectations to produce a rich volume dynamic. We partition the time following the shock into three epochs: a “boom” in which prices rise, volume rises, and all listings sell; a “quiet” in which prices continue to rise, but volume falls and unsold listings accumulate; and a “bust” in which prices fall on low volume. The composition of buyers and sellers varies over the cycle because past buyers are future sellers; time-varying investor composition links volume and prices across periods.

The model focuses on the housing market because data availability allows us to test

directly the model’s predictions about the composition of buyers and sellers. Between 2000 and 2005, house prices in the US doubled while monthly transaction volume rose 40%. Prices and volume fell sharply over the next five years (Figure 1). The quiet describes the time between 2005 and 2007 shown in Figure 1 during which volume sharply fell, inventories of unsold listings sharply rose, and prices increased or stayed roughly stable. A similar dynamic appears in other episodes, such as the tech bubble in the US in the late 1990s (Hong and Stein, 2007) and the bubbles in experimental markets explored by Smith et al. (1988).

We prove that the booms in prices and volume are larger when the frequency of potential buyers with short horizons is greater. This finding ties together prices and volume during bubbles by demonstrating that a single factor is responsible for movements in both. Using the empirical literature on extrapolative expectations and the survey evidence on expected holding times, we calibrate our model and find that the marginal effect of short-term potential buyers on the price and volume booms is quantitatively large and first-order relevant for explaining aggregate price and volume dynamics.

Section 4 evaluates the model’s predictions using transaction-level data from the housing market in the US between 1995 and 2014 for 115 cities that represent approximately 50% percent of the US population. We present four key facts. First, 42% of the rise in home sales between 2000 and 2005 is due to the increase in sales of homes held for less than 3 years. Second, more than half of the rise in sales comes from buyers who did not occupy the property, as suggested by information on the transaction deed. This finding supports the model because it is consistent with the prediction that buyers with low flow utility from housing respond most strongly to expected capital gains and because self-identified “investors” report shorter expected holding times in surveys. Third, volume leads prices with a lag of 15 months in a monthly panel at the metropolitan-area level. Last, the 2000-2012 US house price cycle was larger in metropolitan areas in which the level of existing sales as a share of the housing stock in 2000 was greater. As shown in our model, a higher frequency of short-term buyers increases both steady-state volume and the amplitude of the

price response to the demand shock.

Taken together, the findings lend strong support to the model we present. More broadly, this paper offers new stylized facts about speculative dynamics that expand the set of moments a theory of asset price cycles should match. Two recent papers model volume during bubbles as the outcome of time-varying disagreement. In Barberis et al. (2016), the extent to which investors “waver” between extrapolation and fundamentalism depends on the extent of mispricing, and in Burnside et al. (2016) disagreement varies as optimism diffuses through the population via random meetings. Although investors in our model all hold the same belief, their willingness-to-pay for the asset varies according to their investment horizons. Both time-varying disagreement and heterogeneous expected holding times likely explain important aspects of the joint dynamics of prices and volume.

1 Motivating Evidence

1.1 The Term Structure of Extrapolative Expectations

Much of the early theoretical work on extrapolative expectations is silent on the forward term structure of extrapolation (De Long et al., 1990; Cutler et al., 1990; Barberis and Shleifer, 2003). The two papers we are aware of that explicitly model how past price changes are extrapolated into expectations of future prices at varying horizons are Barberis et al. (2015) and Glaeser and Nathanson (2016).³ In both papers, extrapolation is modeled in a way that leads short term expectations to exhibit more sensitivity to recent price changes than long term expectations. This approach, which we adopt in our model, is supported by a growing body of empirical evidence suggesting that past asset returns do indeed influence annualized expected capital gains more strongly over short versus long future horizons.

In the housing market, Armona et al. (2016) survey expected capital gains over 1- and 5-

³Hong and Stein (1999) assume that past price changes are extrapolated linearly into a fixed future horizon, but their model does not deliver predictions about the effects of recent price changes on expectations at differing future horizons.

year horizons and relate those expectations to perceptions of recent local price changes. They find that 1-year ahead expectations are nearly five times more sensitive to perceived past price changes than annualized 2-5 year ahead expectations.⁴ Furthermore, when provided with new information about local changes in house prices over the last year, respondents in the survey update their forecasts of 1-year price gains more strongly than their 2-5 year forecasts. Both of these facts suggests that short-run house price expectations display significantly more sensitivity to past returns than do long-run expectations.

Similar evidence exists for the US stock market. Vissing-Jorgensen (2004) reports the average expectation of annualized stock market returns over 1- and 10-year horizons among respondents to the UBS/Gallup Index of Investor Optimism survey between 1998 and 2002. Over this period, 1-year expectations moved closely with recent price changes—first rising from 10% to 16% as stock prices increased, and then falling to 6% as prices fell. In contrast, 10-year expectations remained relatively constant over this period and were uncorrelated with the large contemporaneous movements in the stock market.

These patterns persist even in a sample of more sophisticated survey respondents. The Duke CFO Global Business Outlook, which surveys chief financial officers of US firms, provides data on annualized 1- and 10-year stock return expectations. Graham and Harvey (2003) use data from the 2000-2003 waves of this survey and find that the 1-year expected risk premium (expected return less treasury yield) is positively and significantly related to excess returns over the previous week, month, two months, and quarter, whereas the 10-year annualized expected risk premium is slightly negatively related to these past returns. In Appendix Table A1, we use the survey data from 2000-2011 and confirm that the 1-year expectations remain more sensitive to past returns than the 10-year expectations in the longer

⁴The coefficient when regressing 1-year expectations on past 1-year price growth perceptions equals 0.262 (0.029), whereas the coefficient when regressing the implied 2-5 year annualized expectations on 1-year perceptions equals 0.058 (0.012). Case et al. (2012) conduct a similar survey and report the 1- and 10-year annualized capital gains expectations for the housing market at the city-year level. Using CoreLogic county house price indices and their survey data, we find a coefficient of 0.25 (0.02) when regressing 1-year expectations on the past year's house price appreciation and a coefficient of 0.16 (0.04) when regressing the annualized 10-year expectations on the past year's house price appreciation.

sample.⁵ Thus, the available evidence all points toward a term structure for extrapolation in which short-run forecasts are more sensitive to recent prices changes than long-run forecasts.

1.2 Variation in Expected Holding Times

In the presence of a downward sloping term structure for extrapolative expectations, our model implies that recent price changes will differentially draw in short-term investors who amplify volume by selling more frequently and destabilize prices through positive feedback. The magnitude of these effects will depend on the degree of heterogeneity in the distribution of expected holding times among prospective investors. While not much data are available concerning the expected holding times of investors, the best data we are aware of, which come from the housing market, suggest that investment horizons vary considerably across individuals and commove strongly with recent price changes.

Each March, as part of the Investment and Vacation Home Buyers Survey, the National Association of Realtors (NAR) surveys a nationally representative sample of around 2,000 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 for 2006-2015 (2008-2015 for primary residences).

Figure 2 documents the substantial cross-sectional heterogeneity in expected holding times among respondents to the survey.⁶ Each bar reports an equal-weighted average of the share of recent buyers who report a given expected holding time across survey years. Averages are reported separately by property type. Two things stand out. First, the vast majority of

⁵Although the data are available from 2000-2016, we use only 2000-2011 to match the window used by Greenwood and Shleifer (2014), who also find a coefficient of about 0.03 when regressing the 1-year return expectation on the prior year’s return. Interestingly, the coefficients decline considerably when the 2012-2016 sample is included, possibly because declines in interest rates over this time both increased lagged returns and decreased future return expectations.

⁶The bins in Figure 1 are those used by the NAR in its data release (we do not have access to less aggregated data). We reclassify respondents who have already sold their properties as having an expected holding time in $[0,1)$.

recent homebuyers (roughly 80%) report knowing what their expected holding time will be. Second, there is wide variation in expected holding times among those who report. About half of the expected holding times are between 0 and 11 years and are distributed somewhat uniformly over that range. The survey question groups the remaining half of the responses into a single expected holding time of greater than or equal to 11 years; however, there may be substantial variation within that group as well. Expected holding times also vary in an intuitive way across property types. Recent buyers of investment properties report substantially shorter expected holding periods than recent buyers of primary residences or vacation homes.

There is also significant variation in the time series. To demonstrate this, we construct a “short-term buyer share,” which is measured as the fraction of respondents who report an expected holding time of less than 3 years or had already sold their property by the time of the survey.⁷ Across survey years, the short-term buyer share varies from 26% to 41% for investment properties, from 10% to 22% for primary residences, and from 12% to 34% for vacation properties. The weighted average of the short-term buyer share across property types varies from 13% to 26%.

This variation over time is not random. Rather, the short-term buyer share moves closely with recent price appreciation in the housing market. A simple regression of the pooled short term buyer share on the equal-weighted average year-over-year change in the nominal quarterly FHFA US house price index during the survey year yields a statistically significant coefficient estimate of 0.81. This implies that a recent nominal gain of 10% in house prices is associated with an increase in the short-term buyer share of roughly 8.1 percentage points. The nominal house price appreciation in the US in 2005 was equal to 11% and was much larger in some metropolitan areas. Thus, changes in house prices over the last cycle may have induced significant shifts in the distribution of expected holding times among homebuyers at different points in the cycle. We will investigate this hypothesis below using detailed micro-

⁷In constructing this measure, we leave out those who report that they do not know their expected holding time.

data that allows us to construct disaggregated measures of holding times across markets and time periods. Before doing so, however, we first present our model, which is motivated by the evidence just discussed.

2 A Model of Investors with Heterogeneous Horizons

2.1 Primitives and Information Environment

We present an infinite-horizon, continuous-time model of a city with a fixed amount of perfectly durable housing, normalized to have measure one. Agents go through a life cycle with three possible phases: potential buyer, stayer, and mover.

In each instant, agents arrive. Each agent begins as a potential buyer and must decide between buying a home immediately and leaving the city forever. A potential buyer who buys a home becomes a stayer. Stayers receive flow utility $\delta > 0$ from living in the city until receiving an idiosyncratic taste shock and becoming movers. This taste shock arrives with an instantaneous Poisson hazard $\lambda > 0$, which is distributed across potential buyers independently from δ and according to a time-invariant probability density function $f(\lambda)$. For any $\delta_0 > 0$, the measure of agents arriving at t for whom $\delta \geq \delta_0$ equals $A_t \delta_0^{-\epsilon}$, where $\epsilon > 0$ and $\int_0^\infty \lambda^\epsilon f(\lambda) d\lambda$ exists.

Potential buyers and movers maximize the present value of lifetime utility by choosing whether to buy or list, respectively. Stayers do not sell their homes until becoming movers, at which point they choose whether to list their homes for sale at the current price P_t . Until selling, movers decide at each instant whether to list at the current price. Total flow utility is linear in consumption and in the flow benefit from living in the city, which is nonzero only for stayers. All agents may borrow or lend at the common discount rate r .

In addition to their individual types and the current price, all agents observe summary information about the complete history of prices. In particular, there exists a function $\omega(\cdot) \rightarrow \mathbb{R}$ that maps the history of prices into a single factor observed by market participants

at time t . We denote this factor by $\omega_t \equiv \omega(\{P_{t'} \mid t' \leq t\})$. Potential buyers and movers use ω_t to form expectations of future prices, which govern their decisions of whether to buy or list, respectively. Agents form expectations regarding price growth between time t and $t + \tau$ in a manner that is consistent with the following assumption:

Assumption 1. *There exist functions γ and g such that for all $\delta, \lambda, \tau \geq 0$ and $P_t, \omega_t \in \mathbb{R}$*

$$\mathbb{E}[P_{t+\tau}/P_t \mid \delta, \lambda, P_t, \omega_t] = 1 + \gamma(\omega_t)g(\tau) \quad (1)$$

and the following properties hold:

- (a) $(g(\tau)/\tau)' < 0$ for all $\tau > 0$;
- (b) $g(0) = 0$;
- (c) $\gamma(\omega)g'(0) \leq r$ for all $\omega \in \mathbb{R}$; and
- (d) $\int_0^\infty e^{-r'\tau}g(\tau)d\tau > 0$ for all $r' > r$.

Assumption 1(a) endows agents with extrapolative expectations that satisfy the empirical evidence on the forward term structure presented in Section 1. The decrease of $g(\tau)/\tau$ is necessary and sufficient for nontrivial increases in ω_t to raise short-term expected capital gains more strongly than long-term expected capital gains:

Lemma 1. *Given (1), Assumption 1(a) holds if and only if*

$$\frac{\partial^2}{\partial \tau \partial \omega_t} \mathbb{E} \left[\frac{P_{t+\tau} - P_t}{\tau P_t} \mid \omega_t \right] < 0$$

for all $\tau > 0$ and $\omega_t \in \mathbb{R}$ such that $\gamma'(\omega_t) > 0$.

Assumption 1(b) imposes the weak constraint that $\mathbb{E}[P_{t+\tau}/P_t] = 1$ for $\tau = 0$. Assumption 1(c) is necessary and sufficient for the expected growth rate of prices to always fall below r :

Lemma 2. *Given (1) and Assumptions 1(a) and 1(b), $\mathbb{E}[P_{t+\tau}/P_t \mid \omega_t] < e^{r\tau}$ for all $\tau > 0$ and $\omega_t \in \mathbb{R}$ if and only if Assumption 1(c) holds.*

Finally, Assumption 1(d) guarantees that an increase to $\gamma(\omega_t)$ raises the present value of expected capital gains for all potential buyers.

2.2 Equilibrium Quantities

Solving the model requires knowing the number of agents of each type at each point in time, as well as the stock of previous listings that did not sell. In particular, we track the number of potential buyers who decide to buy D_t and the number of stayers S_t . These jointly determine the flow of listings L_t , the inventory of unsold listings I_t , and sales volume V_t .

Due to Lemma 2, $P_t > e^{-r\tau} \mathbb{E}[P_{t+\tau} \mid P_t, \omega_t]$ for all t and $\tau > 0$, so movers always choose to list their homes for sale. As a result, we may describe the evolution of listings using the stock of stayers of each type λ , or $S_t(\lambda)$. Because all new movers list, the flow of listings is simply the total number of stayers receiving idiosyncratic mover shocks:

$$L_t = \int_0^\infty \lambda S_t(\lambda) d\lambda. \quad (2)$$

Given A_t , P_t , and ω_t , a measure D_t of potential buyers decide to buy. If D_t is less than the number of homes listed for sale, then all interested potential buyers are able to buy. Otherwise, homes are rationed randomly among the set of interested potential buyers. Let $D_t(\lambda)$ denote the measure of potential buyers of type λ who decide to buy. Then sales volume to potential buyers of type λ equals

$$V_t(\lambda) = \begin{cases} D_t(\lambda) & \text{if } L_t > D_t \text{ or } I_t > 0 \\ \frac{D_t(\lambda)}{D_t} L_t & \text{if } L_t \leq D_t \text{ and } I_t = 0, \end{cases} \quad (3)$$

where I_t is the inventory of unsold listings. The stayer stocks for each λ evolve according to the law of motion

$$\dot{S}_t(\lambda) = V_t(\lambda) - \lambda S_t(\lambda), \quad (4)$$

which is the number of new buyers of type λ less the number of stayers of type λ who become movers. Unsold listings follow the law of motion

$$\dot{I}_t = L_t - V_t, \tag{5}$$

where $V_t = \int_0^\infty V_t(\lambda)d\lambda$ equals total sales.

These expressions have two key implications for the dynamics of volume. First, volume today depends on volume before, as past buyers become current sellers. Second, the number of listings today depends both on the level of past volume and on the expected holding periods among past buyers. The larger the number of past buyers with short horizons, the larger the flow of current listings.

2.3 The Composition of Buyers

The interesting dynamics in the model concern how the composition of buyers—specifically, the composition of expected holding periods—varies over the cycle. This composition depends on the distribution of λ among buyers. The probability density function of λ among buyers at time t is given by the function $V_t(\lambda)/V_t$. By (3), this function coincides with $D_t(\lambda)/D_t$, the probability density function of demand across potential buyers at t . Thus to understand how the composition of buyers varies over time, we must calculate the distribution of demand across λ .

To derive $D_t(\lambda)$, we assume that potential buyers believe that they will sell their house as soon as they list it:

Assumption 2. *Potential buyers believe that listing movers sell instantaneously.*

It may be possible to microfound Assumption 2 as a type of conditional rationality in which agents believe that “cold” markets are impossible. One consequence of Assumption 2 is that the expected holding time of a buyer of type λ equals $1/\lambda$. The other consequence is that a potential buyer of type (λ, δ) tries to buy if the current price is below the present discounted

value of the flow utility she would receive as a stayer plus the expected resale value of the house at the time she anticipates becoming a mover. That is, a potential buyer tries to buy if and only if

$$P_t \leq \int_0^\infty \lambda e^{-\lambda\tau} \left(\int_0^\tau e^{-r\tau'} \delta d\tau' + e^{-r\tau} \mathbb{E}_t P_{t+\tau} \right) d\tau. \quad (6)$$

The value of δ at which a buyer of type λ is indifferent implies the equation for demand given in Lemma 3.

Lemma 3. *Demand from each λ type equals*

$$D_t(\lambda) = \underbrace{f(\lambda)A_t}_{\substack{\text{potential} \\ \text{buyer} \\ \text{measure}}} \times \underbrace{(rP_t)^{-\epsilon}}_{\substack{\text{fundamental} \\ \text{demand}}} \times \underbrace{\Sigma_\lambda(\omega_t)}_{\substack{\text{speculative} \\ \text{demand}}},$$

where

$$\Sigma_\lambda(\omega_t) = \left(1 - \frac{\lambda\gamma(\omega_t)}{r} \int_0^\infty e^{-(r+\lambda)\tau} g'(\tau) d\tau \right)^{-\epsilon}. \quad (7)$$

Demand for each λ is composed of three terms. The first term $f(\lambda)A_t$ equals the relative measure of potential buyers of type λ . The second term, which we call “fundamental demand,” is a decreasing function of current prices with constant elasticity ϵ . This term reflects the relationship between demand and prices were prices to remain permanently at their current level. The third term, which we call “speculative demand,” links current demand to expected capital gains. If buyers expect prices to remain constant, then $\Sigma_\lambda(\omega_t) \equiv 1$ and speculative demand does not magnify total demand. Otherwise, speculative demand magnifies total demand when buyers expect capital gains and attenuates total demand when buyers expect capital losses, with the force of this multiplier depending on the buyer’s horizon.

Only speculative demand matters for variation in the composition of buyers over time, as the other two demand components are always proportional to each other across λ types. As a consequence, variation in the composition in buyers depends entirely on changes in expected capital gains. Proposition 1 formally states this relationship:

Proposition 1. *At any ω_t such that $\gamma'(\omega_t) > 0$, the following hold for all $\lambda > 0$.*

(a) *Expected capital gains increase demand from all types:*

$$\frac{\partial \log D_t(\lambda)}{\partial \omega_t} > 0.$$

(b) *Short-term (higher λ) buyers are more sensitive to expected capital gains:*

$$\frac{\partial^2 \log D_t(\lambda)}{\partial \lambda \partial \omega_t} > 0.$$

(c) *Expected capital gains skew the composition of buyers shorter-term:*

$$\frac{\partial \int_0^\lambda V_t(\lambda') d\lambda' / V_t}{\partial \omega_t} \leq 0,$$

with equality if and only if $|\text{supp } f| = 1$.

Part (a) formally states that greater expected capital gains increase demand. This effect appears in any user cost model of housing (e.g. Poterba, 1984). The focus in most user cost models is primarily the intensive margin demand for housing capital. Our model highlights the extensive margin instead, as the stimulative effect of expectations on demand operates entirely through drawing new buyers into the market. Consistent with this mechanism, Agarwal et al. (2015) document increased participation in the owner-occupied housing market in response to rising prices.

The extensive margin effect also predicts that expected capital gains stimulate demand more for buyers with low flow utility. Buyers with high flow utility are off the margin, so variation in ω does not impact their decision to buy. Consistent with that observation, in Section 4 we document a large increase in investor participation in the US housing market during the 2000-2006 boom. Investors receive less flow utility than owner-occupants because in a competitive market, the rent received by landlords reflects the flow utility of the marginal renter; in contrast, most owner-occupants are infra-marginal. Investors also receive less flow

utility than owner-occupants due to frictions that arise from the separation of ownership of control (Nathanson and Zwick, 2015).

Part (b) shows that the stimulative effect of capital gains is stronger for buyers with shorter expected holding times. Buyers looking to make a “quick buck” are drawn to rising prices more than those buying for the long run. The proof of Proposition 1 shows that this effect follows from the higher sensitivity of short-term expectations to ω_t embodied by Assumption 1(a).

Part (c) links expected capital gains to the composition of buyers. Because short horizon buyers are more sensitive to capital gains, an increase in expected capital gains skews the composition of buyers towards those with shorter holding times. Proposition 1(c) explains the evidence presented in Section 1 that both expected capital gains and the short-term buyer share respond strongly to recent home price appreciation.

Proposition 1 illustrates the key mechanism generating time-variation in volume in the model, namely, time-variation in the composition of holding periods for buyers and sellers driven by time-variation in expected returns. To close the model, we now specify how prices are determined.

2.4 Equilibrium Prices

For notational ease, we define aggregate speculative demand as $\Sigma(\omega_t) \equiv \int_0^\infty \Sigma_\lambda(\omega_t) f(\lambda) d\lambda$.

Total demand across all potential buyers can then be expressed as

$$D_t = A_t (rP_t)^{-\epsilon} \Sigma(\omega_t). \tag{8}$$

Prices are set to ensure that supply equals demand in the long run. That is, all listings sell ($I_t = 0$) and there is no rationing ($D_t = L_t$). We assume that this adjustment does not occur instantaneously; rather, prices adjust slowly in response to perceived excess demand.

Specifically, we assume that the instantaneous change in prices can be expressed as

$$\dot{p}_t = c \log(D_t/\bar{D}), \quad (9)$$

where $p_t = \log P_t$, \bar{D} is a long run demand target, and $c > 0$ is a constant determining the rate at which prices adjust to achieve this target. The appendix shows that there exists a unique value of \bar{D} given by

$$\bar{D} = \left(\int_0^\infty \lambda^{-1} f(\lambda) d\lambda \right)^{-1} \quad (10)$$

such that a steady state exists in which $L_t = D_t$, $I_t = 0$, and in which potential buyers expect prices to remain constant. For this reason, we adopt (10) as the demand target relevant for price adjustment.

Equations (8) and (9) can generate positive feedback wherein an increase to p increases ω , thereby increasing D and further increasing p . As we show in Section 3, this feedback loop causes overshooting of prices in response to a demand shock. Sluggish price adjustment allows us to study the dynamics of unsold listings I by creating the possibility of mismatch between demand D and listings L . This form of price adjustment is consistent with the empirical short-run autocorrelation of prices in the housing market (Case and Shiller, 1989; Glaeser et al., 2014; Head et al., 2014; Guren, 2016) as well as short-run momentum documented in other asset markets (Cutler et al., 1991; Jegadeesh and Titman, 1993; Asness et al., 2013). We do not specify the precise mechanism through which $c < \infty$ might arise and instead focus on the joint dynamics of prices and volume resulting from it.⁸

⁸Samuelson (1947) introduced an equation similar to (9) to model Walrasian tâtonnement. Since then, a large literature has provided a variety of microfoundations for gradual price adjustment (“sticky prices”), such as staggered contracts (Calvo, 1983) or information sets (Mankiw and Reis, 2002). See Guren (2016) for a microfoundation of gradual price adjustment in the housing market.

3 The Joint Dynamics of Prices and Volume

We use the model in Section 2 to explore the joint dynamics of prices and volume over the course of a boom-bust cycle. We provide a series of propositions that allow for a qualitative characterization of the relationship between prices and volume over the cycle. We then turn to a calibration of the model which allows us to study the potential quantitative relevance of the factors driving the model.

We focus on how volume and prices respond to a one-time permanent demand shock. In particular, we study an impulse response around the unique steady state that results from a single positive shock to the number of potential buyers, A_t , at a time we normalize to $t = 0$. Specifically, A_t follows the path where $A_t = A^i$ for $t < 0$ and $A_t = A^f > A^i$ for $t \geq 0$.

To characterize how prices and volume respond to this shock, we impose additional structure on how agents form expectations. We specify both the information that agents have available to them when they form forecasts of future prices and how that information influences these forecasts, which are governed in the model by $\omega(\cdot)$ and $\gamma(\cdot)$, respectively.

Following Barberis et al. (2015), we assume that agents observe only a weighted average of past price changes:

$$\omega_t = \int_{-\infty}^t \mu e^{-\mu(t-\tau)} \dot{p}_\tau d\tau, \quad (11)$$

where the parameter $\mu > 0$ measures the relative weight put on more recent price changes. To study dynamics, it is useful to know how this average changes in response to an instantaneous change in prices, which is simply the differential form of (11):

$$\dot{\omega} = \mu(\dot{p} - \omega). \quad (12)$$

Our specification of ω is sufficiently general that the impulse response may not always result in a well-behaved boom and bust in prices. In some cases, prices may rise without falling, or they may oscillate indefinitely. We restrict focus to a parameter region in which a boom is followed by a bust that asymptotes without indefinitely oscillating. In particular, we

require $\gamma(\cdot)$, the function mapping past price information to future expected price changes, to satisfy the following assumption:

Assumption 3. $\gamma(\omega) \equiv 0$ for $\omega \leq 0$, $\lim_{\omega \rightarrow 0^+} \gamma(\omega) = 0$, $\gamma'(\omega) > 0$ for $\omega > 0$, and

$$\lim_{\omega \rightarrow 0^+} \gamma'(\omega) > \frac{r}{\min(c\epsilon, \mu)} \left(\int_0^\infty \int_0^\infty \lambda e^{-(r+\lambda)\tau} g'(\tau) d\tau f(\lambda) d\lambda \right)^{-1}.$$

The requirement that $\gamma \equiv 0$ for $\omega < 0$ rules out oscillations after the bust, as agents stop expecting capital gains once the historical average return becomes negative. The rest of Assumption 3 guarantees that price increases initially beget further increases and that prices eventually overshoot. With this additional structure, we are now able to provide a complete characterization of the joint dynamics of prices and volume following the one-time permanent demand shock.

3.1 The Boom

We begin with a series of three propositions which divide the boom-bust cycle into three distinct epochs. We refer to these epochs as “the boom,” “the quiet,” and “the bust.” Proposition 2 presents the conditions that characterize the boom.

Proposition 2. *There exists $t_1 > 0$ such that for $0 < t \leq t_1$: prices rise ($\dot{p}_t > 0$), prices are convex ($\ddot{p}_t > 0$), expected capital gains increase ($\dot{\omega}_t > 0$), demand exceeds listings ($D_t > L_t$), and if $|\text{supp } f| > 1$ volume rises ($\dot{V}_t > 0$).*

As the proof shows, the shock to A at $t = 0$ causes demand D to jump above available listings. As a result, the price of housing begins to increase, and this increase raises ω . The rise in ω stimulates demand, further increasing prices and leading to convexity in the price path. Demand rises more sharply for potential buyers with higher values of λ , causing an increase in listings and hence volume. We define the boom as the time interval $(0, t_1^*]$, where t_1^* is the largest t_1 such that the conditions of Proposition 2 hold.

Proposition 2 fits the 2000-2005 US housing market remarkably well, as shown in Figure 1. Prices and volume rose during this time, with prices rising at an increasing rate. Unsold inventories increased at the same rate as volume, implying that demand was sufficient to exhaust the flow of listings and that a stock of unsold listings did not accumulate.

3.2 The Quiet

To continue characterizing the cycle, we provide a lemma that guarantees that prices do not rise indefinitely:

Lemma 4. *There exists (a finite) $t_2 > 0$ such that $\dot{p}_{t_2} = 0$.*

Lemma 4 implies that the boom must end ($t_1^* < \infty$). It also precludes a price path that asymptotes to some level without overshooting. We define t_2^* to be the smallest $t_2 > 0$ such that $\dot{p}_{t_2} = 0$. Proposition 3 characterizes the time period between t_1^* and t_2^* .

Proposition 3. *Prices rise ($\dot{p}_t > 0$) for all $t \in (t_1^*, t_2^*)$, listings exceed demand ($L_t > D_t$) for some $t \in (t_1^*, t_2^*)$, and volume falls ($\dot{V}_t < 0$) for some $t \in (t_1^*, t_2^*)$.*

As can be seen from the price-adjustment equation (9), $D_{t_2^*}$ equals the long-run level of demand and listings \bar{D} . This level represents a decline from the magnitude of demand during the boom, so demand must fall sometime during (t_1^*, t_2^*) . In contrast, listings remain above this steady-state value because past capital gains continue to lure short-term potential buyers disproportionately. The combined effect is an excess of listings over demand. Inventories of unsold listings accumulate by (5), and volume equals demand and hence falls with demand. Because trading activity is falling, we refer to the time interval $(t_1^*, t_2^*]$ as “the quiet.”

Proposition 3 fits the time between 2005 and 2007 in Figure 1. In 2005, prices reached at inflection point and began to grow at a slower rate, and volume began to fall. Unsold inventories then sharply increased as volume continued to decline.

3.3 The Bust

The final proposition characterizes prices and volume after prices stop rising.

Proposition 4. $\lim_{t \rightarrow \infty} p_t = p_0 + \epsilon \log(A^f/A^i)$, and for $t > t_2^*$ prices decline ($\dot{p}_t < 0$) and volume is below steady-state ($V_t < \bar{D}$) until this limit is reached.

After the quiet, prices decline on low volume, eventually reaching the steady state level. We refer to the time interval (t_2^*, ∞) as “the bust.”⁹

Genesove and Mayer (2001) document low volume during a bust in the Boston apartment market and ascribe it to high prices posted by loss-averse sellers trying to avoid nominal losses. In our setting, low volume during the bust derives from the sticky price adjustment that states that prices decline whenever demand is low. Low demand holds during the bust for two reasons: speculative demand is low because expected capital gains are small or absent, and fundamental demand is low because prices exceed the steady-state value.

The bust corresponds to the period after 2007 shown in Figure 1 during which prices fell and volume was lower than average.

3.4 Short-Term Buyers and the Size of the Cycle

Propositions 2–4 characterize the relative timing of the price and volume responses. We now describe the relative *magnitude* of these responses. In particular, we show that a common factor—the distribution of expected holding times $f(\cdot)$ —determines the magnitude of the price and volume responses as well as the level of steady-state volume.

To discuss the size of the price and volume responses, we define $P^{max} = \max_{t \in (0, t_2^*)} P_t$ and $V^{max} = \max_{t \in (0, t_2^*)} V_t$ to be the largest values of prices and volume attained during the boom

⁹Prices do not overshoot on the decline because Assumption 3 rules out negative expected capital gains. This simplifying assumption allows us to highlight the dynamic interactions between the composition of buyers, volume, and prices during the periods leading to the bust, and how buyer composition can lead to overshooting as prices rise. Without this assumption, prices would overshoot on the way down, which is a standard feature of models with extrapolative expectations (e.g., Glaeser and Nathanson, 2016). Empirically, negative overshooting may occur for a variety of reasons, such as a continuing glut of listed houses (Shleifer and Vishny, 1992) or foreclosures (Guren and McQuade, 2015).

and quiet, and we denote the final steady-state price by P_∞ . The presence of additional short-term buyers magnifies the price response and steady-state volume:

Proposition 5. *An increase to $f(\cdot)$ raises V_0 and P^{max} while keeping P_0 and P_∞ constant.*

The increase to $f(\cdot)$ is under first-order stochastic dominance, which implies a greater frequency of short-term buyers (those with high λ).

As shown in the proof, a larger $f(\cdot)$ raises steady-state volume V_0 and the speculative demand function $\Sigma(\cdot)$. The demand of short-term buyers is more sensitive to expected capital gains, so a greater frequency of such buyers raises aggregate speculative demand. A larger $\Sigma(\cdot)$ then increases the maximal price reached during the cycle without changing the steady states. Proposition 5 makes the empirical prediction that price cycles are larger in markets with higher steady-state volume; we confirm this prediction in Section 4.

To demonstrate how $f(\cdot)$ jointly determines the magnitudes of the price and volume responses, we now apply Proposition 5 to a special case in which we compare two markets. In market A , all potential buyers have the same expected holding time. In market B , potential buyers differ in their expected holding times, none of which are longer than the expected holding time in A . The markets are otherwise identical.

Proposition 6. *If $1 = |\text{supp}(f_A)| < |\text{supp}(f_B)|$ and $f_A < f_B$, then P^{max}/P_0 , P^{max}/P_∞ , V^{max}/V_0 , and V_0 are larger under f_B than f_A .*

Proposition 5 clarifies the importance of volume for understanding asset bubbles in a special case. Volume is not a sideshow to prices, but rather a manifestation of the speculative forces responsible for price dynamics. These speculative forces are captured by the heterogeneity in $f(\cdot)$. We conjecture that a mean-preserving spread in $f(\cdot)$ always increases P^{max} and V^{max} while leaving V_0 unchanged. Although we are not able to prove this conjecture, we verify it in our calibration below.

3.5 Calibration

To study predictions of our model quantitatively, we simulate the impulse response characterized in Propositions 2 through 4. We choose parameter values using surveys and prior literature to discipline the calibration and ask whether, subject to this parameterization, the changes in volume and buyer composition are large.

3.5.1 Parameter Choices

Table 1 lists the model parameters and their sources. We calibrate $f(\cdot)$ using the expected holding times reported in the NAR survey shown in Figure 2.¹⁰ To select μ , we rerun the regression mentioned in Section 1.2 of the short-term buyer share on past house price appreciation by replacing the lagged four-quarter house price change with ω as given by (11). We choose μ to maximize the R^2 of this regression, leading us to $\mu = 1.19$ (standard error 0.65) and $R^2 = 67\%$. This estimate is noisy due to the small amount of data used in the estimation, but it is close to the value of $\mu = 0.5$ estimated by Barberis et al. (2015) in the context of the stock market.

To calibrate $g(\cdot)$, we adopt the functional form $g(\tau) = \rho(1 - e^{-\tau/\rho})$. For all ρ , $g'(0) = 1$, so ρ controls the extent to which the initial gain is extrapolated into the future. The half-life of the cumulative gains implied by $g(\cdot)$ equals $\rho \log 2$, so a larger ρ produces greater relative sensitivity of long-term expected gains to short-term expected gains.¹¹ In each year from 2014-2016, the New York Fed's Survey of Consumer Expectations reports the median expectation of house price growth in the United States over the next 1 and 5 years (see Fuster and Zafar, 2015 and Kuchler and Zafar, 2016 for information on this survey). The ratio of these expectations equals $(1 - e^{-5/\rho})/(1 - e^{-1/\rho})$, so we use the sample ratios to obtain a

¹⁰We map the expected holding time for each bin to its median, except for $[11, \infty)$ which we map to 20. We then associate λ equal to the inverse of the expected holding time to each bin (e.g. $\lambda = 2$ for an expected holding time of 0.5 years). Using the share of sales to each property type in each year, we calculate $f(\cdot)$ for each year and then take an equal-weighted average across years to obtain the distribution used in the calibration.

¹¹The half-life is the value τ_{hl} such that $g(\tau_{hl}) = (1/2) \lim_{\tau \rightarrow \infty} g(\tau)$.

value of $\rho = 20.9$ (half-life of 14.5 years). An alternative method is to use the coefficient estimates from Armona et al. (2016) of the relative sensitivities of 1-year and 5-year forward capital gains expectations to the prior year's house price appreciation. By equating these estimates to $g(\tau) \lim_{\omega \rightarrow 0^+} \gamma'(\omega)$ for $\tau = 1$ and $\tau = 5$, we obtain a much smaller number of $\rho = 1.4$ (half-life of 1.0 year).¹² We use the average of these two numbers as our baseline, and return to each extreme in the sensitivity analysis.

To calibrate $\gamma(\cdot)$, we adopt the functional form $\gamma(\omega) = r(1 - e^{-\phi\omega/r})$ for $\omega > 0$. Here $\phi > 0$ is a free parameter governing the sensitivity of expectations to small increases in ω . As required by Assumption 1, $\gamma(\omega)g'(0) \leq r$ for all ω , and as required by Assumption 3, $\gamma'(\omega) > 0$ for all $\omega > 0$. We use the results of the survey of homeowner expectations conducted by Case et al. (2012) to estimate ϕ . Case et al. (2012) report the average expectation of the next year's price growth of homeowners in Alameda County (CA), Middlesex County (MA), Milwaukee County (WI), and Orange County (CA) in the spring of each year from 2003 to 2012. Using the CoreLogic monthly house price indices going back to 1976, we calculate ω_t for each county and year with (11) and our estimate of μ mentioned above. We then choose ϕ and a constant to minimize the mean-squared error of $g(1)\gamma(\omega)$ plus this constant versus the expectation reported by Case et al. (2012). The resulting value is $\phi = 0.98$ (standard error 0.27).¹³ Our specification explains 70% of the variance in 1-year expectations across counties and years in this sample.

We set $r = 0.07$, which corresponds to a steady-state price-rent ratio of about $1/0.07 = 14$. We choose $c = 1$, which implies a half-life of price adjustment of about 8 months. We set the elasticity of demand, ϵ , equal to 0.6, a value in the range of estimates suggested by Hanushek and Quigley (1980). Finally, for round number convenience, we choose a demand shock size to match a long-run price impact of 10%. This price impact equals $(A^f/A^i)^{1/\epsilon}$, so

¹²Armona et al. (2016) calculate the expected 1-year gain, which equals $\gamma(\omega)g(1)$, and the annualized 2-5 year expected gain, which equals $(1 + \gamma(\omega)(g(5) - g(1))/(1 + \gamma(\omega)g(1)))^{1/4} - 1$. The right derivatives at $\omega = 0$ are $g(1) \lim_{\omega \rightarrow 0^+} \gamma'(\omega)$ and $(1/4)(g(5) - g(1)) \lim_{\omega \rightarrow 0^+} \gamma'(\omega)$. The ratio of these equals $(1/4)(g(5)/g(1) - 1)$, the value of which uniquely identifies ρ .

¹³The value of the constant is 0.022 (0.004).

we set $A^f/A^i = 1.06$: a demand shock of 6%.

3.5.2 Results

The differential equations given by our model allow us to solve for the impulse response in continuous time. In order to quantify the marginal effects of heterogeneous holding times, we supplement the baseline model with one in which λ is the same for all potential homebuyers. We set this value to $(\int_0^\infty \lambda^{-1} f(\lambda) d\lambda)^{-1}$, the unique value at which steady-state volume remains unchanged.

Figure 3 displays the resulting impulse responses. Panel (a) plots our two main objects of study: prices and volume. In the core model, prices significantly overshoot the long-run cumulative growth of 10%, more than doubling before decreasing to the new level. Initially, prices are convex, meaning that price changes beget further changes. In contrast, prices display a much less pronounced boom and bust when expected holding times equal the average.

In the baseline model, volume rises and then falls, beginning to decline 11 months before prices. This delay is very close to the empirical delay of 15 months we document below. The total rise of volume in our simulation equals 22%, a substantial fraction of the 34% rise in existing sales volume in the US between 2000 and 2005. As shown on the right, volume remains constant as prices rise when λ is homogeneous.

Panel (b) documents the changing composition of buyers over the cycle. At each time, we calculate the share of purchases going to buyers whose expected holding time is less than 3 years. In steady state, this share equals 20% (as identified by the NAR survey), and it rises to a high of 39%. This rise occurs as prices increase, and it drives the concomitant and subsequent surge in volume. In contrast, no homebuyers have expected holding times less than 3 years in the homogeneous simulation, as the average holding time (and hence universal holding time in that case) equals 10.5 years.

Finally, panel (c) documents the evolution of unsold listings over the cycle. Until the

quiet begins, all listings sell, so unsold listings equal 0. The stock grows as volume begins to decline. Quantitatively, it reaches 6% of the housing stock in the baseline model, but only 2% when horizons are homogeneous.

In sum, Figure 3 shows that our calibrated model can quantitatively generate large swings in prices and volume during the boom and quiet periods, a dramatic shift in the composition of buyers, and a sharp rise in inventories in the period leading to the bust. These features depend critically on heterogeneity in the expected holding times of potential homebuyers.

3.5.3 Sensitivity Analysis

To provide intuition on how the parameters drive the results, we report key statistics of the simulation under parameters other than our baseline in Table 2. The three statistics we report are the excess price boom $P^{max}/P_{\infty} - 1$, the volume boom $V^{max}/V_0 - 1$, and the maximal inventory of unsold listings $\max_t I_t$. We vary each parameter to a low and high value while keeping the remaining parameters at the baseline values.

First we vary the degree of heterogeneity in $f(\cdot)$. In the “high” treatment, we keep steady-state volume $(\int_0^{\infty} \lambda^{-1} f(\lambda) d\lambda)^{-1}$ constant but put all the mass in $f(\cdot)$ on the most extreme values of λ in its support. The “low” treatment simply replicates the right panel of Figure 3 in which no heterogeneity exists. The booms in price and volume are much larger in the high treatment than in the baseline—prices more than quadruple, and volume almost doubles. Unsold inventories also rise to 18% of the housing stock. These results provide strong evidence tying together price booms, volume booms, and the distribution of expected holding times.

Varying the housing demand elasticity produces similar effects. Our low treatment sets $\epsilon = 0.3$ (half the baseline), whereas our high treatment sets $\epsilon = 1.8$ (an average of values calculated by Diamond, 2016). Prices more than quadruple and volume nearly doubles under the high elasticity, whereas prices and volume are much more stable under the low treatment. Short-term buyers enter the market more aggressively when housing demand is more elastic,

so increasing the elasticity achieves similar results to increasing the frequency of short-term buyers. The simulation results are less sensitive to variations in the other parameters.

4 Speculative Dynamics in the U.S. Housing Bubble

While the calibration in the previous section allows for an assessment of the potential quantitative relevance of the factors that drive our model, their actual empirical relevance has yet to be established. In this section, we provide empirical evidence linking shifts in the distribution of realized holding periods over the course of the 2000–2008 US housing cycle to dynamic patterns in volume and prices that directly mirror the patterns implied by our model. We focus on the housing market both because of its macroeconomic relevance and because the availability of comprehensive, asset-level microdata permits a uniquely rich analysis of holding periods and the details of buyers and sellers.

4.1 Data

To conduct our analysis, we use data on individual housing transactions provided by CoreLogic, a private vendor which collects and standardizes publicly available tax assessments and deeds records from municipalities across the US. Our main analysis sample spans the years 1995–2014 and includes data from 115 Metropolitan Statistical Areas (MSAs), which together represent roughly 50 percent of the US population.

We include all transactions of single-family homes, condos, or duplexes that satisfy the following filters: (a) the transaction is categorized by CoreLogic as occurring at arm’s length, (b) there is a non-zero transaction price, and (c) the transaction is not coded by CoreLogic as being a nominal transfer of title between lenders following a foreclosure. We also drop a small number of duplicate transactions where the same property is observed to sell 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. These restrictions leave us with

a final sample of 49,709,319 transactions. Given the geographic coverage of these data and their source in administrative records, our analysis sample serves as a rough proxy for the population of transactions in the US during our sample period.

4.2 The Composition of Buyers

The key mechanism that generates time-variation in transaction volume in our model is that changes in expected capital gains over the course of the housing cycle differentially attract buyers with shorter-vs-longer expected holding periods. This phenomenon was stated formally in Proposition 1 and implies that large swings in volume should be accompanied by equally large changes in the distribution of realized holding periods among those who choose to sell their homes at various points in the cycle.

As evidence for this prediction, Figure 4 presents a simple yet compelling illustration of the time variation in realized holding periods during the 2000–2008 US housing cycle. We define the holding period of each transaction as the number of days since the last transaction of the same property. We then group all transactions with holding periods less than or equal to 5 years into bins of 1, 2, 3, 4, or 5 years and count the number of transactions falling into each bin. Figure 4 plots these bin counts by year for each year between 2000 and 2008.

During the boom years of 2000–2005, there is a clear compression in the distribution of realized holding periods toward shorter holding periods. This pattern then reverses as national house prices peak in 2006 and begin to fall in the subsequent years. The increase in transaction volume at short holding periods during the boom years represents a non-trivial portion of the overall increase in volume during this period. For example, total volume across all holding periods (including those greater than 5 years) increased from 2,735,490 transactions in 2000 to 3,817,122 transactions in 2005. During the same period, total volume in the 1-, 2-, and 3-year bins increased from 471,057 transactions to 921,766, which implies that these three groups alone can account for 42 percent of the total increase in volume

between 2000 and 2005.¹⁴

This shift in the composition of buyers and sellers toward shorter holding periods during the boom years correlates highly with changes in total volume across local markets. This correlation can be seen clearly in Figure 5, which presents scatter plots of the percent change in total volume at the MSA-level from 2000–2005 versus the percent change in volume for short holding periods (≤ 2 years) in Panel (a) and long holding periods (> 2 years) in Panel (b).¹⁵ Not only does the growth in volume of short holding period transactions correlate strongly with the increase in total volume across MSAs during this period, but this relationship is much stronger for short holding periods relative to long holding periods.

Panel (c) further shows that these cross-sectional differences in the growth rate of short holding period volume explain a significant portion of the differences in the growth in total volume across cities during this period. For each city, we plot the change in short holding period volume divided by initial total volume on the y-axis against the percent change in total volume on the x-axis. The slope of this line provides an estimate of how much of a given increase in total volume during this period came in the form of short holding period volume. The answer is approximately 33 percent. Thus, as predicted by Proposition 1, shifts in the distribution of holding periods of buyers and sellers over the course of the cycle appear to be a major determinant of changes in total transaction volume.

Because expected capital gains increase demand through the extensive margin, Proposition 1 additionally predicts that volume increases more strongly in groups of buyers with low flow utility. While we do not observe flow utility in our data, we do observe whether each purchased property is owner-occupied. Under the assumption that non-occupants receive less flow utility than occupants, we further test Proposition 1 by examining whether non-occupant purchases rose more than occupant purchases from 2000 to 2005.

¹⁴This finding is in line with the evidence provided by Bayer et al. (2015), who document a similar increase in volume among short holding period buyers in the Los Angeles MSA during this period.

¹⁵For visual clarity, we group MSAs into 25 equal-sized bins based on their percent change in total volume during this period and calculate the average percent change in short and long holding period volume in each of these bins.

To track the participation of non-owner-occupants in the market over time, we follow Chinco and Mayer (2016) by marking buyers as non-owner-occupants when the transaction lists the buyer’s mailing address as being distinct from the property address.¹⁶ While this proxy may misclassify some non-owner-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 owner-occupied home sales in the market.

Using this proxy, Figure 6 displays plots that are analogous to those in Figure 5 but use non-owner occupancy as the sorting variable rather than holding periods. Similar to the patterns we documented for short holding periods, we find that non owner-occupant volume is an important driver of total volume during the cycle. The top panels compare volume growth for non owner-occupants and owner-occupants, and show that the relationship between total volume growth and non owner-occupant volume growth is much stronger. The bottom panel shows that this growth is also quantitatively important in accounting for total volume growth. Non owner-occupant volume accounts for more than half of the growth in total volume across cities.

4.3 The Joint Dynamics of Prices, Volume, and Listings

Propositions 2–4 predict that prices and volume both go through a boom and bust cycle, with the volume cycle leading the price cycle. In Figure 7, we present evidence that this relationship holds on average across MSAs in our sample. To do so, we search for the horizon over which a given change in volume has the most predictive power for the contemporaneous change in prices at the MSA level. Changes in volume generally lead changes in prices if the correlation between prices and volume is maximized at a positive lag.

To implement this search, we construct a monthly panel of house prices and total transaction volume at the MSA level running from January 1995 to December 2014. Prices equal

¹⁶In related work, Haughwout et al. (2011) use an alternative proxy for non-owner-occupancy based on the number of first-lien mortgages present on an individual’s credit report. They also find a large increase in non-owner-occupant purchases during this time period.

the log of CoreLogic MSA-level house price indices, demeaned at the MSA level. Volume equals the total number of transactions in our data in a given month and MSA divided by that MSA’s housing stock in the 2000 Census. Because the CoreLogic price indices are seasonally adjusted, we adjust our volume series by subtracting the MSA-specific average volume for the relevant calendar month from each observation. Using this panel, we then run a series of simple regressions of the form

$$p_{i,t} = \beta_{\tau} v_{i,t-\tau} + \eta_{i,t}, \quad (13)$$

where p is price, v is volume, i indexes MSAs, and time is measured in months.

The coefficient β_{τ} provides an estimate of how movements in volume around MSA-calendar month averages at a τ -month lag are correlated with contemporaneous movements in prices around MSA averages. We run these regressions separately for up to 4 years of lags ($\tau = 48$) and one year of leads ($\tau = -12$). Figure 7 plots the implied correlation from each regression along with its 95% confidence interval.¹⁷ The correlation is positive at all leads and lags, but reaches its maximum at a positive lag of approximately 15 months. Thus, changes in volume generally lead changes in prices by a little over a year.

4.4 Initial Volume and the Size of the Cycle

Proposition 5 shows that an increase to the distribution of expected holding times $f(\cdot)$ raises both the level of steady-state volume as well as the magnitude of the increase in prices during the boom and subsequent decreases in prices during the bust. Rather than measure $f(\cdot)$ directly, we test whether steady-state volume and the amplitude of the price cycle are positively correlated across cities. Our measure of steady-state volume equals the number of existing home sales in 2000 as a share of the housing stock. The boom in each city equals the percentage change in prices between January 2000 and the month in which prices peaked,

¹⁷The implied correlation equals $\rho_{\tau} = \beta_{\tau} \text{std}(v_{i,t-\tau}) / \text{std}(p_{i,t} - \bar{p}_i)$. Confidence intervals for each estimate are calculated from standard errors that are clustered at the month level.

and the bust equals the percentage change between the month of the peak and the month in which prices reached their lowest level subsequent to the peak month.¹⁸

Figure 8 plots the relationship between steady-state volume and the magnitude of the boom and bust in prices across cities. Panel (a) shows that there is a clear positive relationship between initial volume and the magnitude of the price boom. Cities with higher initial volume experienced significantly larger house price booms. As shown in Panel (b), these cities also experienced more drastic drops in prices following the boom.

Columns 1 and 3 of Table 3 quantify this relationship by reporting coefficient estimates from simple linear regressions of the price boom (column 1) and bust (column 3) on steady-state volume. A one percentage point increase in the share of the existing housing stock that turned over in 2000 is associated with a 15 percentage point higher increase in prices from January 2000 to peak and a four percentage point larger fall in prices from peak to trough. In columns 2 and 4, we report analogous and nearly identical estimates from regressions which instead assume that the boom ended in January of 2006 for all cities. These results are strongly consistent with the prediction of our model that steady-state volume should be correlated with the magnitude of swings in house prices during boom-bust episodes.

5 Conclusion

This paper shows that short-term investors have the capacity to destabilize financial markets. This observation raises two lines of inquiry.

First: do the expansions in credit that accompany asset price booms appeal disproportionately to short-term investors? Barlevy and Fisher (2011) document a strong correlation across US 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 especially to buyers who expect

¹⁸We restrict the price peak to occur prior to January 2012 since prices in some markets had already recovered to levels higher than those experienced during the boom by the end of our sample.

to resell quickly. The targeting of credit expansions to short-term buyers might explain the amplification effects of credit availability on asset price booms documented by Di Maggio and Kermani (2015) Favara and Imbs (2015), and Rajan and Ramcharan (2015).

Second: do policies that aim to achieve financial market stability work better if they discourage the participation of short-term investors? For instance, consider the financial transactions tax proposed by Tobin (1978), supported by Stiglitz (1989) and Summers and Summers (1989), and analyzed theoretically by Dávila (2015). If the incidence of this tax falls entirely on buyers, then the tax burden is independent of the investment horizon; if the incidence falls entirely on sellers, then the tax burden is larger in present-value terms for short-term investors who plan to resell quickly. Our model suggests that transaction taxes discourage bubbles more powerfully when their incidence falls more strongly on sellers. One policy that discourages short-term investors more directly is the short-term capital gains tax, and our model provides a rationale for this policy. Any tax that discourages short-term investors will also discourage the liquidity provision and, in the case of the housing market, the residential investment they provide. We hope that future work will weigh all of these effects to guide policy carefully.

A Omitted Proofs of Mathematical Statements

Lemma 1

By (1), $E[(P_{t+\tau} - P_t)/(\tau P_t) \mid \omega_t] = \gamma(\omega_t)g(\tau)/\tau$. The cross-partial in Lemma 1 equals $\gamma'(\omega_t)(g(\tau)/\tau)'$. Because $\gamma'(\omega_t) > 0$, this cross-partial is negative for all $\tau > 0$ if and only if Assumption 1(a) holds.

Lemma 2

If Assumption 1(c) fails, then we can find ω_t such that $\gamma(\omega_t)g'(0) > r$. Then $E[P_{t+\tau}/P_t \mid \omega_t] - e^{r\tau}$ equals 0 at $\tau = 0$ and has a positive derivative with respect to τ at $\tau = 0$, which means that $E[P_{t+\tau}/P_t \mid \omega_t] > e^{r\tau}$ for some $\tau > 0$. Now suppose Assumption 1(c) holds. For $\tau > 0$, $g(\tau) = \int_0^\tau g'(\tau_0)d\tau_0 < \int_0^\tau g(\tau_0)/\tau_0 d\tau_0 < g'(0)\tau$. As a result, for all $\omega_t \in \mathbb{R}$ $E[P_{t+\tau}/P_t \mid \omega_t] = 1 + \gamma(\omega_t)g(\tau) < 1 + \gamma(\omega_t)g'(0)\tau \leq 1 + r\tau < e^{r\tau}$. The last inequality follows because $1 + r\tau$ and $e^{r\tau}$ coincide for $\tau = 0$ and the derivative of the latter exceeds that of the former for all $\tau > 0$.

Lemma 3

By (6), a potential buyer buys if and only if

$$\delta \geq rP_t \left(1 - \frac{\lambda}{r} \int_0^\infty (r + \lambda)e^{-(r+\lambda)\tau} \left(E \left[\frac{P_{t+\tau}}{P_t} \mid \omega_t \right] - 1 \right) d\tau \right).$$

Substituting (1) reduces the integral to $\int_0^\infty (r + \lambda)e^{-(r+\lambda)\tau} \gamma(\omega_t)g(\tau)d\tau$ and then integrating by parts further reduces it to $\int_0^\infty e^{-(r+\lambda)\tau} \gamma(\omega_t)g'(\tau)d\tau$. The measure of potential buyers at t of type λ whose flow utility exceeds some $\delta_0 > 0$ equals $f(\lambda)A_t\delta_0^{-\epsilon}$, so we are done.

Proposition 1

We prove the stronger statement of Proposition 1 in which each derivative with respect to ω_t is replaced by the right-sided derivative $\partial_+/\partial\omega_t$ or the left-sided derivative $\partial_-/\partial\omega_t$ throughout. We write the proof in terms of $\partial_+/\partial\omega_t$; the identical proof holds replacing those partials with $\partial_-/\partial\omega_t$. We use this more general form of the proposition in the proof of Proposition 2.

From Lemma 3, $\log D_t(\lambda) = \log(f(\lambda)A_t(rP_t)^{-\epsilon}) + \log \Sigma_\lambda(\omega_t)$. Only $\Sigma_\lambda(\omega_t)$ depends on ω . We write $\log \Sigma_\lambda(\omega_t) = -\epsilon \log(1 - \gamma(\omega_t)i(\lambda))$. From Lemma 2, $1 + \gamma(\omega_t)g(\tau) < e^{r\tau}$ for $\tau > 0$, so $\gamma(\omega_t)i(\lambda) < \lambda/r \int_0^\infty (r + \lambda)e^{-(r+\lambda)\tau}(e^{r\tau} - 1)d\tau = 1$. For ω_t such that $\partial_+\gamma(\omega_t)/\partial\omega_t > 0$, $\partial_+ \log \Sigma_\lambda(\omega_t)/\partial\omega_t = \epsilon(\partial_+\gamma(\omega_t)/\partial\omega_t)i(\lambda)/(1 - i(\lambda)) > 0$ because $i(\lambda) > 0$ by Assumption 1(d). Differentiating again yields $\partial\partial_+ \log \Sigma_\lambda(\omega_t)/\partial\omega_t\partial\lambda = \epsilon(\partial_+\gamma(\omega_t)/\partial\omega_t)i'(\lambda)/(1 - i(\lambda))^2$. Integrating by parts and applying Assumption 1(a) yields

$$ri'(\lambda) = \int_0^\infty e^{-(r+\lambda)\tau} g'(\tau)d\tau - \int_0^\infty \lambda e^{-(r+\lambda)\tau} \tau g'(\tau)d\tau > \frac{r}{r + \lambda} \int_0^\infty e^{-(r+\lambda)\tau} g'(\tau)d\tau > 0,$$

where the final inequality follows because the last integral equals $r^2/(\lambda(r + \lambda))i(\lambda) > 0$.

To prove (c), we first note that $V_t(\lambda)/V_t = D_t(\lambda)/D_t$ by (3). By Lemma 3, $D_t(\lambda)/D_t = f(\lambda)\Sigma_\lambda(\omega_t)/\int_0^\infty f(\lambda')\Sigma_{\lambda'}(\omega_t)d\lambda'$. Thus, we must show that

$$\frac{\partial_+ \int_0^\lambda \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda'}{\partial\omega_t \int_0^\infty \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda'} \leq 0$$

for all λ . Differentiating, subtracting parts of the integral that appear on each side, and multiplying and dividing by $\sigma_{\lambda'}$ reduces this inequality to

$$\begin{aligned} \int_\lambda^\infty \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda' \int_0^\lambda \frac{\partial_+ \log \Sigma_{\lambda'}(\omega_t)}{\partial\omega_t} \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda' \leq \\ \int_0^\lambda \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda' \int_\lambda^\infty \frac{\partial_+ \log \Sigma_{\lambda'}(\omega_t)}{\partial\omega_t} \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda'. \end{aligned}$$

The first part of the proof showed that $\partial_+ \log \Sigma_\lambda(\omega_t)/\partial\omega_t > 0$ and $\partial\partial_+ \log \Sigma_\lambda(\omega_t)/\partial\omega_t\partial\lambda > 0$ for all λ . Thus $\partial_+ \log \Sigma_{\lambda'}(\omega_t)/\partial\omega_t$ increases in λ' and is positive, allowing us to reduce the inequality to

$$\begin{aligned} \int_\lambda^\infty \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda' \int_0^\lambda \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda' \leq \\ \int_0^\lambda \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda' \int_\lambda^\infty \Sigma_{\lambda'}(\omega_t)f(\lambda')d\lambda', \end{aligned}$$

which holds with equality. Strict inequality results if and only if $\partial_+ \log \Sigma_\lambda(\omega_t)/\partial\omega_t$ is distinct across two points in the support of f . Because it strictly increases, strict inequality results if and only if the support of f consists of more than a single point.

Demand Target

Because prices remain constant, $D_t = \bar{D}$ by (9). Because potential buyers expect prices to remain constant, $\sigma_\lambda(\omega_t) = 1$ for all λ and ω_t by (7). Thus, by Lemma 3, $D_t(\lambda)/D_t = f(\lambda)$ for all t . Because $L_t = D_t$, $V_t = L_t$ by (3), so $V_t(\lambda) = f(\lambda)\bar{D}$. In a steady state, each $S_t(\lambda)$ remains constant, so $S_t(\lambda) = V_t(\lambda)/\lambda = \bar{D}f(\lambda)/\lambda$. Because $V_t = L_t$, $U_t = 0$. As a result, the housing stock is comprised entirely of stayers, so $1 = \int_0^\infty S_t(\lambda)d\lambda = \bar{D} \int_0^\infty f(\lambda)/\lambda d\lambda$. Solving for \bar{D} provides (10).

Proposition 2

From (11), ω_t depends on price changes before t , so $\omega_0 = 0$. By (8), $D_0 = A^f/A^i\bar{D}$, so by (9) $\dot{p}_0 = c \log(A^f/A^i) > 0$. It follows that $\dot{p}_t > 0$ for $t \in (0, t_1)$ for some $t_1 > 0$.

By (12), $\dot{\omega}_0 > 0$, so $\dot{\omega}_t > 0$ for $t \in (0, t_1)$ for some $t_1 > 0$.

Substituting (8) into (9), differentiating, and using (12) yields $\ddot{p}/c = -\epsilon\dot{p} + \sigma'(\omega)\mu(\dot{p} - \omega)$

for $\omega > 0$, where $\sigma(\omega) \equiv \log \Sigma(\omega)$. Differentiating yields

$$\sigma'(\omega) = \frac{\epsilon \gamma'(\omega) \int_0^\infty (1 - \gamma(\omega) i(\lambda))^{-\epsilon-1} i(\lambda) f(\lambda) d\lambda}{\int_0^\infty (1 - \gamma(\omega) i(\lambda))^{-\epsilon} f(\lambda) d\lambda},$$

where $i(\lambda)$ is as defined in the proof of Proposition 1. Taking limits yields $\lim_{\omega \rightarrow 0^+} \sigma'(\omega) = (\lim_{\omega \rightarrow 0^+} \gamma'(\omega)) \epsilon \int_0^\infty i(\lambda) f(\lambda) d\lambda > \epsilon / \min(c\epsilon, \mu)$ by the bound in Assumption 3. It follows that $\ddot{p}_0 > 0$ because $\dot{p}_0 > 0$ and $\omega_0 = 0$, so there exists $t_1 > 0$ such that $\ddot{p}_t > 0$ for $t \in (0, t_1)$.

By (2), L_t depends directly $S_t(\lambda)$, and by (4), $S_t(\lambda) = \int_{-\infty}^t e^{-\lambda(t-\tau)} V_\tau(\lambda) d\tau$. Therefore L_t is continuous at 0, so $L_0 = \bar{D} < D_0$ and there exists $t_1 > 0$ such that $D_t > L_t$ for $t \in (0, t_1)$.

By (3), $V_t = L_t$ when $D_t > L_t$ and $I_t = 0$, so to prove that $\dot{V}_t > 0$ we must prove that $\dot{L}_t > 0$. We have $\dot{L}_0 = \int_0^\infty \lambda \dot{S}_0(\lambda) d\lambda$. But $\dot{S}_0(\lambda) = V_0(\lambda) - \lambda S_0(\lambda) = 0$ because $V(\lambda)$ and $S(\lambda)$ are continuous at $t = 0$. So $\dot{L}_0 = 0$. Taking another derivative yields $\ddot{L}_0 = \int_0^\infty \lambda \ddot{S}_0(\lambda) d\lambda$. We have $\ddot{S}_0(\lambda) = \dot{V}_0(\lambda) - \lambda \dot{S}_0(\lambda) = \dot{V}_0(\lambda)$. Thus $\ddot{L}_0 = \int_0^\infty \lambda \dot{V}_0(\lambda) d\lambda$. Because $\dot{\omega}_0 > 0$, by Proposition 1(c) $\int_0^\lambda \dot{V}_0(\lambda') d\lambda' \leq 0$ for all $\lambda > 0$, so $V_0(\lambda) + \dot{V}_0(\lambda)$ first-order stochastically dominates $V_0(\lambda)$ as distributions (strictly iff $|\text{supp } f| > 1$). The former must have a larger mean as a result, so $\int_0^\infty \lambda \dot{V}_0(\lambda) d\lambda > 0$, giving $\ddot{L}_0 > 0$. Because $\dot{L}_0 = 0$, $\dot{L}_t > 0$ for $t \in (0, t_1)$ for some $t_1 > 0$.

Lemma 4

Define $\bar{p} = \log(A^f)/\epsilon - \log(r) - \log(\bar{D})/\epsilon$. Substituting (8) into (9) yields

$$\dot{p} = c\epsilon(\bar{p} - p) + c\sigma(\omega). \quad (\text{A1})$$

Substituting (A1) into (12) gives

$$\dot{\omega} = \mu c\epsilon(\bar{p} - p) + \mu c\sigma(\omega) - \mu\omega. \quad (\text{A2})$$

With the initial conditions $p_0 = \bar{p} - \log(A^f/A^i)/\epsilon$ and $\omega_0 = 0$, (A1) and (A2) specify the joint dynamics of p and ω . Figure A1 illustrates the corresponding phase diagram.

The $\dot{p} = 0$ locus is given by $p = \bar{p} + \sigma(\omega)/\epsilon$. For a given ω , $\dot{p} < 0$ for p above this locus and $\dot{p} > 0$ for p below this locus. By Assumption 3, $\sigma(\omega) = 0$ for $\omega \leq 0$ and $\sigma'(\omega) > 0$ for $\omega > 0$, so the $\dot{p} = 0$ locus equals $p = \bar{p}$ for $\omega < 0$ and increases for $\omega > 0$. The $\dot{\omega} = 0$ locus is given by $p = \bar{p} + \sigma(\omega)/\epsilon - \omega/(c\epsilon)$. For a given ω , $\dot{\omega} < 0$ for p above this locus and $\dot{\omega} > 0$ for p below this locus. For $\omega < 0$, this locus equals a decreasing line, and for $\omega > 0$, this locus lies beneath the $\dot{p} = 0$ locus. The right slope of this locus at 0 equals $\lim_{\omega \rightarrow 0^+} \sigma'(\omega)/\epsilon - 1/(c\epsilon)$, which > 0 because $\lim_{\omega \rightarrow 0^+} \sigma'(\omega) > \epsilon / \min(c\epsilon, \mu)$ as shown in the proof of Proposition 2.

We have drawn the phase diagram such that the $\dot{p} = 0$ locus is bounded for large ω and that the $\dot{\omega} = 0$ locus asymptotes to a decreasing linear function for large ω . These features hold as long as $\sigma(\omega)$ is bounded. As shown in the proof of Lemma 2, $g(\tau) < g'(0)\tau$ for $\tau > 0$, so $i(\lambda) < (\lambda g'(0)/r) \int_0^\infty (r + \lambda) e^{-(r+\lambda)\tau} \tau d\tau = (g'(0)/r)\lambda/(r + \lambda)$. Therefore Assumption 1(c) implies that $\sigma(\omega) < \log \int_0^\infty (r/(r + \lambda))^{-\epsilon} f(\lambda) d\lambda$, which exists because $\int_0^\infty \lambda^\epsilon f(\lambda) d\lambda$ exists.

Tracing the system from the initial point makes it clear that p must decrease in finite time. At first, p and ω increase. Eventually, the right $\dot{\omega} = 0$ locus is reached because this

locus goes to $-\infty$ for large ω due to its linearity. Next, ω begins to increase while p continues increasing. The right $\dot{p} = 0$ locus is then reached because it is bounded from above. After this point, ω continues decreasing while p begins to decrease, as desired.

Proposition 3

By the definition of t_2^* , $\dot{p}_t > 0$ for $t \in (t_1^*, t_2^*)$. By (9), $D_{t_2^*} = \bar{D}$. By (3), $V_{t_2^*} \leq D_{t_2^*} = \bar{D}$. Because $V_0 = \bar{D}$ and $\dot{V}_t > 0$ for $t \in (0, t_1^*)$, there must exist $t \in (t_1^*, t_2^*)$ such that $\dot{V}_t < 0$.

Suppose for a contradiction that $L_t < D_t$ for all $t \in (0, t_2^*)$. Because $D_{t_2^*} = \bar{D}$, by continuity $L_{t_2^*} \leq \bar{D}$, so $t^* \equiv \inf\{t > 0 \mid L_t = \bar{D}\}$ exists and $t^* > 0$ because $L_t > \bar{D}$ for $t \in (0, t_1^*)$. Because $L_{t^*} < D_{t^*}$, $V_{t^*} = L_{t^*}$, so (2) and (4) imply that $\int_0^\infty \dot{S}_{t^*}(\lambda) d\lambda = 0$. If there exists $\lambda > 0$ such that $\int_0^\lambda \dot{S}_{t^*}(\lambda') d\lambda' < 0$, then the mean value theorem for integrals implies that $\dot{L}_{t^*} = \int_0^\lambda \lambda' \dot{S}_{t^*}(\lambda') d\lambda' + \int_\lambda^\infty \lambda' \dot{S}_{t^*}(\lambda') d\lambda' > \lambda \int_0^\lambda \dot{S}_{t^*}(\lambda') d\lambda' + \lambda \int_\lambda^\infty \dot{S}_{t^*}(\lambda') d\lambda' = 0$, an impossibility due to the infimum property of t^* . Thus $\int_0^\lambda \dot{S}_{t^*}(\lambda) d\lambda < 0$ for all $\lambda > 0$. Given that $\dot{p}_t > 0$ for $t \in (0, t^*)$, $\omega_{t^*} > 0$, so $V_t(\lambda)/V_t$ stochastically dominates $f(\lambda)$ by Proposition 1(c). Using (4) then yields $\int_0^\lambda \lambda' S_{t^*}(\lambda') d\lambda' < \int_0^\lambda V_{t^*}(\lambda') d\lambda' < (\int_0^\lambda f(\lambda') d\lambda') (\int_0^\infty \lambda' S_{t^*}(\lambda') d\lambda')$ for all $\lambda > 0$, so $\lambda S_{t^*}(\lambda) / \int_0^\infty \lambda' S_{t^*}(\lambda') d\lambda'$ stochastically dominates $f(\lambda)$. Because $1/\lambda$ decreases, it follows that $\int_0^\infty S_{t^*}(\lambda) d\lambda / \int_0^\infty \lambda S_{t^*}(\lambda) d\lambda < \int_0^\infty f(\lambda) / \lambda d\lambda$, so $L_{t^*} = \int_0^\infty \lambda S_{t^*}(\lambda) d\lambda > (\int_0^\infty \lambda^{-1} f(\lambda) d\lambda)^{-1} = \bar{D}$ because $\int_0^\infty S_{t^*}(\lambda) d\lambda = 1$ as $L_t < D_t$ for $t \in (0, t^*)$. We have reached the necessary contradiction.

Proposition 4

The proof of Lemma 4 showed that prices begin to decline when the right $\dot{p} = 0$ locus shown in Figure A1 is reached. After this point, the system moves left so that $\dot{p} < 0$. From (9), $D_t < \bar{D}$ during this movement. By (3) $V_t \leq D_t$, so $V_t < \bar{D}$ while $\dot{p} < 0$.

The price decline continues until either the $\omega = 0$ axis is reached or convergence to $(0, \bar{p})$ occurs. Before either of these events, the system can never fall below the right $\dot{p} = 0$ locus, and any intersection with it occurs for but an instant. As a result, p continues to decrease until convergence to the steady-state or until $\omega = 0$ but $p > \bar{p}$. In the first case, we are done. In the second case, we know that $\omega < 0$ right after $\omega = 0$ from examining the phase diagram. It is clear that ω remains below 0 for the rest of time until steady-state is reached, as the system remains weakly above the left $\dot{p} = 0$ locus. In this region, $\sigma(\omega) = 0$, so (A1) becomes $\dot{p} = c\epsilon(\bar{p} - p)$. Thus, $\dot{p} < 0$ for the rest of time, as $p > \bar{p}$ when $\omega = 0$.

Proposition 5

Because $V_0 = \bar{D} = (\int_0^\infty \lambda^{-1} f(\lambda) d\lambda)^{-1}$, an increase to $f(\cdot)$ increases V_0 because $1/\lambda$ decreases.

We next show that $\sigma(\cdot)$ increases pointwise if $f(\cdot)$ increases. We have $\partial \Sigma_\lambda / \partial \lambda = \epsilon \gamma(\omega) i'(\lambda) (1 - i(\lambda) \gamma(\omega))^{-\epsilon-1}$, which equals 0 for $\omega \leq 0$ and is positive otherwise. An increase to $f(\cdot)$ thus increases $\sigma = \log \int_0^\infty \Sigma_\lambda f(\lambda) d\lambda$ for $\omega > 0$ and keeps it constant at $\omega \leq 0$.

We now show that P^{max} increases in σ . $P_t = P^{max}$ when the system first intersects the $\dot{p} = 0$ locus shown in Figure A1. Because this locus is given by $p = \bar{p} + \sigma(\omega)/\epsilon$, it shifts up for $\omega > 0$ due to an increase in σ . If the path of (p, ω) also shifts to the right, then the

intersection with this locus must occur at a higher value of p . Thus we prove that the path does shift to the right. This shift occurs if $dp/d\omega$ decreases as σ increases. This derivative equals $\dot{p}/\dot{\omega} = (\mu(1 - \omega/\dot{p}))^{-1}$. Because $\omega > 0$ and $\dot{p} > 0$ before the $\dot{p} = 0$ locus is reached, we must show that ω/\dot{p} decreases in σ . By (A1), \dot{p} increases in σ , so we are done.

Finally, we show that P_0 and P_∞ are independent of f . As shown in the proof of Proposition 4, $\lim_{t \rightarrow \infty} p_t = \bar{p}$, which does not depend on f . The initial condition p_0 given in the proof of Lemma 4 also does not depend on f . Thus σ has no bearing on P_0 or P_∞ .

Proposition 6

Because $f_A < f_B$, by Proposition 5 V_0 and P^{max} are larger under f_B while the steady-state prices P_0 and P_∞ stay unchanged. Under f_A , $L_t = \lambda^* S_t(\lambda^*) \leq \lambda^*$, where λ^* is the sole member of $\text{supp } f_A$, and $V_0 = \lambda^*$. Therefore $V^{max}/V_0 = 1$ under f_A . By Proposition 2, $V^{max}/V_0 > 1$ under f_B because $|\text{supp } f_B| > 1$.

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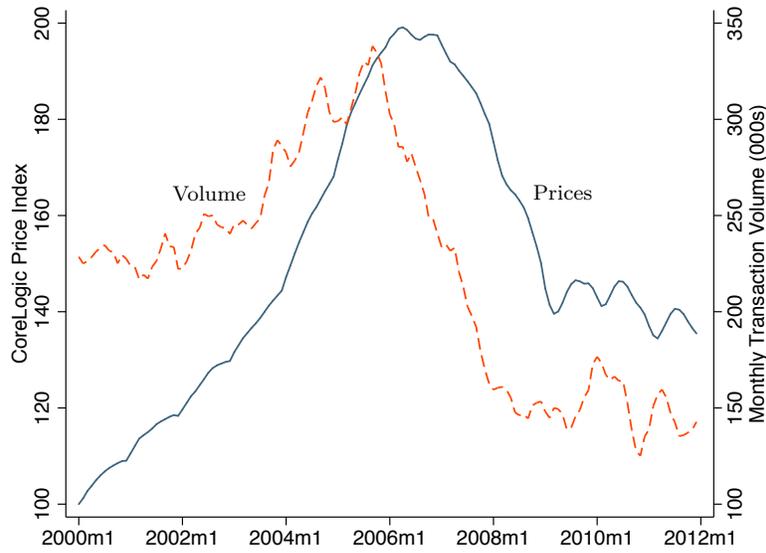
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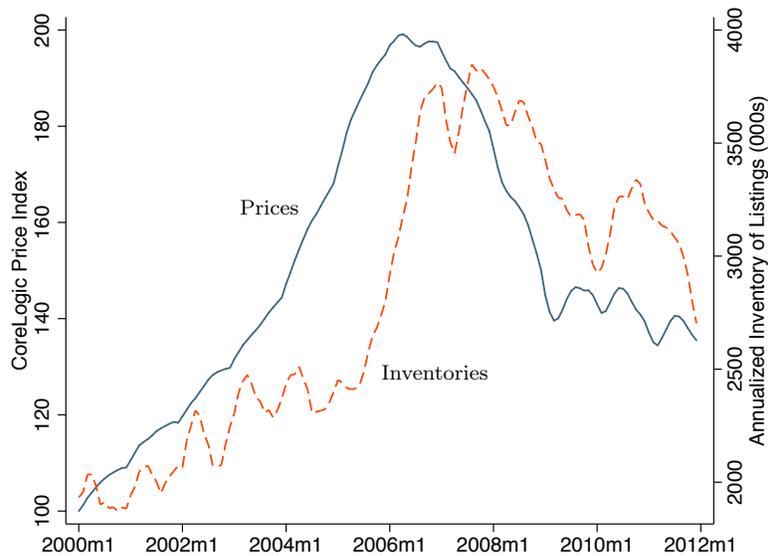
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FIGURE 1
The Dynamics of Prices, Volume, and Inventories

(a) Prices and Volume (2000–2012)

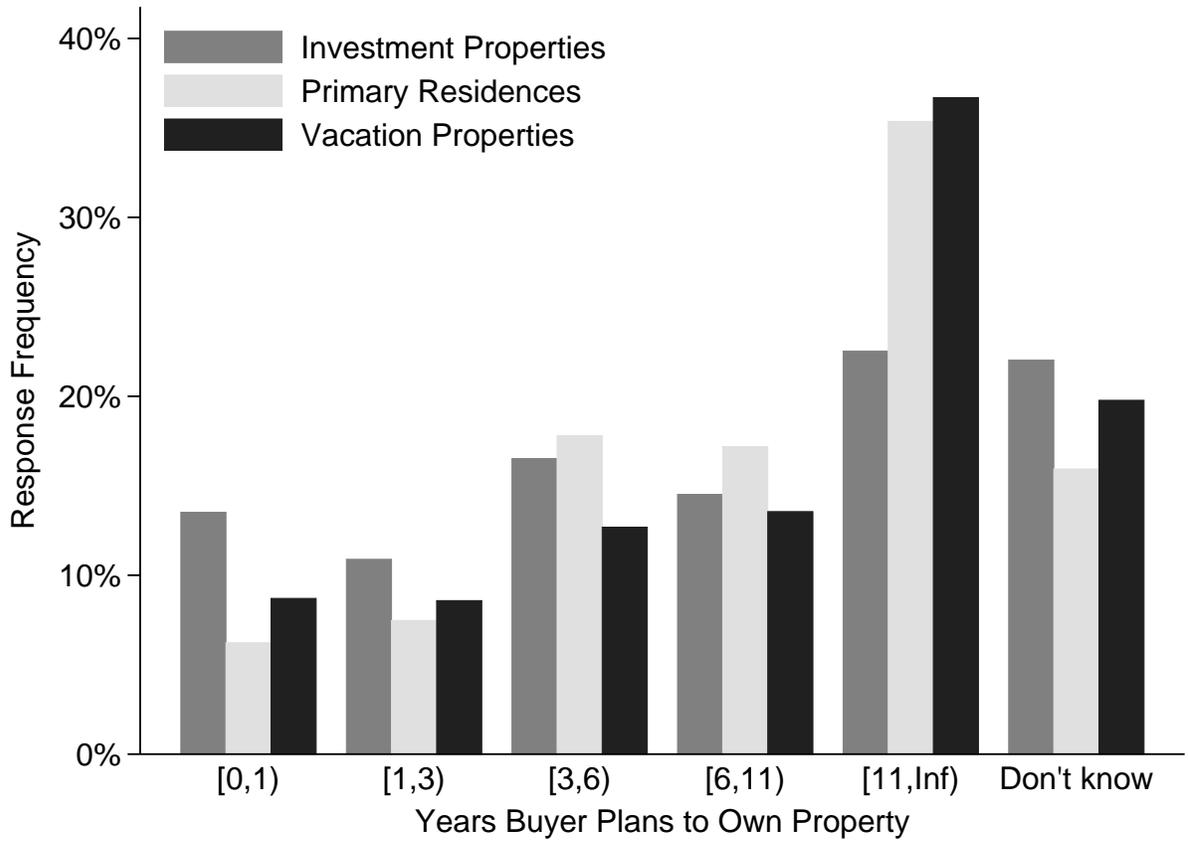


(b) Prices and Inventories (2000–2012)



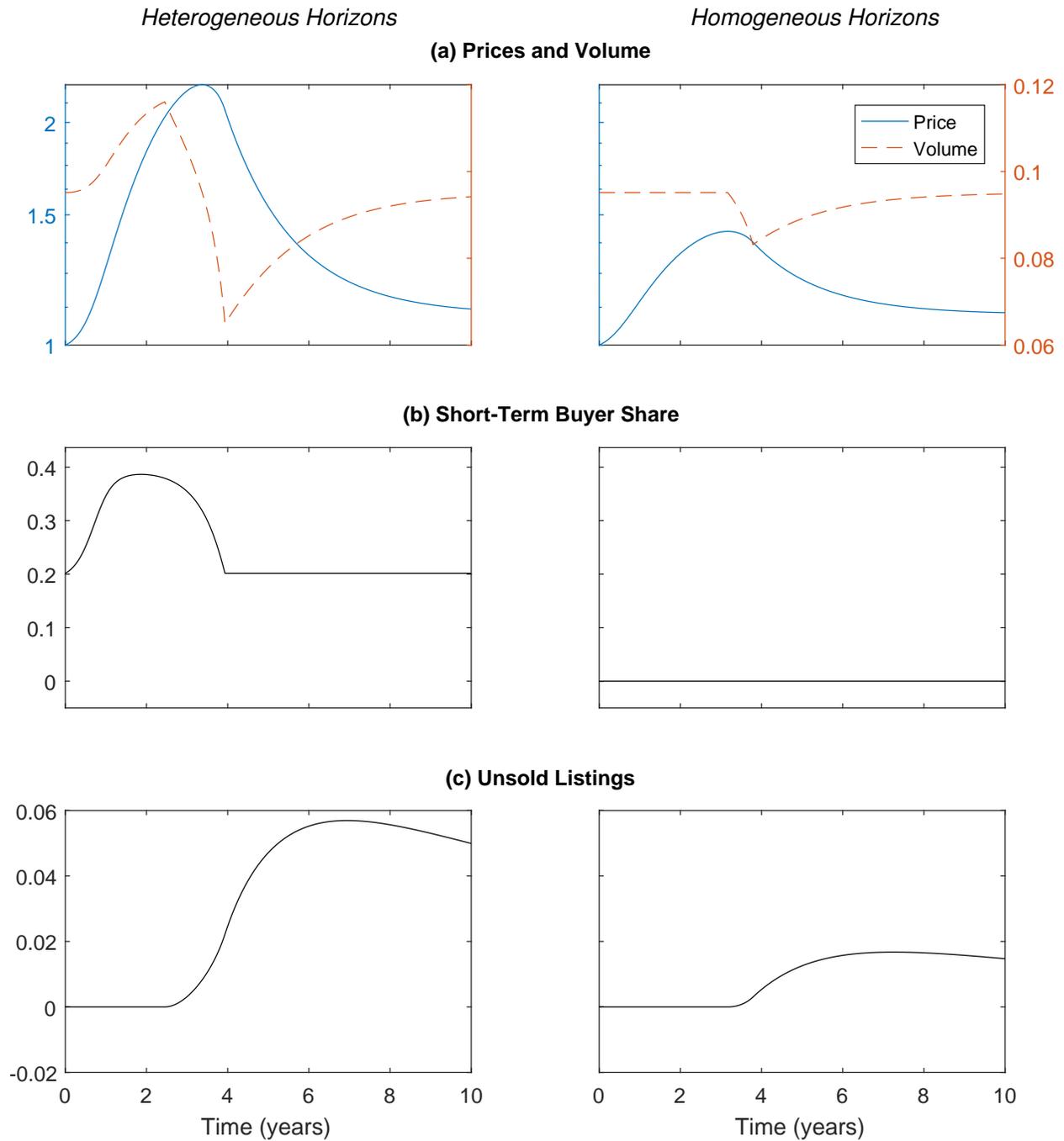
Notes: These figures display the dynamic relationship between prices, transaction volume, and the inventory of listings in the US between 2000 and 2015. Panel (a) plots monthly prices and sales volume and panel (b) plots monthly prices and inventory. For prices we use the national CoreLogic single family home price index, which is based on repeat sales. Inventory information comes from the National Association of Realtors. For volume, we plot the smoothed, seasonally-adjusted count of transactions in our sample of 115 Metropolitan Statistical Areas. We seasonally adjust volume by removing calendar month fixed effects and smooth the subsequent series using a three-month moving average. We apply the same smoothing and seasonal adjustment to inventory levels.

FIGURE 2
 Expected Holding Times of Homebuyers, 2008-2015



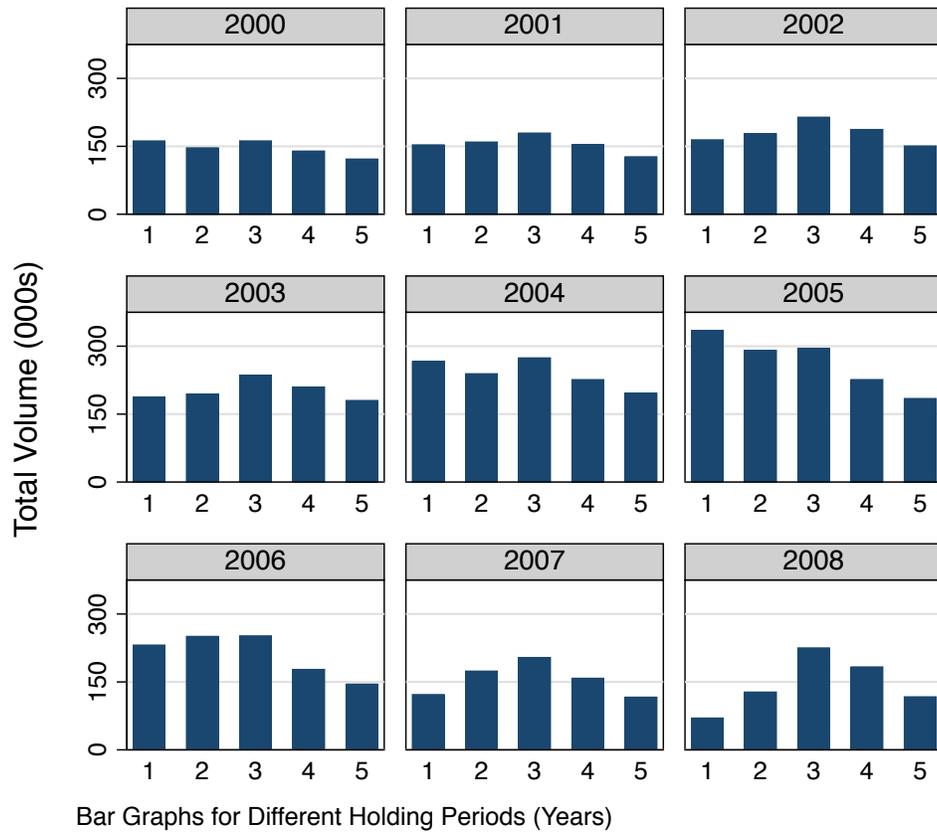
Notes: Data come from the annual Investment and Vacation Home Buyers Survey conducted by the National Association of Realtors. We reclassify buyers who have already sold their properties by the time of the survey as having an expected holding time in [0,1). The figure plots the response frequency averaged equally over each year from 2008 to 2015.

FIGURE 3
Simulation Results



Notes: (a) The price when the demand shock occurs is normalized to 1. Volume is in units of share of the housing stock. (b) Here, “short-term buyer” is defined as one whose expected holding time is less than 2 years. The panel plots the share of such individuals among all buyers. (c) Unsold listings are in units of share of the housing stock.

FIGURE 4
The Dynamics of Holding Times in the Housing Market

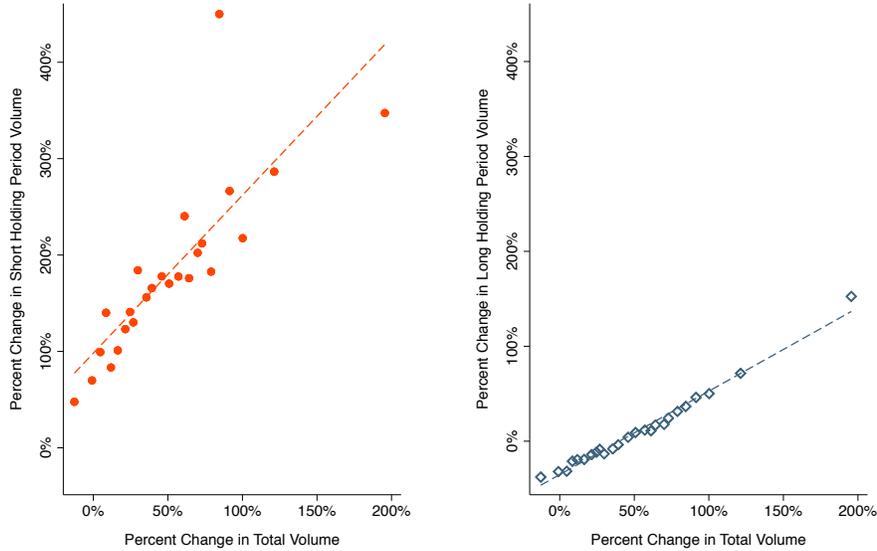


Notes: This figure illustrates the time variation in holding periods during the 2000-2008 housing cycle in the US. For each transaction, we define the holding period as the number of days since the last transaction of the same property. We then group all transactions with holding periods less than or equal to 5 years into bins of 1, 2, 3, 4, or 5 years, respectively. For each year between 2000–2008, we plot aggregate transaction counts in each of these five holding period groups.

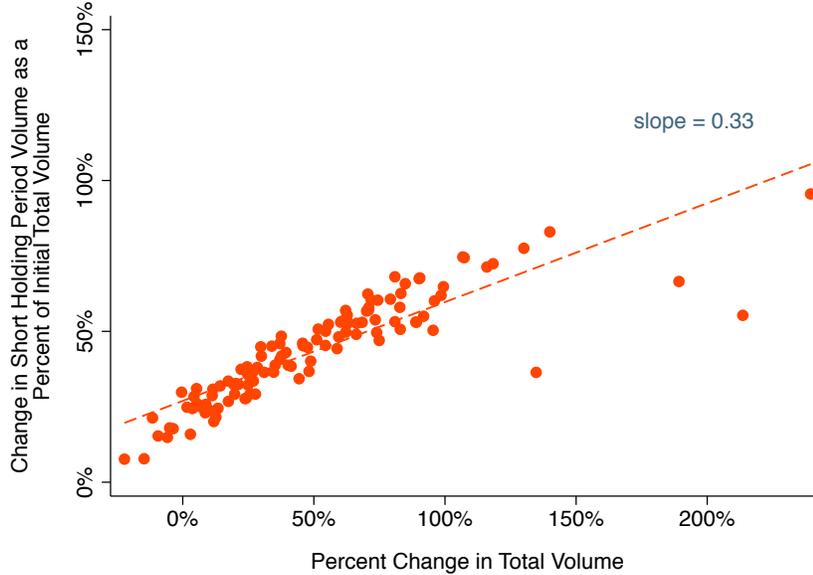
FIGURE 5

The Role of Short Holding Period Volume Growth for Total Volume Growth

(a) Holding Periods ≤ 2 Years (b) Holding Periods > 2 Years

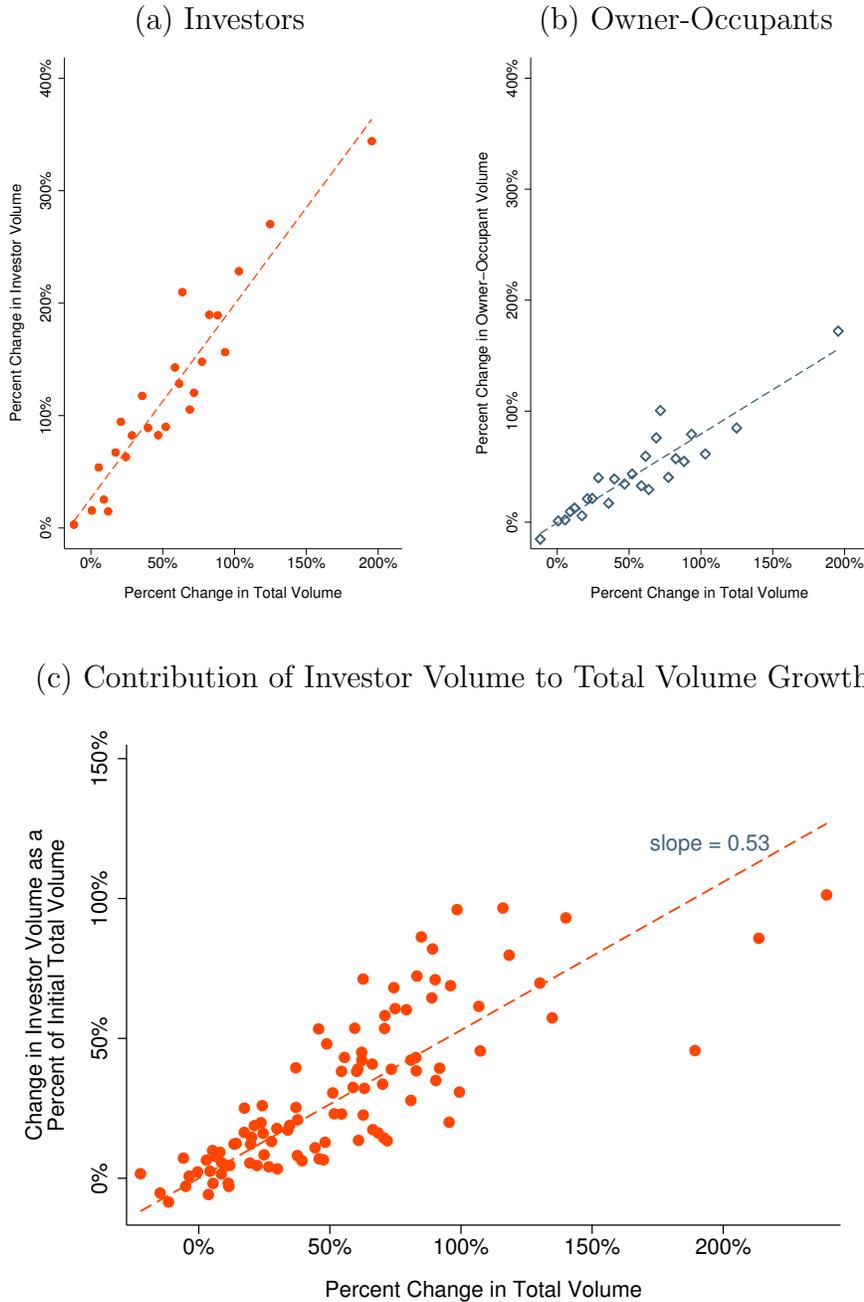


(c) Contribution of Short Volume to Total Volume Growth



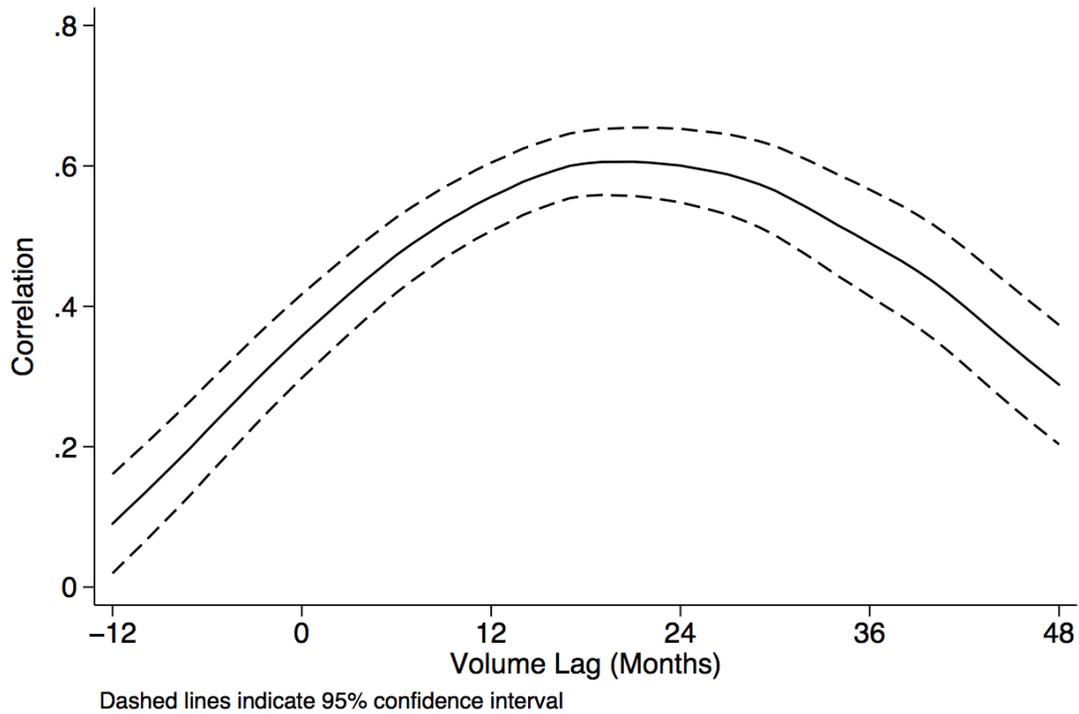
Notes: This figure illustrates of the quantitative importance of short holding period volume in accounting for the increase in total volume between 2000 and 2005. We present binned scatter plots (“binscatters”) of the percent change in total volume from 2000–2005 versus the percent change in volume for short holding periods (≤ 2 years) in Panel (a) and long holding periods (> 2 years) in Panel (b). Panel (c) shows that the growth in short holding period volume is a quantitatively important component of the growth in total volume across cities. For each city, we plot the change in short holding time volume divided by initial total volume on the y-axis against the percent change in total volume on the x-axis.

FIGURE 6
The Role of Investor Volume Growth for Total Volume Growth



Notes: This figure illustrates of the quantitative importance of investor volume in accounting for the increase in total volume between 2000 and 2005. We present binned scatter plots (“binscatters”) of the percent change in total volume from 2000–2005 versus the percent change in volume for investors (defined as transactions with distinct mailing and property addresses) in Panel (a) and owner-occupants (defined as non-investors or having a missing mailing address) in Panel (b). Panel (c) shows that the growth in investor volume is a quantitatively important component of the growth in total volume across cities. For each city, we plot the change in investor time volume divided by initial total volume on the y-axis against the percent change in total volume on the x-axis.

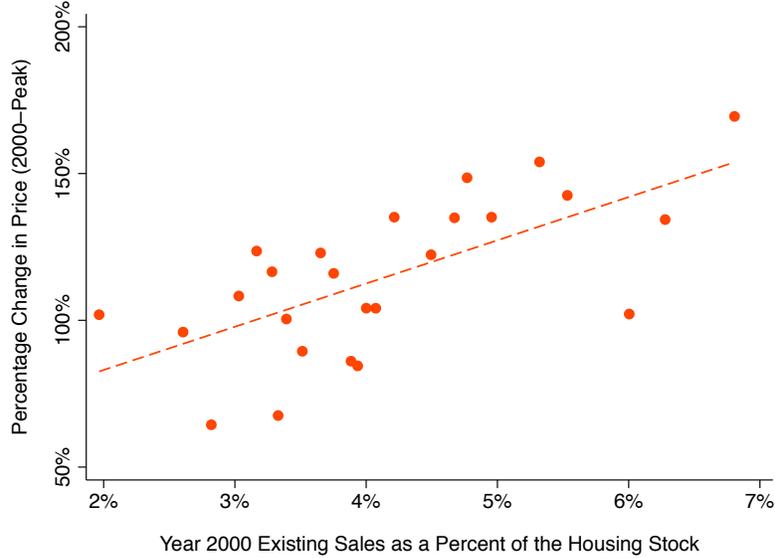
FIGURE 7
The Correlation between Prices and Volume at Various Lags



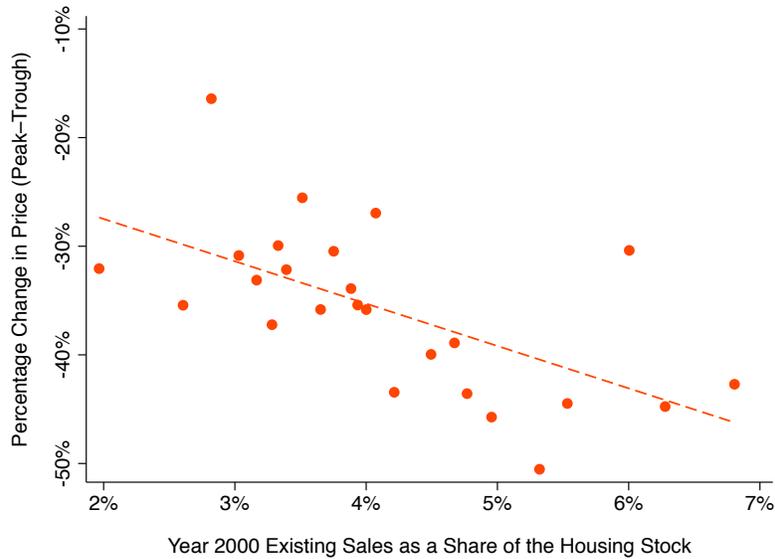
Notes: This figure shows that the correlation between prices and lagged volume is robust across cities and maximized at a positive lag of approximately 15 months. We regress the demeaned log of prices on seasonally adjusted lagged volume divided by the 2000 housing stock for each lag from -12 months to 48 months and plot the implied correlation and its 95% confidence interval calculated using standard errors that are clustered by month.

FIGURE 8
Initial Volume and the Magnitude of the Housing Boom and Bust

(a) Boom

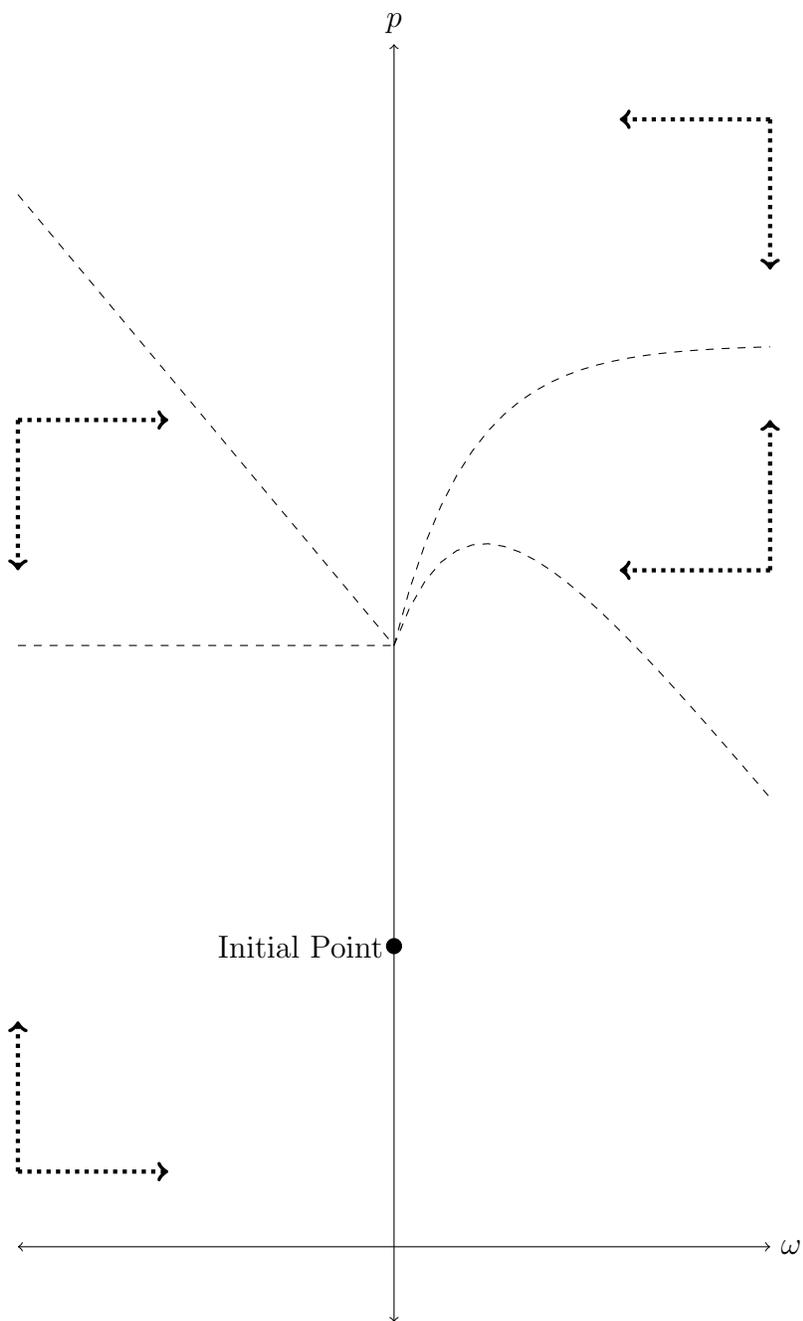


(b) Bust



Notes: This figure provides empirical support for the cross-sectional prediction that the magnitude of price swings during boom-bust episodes should be correlated with the level of steady-state transaction volume across markets. We present binned scatter plots (“binscatters”) of the percent change in prices from January 2000 to peak (Panel (a)) and from peak to trough (Panel (b)) versus total existing homes in 2000. To facilitate comparisons across cities of different sizes, we normalize existing sales by the size of the housing stock in 2000 for each city. House prices are measured using the monthly CoreLogic repeat-sales house price indices. The price peak for each MSA is measured as the highest price recorded for that MSA prior to January, 2012. The trough is measured as the lowest price subsequent to the month in which the peak occurred.

FIGURE A1
Phase Diagram



Notes: This figure illustrates the phase diagram for the (p, ω) system specified by equations (A1) and (A2); p denotes the log house price, and ω denotes the historical average log price change given by equation (11). The dashed loci indicate points at which either $\dot{p} = 0$ or $\dot{\omega} = 0$. The dotted arrows indicate the directions p and ω move in each of the four areas demarcated by the dashed loci. The system begins at the marked point on the p -axis.

TABLE 1
Calibration Sources

Calibrated Quantity	Role in Model	Source or Assumed Value
$f(\cdot)$	Distribution of expected holding times	NAR Investment and Vacation Home Buyers Survey
μ	Relative weight in expectations on recent price changes versus those in distant past	Estimation using NAR survey
$g(\cdot)$	Forward term structure of expectations	Survey of Consumer Expectations; Armona et al. (2016)
$\gamma(\cdot)$	Extrapolation function	Estimation using Case et al. (2012) survey
r	Discount rate	0.07
c	Price stickiness	1
ϵ	Housing demand elasticity	0.6
A^f/A^i	Size of demand shock	1.06

Notes: This table lists the model quantities we calibrate to produce Figure 3. Further details are provided in Section 3.5.

TABLE 2
Sensitivity of Simulation Results to Parameters

	f	ρ	μ	c	ϕ	ϵ	A^f/A^i	r
A. Excess Price Boom								
Low	0.30	0.11	0.83	0.40	0.00	0.36	0.92	1.37
Baseline	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
High	3.31	1.46	0.99	1.48	0.01	3.46	1.17	0.68
B. Volume Boom								
Low	0.00	0.04	0.15	0.11	0.00	0.05	0.21	0.26
Baseline	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
High	0.94	0.26	0.23	0.19	0.00	0.86	0.23	0.17
C. Maximal Unsold Listings								
Low	0.02	0.01	0.05	0.04	0.00	0.02	0.06	0.07
Baseline	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
High	0.18	0.07	0.05	0.05	0.00	0.16	0.06	0.04

Notes: The excess price boom equals $P^{max}/P_\infty - 1$, the volume boom equals $V^{max}/V_0 - 1$, and maximal unsold listings equal $\max_t I_t$. The alternate values for f , ρ , and ϵ are described in the text. The low and high values for the remaining parameters are half and double their baseline values (we half and double $\log(A^f/A^i)$).

TABLE 3
Initial Volume and the Magnitude of the Housing Boom and Bust

	Percentage Change in Prices			
	2000–Peak	2000–2006	Peak–Trough	2006–Trough
Existing Sales/Stock (2000)	15.046***	14.933***	−4.059***	−4.508***
	(3.655)	(3.573)	(1.120)	(1.218)
R^2	0.12	0.12	0.12	0.11
Observations	115	115	115	115

Notes: This table reports estimates of the cross-sectional relationship between the magnitude of the housing boom and bust and initial transaction volume at the MSA level. Each column reports estimates from a separate regression where the dependent variable is the percentage change in prices measured over the indicated horizon. Initial transaction volume is measured as total year 2000 existing home sales in each MSA scaled by the total number of housing units in the MSA as reported in the 2000 Census. House prices are measured using the monthly CoreLogic repeat-sales house price indices. The price peak for each MSA is measured as the highest price recorded for that MSA prior to January, 2012. The trough is measured as the lowest price subsequent to either the month in which the peak occurred (column 3) or January, 2006 (column 4). In columns 1, 2, and 4, price changes are calculated using the January price level in 2000 and 2006. Heteroskedasticity robust standard errors are reported in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE A1
Sensitivity of S&P 500 Return Forecasts to
Historical Returns, 2000Q3 - 2011Q4

	Lagged Annual Return History		75-Year Weighted Average	
	One-Year Forecast	Ten-Year Forecast (Annualized)	One-Year Forecast	Ten-Year Forecast (Annualized)
Historical Return	0.029** (0.014)	−0.013* (0.007)	0.045*** (0.010)	0.011 (0.015)
R^2	0.12	0.06	0.17	0.03
Observations	44	44	44	44

Notes: Return forecasts come from the Duke CFO Global Business Outlook, a quarterly survey of chief financial officers of U.S. firms. Historical returns on the S&P 500 come from CRSP’s daily dividend-inclusive value-weighted return series `vwretd`. The historical return equals $P_t/P_{t-1} - 1$ in the first two columns and $\mu(1 - e^{-\mu T})^{-1} \int_0^T e^{-\mu\tau} \dot{p}_{t-\tau} d\tau$ in the latter two columns, with $p = \log P$, $\mu = 0.5$, and $T = 75$. The sample period is chosen to match that used by Greenwood and Shleifer (2014). Observations for 2001Q3 and 2002Q3 are dropped due to errors or gaps in the Duke CFO Global Business Outlook. Newey-West standard errors are reported in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.