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The 2000s Housing Cycle with 2020 Hindsight: A Neo-Kindlebergerian View

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With "2020 hindsight," the 2000s housing cycle is not a boom–bust but a boom–bust–rebound. Using a spatial equilibrium regression in which house prices are determined by income, amenities, urbanization, and supply, we show that long-run city-level fundamentals predict not only 1997–2019 price and rent growth but also the amplitude of the boom–bust–rebound. This evidence motivates our model of a cycle rooted in fundamentals. Households learn about fundamentals by observing "dividends" but become over-optimistic in the boom due to diagnostic expectations. A bust ensues when beliefs start to correct, exacerbated by a price–foreclosure spiral that drives prices below their long-run level. The rebound follows as prices converge to a path commensurate with higher fundamental growth. The estimated model explains the boom–bust–rebound with a single shock and accounts quantitatively for the dynamics of prices, rents, and foreclosures in cities with the largest cycles. We draw implications for asset cycles more generally.

Key words: Housing, Boom–Bust, Assest Price, Cycles

JEL codes: E32, R21, R31, R51

1. INTRODUCTION

Asset price cycles are a recurring feature of financial history, yet our understanding of such cycles and the structural features that create fragility to them remains incomplete. Among the most consequential and studied in recent history is the 2000s housing cycle, both for its sharpness and its role in triggering the Great Recession. Real house prices in the United States rose by nearly 80% between 1997 and 2006 and then lost over two-thirds of their gain between 2006 and 2012. The boom–bust cycle was even more dramatic in some cities, with areas experiencing the most rapid price growth during the boom also having the largest price declines during the bust. A predominant view is that the boom–bust was the result of the emergence and popping

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of a house price "bubble" that was not rooted in economic fundamentals (Shiller, 2008; Charles *et al.*, 2018).

We reevaluate the 2000s housing cycle from the perspective of 2020.[1] National real house prices grew steadily between 2012 and 2019, with the largest price growth in the same areas that had the largest booms between 1997 and 2006 and busts between 2006 and 2012. As a result, the areas that had the largest booms also had higher long-run price growth over the entire 1997–2019 period. With "2020 hindsight," the 2000s housing cycle is not a boom–bust but rather a boom–bust–rebound.

We argue that this pattern reflects a larger role for fundamentals than previously thought. In a first step, we use a standard spatial equilibrium framework to motivate fundamental determinants of location choice, land costs, housing supply, and house prices. We find that these determinants explain cross-city variation in long-run house price growth in reduced-form and structural regressions, as well as the amplitude of the boom–bust–rebound. In a second step, we introduce a model of a fundamentally rooted house price cycle in which belief over-reaction amplifies the boom and a foreclosure spiral exacerbates the bust and discipline the model using simulated method of moments (SMM). The estimated model generates a boom–bust–rebound from a single fundamental shock and quantitatively matches the cross-city patterns in the metro areas most affected by the 2000s housing cycle. More broadly, our analysis formalizes the Kindleberger (1978) characterization of asset price cycles as initiated by fundamental improvements and amplified by over-optimism in the boom and fire sale dynamics in the bust and highlights the role of low interest rates in catalysing these types of cycles.

Section 2 begins by establishing the strong cross-sectional correlation of price growth across the boom, bust, and rebound. We use the national time series to break the cycle into a boom (1997–2006), bust (2006–12), and rebound (2012–9). At the ZIP Code level, the boom correlates negatively with the bust but the bust correlates negatively with the rebound, each with an R^2 above 0.35. As a result, the boom correlates strongly with price growth between 1997 and 2019, with an R^2 of 0.62. We also show that rents experienced a trend break in the late 1990s, indicative of a fundamental improvement.

Section 3 introduces a long-run spatial equilibrium empirical framework to shed light on whether price growth over the boom–bust–rebound reflects fundamental forces. Building on Saiz (2010), we derive a structurally interpretable supply regression of house price growth as a function of population growth, the land share of prices, housing supply regulation, and the premium to living downtown. We follow Saiz (2010), Diamond (2016), and others in selecting excluded instruments to address endogeneity, including shift-share predictors of local wages and employment, climate amenities, land unavailability, initial population density, taste-based determinants of regulation, and predictors of the movement of college-educated residents into land-scarce downtown areas.

Section 4 contains the empirical analysis of our framework. The excluded instruments strongly predict house price and rent growth over the boom–bust–rebound as well as the house price determinants of population growth, land share, regulation, and the downtown premium. In reduced form, they explain nearly 60% of the 1997–2019 cross-city variation in price growth and the structural IV relationship also has strong explanatory power. We define a city's long-run observed fundamental as the second stage fitted value, which depends only on the instruments and combines both demand and supply-side determinants of house prices using the structure of the spatial equilibrium framework. Areas with higher *long-run* fundamentals *also* have larger booms, deeper busts, and stronger rebounds.

1. We consider developments until 2019 due to COVID-19's independent shock to housing markets.

Section 5 contains our quantitative model of a boom–bust–rebound. House prices equilibrate demand from potential entrants to a city and supply from the construction of new homes and foreclosures. An endogenous boom–bust–rebound cycle occurs in response to a single fundamental change, an increase in the growth rate of the income and amenities or "dividend" from living in the city.

Two model ingredients are instrumental to this result. First, agents learn about the true growth rate from observing dividends, but, in line with survey evidence (Shiller and Thompson, 2022), are over-optimistic in the boom. We formalize over-reaction to news about fundamentals using *diagnostic* expectations (Bordalo *et al.*, 2018, 2020b). Eventually, over-optimism peaks and beliefs start to converge toward the true growth rate, triggering the bust phase. On their own, however, a turn in beliefs cannot generate a bust in which prices fall below their full-information value or as steeply as in the data. This motivates the model's second key ingredient, mortgage borrowing and foreclosures. Consistent with empirical evidence, a foreclosure occurs when an under-water homeowner experiences a liquidity shock. Foreclosures add to housing supply, further depressing prices, putting more owners under-water, and leading to more foreclosures in a price–foreclosure spiral that pushes prices below their long-run level (Guren and McQuade, 2020). Finally, prices rebound as foreclosures recede and ongoing dividend growth causes new entry.

To quantitatively analyse the model, we use SMM to target long-run price movements, house price expectations, supply elasticities, and foreclosures, among other moments. We then assess the model's ability to explain untargeted short-run price dynamics and rent growth across four quartiles of cities grouped by their 1997–2019 price growth. The model fits the boom, bust, and rebound of prices and the growth of rents remarkably well for metro areas in the top half of the long-run growth distribution. It somewhat under-predicts the bust size in lower long-run growth areas, in part due to high supply elasticities in these cities and in part because we do not model spillovers across cities arising from either learning or the balance sheets of national lenders.

While several model features reflect our application to housing cycles, our results shed light on the economics of diagnostic asset price cycles more broadly. In particular, our model highlights how low interest rates create fragility. Intuitively, in a low interest rate environment current demand is more sensitive to expectations about dividends further in the future, making prices more responsive to over-optimism about dividend growth. Indeed, our quantitative analysis indicates the 2000s cycle would have been far milder with interest rates closer to their 1980s level.

1.1. *Related literature*

Our paper differs from other work on asset and housing cycles by presenting a model that generates a boom–bust–rebound from a single fundamental improvement and by using the rebound to infer the source of the cycle.

Most prior work relies on separate exogenous changes in fundamentals or expectations for each turning point to deliver a boom–bust cycle (*e.g.* Kaplan *et al.*, 2020; Jacobson, 2022). Three notable exceptions generate endogenous cycles from a single initial shock as in our paper. First, Barberis *et al.* (1998) show that belief disagreement, over-optimism, or extrapolation in asset markets can generate a boom–bust. Second, Burnside *et al.* (2016) present a model in which boom–busts occur through "social dynamics" similar to the epidemiological spread of disease. Third, in the context of housing, Glaeser and Nathanson (2017) show that sufficiently extrapolative expectations lead to persistent price oscillations. Crucially, ours is the only theory that generates a boom–bust–rebound; the first two generate a boom–bust as over-optimism spreads and recedes about a fundamental improvement that is ultimately not realized, while the third leads to continual oscillations (see Supplementary Appendix D for details).

Empirically, prior work on housing has primarily considered the contribution of specific factors such as changes in credit conditions (Mian and Sufi, 2009; Favara and Imbs, 2015), speculators (Gao *et al.*, 2020), over-optimism and expectations (Shiller and Thompson, 2022), or foreclosures (Guren and McQuade, 2020), although structural models have been used to disentangle the role of various factors (Favilukis *et al.*, 2017; Kaplan *et al.*, 2020; Greenwald and Guren, 2021). This literature has not focused on fundamentals, with a few notable exceptions.[2] Writing near the peak of the boom, Himmelberg *et al.* (2005) found "little evidence of a housing bubble" in part due to fundamental growth. Ferreira and Gyourko (2018) show that the timing of the boom start in each city was "fundamentally based to a significant extent" but that fundamentals revert in roughly three years.[3] Kaplan *et al.* (2020) and Glaeser and Nathanson (2017) micro-found changes in expectations with shocks to future fundamentals but do not treat fundamentals as a measured and central feature of the cycle.

Our focus on fundamentals accommodates a role in the boom–bust for forces such as subprime credit expansion or speculation, which we show are essentially uncorrelated with our measured fundamental in the cross-section of cities. Such transitory factors cannot, however, explain the rebound or why places with large booms also had higher growth over the full cycle. Likewise, extrapolation of fundamentals does not preclude extrapolation of returns (Bordalo *et al.*, 2020a), but extrapolation of returns by itself would generate counterfactual downside over-shooting of expectations by the trough of the bust.

Methodologically, our empirical analysis builds on an urban economics literature on the long-run determinants of housing costs and location choice, notably (Saiz, 2010). Our theoretical framework incorporates diagnostic expectations (Bordalo *et al.*, 2019, 2020a) into a continuous time framework with asset supply-and-demand and contains methodological innovations that may prove useful in other contexts, including a new characterization of the impulse response of diagnostic beliefs.

Finally, our interpretation of the 2000s housing cycle echoes the seminal work of Kindleberger (1978). For instance, Kindleberger writes that "virtually every economic mania is associated with a robust economic expansion".[4] As in Kindleberger, our focus on long-run fundamentals does not imply that there was no "housing bubble". Our work expands on Kindleberger by emphasizing the role of the rebound in diagnosing the driving forces of the cycle and by estimating a quantitative model of a fundamentally rooted cycle.

2. BOOM, BUST, AND REBOUND

This section documents the boom, bust, and rebound phases of the 2000s housing cycle in both national and local data and the rise in rent growth around the start of the boom.

Figure 1 shows the national Case-Shiller house price index (HPI), deflated using the Gross Domestic Product (GDP) price index. The series begins to rise in the late 1990s, peaks in 2006Q2, reaches a local trough in 2012Q1, and then grows again through the end of our sample

2. For instance, Charles *et al.* (2018) describe a "consensus that much of the variation in housing prices during the boom and bust derived from a speculative 'bubble' and not from changes in standard determinants of housing values such as income, population, or construction costs."

3. More recently, Howard and Liebersohn (2022, 2021) examine divergence in demand across areas as a fundamental, and Schubert (2021) identifies spillovers of fundamentals across cities via migration networks.

4. Barberis *et al.* (2018) also emphasize this feature of Kindleberger, but they interpret the fundamental improvement as repeated good news about fundamentals rather than an actual fundamental improvement.

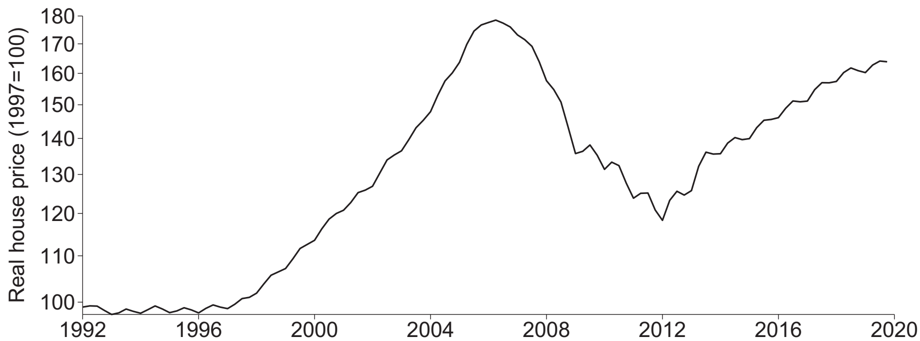

FIGURE 1
National boom, bust, and rebound

Notes: The figure shows the national Case-Shiller index deflated by the GDP price index.

in 2019. We use this timing to define the boom, bust, and rebound periods for the remainder of the paper.[5]

Figure 2 shows the correlation of the boom, bust, and rebound at the local level. Each open circle represents one ZIP Code and the overlaid dark filled circles show the mean value of the y-axis variable in each of 50 quantiles of the x-axis variable. Panel (a) shows the correlation of price growth in the boom and the bust. Each additional percentage point of house price appreciation in the boom is associated with an additional decline of 0.51% point in the bust and the R^2 of this relationship is 0.38.

Panel (b) reveals an equally strong correlation between the bust and post-2012 price growth, with each additional percentage point decline during 2006–12 associated with an additional 0.52% point of growth during 2012–9 and an R^2 of 0.37. The negative correlation between bust and rebound suggests an over-shooting of prices on the downside during the bust, just as the negative correlation between boom and bust points to a bubble in the boom. Putting the bust and rebound together in panel (c), house price growth in the boom has a much weaker correlation with total price growth after 2006 than with the bust only. Panel (d) displays the corollary of this result: house price growth during the boom correlates strongly with growth over the entire 1997–2019 boom-bust-rebound period (BBR for short), with a slope coefficient of 0.81 and R^2 of 0.62. The boom was not ephemeral.

Figure 3 shows the paths of rents for all cities and for averages of each of four quartiles of 1997–2019 house price growth based on an unbalanced sample of 27 core-based statistical areas (CBSAs) over this period. CBSAs with faster long-run price growth also had faster rent growth. Moreover, there is a visible trend break in the late 1990s that is stronger in higher price-growth areas, which we confirm in Table B.2 using structural break tests. Supplementary Appendix C.5 associates such rent growth acceleration with improving fundamentals. We nonetheless focus mostly on prices rather than rents because of their wider coverage and higher quality.[6]

5. Supplementary Appendix Figure B.3 shows the timing of the boom start across cities using a procedure similar to Ferreira and Gyourko (2018). Because few booms start before 1997, we use 1997 as the boom start for our analysis. The figure shows much more uniformity in the timing of the price peak and trough across cities.

6. Crone *et al.* (2010) document important methodological deficiencies prior to 1988 in the consumer price index (CPI) repeat-sampling methodology. The only other yearly city-level data set dating to the 1990s, the Department of Housing and Urban Development (HUD) fair market rents, has imputations in most CBSAs prior to 2003 and has a break in 1995 when the reference percentile changes.

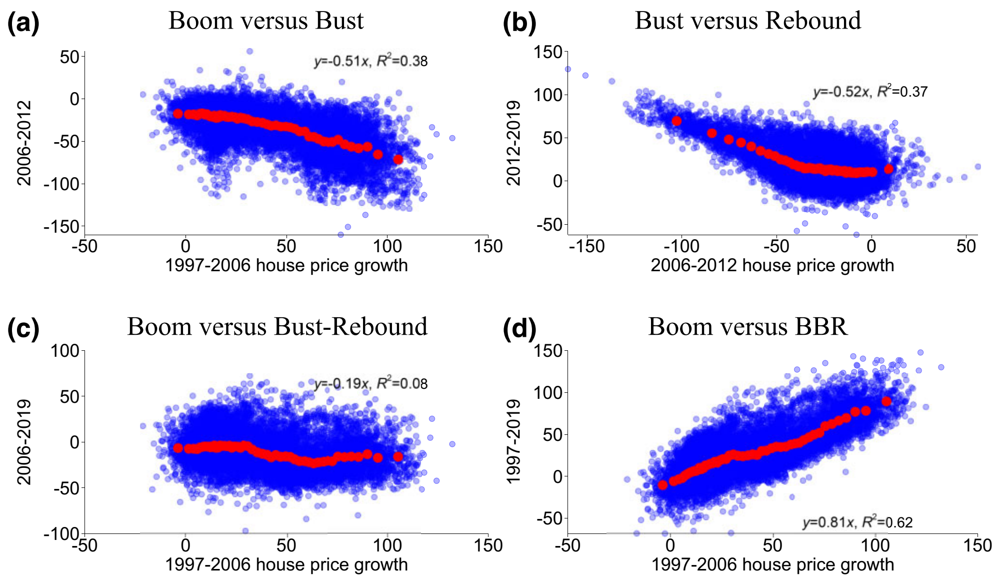

FIGURE 2
Zip Code boom, bust, and rebound

Notes: Each light circle represents one ZIP Code. The dark circles show the mean of the y-axis variable for 50 bins of the x-axis variable. Data from Federal Housing Finance Agency (FHFA) deflated using the national GDP price index.

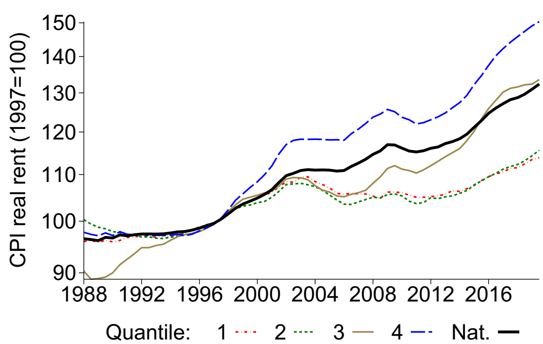

FIGURE 3
Rent growth by house price quartile

Notes: The figure plots rent indexes from the Bureau of Labor Statistics' Consumer Price Index deflated by the national GDP price index for CBSAs grouped into quartiles based on 1997–2019 house price growth.

3. LONG-RUN FUNDAMENTALS: FRAMEWORK

This section introduces a long-run supply-and-demand framework for house prices and describes our data. The framework allows us to move beyond correlations and associate areas with faster growth over the full 1997–2019 period with fundamental determinants of house prices. As a by-product, it produces housing supply elasticities that we use to calibrate the model in Section 5.

3.1. *Structural system*

The supply block starts with an additive decomposition of house prices into the value of the structure and the land:

$$P_{i,t} = C_{i,t} + L_{i,t}, \tag{1}$$

where $P_{i,t}$ is the price of a house in area i at date t, $C_{i,t}$ is the replacement cost of the structure, and $L_{i,t}$ is the land cost.[7] Gyourko and Saiz (2006) argue that the construction sector is sufficiently competitive to justify this decomposition.

Both construction and land costs may increase with population in a city:

$$C_{i,t} = A_{i,t} H_{i,t}^{\alpha_i}, \tag{2}$$

$$L_{i,t} = B_{i,t} H_{i,t}^{\beta_i}. \tag{3}$$

Here, $H_{i,t}$ is total city population (H for houses), α_i and β_i are city-specific long-run elasticities, and $A_{i,t}$ and $B_{i,t}$ are cost shifters unrelated to population.[8] Letting $s_{i,t} = L_{i,t}/P_{i,t}$ denote the land share of prices, the overall long-run supply elasticity is $\eta_{i,t} \equiv [\alpha_i + s_{i,t}(\beta_i - \alpha_i)]^{-1}$. Importantly, these cost functions apply to long-run changes, as they omit short-run dynamics stemming from accelerating population growth or foreclosure dynamics that we introduce in Section 5. We apply equations (1)–(3) to price growth between 1997 and 2019, effectively assuming that *on average* across cities house prices at these two end points reflect long-run fundamentals.[9]

A spatial equilibrium demand equation relates population growth $\dot{H}_{i,t}/H_{i,t}$ to the present value of the income and amenities from living in city i, $V_{i,t}$, and the price:

$$\dot{H}_{i,t}/H_{i,t} = G_i \left(V_{i,t}/P_{i,t}\right)^{\gamma} \quad \text{where } V_{i,t} = \mathbb{E}_t \int_t^{\infty} e^{-\rho s} D_{i,s} ds. \tag{4}$$

Here, G_i is a constant, γ is the elasticity of demand, ρ is the discount rate, and $D_{i,t}$ is the "dividend" that captures the income/amenities from living in an area. Equation (4) is a dynamic spatial equilibrium condition in which households choose location to maximize their earning potential and amenity value net of housing costs. Section 5 provides a micro-foundation for this functional form (see equation (17)); intuitively, $V_{i,t}/P_t$ is the Tobin's Q associated with an area.[10]

We next derive a regression specification that relates observable counterparts of the terms in equations (1)–(4) to the cross-section of 1997–2019 price growth.

7. Other proportional costs such as broker fees drop out when we take log changes below. We abstract throughout from changes in average house size.

8. Supplementary Appendix A.1 provides a micro-foundation of equation (2) from the cost-minimization problem of a competitive construction sector. Supplementary Appendix A.2 provides a micro-foundation of equation (3) as in Saiz (2010) from an Alonso-Muth-Mills intra-city spatial equilibrium condition, wherein average land prices in a city grow with population because the premium to living in the city centre (or equivalently most desirable neighbourhoods) rises to induce new housing in less desirable locations.

9. City-specific, idiosyncratic deviations from fundamentals are in the structural residual, as are city-specific changes in fundamentals not captured by our instruments. The latter make our conclusions about the role of fundamentals a likely *lower bound* for the total role of fundamental drivers.

10. The assumption that V does not depend on P holds if utility from housing is independent of non-housing goods or both enter Cobb-Douglas.

3.2. *Regression specification*

Taking logs of equation (1), differencing over time, and letting lower case p, c, ℓ, a, b denote the log differences of their respective upper case letters, we obtain:

$$p_{i,t} = \left(1 - s_{i,t}\right) c_{i,t} + s_{i,t}\ell_{i,t} \tag{5}$$

$$= a_{i,t} + s_{i,t}\left(b_{i,t} - a_{i,t}\right) + \left(\alpha_i + s_{i,t}\left(\beta_i - \alpha_i\right)\right) h_{i,t}. \tag{6}$$

Equation (5) decomposes house price growth into a weighted average of the growth of construction and land costs. Equation (6) imposes our functional forms. We further parameterize $\alpha_i = \alpha_0 + \alpha_1 m_i$ and $\beta_i = \beta_0 + \beta_1 m_i$, where m_i measures the regulatory burden of new construction in city i relative to the cross-city mean and α_0 and β_0 are the average elasticities. This parameterization allows construction and land costs to increase more steeply with the number of houses in places with stricter land-use regulations.

The component $b_{i,t}$, the growth in land prices unrelated to total population growth, contains the trend toward urbanization and gentrification that began in many cities around the turn of the millennium (Couture and Handbury, 2020). This movement of college-educated, high-income individuals into downtown neighbourhoods where land is relatively scarce pushed up the cost premium to living in the city centre, causing land and house prices to rise everywhere (Su, 2022). We capture the city-specific dimension of this trend by parameterizing $b_{i,t} = bu_{i,t} + \bar{b}_t + \hat{b}_{i,t}$, where $u_{i,t}$ denotes the log change in the house price premium for buying downtown relative to the rest of the city, $\bar{b}_t$ is the cross-city average secular land price growth, and $\hat{b}_{i,t} = b_{i,t} - bu_{i,t} - \bar{b}_t$. We similarly demean $a_{i,t}$ and let $\epsilon_{i,t} = \hat{a}_{i,t} + s_{i,t}(\hat{b}_{i,t} - \hat{a}_{i,t})$ to arrive at the structural equation:

$$\begin{aligned} p_{i,t} = {} & \bar{a}_t + s_{i,t}\left(\bar{b}_t - \bar{a}_t\right) + \alpha_0 h_{i,t} + \left(\beta_0 - \alpha_0\right) s_{i,t} h_{i,t} \\ & + \alpha_1 m_i h_{i,t} + \left(\beta_1 - \alpha_1\right) m_i s_{i,t} h_{i,t} + s_{i,t} b u_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{7}$$

Equation (7) corresponds to the regression equation:

$$\begin{aligned} p_{i,t} = {} & c_0 + c_1 s_i + c_2 h_{i,t} + c_3\left(s_i \times h_{i,t}\right) \\ & + c_4\left(m_i \times h_{i,t}\right) + c_5\left(m_i \times s_i \times h_{i,t}\right) + c_6\left(s_i \times u_{i,t}\right) + e_{i,t}, \end{aligned} \tag{8}$$

with $c_0 = \bar{a}_t$, $c_1 = \bar{b}_t - \bar{a}_t$, $c_2 = \alpha_0$, $c_3 = \beta_0 - \alpha_0$, $c_4 = \alpha_1$, $c_5 = \beta_1 - \alpha_1$, $c_6 = b$.

Equation (8) is a long-run supply equation.[11] The coefficient c_1 identifies average excess secular (not driven by population) increase in land prices over construction costs, c_2 is the average long-run elasticity of construction costs to population, c_3 is the difference in the average elasticities of land and construction costs to population growth, c_4 is the increase in the construction cost elasticity from higher regulatory strictness, c_5 is the difference in the increases in the land and construction cost elasticities, and c_6 is the contribution of city-specific urbanization. The inverse supply elasticity is $c_2 + c_3 \times s_i + c_4 \times m_i + c_5 \times s_i \times m_i$.

11. Equation (8) generalizes (Saiz, 2010) by treating the land share as observable, by allowing for construction costs to respond endogenously to population, and by explicitly modelling urbanization. Specifically, the Saiz (2010) model starts with equations (1)–(3) with $\alpha_i = 0 \; \forall i$ and $b = 0$. In our notation, the final specification in Saiz (2010) is $p_{i,t} - c_{i,t} = k_1(1 - \Lambda_i) \times h_{i,t} + k_2 \ln H_{i,0} \times (1 - \Lambda_i) \times h_{i,t} + k_3 \times m_i \times h_{i,t} + e_{i,t}$, where Λ_i denotes the share of land available for development. Our approach instead treats Λ_i and $\ln H_{i,0}$ as excluded instruments that help to identify the land share terms in the supply elasticity.

3.3. *Data, measurement, and excluded instruments*

3.3.1. Outcome and endogenous variables. We estimate equation (8) across 308 CBSAs over 1997–2019. House price data come from Freddie Mac, deflated by the national GDP price index. We measure quantity growth by aggregating Census intercensal estimates of county housing units. We obtain the CBSA land share in 2012 from Larson *et al.* (2021). We equate regulatory strictness with the 2006 Wharton Residential Land Use Regulatory Index (WRLURI) developed in Gyourko *et al.* (2008). We measure growth in the urban premium by defining a downtown as in Couture and Handbury (2020) and using ZIP-Code house price indexes to compute relative price growth, as described in Supplementary Appendix B.4. Supplementary Table B.4 presents summary statistics.

3.3.2. Excluded instruments. We treat population growth, land share, regulatory strictness, urbanization, and their interactions as potentially endogenous and estimate equation (8) using instrumental variables. A simultaneity problem arises because $\epsilon_{i,t}$ contains city-specific, secular (*i.e.* unrelated to population) changes in land or construction costs that increase house prices and reduce population growth or urbanization. Since we observe land share and zoning regulation only well into the cycle, if these variables respond to population or prices they are endogenous as well. We heuristically group excluded instruments by which endogenous variable they most closely affect and appropriately interact these groups as well to produce the complete excluded instrument set. We purposely follow the existing literature in choosing excluded instruments to make the point that a fundamentally rooted interpretation of the 2000s cycle emerges from standard house price determinants.

Equation (4) motivates excluded instruments for population growth, which form the basis for the CBSA-level observable demand-side components of long-run fundamental growth. Specifically, labour demand and amenities that shift the growth of $V_{i,t}$ constitute valid demand shifters to identify the long-run supply elasticity. We follow Saiz (2010) and use shift-share predictors of employment and wage growth as labour demand shifters (see Supplementary Appendix B.3 for details). We use January temperature and sunlight and July humidity as climate-related amenities that capture population movement toward the "sunbelt". We additionally follow Diamond (2016) and use the 1997 share of employment in restaurants.

We also follow Saiz (2010) in choosing instruments relevant for the land share of the price and regulatory strictness, which form the basis for the supply-side components of long-run fundamental growth. For land share, we use the fraction of land available for development (not water or steep slope) from Lutz and Sand (2019) and 1997 population density.[12] For regulatory strictness, we use the ratio of public expenditure on protective inspection to total tax revenue in the 1992 Census of Governments and the share of Christians in non-traditional denominations in the 1990 Census.[13]

Our instruments for the change in the downtown price premium draw on recent work that pinpoints changing tastes by college-educated residents for urban amenities such as bars and restaurants that started around the late 1990s (Baum-Snow and Hartley, 2020; Couture and Handbury, 2020). Supplementary Appendix A formalizes this force by extending the Alonso-Muth-Mills model of intra-city spatial equilibrium to include college and non-college residents

12. Supplementary Appendix A.2 provides a formal motivation for these instruments in the context of the Alonso-Muth-Mills intra-city spatial equilibrium micro-foundation of equation (3) (equation (A.10)).

13. Saiz (2010) motivates protective expenditure as revealing an area's taste for regulation and the non-traditional Christian share because these denominations' ethos of individualism leads to reduced regulation.

with time-varying preferences for living in a downtown core and motivates two excluded instruments (see equation (A.15)): (1) the interaction of the pre-boom (1990) share of college workers in the CBSA and pre-boom urban amenities, which we measure as the ratio of restaurant density in the downtown and non-downtown and (2) the interaction of the pre-boom relative likelihood of living downtown for college and non-college residents and the predicted change in the CBSA college share using a Bartik shift-share. Supplementary Appendix B.4 contains details of the measurement.

Let $\mathcal{H}$, $\mathcal{L}$, $\mathcal{M}$, and $\mathcal{U}$ denote the sets of instruments heuristically assigned to population growth, land share, WRLURI, and urbanization, respectively. The full excluded instrument set consists of $\mathcal{H}, \mathcal{L}, \mathcal{M}, \mathcal{H} \times \mathcal{L}, \mathcal{H} \times \mathcal{M}, \mathcal{H} \times \mathcal{L} \times \mathcal{M}$, and $\mathcal{L} \times \mathcal{U}$, where $\times$ denotes element-wise cross-set multiplication. The linear combination of these instruments formed by the second stage fitted value is the long-run observable fundamental.

3.3.3. What is the shock? Many of the excluded instruments are either persistent or time invariant. Consistent with this fact, areas with higher predicted house price growth over 1997–2019 based on these measures also had faster house price and population growth over 1975–97. Persistence in instruments associated with land share and regulation occurs naturally, since supply heterogeneity is a persistent feature of areas. Nothing in the econometric set-up precludes using persistent demand instruments to identify a long-run supply elasticity; instead, the framework simply requires demand instruments that shift population growth and are orthogonal to unobserved, location-specific supply shifters.

Persistence in some instruments, however, raises the question of what changed to trigger the cycle. Several of the instruments do embody changes in the late 1990s, notably educated workers moving to downtown neighbourhoods and changes in industry growth.[14] Other, more persistent attributes such as climate may have coincided with changing preferences for amenities that accelerated in the late 1990s. More generally, rising tastes for city dwelling, due for example to the widespread decline in crime (Pope and Pope, 2012; Ellen *et al.*, 2019) or changing preferences for urban amenities, increased urban land values nation-wide, with the largest impact on house prices in areas with high land shares or already experiencing rapid growth.[15] These forces together comprise the shock.

4. LONG-RUN FUNDAMENTALS: RESULTS

This section contains our main empirical results. Section 4.1 shows that the excluded instruments strongly predict house price growth over 1997–2019. Section 4.2 reports the IV results. Section 4.3 defines observed long-run fundamental growth as a linear combination of the excluded instruments and shows that higher fundamental growth predicts a larger amplitude of the boom–bust–rebound cycle.

14. A regression of the predicted employment growth instrument on a shift-share for predicted employment growth over 1986–96 has an R^2 of 0.35, indicating some but far from full persistence.

15. Because the present value of dividends in high growth areas is dominated by dividends farther in the future, marginal increases in demand growth matter more, similar to convexity in bond pricing. Formally, if the present value of income/amenities $V_{i,t}$ has a Gordon growth representation with discount rate ρ and spot dividend growth μ_i, $V_{i,t} = D_{i,t}/(\rho - \mu_i)$, then a common increase in μ_i will increase V by more in places where μ_i was already large. The calibration in Section 5 accounts for differences in pre-boom house price-growth rates across CBSAs, so this force is present in our model.

4.1. *Reduced-form results*

Supplementary Appendix Table B.5 reports first-stage-type regressions for each endogenous variable separately, using only the excluded instruments motivated by that variable and also using the full set of uninteracted instruments. In brief, the instruments act as expected and strongly predict their respective endogenous variables.

Figure 4 plots the fitted values from regressing house price growth over 1997–2019 on all of the uninteracted instruments against actual house price growth in various sub-periods. Panel (a) shows a strong reduced form fit with an R^2 of 0.58, illustrating that fundamental drivers of location choice, land share, regulation, and urbanization measured prior to the start of the boom explain a substantial amount of the variation in house price growth over 1997–2019. Panels (b)–(d) show that higher predicted long-run growth correlates positively with the magnitudes of the boom, bust, and rebound separately. Thus, the reduced-form evidence establishes a correlation between long-run fundamental determinants of house price growth and a boom–bust–rebound cycle without imposing the structure of equations (1)–(4) and the IV specification. Panel (e) shows that these fundamental determinants also predict 2000–19 rent growth, with an R^2 of 0.39.[16]

4.2. *Structural IV results*

The full IV results impose additional restrictions by forcing the instruments to act through the endogenous variables in the model. They also yield structurally interpretable long-run housing supply elasticities that we use to calibrate the model in Section 5.

Table 1 presents the results from estimating equation (8). Column (1) shows ordinary least squares (OLS). CBSAs with higher land share and faster population growth had higher house price growth over the full BBR, and especially so in places with both high land share and high regulation. Evaluated at the (unweighted) mean land share and regulatory burden, the long-run inverse supply elasticity is 0.54 with a standard error of 0.26 using the delta method.

Columns (2) and (3) report our main IV results. Column (2) reports the IV specification with all of the interaction terms. Given the large number of interaction terms and instruments, the data are unable to tightly identify each interaction in column (2). Column (3) consequently constrains the coefficients on land share $\times$ population growth and WRLURI $\times$ population growth to be zero.[17] Imposing these restrictions results in tightly identified coefficients without sacrificing fit: The remaining coefficients have much smaller standard errors, the R^2 *rises* slightly, and the mean inverse supply elasticity is unchanged. Column (3) is thus our preferred specification.[18]

Several features merit comment. The R^2 of 0.45 in column (3) reveals strong explanatory power of land share, population growth, WRLURI, and urbanization when imposing the IV coefficients, illustrating the central message that fundamentals can explain a substantial amount of the variation in house price growth over the entire BBR. The impact of population growth and the average inverse elasticity are larger with IV, consistent with the expected bias of OLS

16. Panel (e) uses Census median rents rather than the Bureau of Labor Statistics (BLS) data in Figure 3 to have a larger sample. The main drawbacks are that the Census data start in 2000 and there are no quality adjustments.

17. The supply framework interprets these restrictions as the intercepts of the elasticities of land and construction are the same, $\beta_0 = \alpha_0$, and the construction elasticity α_i does not vary with land-use regulation.

18. Supplementary Appendix B.5 collects several alternative specifications that address various potential concerns, including (1) alternative house price indexes; (2) using the Saiz (2010) measure of land unavailability, or population in place of housing units; (3) weighting by population or dropping areas with fewer than 150,000 people or shrinking population; (4) changing the estimator to general method of moments (GMM), jackknife instrumental variables estimation (JIVE), or bias-adjusted two-stage least squares; (5) excluding groups of excluded instruments one-at-a-time; and (6) controlling for lagged house price or units growth.

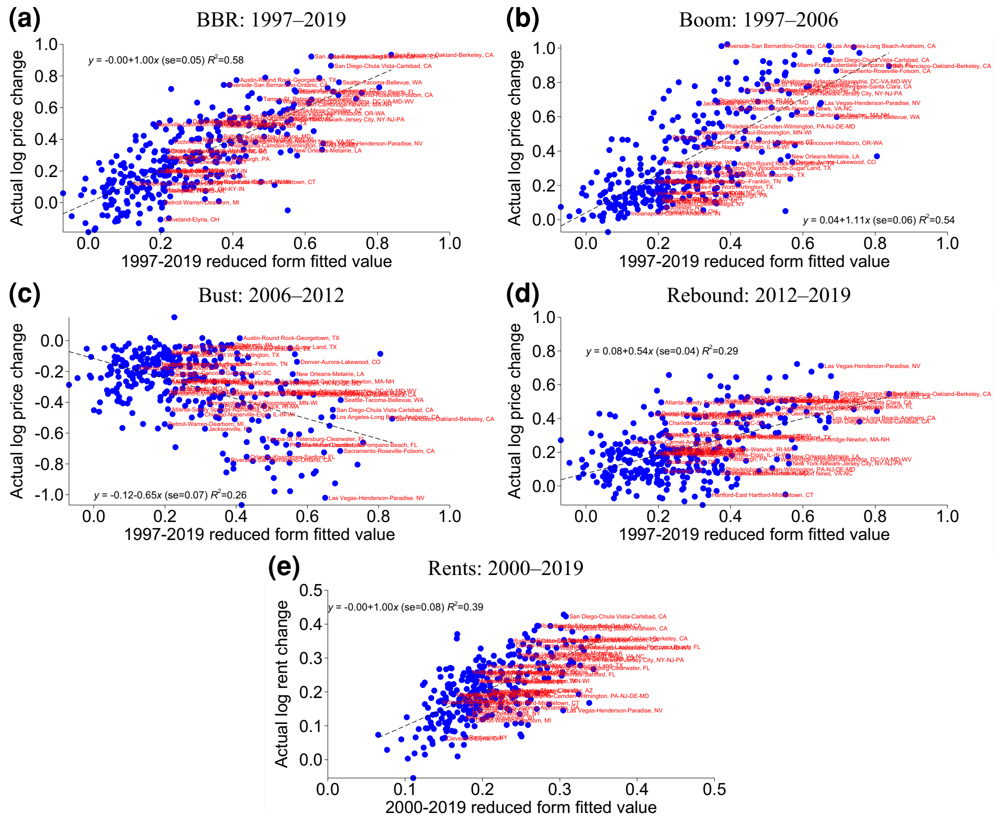

FIGURE 4

Reduced-form correlations

Notes: In panels (a)–(d), each dot is the real house price growth in a CBSA over the period indicated on the vertical axis plotted against the predicted real house price growth over the period 1997–2019 based on column (7) of Table B.5. In panel (e), each dot is real rent growth between the 2000 Census and 2019 one-year American Community Survey (ACS) on the vertical axis plotted against the fitted value from a regression on the excluded instruments. CBSAs with more than 1 million people in 1997 are labelled.

due to area-specific cost shocks. The coefficient on the triple interaction term indicates a larger inverse elasticity (price growth more sensitive to population) in areas with high land share and high regulation. The land share coefficient of 78 log points suggests a significant role for nationwide forces affecting land prices as discussed previously and is consistent with Nichols (2019). The large and positive coefficient on land share × urbanization indicates that a portion of the land share increase is due to increasing desirability of land-scarce downtown neighbourhoods, underscoring the role of this particular channel in triggering the increase in fundamental growth in the late 1990s.

The IV fitted value permits a decomposition of price growth into the part coming from CBSA-wide population growth, which is the fitted value of the terms including $h_{i,t}$ in equation (8), and the remainder which includes within-CBSA urbanization and the contribution of rising average land prices nationally. Applying this decomposition, CBSA-wide population growth at the estimated long-run elasticities explains 57% of average house price growth, but land price growth and urbanization explain slightly more of the cross-CBSA variance. Figure B.5 provides a less structural decomposition and shows that the supply-and-demand instruments have approximately equal power for predicting 1997–2019 price growth and both predict more pronounced

TABLE 1
Long-run OLS and IV results

	House price growth 1997–2019			Rent growth 2000–19
Dep. var.:	(1)	(2)	(3)	(4)
Land share	0.64^{**}	0.91^{*}	0.78^{**}	0.17^{*}
	(0.24)	(0.37)	(0.20)	(0.08)
Units growth	0.34	0.81	0.63^{**}	0.16^{**}
	(0.26)	(0.49)	(0.10)	(0.04)
Land share × Units growth	0.72	−0.64		
	(0.92)	(1.63)		
WRLURI × Units growth	−0.01	0.32		
	(0.12)	(0.23)		
Land share × WRLURI × Units growth	0.79^{*}	0.34	1.30^{**}	0.34^{**}
	(0.37)	(0.75)	(0.28)	(0.11)
Land share × Urbanization	1.22^{**}	1.42^{**}	1.40^{**}	0.40^{**}
	(0.19)	(0.37)	(0.38)	(0.14)
Constant	−0.05	−0.13	-0.11^{+}	0.11^{**}
	(0.06)	(0.11)	(0.06)	(0.02)
Estimator	OLS	2sls	2sls	2sls
Elasticity at $\bar{s}_j$	0.54	0.63	0.63	
Standard error of elasticity	0.26	0.50	0.10	
R^2	0.49	0.43	0.45	0.17
Observations	308	308	308	272

Notes: The table reports OLS (column 1) and IV (columns 2–4) regressions of real CBSA house price growth over 1997–2019 or rent growth over 2000–10 on land share, housing unit growth over 1997–2019, their interactions with WRLURI and each other, and the interaction of land share and the change in the downtown price premium, as in equation (8). The standard error of the elasticity at the mean of land share is computed using the delta method. Heteroskedastic-robust standard errors in parentheses. **,* ,$^{+}$ denote significance at the 1, 5, and 10% levels, respectively.

cycles. We conclude that all of the elements of the long-run framework matter to explaining house price growth in our sample.

Column (4) shows that long-run fundamentals also predict rent growth. The structural coefficients are smaller than for price growth, reflecting the fact that prices rose faster than rents over the full 1997–2019 period, a result we return to in Section 5, and the data limitation that we measure rents in the 2000 Census and 2019 ACS to maximize sample coverage and therefore lose the first few years of the boom.

4.3. *Long-run fundamental and boom–bust–rebound*

We define the long-run observable fundamental as the second stage fitted value corresponding to column (3) of Table 1. Associating the fundamental with the second stage fitted value makes it a linear combination of the excluded instruments, none of which depends on local characteristics that evolve after the start of the boom.

Figure 5 reports the coefficients $\{\beta_{1,h}\}$ from a cross-sectional regression of log real price growth between 1997 and 1997+h on the long-run fundamental. Areas with higher long-run fundamentals have more pronounced booms, busts, and rebounds.[19] Supplementary Appendix B.1 and Supplementary Figure C.2 further show that fundamentals are essentially orthogonal to

19. This pattern is not driven only by cities that are historically more sensitive to aggregate dynamics. Controlling for the 1978–96 cyclical sensitivity using the procedure in Guren *et al.* (2021b) results in yearly coefficients that never differ by more than 0.002 from those plotted in Figure 5.

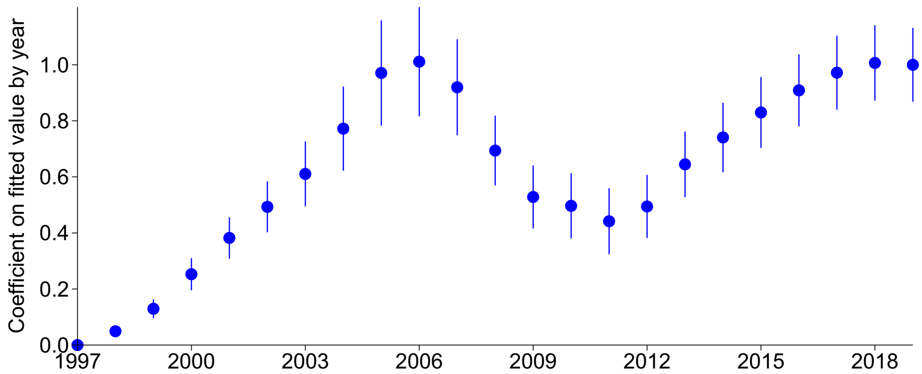

FIGURE 5
Fundamentals and house prices over time

Notes: The figure plots the coefficients $\{\beta_{1,h}\}$ and 95% confidence intervals from regressions at each horizon h of house price growth between 1997 and 1997+h on the long-run fundamental using the specification $p_{i,t,t+h} = \beta_{0,h} + \beta_{1,h}\hat{p}_{i,t} + \nu_{i,h}$, where $\hat{p}_{i,t}$ denotes the second stage fitted value from column (3) of Table 1.

other forces such as speculation or subprime credit expansion. These results together motivate a quantitative model of a fundamentally driven boom–bust–rebound cycle.

5. A QUANTITATIVE NEO-KINDLEBERGERIAN MODEL

Areas experiencing faster price growth over 1997–2019 had higher fundamental growth and also experienced a larger boom–bust–rebound. We now offer a "neo-Kindlebergerian" interpretation of this finding using a structural model calibrated to the cross-section of cities. The model nests the empirical framework in the sense that it gives rise to the same long-run supply-and-demand system as in equations (1)–(4), and we use the estimated supply elasticities in the calibration. It enriches the prior framework by introducing an explicit stochastic process for income/amenities, non-rational beliefs, adjustment costs to housing, and mortgages with foreclosures that together give rise to the boom–bust–rebound.

As in Kindleberger's *Manias, Panics, and Crashes*, a single change in the economy's fundamentals sets off the asset price cycle. In our urban setting, this change takes the form of an increase in the growth rate of the "dividend" from living in a city. Agents learn about the growth rate by observing the history of dividends but become overly optimistic due to *diagnostic* expectations, causing a boom. Eventually, beliefs correct, causing house prices to fall. As prices fall, some under-water homeowners default, triggering a price–foreclosure spiral in the bust. This "crash" causes prices to fall below their long-run level. Finally, ongoing dividend growth induces new buyers to enter and prices to rebound. Both over-optimism and credit with foreclosures are necessary to generate a realistic boom–bust–rebound from the single change in the economy's fundamentals.

5.1. *Environment*

Time is continuous. The economy consists of cities each with population $H_{i,t}$ and a residual "hinterland". We describe the determination of population, house prices, mortgage distribution, and foreclosures in each city and suppress the i subscript for convenience.

5.1.1. Dividend and beliefs. The driving force in the economy is the “dividend”, D_t, from living in the city. As in equation (4), this unidimensional object captures the combination of income prospects and amenities from living in the city relative to the hinterland. The value of D_t evolves as a geometric Brownian motion with stochastic drift:

$$dD_t = \mu_t D_t dt + \sigma_D D_t dW_{D,t}, \tag{9}$$

where $dW_{D,t}$ is a standard Wiener process. The drift μ_t follows an Ornstein-Uhlenbeck process:

$$d\mu_t = \vartheta\,(\bar{\mu} - \mu_t)\,dt + \sigma_\mu dW_{\mu,t}, \tag{10}$$

where ϑ determines the rate of convergence to the unconditional mean $\bar{\mu}$ and $dW_{\mu,t}$ is a standard Wiener process uncorrelated with $dW_{D,t}$. Agents observe D_t but do not know the instantaneous drift rate μ_t. The single realized shock in the model will be an increase from $\bar{\mu}$ to $\mu_0 > \bar{\mu}$ at the start of the boom at date 0.

A Bayesian agent would form beliefs over μ_t from the path of observed dividends. Let $\mathcal{F}_t = \sigma\{D_s : -\infty \leq s \leq t\}$ denote the information set at time t. Applying the Kalman-Bucy filter, the Bayesian posterior belief has a normal distribution, $h_t(\mu_t|\mathcal{F}_t) \sim \mathcal{N}(m_t, \sigma_m^2)$, where the current mean belief, m_t, follows the process:

$$dm_t = \vartheta\,(\bar{\mu} - m_t)\,dt + KdB_t, \tag{11}$$

and where the surprise innovation dB_t follows:

$$dB_t = \sigma_D^{-1}\,(dD_t/D_t - m_t dt)\,. \tag{12}$$

A surprise dB_t causes the rational agent to update her mean belief according to the Kalman gain $K = \sigma_m^2/\sigma_D$, where the gain is increasing in the signal-to-noise ratio.[20]

As we show below, generating a boom–bust–rebound in prices following an increase from $\bar{\mu}$ to μ_0 requires over-optimism relative to the fully rational process described by equations (11) and (12). Bordalo *et al.* (2018) propose *diagnostic* expectations as one such departure that formalizes the representativeness heuristic of Tversky and Kahneman (1983). The representativeness heuristic causes agents to over-weight the likelihood of a trait in a class when that trait has a higher likelihood in the class than in a reference population. Bordalo *et al.* (2018) give as an example the higher prevalence of red hair among Irish than non-Irish, which causes people to overestimate the share of Irish with red hair. In the asset price cycle context, the reference population is the full history of dividends and the class is recent dividends, with inference over the current drift rate.

We implement diagnostic expectations as follows. For a “look-back” parameter k, the background context at date t consists of information observed up to date $t-k$, $\mathcal{F}_{t-k}$. The diagnostic belief distribution of the drift rate is then:

$$h_t^\theta\,(\mu_t) = h_t\,(\mu_t|\mathcal{F}_t)\left[\frac{h_t\,(\mu_t|\mathcal{F}_t)}{h_t\,(\mu_t|\mathcal{F}_{t-k})}\right]^\theta Z, \tag{13}$$

20. We assume the asymptotic variance of the posterior drift rate, *i.e.* $\sigma_m^2 = \sigma_\mu^2/(2\vartheta + K/\sigma^D)$. Suppressing the city subscript i implicitly assumes that agents learn only from the dividends of a single city, even if the Wiener shocks across cities were correlated. Because learning from correlated shocks has an effect similar to a rescaling of the posterior variance, this assumption does not materially impact our results.

for a constant Z that ensures the density integrates to 1. The diagnostic distribution over-weights states that have become relatively more likely in light of recent dividend news, that is, where $h_t(\mu_t|\mathcal{F}_t) > h_t(\mu_t|\mathcal{F}_{t-k})$. This "kernel-of-truth" property causes over-reaction to good news when the distribution of states satisfies the monotone-likelihood property—as with normally distributed innovations—because higher growth states become more likely following positive news. The parameter θ controls the magnitude of departure from rational expectations and nests the rational case when $\theta = 0$. As in Bordalo *et al.* (2020b), the diagnostic posterior mean is simply shifted from the rational case by a term $\theta\mathcal{I}$:

$$h_t^\theta(\mu_t) \sim N\left(m_t^\theta, \sigma_m^2\right), \quad m_t^\theta \equiv \mathbb{E}_t^\theta[\mu_t] = m_t + \theta\mathcal{I}_t, \tag{14}$$

$$\text{where: } \mathcal{I}_t \equiv m_t - \mathbb{E}_{t-k}m_t = K\int_{t-k}^{t} e^{-\vartheta(t-s)}dB_s. \tag{15}$$

$\mathcal{I}$ is the information the diagnostic agent neglects in forming her background context.[21]

The key driving force is the expected present value of dividends P^*. Denoting the discount rate by ρ, Supplementary Appendix C.1 proves that P^* depends only on D_t, m_t^θ, and parameters[22] :

$$P^*\left(D_t, m_t^\theta\right) \equiv \int_{-\infty}^{\infty} \mathbb{E}_t\left[\int_t^\infty e^{-\rho(s-t)}D_s ds|\mu_t\right] h_t^\theta(\mu_t)\,d\mu_t. \tag{16}$$

The present value $P^*(D_t, m_t^\theta)$ encodes all relevant information coming from the evolution of the dividend and beliefs. Any belief process that produces the same path of P^* will produce the same results in our model. Diagnostic expectations offer an especially attractive micro-foundation for beliefs about house prices because they immediately imply two key features of the cycle—independence of the lengths of the boom, bust, and rebound from their amplitude in the cross-section and no over-shooting of house price expectations on the downside during the bust—in addition to their grounding in evidence from psychology, their tractability, and their success in non-housing settings as well. The non-over-shooting of beliefs in the bust in particular distinguishes the path of P^* from models of learning from prices in which expectations overshoot on the downside.

To summarize, dividends follow a geometric Brownian motion with a drift rate that follows an Ornstein-Ulhenbeck process. When dividends rise unexpectedly, agents over-weight the likelihood of high trend growth. Eventually, the positive surprises fall out of the diagnostic window and expected growth starts to converge towards the rational posterior.

5.1.2. Spatial equilibrium and housing demand. Each instant a mass $g_H H_t$ of potential entrants choose between purchasing in the city or in the hinterland. We normalize to 0 the dividend and hence the house price from living in the hinterland.[23] The total cost of purchasing in

21. Equations (14) and (15) extend the Bordalo *et al.* (2019) implementation of "slow-moving" information to our continuous time setting. Maxted (2024) proposes an alternative formulation that instead generalizes the decay parameter in equation (15) not to necessarily equal mean reversion ϑ. We prefer the formulation in equation (15) because it has a direct interpretation of the information received over a recent horizon and because the parameter k controls the length of the boom without directly impacting the length of the bust.

22. Convergence of this present value requires $\bar{\mu} + \frac{1}{2}\frac{\sigma_\mu^2}{\vartheta^2} < \rho$. We set σ_μ^2 to ensure this inequality holds and verify that at the estimated parameters our results are not sensitive in the range of admissable values.

23. Potential entrants consider a single city, which arises naturally in continuous time as multiple "offers" never arrive in the same instant. More substantively, the normalization of hinterland house prices to 0 requires that potential entrants do not value the possibility of a future opportunity with a higher idiosyncratic component ξ (introduced below).

the city is the price of a house, P_t, plus the cost of a mortgage in up front origination fees or "points", W_t, as in Kaplan *et al.* (2020).

The value to a potential entrant from purchasing in the city has a common component, V_t, and an idiosyncratic component, ξ, which creates a downward-sloping demand curve. The common component comprises the expected dividends received while living in the city, $V_t = P^*(D_t, m_t^\theta)$.[24] The idiosyncratic component ξ is drawn from a Pareto distribution with $P(\xi > x) = (\frac{x_m}{x})^\gamma$, such that γ governs the slope of the housing demand curve.

In spatial equilibrium, a potential entrant purchases a house in the city if ξV_t exceeds the cost $P_t + W_t$. The total demand for houses from new entrants, Q_t, thus parallels equation (4) but augmented to account for points and foreclosures:

$$Q_t = g_H H_t P\left(\xi > (P_t + W_t)/V_t\right) = g_H H_t x_m^\gamma \left[V_t/(P_t + W_t)\right]^\gamma . \tag{17}$$

5.1.3. Construction. The cost of building an additional house, C_t, takes the form:

$$C_t = \left[A H_t^{1/\eta}\right] \left(I_t/\bar{I}_t\right)^{1/\chi}, \tag{18}$$

where $I_t \equiv dH_t/H_t$ denotes the construction rate and $\bar{I}_t \equiv \alpha I_{t-1} + (1-\alpha)\bar{I}_{t-1}$ is a trailing geometric average.[25] Equation (18) parallels the empirical specification for housing costs in equations (1)–(3), with two differences. First, for simplicity we do not separately model land and construction and instead directly set η as the overall long-run elasticity of supply. Second, the short-run adjustment cost $(I_t/\bar{I}_t)^{1/\chi}$ captures deviations from the existing capacity of the construction sector. The parameter χ governs the short-run inverse elasticity of supply, which is $d\ln C_t/d\ln H_t = \eta^{-1} + (\chi I_t)^{-1}$. The adjustment cost term disappears at long horizons as I_t approaches $\bar{I}_t$, leaving only the long-run supply equation.

5.1.4. Mortgages and foreclosures. A home-buyer at date t obtains an interest-only mortgage of $M_t = \phi P_t$, where the loan-to-value (LTV) ϕ is idiosyncratic for each buyer.[26] Mortgages end at the first date τ at which the mortgagee receives a "liquidity shock" and either refinances or defaults. Liquidity shocks arrive with Poisson intensity ι. A cash-out refinance occurs if the owner has positive equity, $M_t \leq RP_\tau$, where $R \sim N(1, \sigma_R^2)$ is an idiosyncratic house price shock. In a refinance, the owner pays off the old mortgage and obtains a new mortgage of $M_\tau = \phi P_\tau$. A default occurs if the owner receives the liquidity shock and has negative equity, $M_t > RP_\tau$. Thus, as in Guren and McQuade (2020), default requires a "double trigger".[27]

We may justify this neglect either by assuming once-and-for-all decisions or by assuming a negative dividend to living in the hinterland that exactly offsets the option value.

24. We assume that agents expect to live in the city forever for simplicity. One can motivate $V_t = P^*(D_t, m_t^\theta)$ as a 0th order approximation in the moving probability to the value incorporating the possibility of leaving the city. In the data, the probability of moving across cities is approximately 2%.

25. We set α to 1/30 years. The results are not sensitive to this value as long as $\bar{I}$ moves slowly.

26. We consider interest-only mortgages in order to realistically capture the upper tail of the LTV distribution. In practice, the vast majority of defaulters took out a new loan relatively recently and principal pay-down is minimal at the beginning of a 30-year amortizing loan.

27. This is consistent with empirical evidence in Foote *et al.* (2008), Gerardi *et al.* (2018), Gupta and Hansman (2022), and Gupta *et al.* (2019). Gupta *et al.* in particular show that health shocks lead to foreclosure with negative equity and refinancing with positive equity as in our model. Ganong and Noel (2022) ascribe a larger role to liquidity shocks alone than to double trigger. If there were significant default unrelated to equity, our calibration would require a larger price impact of foreclosures or a higher rate of liquidity shocks during the bust. That being said, our model does have significant above water (to the econometrician) default, as the idiosyncratic house price shock R smooths the cliff function for default probability as a function of LTV as in Greenwald *et al.* (2021).

Defaulters exit the housing market and the foreclosed homes enter supply in the instant after the default occurs.[28] The mortgage balance measure density, $g(M,t)$, evolves according to the Fokker-Planck equation:

$$\frac{\partial}{\partial t} g(M,t) = \underbrace{(I_t+\iota) H_t \phi(M/P_t)/P_t}_{\text{New originations}} - \underbrace{\iota g(M,t)}_{\substack{\text{Refis/}\\ \text{foreclosures}}}. \quad (19)$$

Competitive, risk-neutral lenders provide mortgages. These lenders have the same beliefs as buyers.[29] They set points W_t to make zero expected profits on each loan given that they only recover a fraction ψ of a house's value in a foreclosure:

$$W_t = \mathbb{E}^\tau \left\{ \mathbb{E}_t^\theta \left[e^{-\rho(\tau-t)} \max\{M_t - \psi R P_\tau, 0\} \right] \right\}. \quad (20)$$

5.2. *Equilibrium*

An equilibrium in each city consists of paths for the prospective home buyers' common valuation V_t, house price P_t, city size H_t, mortgage points W_t, and mortgage balance measure density $g(M,t)$ such that:

(i) Buyers' common valuation $V_t = P^*(D_t, m_t^\theta)$ reflects their beliefs, where $P^*(D_t, m_t^\theta)$ satisfies equation (16).

(ii) Price equals the marginal cost of construction given by equation (18):

$$P_t = \left[A H_t^{1/\eta} \right] \left(I_t / \bar{I}_t \right)^{1/\chi}, \text{ where } I_t = \dot{H}_t / H_t. \quad (21)$$

(iii) Lenders make zero expected profits such that W_t satisfies equation (20).

(iv) Housing demand (equation (17)) equals new construction plus foreclosures:

$$g_H H_t x_m^\gamma \left[V_t / (P_t + W_t) \right]^\gamma = \dot{H}_t + \iota \int \Phi_R (M/P_{t-}) g(M, t_-) dM, \quad (22)$$

where $\Phi_R(\cdot)$ denotes the cumulative density of a mean-one normal distribution with standard deviation σ_R.

(v) The mortgage density distribution $g(M,t)$ satisfies the Fokker-Planck equation (19).

The equilibrium describes a supply-and-demand framework that determines the equilibrium house price at any instant, as illustrated in Figure 6. The demand curve for housing as a function of price P slopes down with elasticity determined by γ and shifts due to changes in beliefs about future dividends V or mortgage points W, as indicated by the downward-sloping green line. The supply curve slopes up due to construction with elasticity determined by χ, as indicated by the dashed upward-sloping red line, and shifts out due to foreclosures, as indicated by the shift from the dashed to solid red line. Over time the supply curve shifts in as population grows, according to the long-run elasticity η.

28. Formally, a foreclosure at time t enters at time step $t+\Delta$ where in the limit $\Delta \to 0$. This timing assumption eliminates multiple equilibria that can arise if foreclosures and prices are determined jointly. The assumption that all defaulters exit (leave the city or move in with relatives) is made for simplicity; instead assuming a fraction of defaulters move into rental units would not change the qualitative conclusions but would impact the estimated values of parameters that govern the severity of the price–foreclosure spiral.

29. Consistent with this assumption, Gerardi *et al.* (2008) show that lenders during the boom understood the consequences of falling house prices but put little weight on this possibility and Cheng *et al.* (2014) show that mortgage lenders behaved similar to the rest of the population in their own housing choices.

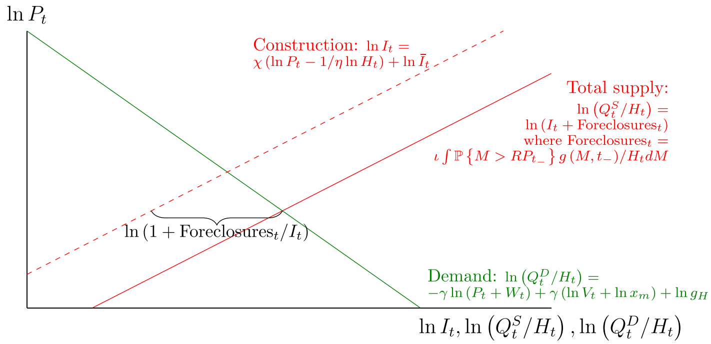

FIGURE 6

Short-run supply-and-demand diagrammatic treatment of equilibrium

We solve the model globally by collocation on a Smolyak grid, simulating the expectation in equation (20) by Monte Carlo. We compute impulse responses to a one-time innovation $dW_{\mu,0}$ that increases the drift rate from $\bar{\mu}$ to μ_0. Supplementary Appendix C.2 derives a novel, closed-form expression for the mean impulse response of beliefs m_t^θ to a one-time increase that we use to compute the path of $P^*(D_t, m_t^\theta)$, which facilitates the efficient calculation of impulse responses for prices and other model outcomes used in our estimation.

5.3. *Calibration*

We choose city-level targets for our calibration. Since we compute impulse responses of variables without the idiosyncratic Wiener shocks, we treat the model paths as representing groups of cities. Accordingly, we compute data moments after grouping the CBSAs in our sample into four (1997-population-weighted) quartiles of 1997–2019 house price growth. Crucially, we target long-run moments and expectations and evaluate how well the model can match untargeted short-term price dynamics.

We calibrate several parameters externally and set the remaining parameters by SMM. Table 2 lists the model parameters, their value for each quartile of CBSAs, and the rationale for each parameter. Table 3 lists the moments (numbered) as well as the non-targeted short-run house price growth in the boom, bust, and rebound (unnumbered).[30]

We begin by describing the externally calibrated parameters relating to beliefs. In a balanced growth path, prices grow at the rate μ (see Supplementary Appendix C.3). Accordingly, we set the long-run mean drift rate $\bar{\mu}$ in each quartile to the annualized average log change in real house prices over the 1977:Q1–96:Q4 period.[31] We set the mean reversion rate ϑ to 0.005 so that the increase in the drift rate at date 0 is highly persistent.[32] We select a diagnostic window, *k*, of 8 to achieve a boom length of eight years.

30. We define the model boom as time zero to the price peak, the bust as the price peak to the price trough and the rebound as the seven years following the price trough given the lack of an end date for the rebound.

31. The Freddie Mac house price index starts in 1975 but repeat sales indices are noisy in the first few years of a data set, so we allow for two years of burn in and start in 1977.

32. Mean reversion in μ must be slow for a shock at the start of the boom to continue to drive house prices during the rebound. A value of 0.005 means that even 25 years after the boom start, μ_t has declined only $1 - e^{-.005\times 25} \approx 12\%$ of the distance from μ_0 to $\bar{\mu}$. Total mean reversion in prices or rents will be larger in any given city, reflecting the role of the idiosyncratic Wiener shocks.

TABLE 2
Model parameterization

Symbol	Description	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Rationale
Beliefs						
$\bar{\mu}$	Pre-boom drift rate	0.41%	0.58%	0.96%	1.51%	1977–96 growth rate
μ_0	New drift rate	0.63%	4.40%	4.90%	5.03%	SMM by quartile
θ	Diagnostic over-shooting	2.75	2.75	2.75	2.75	SMM in Q4
K/σ_D	Normalized Kalman gain	0.13	0.13	0.13	0.13	SMM in Q4
k	Diagnostic window	8.00	8.00	8.00	8.00	Boom length in data
ϑ	Mean reversion in drift	0.005	0.005	0.005	0.005	
Preferences						
ρ	Discount rate	7.75%	7.75%	7.75%	7.75%	SMM in Q4
γ	Demand elasticity	3.00	0.50	0.50	0.50	SMM by quartile
Construction and foreclosures						
η	Long-run supply elasticity	1.89	1.58	1.17	0.87	Empirical regressions
χ	Construction elasticity	4.50	3.51	2.40	1.69	Empirical regressions
g_H	Potential entrants	0.08	0.08	0.08	0.08	Normalization
ι	Liquidity shock	6.70%	4.55%	4.50%	5.30%	SMM by quartile
R	House price shock	*N(1,0.0.13)*	*N(1,0.11)*	*N(1,0.08)*	*N(1,0.09)*	SMM by quartile
ϕ	New origination LTV	*N(0.87,0.09)*	*N(0.87,0.09)*	*N(0.87,0.09)*	*N(0.87,0.09)*	Adelino *et al.* (2018)
ψ	Foreclosure recovery rate	0.645	0.645	0.645	0.645	Guren *et al.* (2021)

TABLE 3
SMM targeted and untargeted moments

		Quartile 1		Quartile 2		Quartile 3		Quartile 4	
Moment	Source	Data	Achieved	Data	Achieved	Data	Achieved	Data	Achieved
Long-run house price growth and expectations (annualized log points)									
1. 1997–2019 HPI	Freddie Mac	0.3	0.3	1.4	1.5	2.3	2.5	3.5	3.4
2. Expectations 2006	Shiller–Thompson							5	4.1
3. Expectations 2019	Shiller–Thompson							3.1	3.4
Phase length (years)									
4. Bust	Freddie Mac	6.00	3.67	5.75	7.29	6.00	6.67	6.00	5.58
Role of foreclosures									
5. Max foreclosure rate	CoreLogic	1.10	1.23	1.49	1.03	1.74	2.05	2.26	2.42
6. % Jan-07 Equity < 20%	Beraja et al.	32.4	47.6	25.6	21.8	17.8	19.8	18.2	19.9
7. % Jan-07 Equity < 10%	Beraja *et al.*	16.8	21.9	12.4	9.3	7.9	9.4	8.8	10.0
8. % Jan-07 Equity < 0%	Beraja *et al.*	4.9	4.4	3.0	2.0	2.1	2.5	3.5	2.9
9. Bust speed (log points)	Freddie Mac	−9.2	−1.2	−9.4	−4.5	−13.1	−12.9	−23.4	−22.6
Standard deviation of house price shocks (log points)									
10. Repeat sales resid SD	DataQuick	9	13	9	11	9	8	9	9
Non-targeted short-run house price growth (unannualized log points)									
Boom	Freddie Mac	20.0	4.2	35.3	43.1	59.4	67.1	84.9	85.6
Bust	Freddie Mac	−29.7	−1.8	−29.7	−21.2	−38.6	−48.1	−53.4	−60.4
Rebound	Freddie Mac	14.8	4.9	21.9	13.0	28.1	36.3	44.4	48.6

We next turn to externally calibrated parameters relating to housing supply, mortgages, and foreclosures. We set the long-run supply elasticity, η, to the inverse of the empirically estimated value from Table 1 obtained by multiplying the column (3) population growth and triple interaction coefficients by the respective endogenous variables and taking quartile averages. We set the short-run construction elasticity, χ, by imposing these long-run elasticities and estimating the analogous specification for short-run construction dynamics, as explained in Supplementary Appendix B.6. We set the distribution of LTVs at mortgage origination, ϕ, to $N(0.87, 0.09)$ based on Adelino *et al.* (2018). We set the foreclosure recovery rate, ψ, to 64.5% as in Guren *et al.* (2021a). We set the growth rate of potential entrants, g_H, to 8.0% annually; this parameter has no impact on the impulse responses.

We set the remaining seven parameters—the drift rate at date 0, μ_0, the diagnostic overshooting parameter, θ, the Kalman gain relative to the dividend noise, K/σ_D, the discount rate, ρ, the demand elasticity, γ, the liquidity shock, ι, and the idiosyncratic house price shock, σ_R^2—to fit quartile-specific moments on long-run house price growth, long-run house price expectations in 2006 and 2019, the bust length, several moments relating to foreclosure dynamics, and idiosyncratic house price volatility. Because expectations data in the boom are only available for cities in the fourth quartile, we treat the learning parameters θ and K/σ_D and the discount rate ρ as deep parameters and fix their values at the levels estimated in the fourth quartile, giving seven parameters to match 10 fourth quartile moments. We then set quartile-specific values of μ_0, ι, and σ_R^2, giving three parameters to fit eight quartile-specific moments in the remaining quartiles.

The first moment measures the growth in house prices over the full 1997–2019 BBR. The next two moments are average expected house price growth over the next 10 years at the peak in 2006 and in 2019 from Shiller and Thompson (2022) adjusted for inflation expectations using the Michigan Survey median. This is the only survey of house price expectations that covers the boom. Three of the four counties surveyed (Middlsex, MA, Alemeda, CA, and Orange, CA) are in quartile four, and we assume the average expectation for these counties is representative of the quartile. Heuristically, the size of the full boom–bust–rebound most directly informs μ_0, ρ, and γ as it reflects the actual path of dividends and their impact on the price. The over-shooting of the boom expectations relative to the long-run informs the learning parameters θ and K/σ_D.

The next moment is the length of the bust. In the model, the bust ends when beliefs begin to stabilize and actual dividends have risen enough to offset the earlier over-optimism. The speed of learning, K/σ_D, and the initial drift μ_0 influence this timing.

The next set of moments characterize the role of foreclosures. The fifth moment is the peak annualized foreclosure rate, which we compute using proprietary data from CoreLogic. The next three moments are the shares of properties with equity <20%, <10%, and <0% (underwater) in January 2007 from the Beraja *et al.* (2019) data set. The equity distribution informs the liquidity shock ι, with the foreclosure moment additionally informing the supply-and-demand curve parameters χ and γ. Finally, we discipline the speed of the price–foreclosure spiral using the maximum four-quarter price decline in the bust.

The final moment closely corresponds to σ_R, the standard deviation of the house price shock. Using 1988–2013 DataQuick deeds data for non-distressed sales of single family homes and condominiums, we run a repeat sales regression of log price on house fixed effects and census tract-by-quarter fixed effects. The residuals of this regression reflect idiosyncratic variation in house prices. To mitigate outliers, the moment is the standard deviation of a normal distribution with the same inter-quartile range as the residuals.

We choose parameters to minimize the weighted sum of squared residuals between the model and the data moments. We calculate the model moments for the impulse response to a one-time increase from $\bar{\mu}$ to μ_0, using the analytic mean path of beliefs and starting from steady state values for all variables except the loan balance distribution, which is calibrated to match the

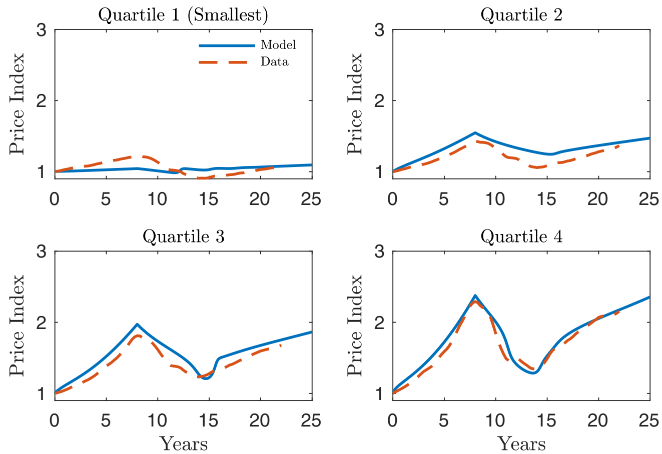

FIGURE 7
Quartile price paths in model and data

Notes: Each panel displays the path of house prices in the model following a change from μ_0 to $\bar{\mu}$ and in the data for a quartile of CBSAs, grouped by their their long-run 1997–2019 price growth.

1995 Survey of Consumer Finances. We weight the three equity distribution moments together as much as each of the other moments. We then increase the weight on the long-run house price growth moment in each quartile to ensure this moment is within 10% of the data. This binds only for the lower two quartiles and enforces the spirit of the exercise of matching the overall BBR price growth.

5.4. *Model fit*

Table 3 and Figure 7 show that the estimated model fits the targeted moments very well in quartile four, for which we estimate all parameters. All moments except the equity distribution and expectation moments are within ten percent of their target values. The equity distribution moments are close in percentage point terms. The model expectations are too low in 2006 and slightly too high in 2019. In fact, Laibson (2012) argues the survey expectations may be erroneously high in the boom because agents misunderstood the survey question in this period before it was rephrased.[33] The miss in 2019 reflects a tension between matching the expectation moment and average 1997–2019 price growth.

As shown at the bottom of Table 3 and in Figure 7, the model closely matches the short-run boom, bust, and rebound sizes in quartile four even though these moments are not targeted. The model also fits the third quartile targeted and untargeted short-run price moments well despite the deep parameters being held fixed in estimation, leading to many fewer degrees of freedom. In the second quartile, the model matches the boom quite well but does not generate enough of a price–foreclosure spiral to match the size of the bust and rebound. In the first quartile, the model generates very little price movement, in large part because this quartile has the most elastic short-run and long-run supply. One partial explanation for the model's failure in these lower quartiles

33. Alternatively, agents may neglect that long-run supply is more elastic than short-run supply. A calibration where agents compute expectations as if on the balanced growth path matches the 2006 expectation better while still matching short-run price dynamics. The main change is a lower diagnosticity.

may be that the price–foreclosure spiral in the real world works in part through a tightening of credit standards by nation-wide lenders, which spread the bust from the third and fourth quartiles to the first and second (Guren and McQuade, 2020). Another possible explanation is cross-quartile learning. In the model, we treat each quartile independently and shut down such linkages.

Several of the estimated parameters that deliver this fit merit comment. The new drift rate μ_0 is increasing across quartiles. The diagnosticity parameter θ of 2.75 is larger than the value of 0.9 in Bordalo *et al.* (2019) or the 0.3– 1.5 range estimated in Bordalo *et al.* (2020b), perhaps reflecting the difference between the households in our setting and the financial analysts or professional forecasters in theirs or the subtleties described above in matching the expectations moments. The liquidity shock ι being in the neighbourhood of 5% accords with mortgage prepayment rates during the boom in Berger *et al.* (2021).

5.5. *Implications for rent growth*

We introduce rents in Supplementary Appendix C.4 via a user-cost indifference relationship.[34] Along the balanced growth path, this relationship takes the form $R_t^{\mathrm{BGP}} = (\rho - \mu)P_t + \zeta D_t$ (see equation (C.15)), where ζ encompasses the maintenance and property tax component of owning and is chosen to match an average price–rent ratio in quartile 4 of 19, which is what Lowenstein and Willen (2022) find for California. We make the following assumptions to calculate the transition path of rents: (1) households re-optimize their rent/own decision with Poisson intensity λ, where we parameterize $\lambda = 1/6$ to match tenure rates, (2) during a rental contract signed at date t, rents grow at a fixed rate m_t^{θ}, the nowcast of the dividend drift rate, (3) households use the path of expectations for prices and dividends at each point in time. These assumptions capture the long-term nature of rent/own decisions, the stickiness of contract rents, and the volatility of expected house price appreciation off the balanced growth path. In Supplementary Appendix C.4, we show that the path of average rent R_t is characterized by a "reset" rent $R_{t|t}$ for contracts signed at date t and laws of motion for R_t and the average within-contract growth rate g_t (see equations (C.12)–(C.14)).

Figure 8 shows rents in the model and data. Three features stand out. First, model rent growth substantially lags dividend growth over the full period, reflecting the decline in the rent–price ratio when expected price growth rises. Second, the model explains rent growth in each quartile over the entire 1997–2019 period reasonably well despite the fact that this moment is untargeted, with model rent growth a little low in quartiles 1 and 2 and high in quartiles 3 and 4. Third, the model features counterfactual rent drops in the bust in quartiles 3 and 4. These declines reflect the over-shooting of prices due to foreclosures, as low prices and high expected price growth both drag down user-cost implied rent. Factors outside of the model such as downward stickiness of rents or a failure of rent–price arbitrage in the crisis could explain why rents in the data do not fall as much. Overall, the model's ability to explain rent growth across quartiles over the full BBR supports a fundamentals-based explanation of the path of prices.

5.6. *Unpacking the mechanism*

We now discuss the model features that generate a boom–bust–rebound. For parsimony, we use the parameters estimated for the fourth quartile. Panels (a)–(c) of Figure 9 show the evolution of prices, foreclosures, and beliefs following a change from $\bar{\mu}$ to μ_0. The solid blue lines show the paths at the estimated parameter values. Each remaining line shows a model permutation

34. In the background are deep-pocketed landlords willing to sell or to rent to households.

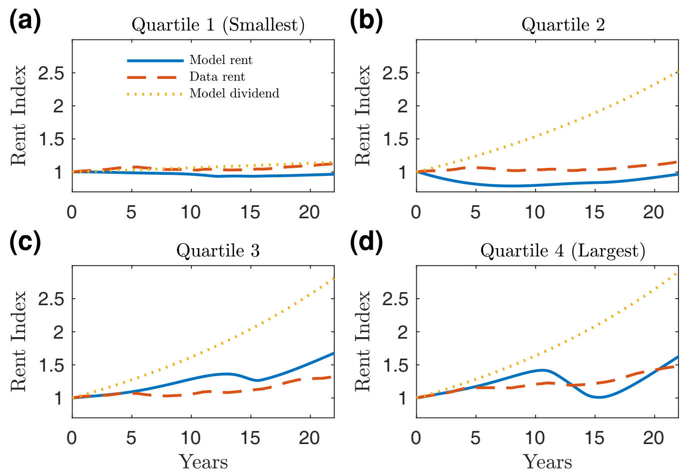

FIGURE 8
Quartile rent paths in model and data

Notes: The solid lines plot model simulated rents for each quartile. The dashed lines plot indexes of annual average rent deflated by the national GDP price index for 22 CBSAs with CPI rent data available from 1988, grouped into the same quartiles. The dotted lines plot dividends.

holding other parameters fixed: the dash-dot gold lines show the paths without diagnostic expectations ($\theta = 0$), the dashed red lines show the paths with no foreclosures ($\iota = 0$), and the thin dashed black line shows the full-information rational expectations (FIRE) model with immediate learning ($\theta = 0$, $K/\sigma_D \to \infty$).

The comparisons across lines in panels (a)–(c) illustrate the importance of both belief over-shooting and foreclosures to generating a realistic boom–bust–rebound. Under FIRE, beliefs equal the true μ, which jumps on impact and gradually mean reverts. Prices jump on impact due to the increase in the capitalization rate $\rho - \mu$ and then converge to the balanced growth path from above. Without diagnosticity but with learning ($\theta = 0$), beliefs monotonically and smoothly increase towards the truth and prices smoothly converge to the balanced growth path. The steady price appreciation reflects the increase in the capitalization rate and the increase over time in the dividend.

Diagnostic learning generates an over-shooting of beliefs about the drift rate μ, as shown in panel (c). These beliefs rise from their initial level of 1.5% up to above 9% before nearly converging to the true value of around 5% (shown by the FIRE thin dashed line) by the end of the sample window. The turning point coincides with the peak of the boom. Unlike in models of price extrapolation that generate over-shooting of expectations on the downside, with diagnostic expectations the convergence is gradual and monotonic. The path of beliefs in the bust matches the time series of beliefs in the Shiller and Thompson (2022) survey, in which long-run expectations fall gradually from their boom peak.

Without foreclosures, however, the over-shooting of prices from diagnostic learning alone generates a much smaller boom and bust than in the data. The attenuation of the boom occurs for two reasons: credit expands in the baseline case as lenders perceive a decline in default risk and the increase in prices causes foreclosures to decline relative to the pre-boom period, contracting supply and further pushing up prices. The correction in beliefs on its own generates a counterfactually small price dip in the bust, as prices converge smoothly toward their long-run path.

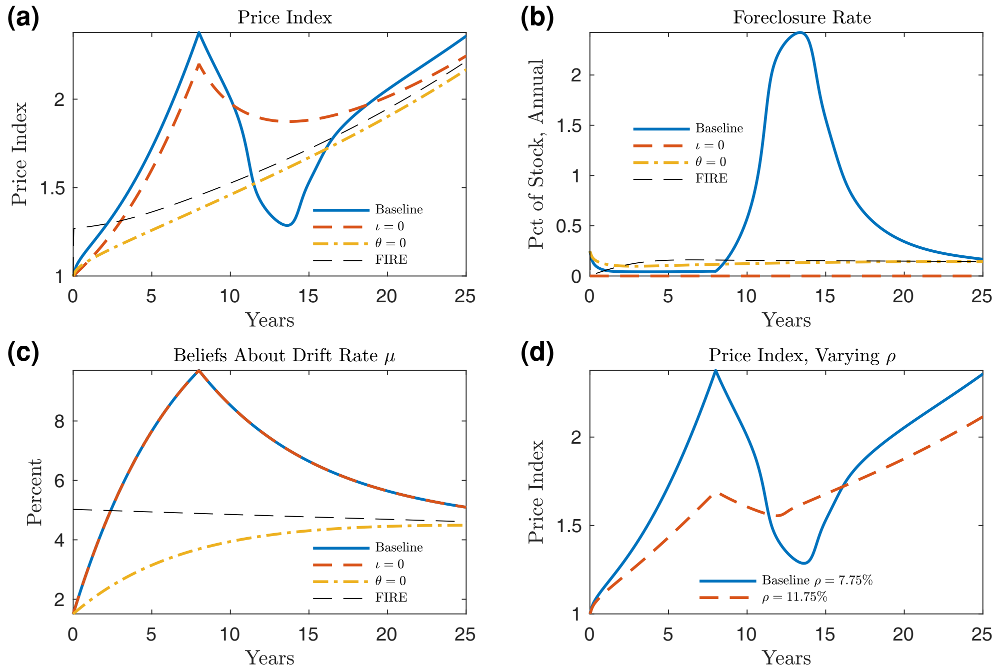

FIGURE 9

Role of structural elements

Notes: This figure shows the simulated boom–bust–rebound in the model resulting from a single change from $\bar{\mu}$ to μ_0 at time $t = 0$. The solid blue line shows the baseline model with parameters estimated for the fourth quartile of CBSAs. In panels (a)–(c), the bold dashed line shows the model without foreclosures, the dash-dot line shows a parameterization with foreclosures but no diagnostic expectations, and the thin dashed line shows full-information rational expectations. Panel (d) shows the effect of varying the discount rate ρ (held constant over the simulation) holding all other parameters unchanged. Panels (a) and (d) show the price index, panel (b) shows the foreclosure rate in annualized percent of the housing stock, and panel (c) shows beliefs about the drift μ in annualized percentage points.

Foreclosures generate a much larger bust in prices, to below the level that would prevail with rational learning or FIRE.[35] The over-shooting occurs because of a price–foreclosure spiral (Guren and McQuade, 2020): foreclosures add to housing supply, which further depresses prices, putting more owners under-water, leading to more foreclosures. Reflecting this dynamic, the increase in foreclosures in panel (b) reaches a local extrema near the trough of the bust in prices. In sum, both elements—belief over-optimism and foreclosures—are required to generate the boom–bust–rebound.

An important implication of our analysis is that asset price cycles like the 2000s housing cycle are more likely when discount rates are low (or initial dividend growth is high). Under these conditions, the present value of dividends is dominated by terms further out in the future, so a shock to the expected dividend growth rate has a larger effect on $V_{i,t}$. This makes diagnostic cycles stronger. To illustrate, panel (d) of Figure 9 shows the baseline price path and an

35. The price–foreclosure spiral in our model is quantitatively large: the quartile four bust size without foreclosures is 15.2 log points relative to 60.4 in the baseline model. The speed and magnitude of the bust and rebound explain why our exercise requires a substantial impact of foreclosures. For comparison, Guren and McQuade (2020) find a similarly large role for foreclosures, albeit split between supply-and-demand and bank balance sheet effects. Mian *et al.* (2015) conduct an empirical analysis with foreclosures instrumented by judicial requirements; extrapolating their local treatment effect elasticity to total foreclosures from 2007 to 2013 implies a 16 to 32 percentage point decline in national house prices due to foreclosures.

alternative where we feed in the same shock to μ but with the discount rate 4.0% points higher, approximately the difference between the real interest rate during 1997–2019 and the average rate in the 1980s. A higher ρ substantially dampens the cycle, indicating the importance of the low *level* of discount rates throughout the 2000s.

This begs the question of the role of *time-varying* mortgage rates or credit conditions, which our analysis has so far omitted. In brief, while the decline in interest rates during the BBR constitutes another fundamental force affecting house prices, neither the timing of rate changes nor their magnitude suggest a pre-eminent role.[36] Changes in under-writing costs, including credit spreads or screening costs, have relatively small effects on prices in our model simply because W_t is small relative to P_t.[37] Changes in credit that affect approval rates on the extensive margin offer greater potential for credit to impact prices, as they shift the number of entrants g_h and thus the demand curve directly. Such extensive margin shifts complement our focus on fundamentals and could operate independently or interact with changing fundamentals to the extent they reflect lender optimism or relax otherwise tightening payment-to-income constraints as prices rise.

6. CONCLUSION

We revisit the 2000s housing cycle with "2020 hindsight". At the city level, the areas with the largest price increases during the 1997–2006 boom had the largest busts but also the fastest growth after the 2012 trough, and as a result had the largest price appreciation over the full cycle. A long-run spatial equilibrium framework of house price growth determined by local income, amenities, and supply determinants fits the cross-section of city house price growth between 1997 and 2019. The implied long-run fundamental is correlated not only with long-run price growth but also with a strong boom–bust–rebound pattern.

Our neo-Kindlebergerian interpretation emphasizes the role of economic fundamentals in setting off asset price cycles. In our model, the boom results from over-optimism about an increase in the "dividend" growth rate, the bust ensues when beliefs correct, exacerbated by a price–foreclosure spiral that pushes prices below their full-information level, and eventually a rebound emerges as foreclosures recede and the economy converges to a price path commensurate with fundamental growth. We emphasize the low interest rate environment as a crucial catalyst of this cycle. We view our approach as complementary to work on the role of changes in credit availability and speculation, which we see as additional forces that may work in concert with over-reaction to fundamentals.

Our conclusion about the fundamentally driven roots of the 2000s housing cycle is important not only for understanding the cause of the cycle and asset bubbles more generally but also for macroprudential policy. If a boom–bust cycle were only due to exogenously changing expectations or credit supply, a macroprudential policy maker might want to aggressively stamp out the boom phase. Our findings suggest a more delicate balance; while policy may want to

36. Figure C.3 shows that mortgage rates fell <1 p.p. during the boom, fell in the bust, and rose slightly during the rebound, a pattern inconsistent with declining mortgage costs explaining the periods of rising prices or rising mortgage costs explaining the bust. Using a richer mortgage structure than in our model, we calculate in Supplementary Appendix C.6 that the 2.7 p.p. mortgage rate decline over the full BBR could on its own explain roughly 20 p.p. of house price growth, relative to the more than doubling in the top quartile.

37. Figure C.1 confirms this intuition in a quantitative exercise where we replace lenders' diagnostic beliefs with perfect foresight, so that they perfectly anticipate the peak in buyers' beliefs and hence in prices. In this extreme case, W_t/P_t rises by 9.6 p.p., but the price path changes little. The reason W_t/P_t does not rise more is that lenders receive substantial cash flows even on mortgages made just prior to the price peak.

temper over-optimism and aggressively mitigate fire sales, it is also important not to suffocate fundamentally driven growth. Conversely, the consequences of over-optimism appear most dire when initial price growth is high and interest rates are low. Of course hindsight is 20–20; distinguishing fundamental growth from over-optimism in real time rather than after observing a full boom–bust–rebound poses a formidable task. Nonetheless, our findings imply that policy makers should heed Kindleberger's dictum that essentially all manias are to some degree grounded in fundamentals.

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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

Data Availability Statement

This section summarizes all of the data we use in the paper and its availability. Details on our code and computational requirements can be found in the Replication Package ReadMe file. The programs and much of the data underlying this article are available at Zenodo.org at https://doi.org/10.5281/zenodo.7764704.

- From Fred (Federal Reserve Bank of St. Louis, 2022), we obtain four series using Stata's "import fred" command:
  - Case-Shiller National House Price Index: Series CSUSHPINSA (accessed August 2021)
  - GDP Price Index: Series GDPCTPI (accessed August 2021)
  - GDPI Price Index: Series A191RG3A086NBEA (accessed November 2020)
  - Nominal Mortgage Rate: Series MORTGAGE30US (accessed September 2022)
- We obtain the Freddie Mac House Price Indices (Freddie Mac, 2021) for our main analysis at the CBSA level. These data can be directly downloaded from https://www.freddiemac.com/research/indices/house-price-index.
- We obtain the FHFA 5-Digit ZIP Code House Price Indices (Federal Housing Finance Agency, 2020) four our ZIP-Code level analysis. We use the annual, not seasonally adjusted "developmental" index, which can be downloaded at https://www.fhfa.gov/DataTools/Downloads/Documents/HPI/HPI˙AT˙BDL˙ZIP5.xlsx.
- We obtain the CoreLogic House Price Indices (CoreLogic, 2018) for robustness at the CBSA level. These data are available for purchase from CoreLogic. Researchers interested in obtaining these data should contact the academic sales team; in 2021 we contacted Alec Henderson at alechenderson@corelogic.com. It can take several months to negotiate data use agreements and gain access to the data. The specific data series we use is the Tier 11 Single Family Combined CBSA house price index as of September 2018.
- We obtain the ZIP-Code level Zillow Home Value Index (Zillow, 2022). The data may be downloaded at https://www.zillow.com/research/data/. We use the all homes, seasonally adjusted series for our calculation of the downtown premium. We also obtain the CBSA-level Zillow Home Value Index for some robustness, which can be downloaded from the same source.
- We obtain survey measures of median inflation expectations form the Michigan Survey (University of Michigan Surveys of Consumers, 2022). We use Table 33, which can be downloaded from https://data.sca.isr.umich.edu/data-archive/mine.php.
- We use the 1995 Survey of Consumer Finances from 1995 (Federal Reserve Board of Governors, 1995) for the 1995 loan balance distribution. The data can be downloaded from the Federal Reserve at https://www.federalreserve.gov/econres/files/scfp1995s.zip.
- We obtain the Land Share from Larson *et al.* (2021). The data are available for download from the Federal Housing Finance Agency at https://www.fhfa.gov/PolicyProgramsResearch/Research/Pages/wp1901.aspx. We use the data as updated in November, 2020.
- We obtain measures of the number of housing units form the Census' annual estimates of housing units for counties in the United States (United States Census Bureau, 2022a). The 2010–2019 data we use can be found at https://www2.census.gov/programs-surveys/popest/tables/2010-2019/housing/totals/CO-EST2019-ANNHU.xlsx. The 2000–2010 data can be found at https://www2.census.gov/programs-surveys/popest/tables/2000-2010/intercensal/housing.

- We obtain the Wharton Residential Land Use Regulatory Index (Gyourko *et al.*, 2008) from Wharton at http://real-faculty.wharton.upenn.edu/wp-content/uploads/~gyourko/WRLURI/WHARTON%20LAND%20REGULATION%20DATA_1_24_2008.zip.
- We compute population density from the United States Census by dividing county-level population estimates (United State Census Bureau, 2022b) by land area (United States Census Bureau, 2011). The population counts can be downloaded from https://www.census.gov/programs-surveys/popest.html. The land mass is variable LND110200D and can be downloaded from https://www.census.gov/library/publications/2011/compendia/usa-counties-2011.html#LND.
- We use the County Business Patterns (United States Census Bureau, 2020) data to calculate our Bartik shocks for employment and wages. The CBP data can be downloaded at https://www.census.gov/programs-surveys/cbp/data.html. We also calculate restaurant density using the CBP data.
- We use weather data on January Temperature, January Sunlight, and July Humidity from the U.S. Department of Agriculture's Natural Amenities Scale (United States Department of Agriculture, 2022). The data can be downloaded from https://www.ers.usda.gov/data-products/natural-amenities-scale/.
- We use land unavailability from Lutz and Sand (2019). These data can be downloaded from https://github.com/ChandlerLutz/LandUnavailabilityData.
- We use a secondary land unavailability measure from Saiz (2010). This can be obtained from the author.
- We apportion 1990 Census population counts to 2010 tract definitions using the Longitudinal Tract Database (Logan *et al.*, 2022). These data can be downloaded from https://s4.ad.brown.edu/Projects/Diversity/Researcher/Bridging.htm.
- We obtain several variables from IPUMS USA (Ruggles *et al.*, 2022), available at https://usa.ipums.org. These include:
  - Mean rent by CBSA, where Census rent is the variable rentgrs and the mean is a weighted average by the variable hhwt.
  - The 1990 national college share by industry.
  - Actual employment growth by industry between the 1990 Census and 2019 ACS.
- We calculate the non-traditional Christian share in 1990 from data on church membership from the Association of Statisticians of American Religious Bodies (Statisticians of American Religious Bodies, Association of, 1992). The data can be downloaded at https://www.thearda.com/data-archive?fid=CMS90CNT.
- We use data on local government expenditures from the Census (United State Census Bureau, 1993) to create a ratio of inspection expenditures to tax revenue. The data are available for download at https://www.census.gov/data/datasets/1993/econ/local/public-use-datasets.html. We use codes E66, F66, G66, K66, L66, M66, N66, and R66 as inspection categories.
- We use data on the 1990 College share from the Longitudinal Tract Database (Logan *et al.*, 2022). These data can be downloaded from https://s4.ad.brown.edu/Projects/Diversity/Researcher/Bridging.htm.
- 1990 national collage share by industry from IPUMS USA, predicted employment growth by industry from IPUMS.
- We use Home Mortgage Disclosure Act (HMDA) data (Consumer Financial Protection Bureau, 2022) to calculate the mean non-owner occupier share of purchase mortgages as in Gao *et al.* (2020). The HMDA data can be downloaded from the Consumer Financial Protection Bureau.
- We use proprietary deeds and assessor records from DataQuick to calculate the repeat sales standard deviation moment for our calibration. DataQuick no longer exists as a company, but the archive of the DataQuick data we use in our analysis is maintained by the Harvard Kenned School's Taubman Center for State and Local government and detailed in Online Appendix B of Guren (2018).
- We use data on expectations from Shiller and Thompson (2022), Table 3. We hand code the averages from their paper into our Matlab files.

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