The 2000s Housing Cycle with 2020 Hindsight

Online Appendix

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In Section A, we microfound the construction and land costs in the empirical framework in Section 3. In Section B, we present additional empirical results on the role of investors and speculators, on the Bartik and urbanization instruments, on the robustness of our IV results, and a number of additional empirical results. In Section C, we present a number of model derivations and proofs. In Section D, we discuss the literature in greater detail.

A Microfounding Construction and Land Costs

A.1 Construction

Assume a construction function for producing houses out of materials $M_{i,t}$ and labor $N_{i,t}$:

$$\dot{H}_{i,t} = \tilde{A}_{i,t}\left(M_{i,t}^{\kappa}N_{i,t}^{1-\kappa}\right)H_{i,t}^{-\alpha_i}. \tag{A.1}$$

The term $H_{i,t}^{-\alpha_i}$ captures the possibility that construction becomes more difficult as easier-to-develop plots get built first. Competitive construction firms obtain materials at a price P_t^M on the national market and hire labor at local wage $W_{i,t}$. The FOC for cost minimization yields a cost-per-new-home $C_{i,t}$ of:

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

$$\text{where:} \quad A_{i,t} = (P_t^M)^{\kappa}(W_{i,t})^{1-\kappa}/\tilde{A}_{i,t}. \tag{A.3}$$

The same result would arise if the local construction wage $W_{i,t}$ depended on population, with a re-definition of the exponent α_i.

A.2 Land

We extend Alonso (1964), Muth (1969), and Mills (1967) and Saiz (2010) to incorporate population growth, permitting restrictions, and an additional downtown premium.

We consider a city with population $H_{i,t}$ laid out on a disk with radius $\Phi_{i,t}$, of which a fraction $\Lambda_{i,t}$ is buildable land. A share $1-\varsigma_i$ of the population are spaced uniformly on the buildable part of the disk and the remaining share ς live in an "urban core" at the center of the disk, giving:

$$\Phi_{i,t} = \sqrt{\frac{(1-\varsigma)\, H_{i,t}}{\Lambda_{i,t}\pi}}, \tag{A.4}$$

where we have normalized lot size to 1. We allow the buildable share to increase with population with a semi-elasticity that depends on permitting restrictions:

$$\Lambda_{i,t} = \Lambda_{i,0} H_{i,t}^{g(m_i)}, \tag{A.5}$$

where m_i measures regulatory and permitting hurdles and $g'(m_i) < 0$.[1]

Outside of the urban core mass point, the rental cost of a plot of land $\nu_{i,t}(\tau)$ depends on its distance τ from the city center:

$$\nu_{i,t}(\tau) = \kappa_{i,t}\left(\Phi_{i,t}^{\chi} - \tau^{\chi}\right). \tag{A.6}$$

At the city's edge ($\tau = \Phi$), the rental value of land equals 0, a normalization that reflects a residual supply of unused land. The city-specific parameter $\kappa_{i,t} > 0$ shifts the value of all plots of land in a city proportionally. The parameter $\chi > 0$ is the elasticity of the premium to living one step outside the urban core, $\nu_{i,t}(0)$, relative to living 1% of the city radius outside of the center; denoting $\hat{\nu}_{i,t}(\tau) \equiv \frac{\nu_{i,t}(0)-\nu_{i,t}(\tau)}{\nu_{i,t}(0)} = \left(\frac{\tau}{\Phi_{i,t}}\right)^{\chi}$, $\chi = \frac{\partial \ln \hat{\nu}_{i,t}(\tau)}{\partial(\tau/\Phi_{i,t})}$. The term $\left(\Phi_{i,t}^{\chi} - \tau^{\chi}\right)$ has the literal interpretation of offsetting commuting costs to the city center;

[1] This functional form allows Λ to rise above 1, with the interpretation of allowing high-rises.

more generally it reflects the desirability of different neighborhoods. As a city grows, the premium to living closer to the city-center rises to preserve intra-city spatial equilibrium.

The urban core provides special amenities that create an additional premium (willingness-to-pay) above the value one step outside the core. This valuation is individual-specific and given by $U_{j,t}\nu_{i,t}(0)$, where $P(U > x) = 1 - F(U)$ for a CDF $F(.)$. Market clearing for living in the downtown core defines a cutoff $U^*_{i,t}$ such that $\varsigma_i = P(U > U^*_{i,t})$. Below we parameterize the CDF and characterize the cutoff $U^*_{i,t}$ as a function of resident types and preferences; for now we treat it as exogenous. Denoting the rental value in the urban core as $\nu^U_{i,t}(0)$ (superscript U for "urban"), we have:

$$\nu^U_{i,t}(0) = U^*_{i,t}\nu_{i,t}(0) = U^*_{i,t}\kappa_{i,t}\Phi^{\chi_i}_{i,t}. \tag{A.7}$$

Thus $U^*_{i,t}$ is the urban premium.

The price of a plot of land is the discounted future rents:

$$\text{Not in core:} \qquad L_{i,t}(\tau) = \int_t^\infty e^{-\rho(s-t)}\kappa_{i,s}\left(\Phi^{\chi_i}_{i,s} - \tau^{\chi_i}\right)ds, \tag{A.8}$$

$$\text{Urban core:} \qquad L^U_{i,t}(0) = \int_t^\infty e^{-r(s-t)}U^*_{i,s}\kappa_{i,s}\Phi^{\chi_i}_{i,s}ds. \tag{A.9}$$

We consider a balanced growth path with $\kappa_{i,s} = \kappa_i$, $U_{i,s} = U_i$, and population growth of I_i, giving $\Phi_{i,s} = \sqrt{\frac{(1-\varsigma_i)H_{i,s}}{\Lambda_i\pi}} = \sqrt{\frac{e^{I_i(s-t)}(1-\varsigma_i)H_{i,t}}{\Lambda_i\pi}} = e^{\frac{I_i}{2}(s-t)}\Phi_{i,t}$. Along this path:

$$\begin{aligned} L_{i,t}(0) &= \int_t^\infty e^{-\rho(s-t)}\kappa_i e^{\frac{\chi_i I_i(1-g(m_i))}{2}(s-t)}\Phi^{\chi_i}_{i,t}ds = \frac{\kappa_i\Phi^{\chi_i}_{i,t}}{\rho - \chi_i I_i(1-g(m_i))/2}, \\ L_{i,t}(\tau) &= L_{i,t}(0) - \frac{\kappa_i\tau^{\chi_i}}{\rho}, \text{ and } L^U_{i,t}(0) = U^*_i L_{i,t}(0). \end{aligned}$$

With positive population growth, the price $L_{i,t}(\Phi_{i,t})$ of land at the city boundary is strictly positive, reflecting the capitalization of future non-zero rents.

We obtain the analog of equation (3) in the main text by integrating over the available land at each distance τ to arrive at the average price of a plot of land in the city:

$$L_{i,t} = \frac{1}{H_{i,t}} \int_0^{\Phi_{i,t}} L_{i,t}(\tau) \Lambda_{i,t} 2\pi\tau d\tau + \varsigma_i L^U_{i,t}(0)$$
$$= B_{i,t} H^{\beta_i}_{i,t}, \tag{A.10}$$

$$\text{where:} \quad B_{i,t} = \kappa_i \left(\frac{1 + \varsigma_i (U^*_i - 1)}{\rho - \chi_i I_i (1 - g(m_i))/2} - \frac{(1 - \varsigma_i)}{\rho(\chi_i/2 + 1)} \right) \left(\frac{(1 - \varsigma_i)}{\Lambda_{i,0}\pi} \right)^{\frac{\chi_i}{2}}, \tag{A.11}$$

$$\beta_i = (1 - g(m_i)) \chi/2. \tag{A.12}$$

Setting $g(m_i) = \zeta_0 - \zeta_1 m_i$, we have $\beta_i = \beta_0 + \beta_1 m_i$, where $\beta_0 = (1 - \zeta_0)\chi_i/2$ and $\beta_1 = \zeta_1 \chi_i/2$, as in the main text. Furthermore, as in Saiz (2010) the average price of land is higher in places with a smaller share $\Lambda_{i,0}$ of land available for development. In addition, equation (A.11) illustrates how a reduction in the discount rate ρ or increase in the city center premium $U^*_{i,t}$ both raise average land prices in a city.

We next use this framework to motivate instruments for a changing city center premium, $u^*_{i,t} = d\ln U^*_{i,t}$. We partition the city's residents into two types, college graduate (E) and non-college graduate ($\not{E}$), with a population share $\omega_{i,t}$ of college graduates. An individual's willingness-to-pay to live in the urban core, $U_{j,t}\nu_{i,t}(0)$, is $U_{j,t} = U^E_{i,t} \exp(\epsilon_j)$ if a college graduate and $U_{j,t} = U^{\not{E}}_{i,t} \exp(\epsilon_j)$ if not, where ϵ_j is a random variable drawn from a uniform distribution with support $[0, \bar{\epsilon}]$. Let $\varsigma^E_{i,t} = P\left(U > U^*_{i,t} | E\right)$ and $\varsigma^{\not{E}}_{i,t} = P\left(U > U^*_{i,t} | \not{E}\right)$ denote the share of college graduates and of non-college graduates who live in the downtown core, respectively. For $k \in \{E, \not{E}\}$, we have:

$$\varsigma^k_{i,t} = P\left(U > U^*_{i,t} | k\right) = 1 - (1/\bar{\epsilon}) \left(\ln U^*_{i,t} - \ln U^k_{i,t}\right). \tag{A.13}$$

Substituting equation (A.13) into the market clearing condition $\varsigma_i = \omega_{i,t}\varsigma^E_{i,t} + (1 - \omega_{i,t}) \varsigma^{\not{E}}_{i,t}$

and rearranging gives:

$$\ln U_{i,t}^{*} = \omega_{i,t}\left(\ln U_{i,t}^{E} - \ln U_{i,t}^{\not{E}}\right) + (1-\varsigma_{i,t})\,\bar{\epsilon} + \ln U_{i,t}^{\not{E}}, \tag{A.14}$$

$$u_{i,t}^{*} = \omega_{i,t}\left(d\ln U_{i,t}^{E} - d\ln U_{i,t}^{\not{E}}\right) + d\omega_{i,t}\left(\ln U_{i,t}^{E} - \ln U_{i,t}^{\not{E}}\right) + \text{other}. \tag{A.15}$$

Equation (A.15) motivates two instruments for the change in the downtown premium: (i) from the first term, the initial share of the CBSA that are college graduates interacted with the relative change in valuation of downtown amenities by college graduates, which we measure using the initial relative restaurant density downtown; and (ii) from the second term and using $\ln U_{i,t}^{E} - \ln U_{i,t}^{\not{E}} = \bar{\epsilon}\left(\varsigma_{i,t}^{E} - \varsigma_{i,t}^{\not{E}}\right)$, the predicted change in the CBSA college share interacted with the initial difference in the share of each type who live downtown.[2]

B Empirical Appendix

Appendix B.1 characterizes the relationship between our fundamental and investors/speculators. Appendix B.2 reports time series break tests for rent growth. Appendix B.3 provides details on the Bartik instruments. Appendix B.4 describes the data and measurement underlying the downtown housing premium and associated excluded instruments. Appendix B.5 demonstrates robustness of our main IV results. Appendix B.6 explains how we estimate the short-run elasticity χ. Appendix B.7 contains additional empirical results.

B.1 Investors/Speculators

In this appendix we explain how our long-run fundamental determinant of house prices relates to work emphasizing the role of speculation in the boom. We make five observa-

[2]This framework also accommodates forces discussed in the urbanization literature that do not suggest obvious city-specific instruments, including: (i) a rising skill-premium and convexity in the wage-hours worked profile, which increased the value of time for high-skill workers and hence their demand for short commutes to the city business center (Edlund et al., 2015; Su, 2022); (ii) exogenous improvement in downtown amenities, such as the decline in crime (Pope and Pope, 2012; Ellen et al., 2019); and (iii) endogenous improvement in downtown amenities in response to rising average incomes (Diamond, 2016; Su, 2022).

tions: (i) speculative activity appears potentially important to house price growth late in the boom in some places such as Las Vegas; (ii) long-run fundamentals also explain price growth late in the boom; (iii) speculative activity has much less explanatory power for price growth in the boom up to 2004 or for the full 1997-2019 period, especially compared with the explanatory power of long-run fundamentals; (iv) the degree of speculative activity in the late boom is uncorrelated with the long-run fundamental in an area; and (v) speculators did not contribute disproportionately to selling pressure during the bust. These observations suggest forces orthogonal to fundamentals that made some areas prone to speculation late in the boom, rather than systematic price return chasers who reversed course and added to selling pressure during the bust.

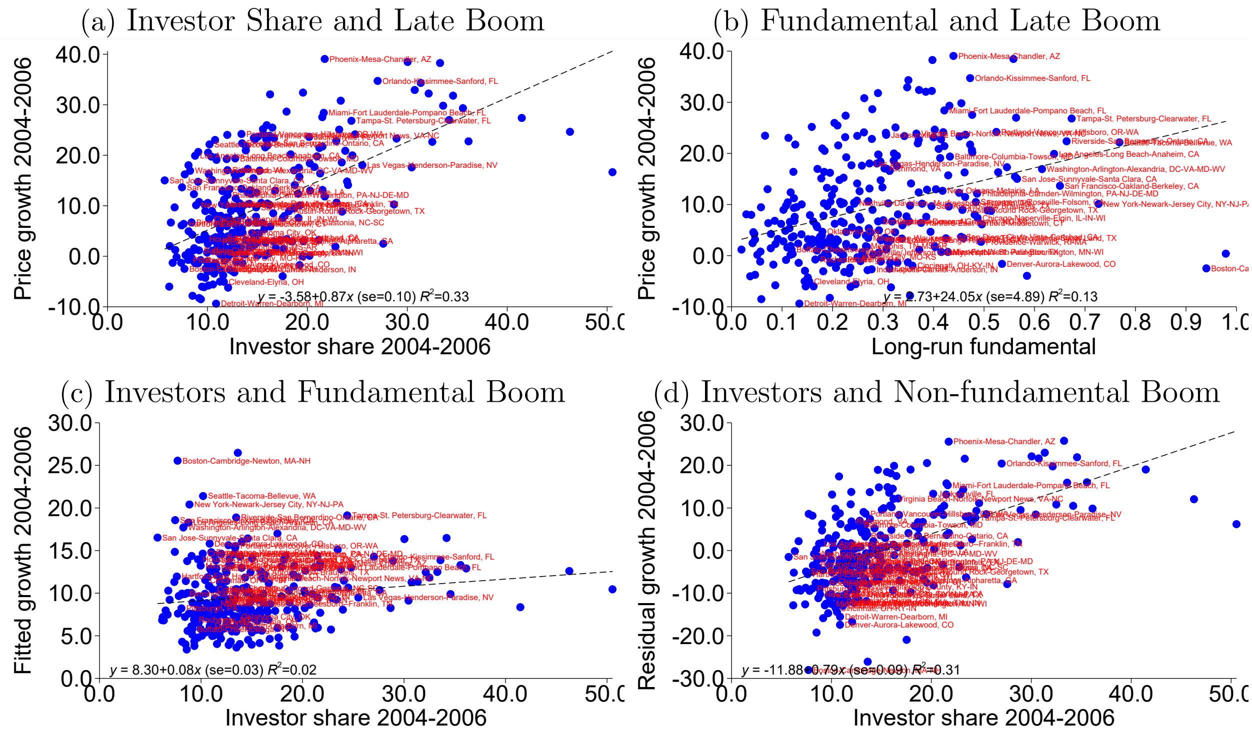
We follow Gao et al. (2020) and associate speculative activity by investors with the non-owner occupier share of purchase mortgages, measured using Home Mortgage Disclosure Act (HMDA) data.[3] Gao et al. (2020) show that the investor share in 2004-06 predicts house price growth in the same period, including when instrumented with state tax treatment of capital gains. Panel (a) of Figure B.1 replicates in our sample of CBSAs the OLS result found in Gao et al. (2020) and shows a strong positive relationship.[4]

Panel (b) shows that house price growth during 2004-2006 also correlates strongly with

[3]DeFusco et al. (2017) show that non-occupant buyers are somewhat more likely to pay in cash, suggesting the HMDA-based measure may understate the investor share. On the other hand, some non-occupant buyers likely purchase for reasons other than speculation, such as for the utility of a vacation home. Any such differences should have minimal impact on the conclusions that follow, because uniform level differences between the HMDA-based measure and the actual share of speculators rescale the investor measure and the comparisons across periods in Table B.1 hold fixed the investor share.

[4]For readability, the figure omits the seven CBSAs with pre-boom, 1994-1996 average share above 20%: Barnstable Town, MA (Cape Cod, 28.3%); Cape Coral-Fort Myers, FL (26.6%); Daphne-Fairhope-Foley, AL (25.6%); Hilton Head Island-Bluffton, SC (27.8%); Myrtle Beach-Conway-North Myrtle Beach, SC-NC (37.6%); Napes-Marco Island, FL (34.4%); and Ocean City, NJ (45.1%). The investor share in 1994-1996 correlates strongly with the share in 2004-2006 (correlation coefficient of 0.81), reflecting persistence in tax treatment of capital gains and that some areas have high non-owner occupier shares because they are common vacation destinations, as suggested by the list of areas with the highest shares in 1994-1996. The patterns shown in Figure B.1 and Table B.1 continue to hold if we replace the 2004-2006 level of the investor share with the change in the share from 1994-1996.

Figure B.1: Investors' Role in the Late Boom and Relation to Fundamentals



Notes: Panel (a) plots the HMDA investor share of purchases averaged over 2004-2006 against house price growth in 2004-2006. Panel (b) plots the long-run fundamental against house price growth in 2004-2006. Panel (c) plots the investor share against the fitted value from a regression of 2004-2006 house price growth on the long-run fundamental. Panel (d) plots the investor share against the residual from this regression. All panels exclude seven CBSAs with a 1994-96 share above 20%: Barnstable, Town, MA (Cape Cod, 28.3%); Cape Coral-Fort Myers, FL (26.6%); Daphne-Fairhope-Foley, AL (25.6%); Hilton Head Island-Bluffton, SC (27.8%); Myrtle Beach-Conway-North Myrtle Beach, SC-NC (37.6%); Napes-Marco Island, FL (34.4%); and Ocean City, NJ (45.1%). CBSAs with more than 1 million persons in 1997 are labeled in red.

the long-run fundamental, measured as usual as the fitted value from column (3) of Table 1. Thus, even at the end of the boom when speculative activity was plausibly most rampant, long-run fundamentals continue to explain house price growth.

Table B.1 summarizes the relationship among investors, fundamentals, and house price growth for several periods. Columns (1)-(2) reproduce the positive correlations shown in panels (a) and (b) of Figure B.1 of investor share and fundamentals with 2004-2006 house price growth. Column (3) shows that both variables contain predictive power when entered into a joint regression. Consistent with speculative activity peaking in the late boom,

Table B.1: House Price Growth, Investors, and Fundamentals

House price growth:	2004-2006			1997-2004			1997-2019		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Investor share	0.87^{**}		0.81^{**}	0.57^{**}		0.32^{*}	0.92^{**}		0.58^{**}
	(0.10)		(0.09)	(0.16)		(0.15)	(0.16)		(0.14)
Long-run fundamental		0.24^{**}	0.19^{**}		0.73^{**}	0.71^{**}		1.01^{**}	0.97^{**}
		(0.05)	(0.04)		(0.08)	(0.08)		(0.07)	(0.08)
Standard deviation of explanatory variables:									
Investor share	6.6	6.6	6.6	6.6	6.6	6.6	6.6	6.6	6.6
Fundamental ($\times$100)	15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6
R^2	0.330	0.131	0.407	0.034	0.290	0.300	0.068	0.429	0.455
Observations	301	301	301	301	301	301	301	301	301

Notes: The table reports the coefficients from regressions of real house price growth by CBSA on the investor share, measured as the 2004-2006 average share of purchase mortgages to non-owner occupiers in HMDA, and the long-run fundamental, measured as the fitted value of column (3) of Table 1. Robust standard errors in parentheses. **,$^{+}$ denote significance at the 1, and 10 percent levels, respectively.

the investor share has much less explanatory power for 1997-2004 house price growth ($R^2 = 0.03$, column (4)), especially compared to the explanatory power of the long-run fundamental for the early boom ($R^2 = 0.29$, column (5)). The R^2 of the long-run fundamental for house price growth over the full 1997-2019 period of 0.43 (column (8)) substantially exceeds the R^2 of 0.07 for the investor share (column (7)).

Panels (c) and (d) of Figure B.1 decompose the correlation from Panel (a) into the correlation of investor share with the part of house price growth explained by long-run fundamentals and a residual, respectively. We measure the part explained by fundamentals as the fitted value from the relationship plotted in Panel (b) and the non-fundamental part as the residual from this regression. Panel (c) displays a small positive correlation between the investor share and the part of 2004-2006 price growth correlated with fundamentals, but the explanatory power is weak ($R^2 = 0.02$) and the positive sign does not survive weighting by population. In other words, the 2004-2006 investor share is essentially uncorrelated with the long-run fundamental that is the focus of our paper. Las Vegas provides an example of a CBSA with a high investor share but a relatively low long-run fundamental and hence a small predicted value for 2004-2006 house price growth.

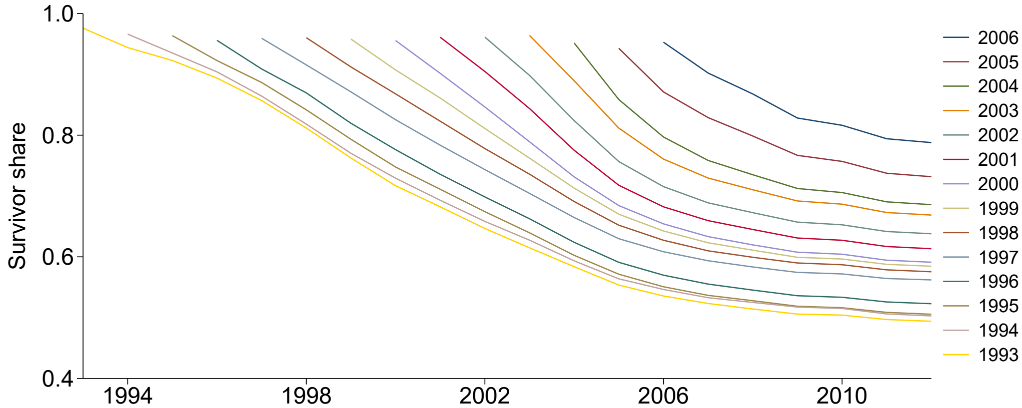
Panel (d) plots the investor share against the non-fundamental component of house price growth in 2004-2006. Areas with late price booms not explained by their long-run fundamental had higher investor shares of purchases, explaining essentially all of the overall correlation shown in Panel (a). Las Vegas again provides a leading example, with faster house price growth than its fundamental would predict and a high investor share.

Finally, we show empirically that investors do not contribute to significant selling pressure in the bust. Using a merge of HMDA and the DataQuick deeds data from Diamond et al. (2019) and the HMDA-based investor measure, we identify the next arms-length transaction on a property previously purchased by an investor. Figure B.2 shows that the survival functions for continuing to own the property flatten around 2006 for all investor cohorts; rather than dump their properties *en masse* in the bust, investors became *less* likely to sell. Consequently, while the emergence and receding of investor demand can potentially also explain a rise and fall in prices, it cannot substitute for the role of foreclosures in explaining why prices fell far below their long-run level in the bust.[5]

Overall, these results are consistent with speculation playing a role late in the house price boom in areas such as Las Vegas. However, they also suggest that the role of investors was mostly or wholly orthogonal to the role of fundamentals, less important than fundamentals to explaining the entirety of the boom or the full 1997-2019 period, and mostly unrelated to the over-shooting of prices in the bust.

[5] Las Vegas again illustrates the exception that proves the rule: It had a larger-than-predicted bust given the size of its fundamental and a relatively muted rebound given the magnitude of the boom, indicating a larger role for speculation in driving the boom-bust cycle than in the typical area. This pattern is representative; a regression of 2006-2019 house price growth on the 2004-2006 investor share indicates 5 percentage points lower house price growth in the bust-rebound for each 10 percentage points higher investor share (Table B.1 column (7) less sum of columns (1) and (4)).

Figure B.2: Survival Function For Investors From Matched HMDA-DQ Data



Notes: This figure shows survival functions for cohorts of investors in the matched HMDA-DataQuick data. Investors are defined as non-owner-occupiers in the HMDA data. For each cohort of investors that purchased in a given year, we compute the fraction of investors who have yet to sell at each year. The figure plots this survival function for each cohort.

B.2 Rent Break Tests

Table B.2 investigates the acceleration in rent growth around the start of the housing boom using a structural break test. The upper panel shows that the national break in rent growth in 1997Q3 closely coincides with the break in price growth in 1998Q2. The lower panel shows that among the 17 CBSAs with a statistically significant price break between 1994Q1 and 2000Q4 and with CPI rent data, 10 have statistically significant breaks in rent growth within two years of the price break. Moreover, these cities have larger and more statistically significant mean jumps in price at the timing of their breaks.

B.3 Bartik Instrument Details

We combine the CBP files provided by the Census with the files from Eckert et al. (2020) that optimally impute suppressed employment cells and provide a consistent correspondence to NAICS 2012. We use 1998 rather than 1997 as the initial year because the NAICS version of the data start in that year. The final year of data available is 2018. We implement "leave-one-out" shift shares: defining $E_{i,j,0}$ as employment in area i and industry j as

Table B.2: Rent Break Timing

National price growth break:			1998Q2	
National CPI rent growth break:			1997Q3	

Price-rent break gap	Number of CBSAs	Mean price jump (p.p.)	Mean rent jump (p.p.)	Mean price break test statistic
0-1 year	5	2.5	1.7	98.5
1-2 years	5	2.1	1.3	109.3
3-4 years	1	0.8	1.1	54.7
No rent break	6	0.9	.	55.5

Notes: The top panel reports the quarter (price) or half-year (rent) date of the Bai and Perron (1998) test for a series break between 1992 and 2006 as implemented in Ditzen et al. (2021). Both breaks are statistically significant at the 1% level. The bottom panel reports statistics grouped by the gap in years between the break date for prices and rents for the 17 CBSAs with a price break significant at the 5% level and CPI rent data. The last column reports the mean of the double maximum test statistic for the price break.

a share of total date 0 employment in area i, $g_{-i,j}$ as the growth rate of employment in industry j in all other areas between dates 0 and 1, $w_{-i,j,t}$ as the wage (payroll per employee) in industry j in all other areas at date t, and $\hat{E}_{i,j,1} \equiv E_{i,j,0} \times g_{-i,j} / \left[\sum_k E_{i,k,0} \times g_{-i,k}\right]$ as the predicted date 1 area i employment share in industry j, the shift-share for the growth of employment is $\sum_j E_{i,j,0} g_{-i,j}$ and the shift-share for the growth of the average wage is $\left[\sum_j \hat{E}_{i,j,1} \times w_{-i,j,1}\right] / \left[\sum_j E_{i,j,0} \times w_{-i,j,0}\right] - 1$, where date 0 is 1998 and date 1 is 2018. For area-industries with suppressed wage data, we replace $w_{-i,j,t}$ with $w_{j,t}$, where $w_{j,t}$ is the national wage in industry j at date t.

B.4 Urbanization Measurement and Instrument Details

We measure the downtown price premium and associated excluded instruments as follows. We follow Holian and Kahn (2012) and define the center of the downtown of each CBSA as the coordinates returned from inputting the largest city in the CBSA into Google Earth. As in Couture and Handbury (2020), we then rank all Census tracts in the CBSA by their distance to the downtown center and define the downtown as those tracts covering the closest 5% of population using 2010 tract definitions and 1990 Census population counts apportioned to 2010 tract definitions by the US2010 Project webpage.[6]

We compute the downtown price premium using ZIP code-level house price data from Zillow and FHFA and tract-level data from the Census. We map tracts into ZIP codes using the 2014 crosswalk from the Missouri Census Data Center, assigning partial downtown shares to ZIP codes covering tracts in and out of the downtown. We compute population-weighted house price growth for ZIP codes or tracts in the downtown and not in the downtown for each CBSA. Both Zillow and FHFA have incomplete coverage of ZIP codes in 1997. We use the log change in the downtown premium from Zillow if data exist and from FHFA otherwise. If neither Zillow nor FHFA cover ZIP codes in the downtown and remainder of a CBSA in 1997 (30 of 308 and CBSAs), we use the fitted value from a regression of the log change in the Zillow/FHFA premium from 1997 to the end year on the log change in the premium from the 2000 Census to the 2015-2019 ACS.

We measure the 1990 share of the CBSA that are college graduates using the decennial Census as compiled in the US2010 Project webpage. We measure the relative density of restaurants (SIC code 5812) in the downtown using the 1997 County Business Pattern ZIP code files and the mapping described above from ZIP codes to downtown. We measure the 1990 shares of college and non-college residents who live in downtown tracts using the Census data from the US2010 Project webpage. Finally, we predict for each CBSA the change in the share of the CBSA with a college degree by combining the actual 1990 CBSA industry distribution from the County Business Patterns, the national share of workers in each industry with a college degree in the 1990 Census and 2019 ACS, and the predicted 2019 industry distribution obtained by applying the national industry growth rates between the 1990 Census and 2019 ACS to the actual 1990 industry distribution.

[6] http://www.s4.brown.edu/us2010/Researcher/Bridging.htm.

Table B.3: Robustness of Long-run Regression

Regressor:	s		h		$s \times m \times h$		$s \times u$		Obs.
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	
Specification:									
1. Baseline	**0.78**	0.20	**0.63**	0.10	**1.30**	0.28	**1.40**	0.38	308
2. FHFA HPI	**0.70**	0.21	**0.55**	0.09	**1.22**	0.27	**1.26**	0.37	306
3. CoreLogic HPI	**0.80**	0.21	**0.46**	0.10	**1.20**	0.29	**1.35**	0.38	308
4. Zillow HPI	**0.81**	0.24	**0.37**	0.10	**1.01**	0.25	**1.07**	0.34	225
5. Saiz unavail.	**0.92**	0.21	**0.76**	0.10	**1.10**	0.28	**1.21**	0.35	260
6. Alt. pop.	**0.87**	0.18	**0.61**	0.08	**1.70**	0.29	**1.14**	0.37	308
7. Pop. weighted	**1.71**	0.28	**0.87**	0.14	**1.22**	0.39	0.07	0.21	308
8. Drop pop.$< 150K$	**0.80**	0.23	**0.60**	0.10	**0.97**	0.23	**1.42**	0.35	219
9. Drop shrinking	**1.00**	0.22	**0.55**	0.10	**1.12**	0.26	**0.98**	0.36	277
10. GMM	**0.57**	0.14	**0.79**	0.08	**1.46**	0.22	**1.60**	0.32	308
11. Bias-adjusted 2SLS	**0.69**	0.28	**0.71**	0.14	**1.83**	0.62	1.34	0.71	308
12. JIVE	0.31	0.42	**0.70**	0.18	**2.25**	0.84	1.82	1.81	308
13. No climate instr.	**1.01**	0.24	**0.76**	0.13	**1.45**	0.40	**1.09**	0.41	308
14. No lifestyle instr.	**0.78**	0.20	**0.63**	0.10	**1.30**	0.28	**1.40**	0.38	308
15. No Bartik instr.	**0.72**	0.22	**0.66**	0.10	**1.41**	0.32	**1.55**	0.47	308
16. No land avail. instr.	**0.77**	0.25	**0.83**	0.12	**1.45**	0.35	**1.09**	0.37	308
17. No density instr.	**0.89**	0.22	**0.59**	0.11	**1.52**	0.34	**1.65**	0.59	308
18. Control lag units	**0.75**	0.20	**0.61**	0.15	**1.29**	0.28	**1.39**	0.39	308
19. Control lag HPI	**0.76**	0.21	**0.64**	0.09	**1.33**	0.29	**1.32**	0.38	308

Notes: Each row reports coefficients and standard errors from a separate modification of the specification in column (3) of Table 1. In the table header, s denotes the land share, h units growth, m the 2006 WRLURI, and u the growth of the price premium in downtown neighborhoods. Coefficients in bold font are statistically different from 0 at the 5% level.

We construct this shift-share using the ind1990 variable from IPUMS adjusted to give a balanced panel by updating the file from David Dorn and a Census crosswalk from the 1987 SIC variable in the County Business Patterns to ind1990.[7]

B.5 IV Robustness

Table B.3 collects several specifications that address potential concerns with the baseline IV regression. Each row reports the coefficients and standard errors from a separate specification. The first row reproduces the baseline coefficients from column (3) of Table 1.

[7] See https://www.ddorn.net/data/subfile_ind1990dd.zip and https://www.census.gov/content/dam/Census/library/working-papers/2003/demo/techpaper2000.pdf.

Rows (2)-(4) show robustness to alternative house price indexes from FHFA, CoreLogic, and Zillow. Although these indexes vary in their samples and methodologies, all yield similar results.[8] Row (5) replaces the land unavailability instrument with the measure from Saiz (2010).[9] Because Saiz (2010) developed his measure for 1999 MSA definitions, we lose 16% of the sample, but the coefficients change little. Row (6) replaces housing units growth with the growth of population with little change.

Rows (7) to (9) explore robustness to the sample, in row (7) by weighting by population, in row (8) by excluding 89 CBSAs with 1997 population below 150,000, and in row (9) by excluding CBSAs with declining population. The only notable difference is that the weighted specification has a higher loading on the main effect on land share and a smaller loading on the urbanization term, reflecting the fact that much of the variation in urbanization occurs across large and small CBSAs (Couture and Handbury, 2020).

Rows (10) to (12) explore robustness to the estimator, in row (10) by replacing two-stage least squares with GMM, in row (11) with the JIVE estimator of Angrist et al. (1999), and in row (12) with the biased-adjusted estimator of Donald and Newey (2001). The JIVE and bias-adjusted estimators address a particular concern that many instruments over-fit the first stage, biasing the second stage toward OLS (Bekker, 1994; Bound et al., 1995).[10] Unlike in the canonical many weak instrument case of Angrist and Krueger (1991), however, Table B.5 shows that the instruments are generally strong predictors of the endogenous variables, and these specifications produce qualitatively similar coefficients.

[8]Like Freddie Mac, FHFA uses a repeat-sales methodology in a sample of loans purchased by Fannie Mae or Freddie Mac, but weights the sales differently. CoreLogic also uses a repeat sales methodology but includes sales not associated with mortgages purchased by a GSE. Zillow combines sales and other data in order to estimate the average price of a home in the middle tercile of each market regardless of whether it transacts in a period. Row (4) contains all CBSAs with non-missing Zillow data in 1997.

[9]Lutz and Sand define the CBSA boundary as the polygon containing the CBSA plus a 5% buffer. They argue that this improves on the Saiz (2010) measure of the 50km radius around each metropolitan city.

[10]JIVE avoids overfitting by obtaining the fitted value for each observation using a first-stage coefficient vector estimated by excluding that observation from the sample. The Donald and Newey (2001) bias adjustment is a K-class estimator that exactly corrects the IV bias when residuals are homoskedastic.

Rows (13)-(17) remove groups of excluded instruments. The estimation does not critically depend on any particular instrument for population or land, with similar results omitting the climate variables (row 13), CBSA restaurant employment (row 14), shift-shares (row 15), land unavailability (row 16), and population density (row 17). Rows (18) and (19) show that the results change little after controlling for lagged growth.

B.6 Estimation of Short-run Elasticity χ

We augment equations (2) and (3) in the main text to include short-run adjustment costs:

$$
\begin{aligned}
C_{i,t} &= A_{i,t} H_{i,t}^{\alpha_i} \left(I_{i,t}/\bar{I}_i\right)^{1/\chi_i^c}, \\
L_{i,t} &= B_{i,t} H_{i,t}^{\beta_i} \left(I_{i,t}/\bar{I}_i\right)^{1/\chi_i^\ell}, \\
\text{where: } 1/\chi_i^c &= \alpha_0^\chi + \alpha_1^\chi m_i, \quad 1/\chi_i^\ell = \beta_0^\chi + \beta_1^\chi m_i.
\end{aligned}
$$

Then applying the same transformations and zero restrictions as in the main text and letting $i_{i,t} = d \ln I_{i,t}$, we have the analogous regression to equation (8):

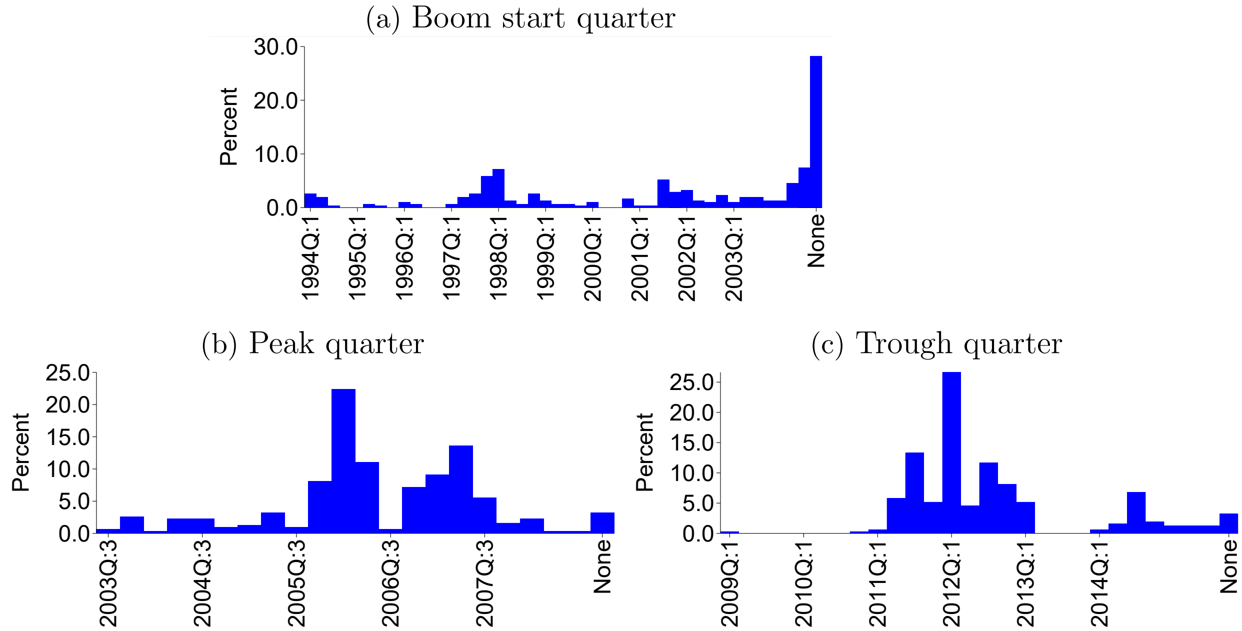
$$
p_{i,t} - (1/\eta_i) h_{i,t} = c_0 + c_1 s_{i,t} + c_2 i_{i,t} + c_5 \left(s_{i,t} \times m_i \times i_{i,t}\right) + c_6 \left(s_{i,t} \times u_{i,t}\right) + e_{i,t}, \qquad \text{(B.1)}
$$

where we form the left hand side using the estimated values of η_i implied by column (3) of Table 1. The inverse short-run supply elasticity is $c_2 + c_5 \times s_i \times m_i$. We estimate equation (B.1) over the period 2000-2005 (to avoid the censal break in 2000) using the same excluded instruments as in the long-run regression and obtain $c_1 = 1.02$ ($s.e.$ 0.23), $c_2 = 0.29$ ($s.e.$ 0.05), $c_5 = 0.78$ ($s.e.$ 0.19), $c_6 = 0.65$ ($s.e.$ 1.10), from which we form $1/\chi_i$.

B.7 Additional Empirical Results

Figure B.3 plots the timing of boom starts, peaks, and bust troughs across CBSAs. Figure B.4 replicates Figure 2 across CBSAs, as discussed in Footnote 5. Table B.4 reports

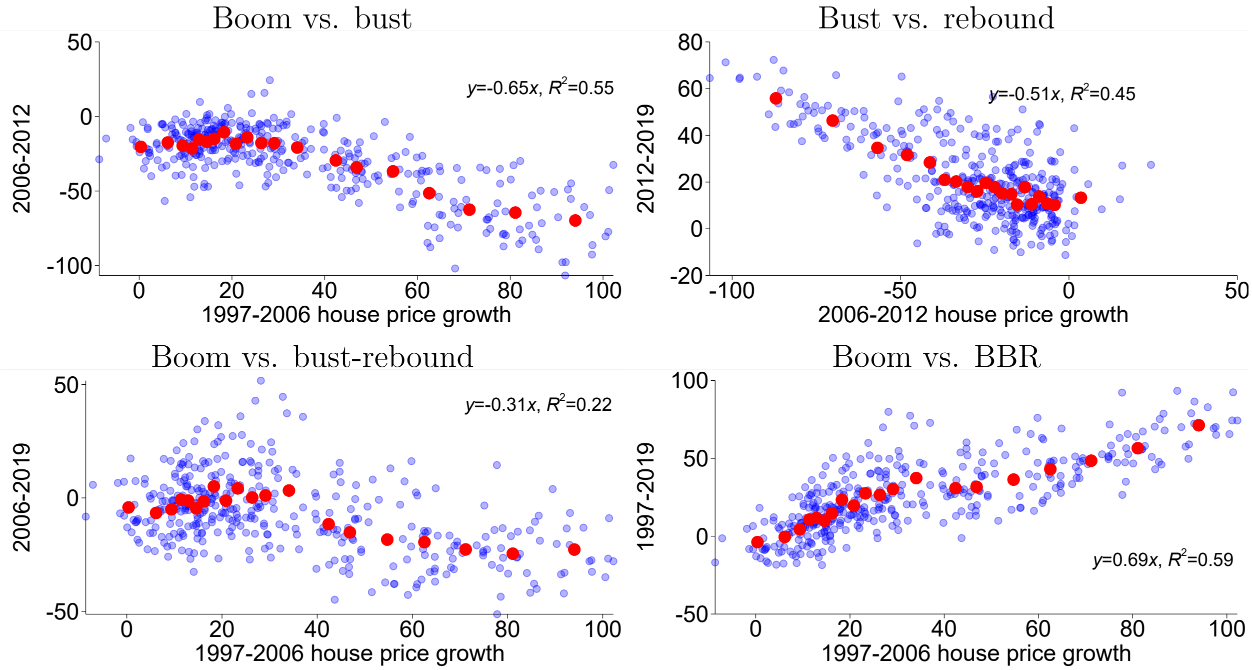
Figure B.3: CBSA Boom, Peak, and Trough Timing



Notes: Panel (a) reports a histogram of the first quarter between 1992:Q1 and 2006:Q2 with a positive structural break in the growth rate of real house prices, using the structural break test of Bai and Perron (1998, 2003) as implemented in Ditzen et al. (2021). Areas without a break identified at the 95% confidence level are shown in the bar labeled "None." Panels (b) and (c) report histograms of the quarter with the peak in real house prices between 2003:Q2 and 2009:Q2 and trough in prices between 2007:Q1 and 2015:Q4, respectively, with areas without an interior extremum shown in the bar labeled "None."

summary statistics. 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 to establish the explanatory power of the instruments without broaching many-instrument asymptotics. As discussed in Section 4.1, the instruments are strong and enter with the expected sign. The final column shows the reduced form of house price growth over the BBR on the (uninteracted) instruments, which corresponds to Figure 4. Figure B.5 repeats Figure 4 using only the supply or demand instruments separately and shows that both contribute to higher long-run growth and to the boom-bust-rebound pattern, as discussed in Section 3.3.

Figure B.4: CBSA Boom, Bust, and Rebound



Notes: Each blue circle represents one CBSA. The red circles show the mean value of the y-axis variable for 20 bins of the x-axis variable. Data from Freddie Mac deflated using the national GDP price index.

Table B.4: Summary Statistics

Variable	Mean	SD	P10	P50	P90	Obs.
House price growth 1997-2019	28.0	23.4	−0.6	25.5	59.9	308
Population growth 1997-2019	19.9	17.2	−0.1	17.7	42.3	308
Units growth 1997-2019	25.2	14.8	8.1	23.0	45.0	308
Land share	28.0	9.4	17.8	26.2	40.8	308
WRLURI 2006	−11.8	81.9	−104.5	−23.0	89.7	308
Log change in downtown premium	1.4	15.7	−14.3	0.8	18.5	308
Bartik employment 1998-2018	22.8	6.3	15.6	22.9	30.4	308
Bartik wage 1998-2018	84.5	9.1	71.5	85.4	94.1	308
January temperature	35.6	12.1	21.4	34.3	51.9	308
January sunlight hours	151.1	39.0	104.0	150.9	210.0	308
July humidity	56.4	16.4	26.0	60.3	73.6	308
Land unavailable	30.8	20.4	6.7	26.8	62.7	308
1997 population density	26.6	30.7	5.7	17.3	52.7	308
Non-traditional Christian share	41.5	23.0	10.4	39.5	73.8	308
Inspection/tax revenue	0.8	0.8	0.2	0.5	1.7	308
Col. share × restaurants	27.1	17.5	9.6	22.9	47.9	308
Downtown diff. ×Δ col. share	−1.3	25.8	−32.9	−3.1	30.8	308

Notes: This table shows summary statistics for our cross-section of CBSAs.

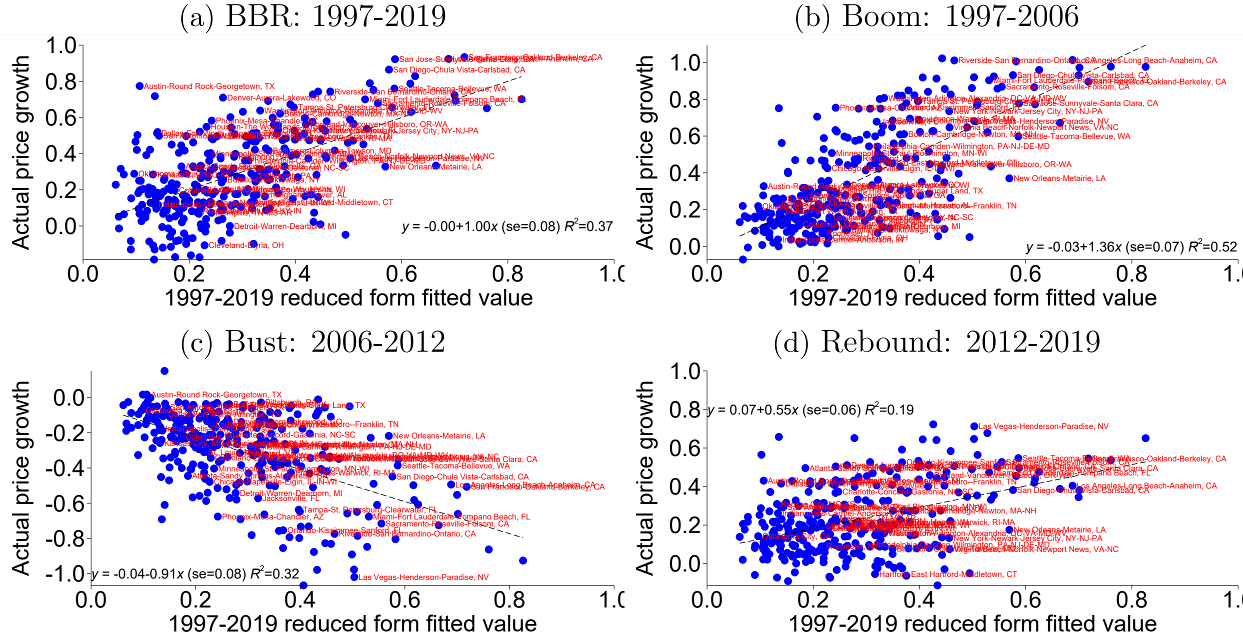
Table B.5: Pseudo First-stage and Reduced Form Regressions

Dep. var.:	s		h		m		u		p
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unavailability	3.0^{**}	3.0^{**}		-0.6		22.6^{**}		1.3^{+}	10.0^{**}
	(0.5)	(0.5)		(0.9)		(4.5)		(0.8)	(1.1)
Pop. density	4.8^{**}	4.4^{**}		-2.3^{**}		18.3^{**}		2.5^{*}	2.2^{+}
	(0.5)	(0.5)		(0.5)		(5.7)		(1.2)	(1.2)
Bartik wage		0.3	1.3	1.1		3.8		-0.3	1.8^{+}
		(0.5)	(0.8)	(0.7)		(4.4)		(0.7)	(1.0)
Bartik emp.		-0.3	-0.1	1.5^{+}		7.7^{+}		1.8^{*}	2.2^{*}
		(0.5)	(0.8)	(0.8)		(4.3)		(0.8)	(1.0)
January temp.		0.4	4.5^{**}	3.7^{**}		-2.1		-0.2	3.2^{*}
		(0.6)	(0.9)	(1.3)		(6.4)		(1.1)	(1.5)
January sunlight		0.3	2.2^{*}	2.7^{**}		9.2^{+}		1.7^{*}	3.2^{**}
		(0.5)	(0.9)	(0.9)		(5.1)		(0.8)	(1.2)
July humidity		-0.2	-4.6^{**}	-3.7^{**}		-14.3^{**}		-2.0^{*}	-7.0^{**}
		(0.5)	(0.9)	(0.9)		(5.0)		(0.8)	(1.2)
Restaurants		1.9^{**}	4.5^{**}	3.1^{**}		-2.9		-1.0	0.9
		(0.4)	(0.8)	(0.9)		(5.2)		(0.9)	(1.0)
Nontrad. Christ.		-1.2^{*}		1.5	-26.7^{**}	-23.1^{**}		-0.7	-3.1^{**}
		(0.6)		(1.1)	(4.3)	(5.1)		(1.0)	(1.1)
Inspection/tax		0.9^{+}		-1.4	21.9^{**}	8.1^{*}		-0.1	3.7^{**}
		(0.5)		(0.9)	(3.4)	(3.7)		(0.7)	(1.1)
Col. share × rest.		1.1^{*}		0.8		2.7	5.6^{**}	4.5^{**}	4.8^{**}
		(0.5)		(0.8)		(4.9)	(0.9)	(1.0)	(1.2)
Downtown diff. ×		-0.4		2.9^{**}		-1.2	2.0^{*}	2.8^{**}	0.3
$\widehat{\Delta\text{col. share}}$		(0.4)		(0.8)		(4.0)	(0.9)	(0.8)	(0.9)
Effective F	64.5	19.2	19.1	13.9	39.3	12.3	24.1	8.8	
R^2	0.366	0.444	0.295	0.382	0.179	0.341	0.158	0.241	0.575
Observations	308	308	308	308	308	308	308	308	308

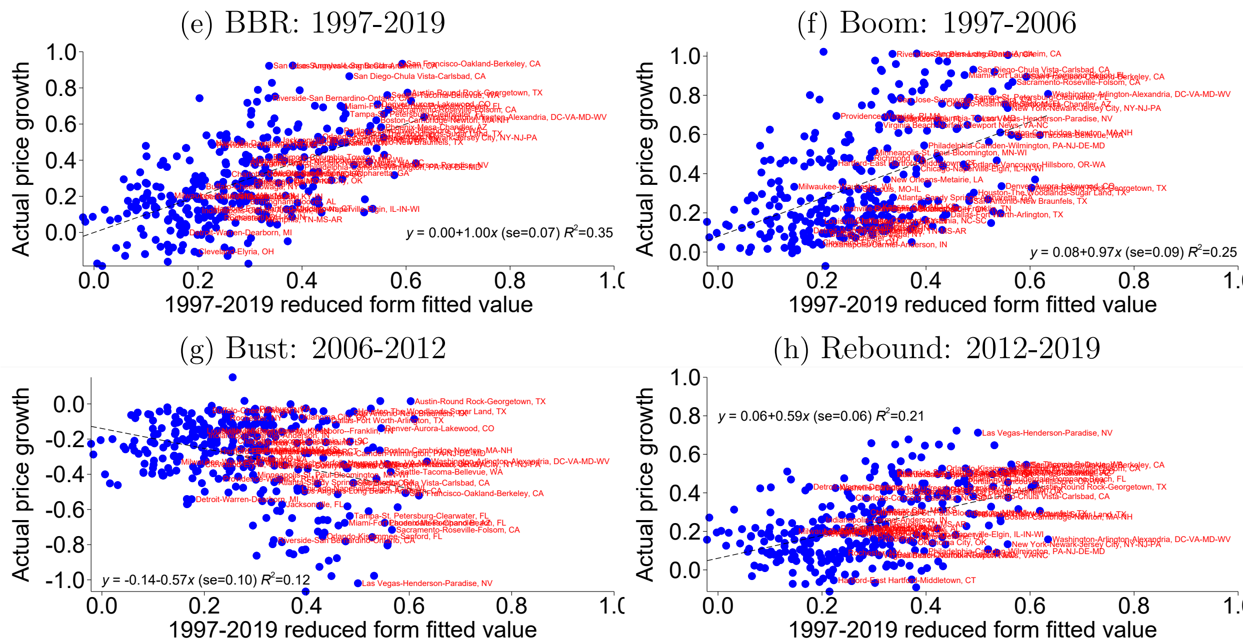
Notes: Columns (1), (3), (5), and (7) report regressions of an endogenous variable on the group of excluded instruments associated with that variable. Columns (2), (4), (6), and (8) report regressions of an endogenous variable on all excluded instrument main effects. Column (9) reports the reduced form regression of house price growth on all excluded instrument main effects. In the table header, s denotes the land share, h units growth from 1997 to 2019, m the 2006 WRLURI, u the growth of the price premium in downtown neighborhoods from 2007 to 2019, and p the log change in the house price from 2007 to 2019. All independent variables normalized to have unit variance. Heteroskedastic-robust standard errors in parentheses. The effective F-statistic is computed as in Montiel Olea and Pflueger (2013). **,* ,$^{+}$ denote significance at the 1, 5, and 10 percent levels, respectively.

Figure B.5: Predicted and Actual Price Growth

Land Share and Regulation Instruments Only



Population and Urbanization Instruments Only



Notes: In each panel, each blue 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. Panels (a)-(d) predict price growth using only the excluded instruments associated with land share and WRLURI (land unavailability, 1997 population density, non-traditional Christian share, and public expenditure on protective inspection). Panels (e)-(h) predict price growth using only the excluded instruments associated with population growth and urbanization (employment and wage shift-shares, climate variables, CBSA restaurant density, relative restaurant density in the downtown × the 1990 college share, and the 1990 difference in the college/non-college likelihood of living downtown × the CBSA predicted change in college share). CBSAs with more than 1 million persons in 1997 are labeled in red.

C Model Appendix

This appendix provides derivations and proofs for the model in Section 5. Appendix C.1 derives the present value of dividends. Appendix C.2 provides an analytic path of beliefs that we use to calculate impulse responses. Appendix C.3 defines the balanced growth path. Appendix C.4 derives the user cost for rents. Appendix C.5 associates rent acceleration with dividend growth. Appendix C.6 shows impulse responses when lenders have perfect foresight rather than diagnostic beliefs.

C.1 Present Value of Dividends

We restate equation (16) for convenience:

$$P_t^* = \int_{-\infty}^{\infty} \mathbb{E}_t \left[\int_t^{\infty} e^{-\rho(s-t)} D_s ds | \mu_t \right] h_t^{\theta}\left(\mu_t\right) d\mu_t.$$

We want to prove that this integral depends only on D_t, m_t^{θ}, and parameters. Start by fixing μ_t and D_t. Since D_t is a geometric Brownian motion, we have $e^{-\rho(s-t)} D_s = D_t \exp\left(-\rho\left(s-t\right) - \frac{1}{2}\sigma_D^2\left(s-t\right) + \int_t^s \mu_\tau d\tau + \sigma_D \int_t^s dW_{D,\tau}\right)$. Taking an expectation:

$$\mathbb{E}_t \left[e^{-\rho(s-t)} D_s | \mu_t \right] = D_t \exp\left[-\rho\left(s-t\right) + \mathbb{E}_t \left[\int_{\mathrm{t}}^{\mathrm{s}} \mu_\tau \mathrm{d}\tau | \mu_{\mathrm{t}} \right] + \frac{1}{2} \mathrm{Var}\left(\int_{\mathrm{t}}^{\mathrm{s}} \mu_\tau \mathrm{d}\tau | \mu_{\mathrm{t}} \right) \right].$$

$$\text{One can show: } \mathbb{E}_t \left[\int_{\mathrm{t}}^{\mathrm{s}} \mu_\tau \mathrm{d}\tau | \mu_t \right] = \bar{\mu}\left(s-t\right) + \frac{1}{\vartheta}\left(1 - e^{-\vartheta(s-t)}\right)\left(\mu_t - \bar{\mu}\right),$$

$$\mathrm{Var}\left(\int_{\mathrm{t}}^{\mathrm{s}} \mu_\tau \mathrm{d}\tau | \mu_t \right) = \frac{\sigma_\mu^2}{\vartheta^2}\left(s-t\right) - \frac{3\sigma_\mu^2}{2\vartheta^3} + \frac{\sigma_\mu^2}{2\vartheta^3}\left[4e^{-\vartheta(s-t)} - e^{-2\vartheta(s-t)} \right],$$

giving: $$\mathbb{E}_t \left[e^{-\rho(s-t)} D_s | \mu_t \right] = D_t \exp\left[-\left(\rho - \bar{\mu}\right)\left(s-t\right) + \frac{1}{\vartheta}\left(1 - e^{-\vartheta(s-t)}\right)\left(\mu_t - \bar{\mu}\right) + G\left(s-t\right) \right],$$

where: $$G\left(s-t\right) = \frac{\sigma_\mu^2}{2\vartheta^2}\left(s-t\right) - \frac{3\sigma_\mu^2}{4\vartheta^3} + \frac{\sigma_\mu^2}{4\vartheta^3}\left[4e^{-\vartheta(s-t)} - e^{-2\vartheta(s-t)} \right].$$

Substituting these expressions into equation (16) gives the desired result:

$$\begin{aligned}
P_t^*/D_t &= \int_0^\infty \mathbb{E}_{\mu_t}^\theta \exp\left[-\left(\rho-\bar{\mu}\right)\tau + \frac{1}{\vartheta}\left(1-e^{-\vartheta\tau}\right)\left(\mu_t-\bar{\mu}\right)+G\left(\tau\right)\right]d\tau \\
&= \int_0^\infty \exp\left[-\left(\rho-\bar{\mu}\right)\tau + \frac{1}{\vartheta}\left(1-e^{-\vartheta\tau}\right)\left(m_t^\theta-\bar{\mu}\right)+G\left(\tau\right)\right]\exp\left[\frac{\sigma_m^2}{2\vartheta^2}\left(1-e^{-\vartheta\tau}\right)^2\right]d\tau.
\end{aligned} \tag{C.1}$$

C.2 Analytic Path of Beliefs

We solve for the mean path of beliefs m_t^θ starting from the initial condition $m_0 = \bar{\mu}$ and the initial drift rate μ_0. That is, we solve for m_t^θ if all subsequent Wiener shocks are equal to 0. From equation (14), we have:

$$m_t^\theta = m_t + \theta\mathcal{I}_t. \tag{C.2}$$

We first characterize the path of m_t, and then the path of $\theta\mathcal{I}_t$.

We first solve the SDE for m_t. Substituting equations (9) and (12) into equation (11):

$$\begin{aligned}
dm_t &= \vartheta\left(\bar{\mu}-m_t\right)dt + KdB_t \\
&= \vartheta\left(\bar{\mu}-m_t\right)dt + K\sigma_D^{-1}\left(\mu_t dt + \sigma_D dW_{D,t} - m_t dt\right) \\
&= \left(\vartheta\bar{\mu} + \kappa\mu_t - \left(\kappa+\vartheta\right)m_t\right)dt + KdW_{D,t},
\end{aligned} \tag{C.3}$$

where $\kappa \equiv K/\sigma_D$. The solution to this SDE is:

$$m_t = m_0 e^{-(\kappa+\vartheta)t} + \vartheta\bar{\mu}\int_0^t e^{-(\kappa+\vartheta)(t-s)}ds + \kappa\int_0^t e^{-(\kappa+\vartheta)(t-s)}\mu_s ds + K\int_0^t e^{-(\kappa+\vartheta)(t-s)}dW_{D,s}. \tag{C.4}$$

Note that equation (10) implies:

$$\mathbb{E}_0\left[\mu_t|\mu_0\right] = e^{-\vartheta t}\mu_0 + \left(1-e^{-\vartheta t}\right)\bar{\mu}. \tag{C.5}$$

Taking a conditional expectation of (C.4), using (C.5), and simplifying terms:

$$\mathbb{E}_0\left[m_t|\mu_0, m_0\right] = \bar{\mu} + (\mu_0 - \bar{\mu})\, e^{-\vartheta t} - (\mu_0 - m_0)\, e^{-(\kappa+\vartheta)t}. \tag{C.6}$$

We next solve for the mean path of $\theta\mathcal{I}_t$. Using equations (9), (12) and (15), we have:

$$\theta\mathcal{I}_t = K\theta \int_{t-k}^{t} e^{-\vartheta(t-s)} dB_s \quad = \theta\kappa \int_{t-k}^{t} e^{-\vartheta(t-s)} (\mu_s - m_s)\, ds + \theta K \int_{t-k}^{t} e^{-\vartheta(t-s)} dW_{D,s}. \tag{C.7}$$

Note that equations (C.5) and (C.6) together imply that for any $s \geq 0$, $\mathbb{E}_0\left[\mu_s - m_s|\mu_0, m_0\right] = (\mu_0 - m_0)\, e^{-(\kappa+\vartheta)s}$. Therefore:

$$\begin{aligned}\mathbb{E}_0\left[\theta\mathcal{I}_t|\mu_0, m_0\right] &= \theta\kappa \int_{\max\{t-k,0\}}^{t} e^{-\vartheta(t-s)} (\mu_0 - m_0)\, e^{-(\kappa+\vartheta)s} ds \\ &= \theta\,(\mu_0 - m_0)\left(e^{-\kappa \max\{t-k,0\}-\vartheta t} - e^{-(\kappa+\vartheta)t}\right).\end{aligned} \tag{C.8}$$

Equations (C.6) and (C.8) together characterize the mean path of diagnostic beliefs $\mathbb{E}_0\left[m_t^\theta|\mu_0, m_0\right]$ that we use to solve for the path of $P^*\left(D_t, m_t^\theta\right)$.

C.3 Balanced Growth Path

A balanced growth path (BGP) consists of a fixed μ, constant rate of construction and foreclosures, and constant ratio of points to price. Let δ^f denote the BGP ratio of foreclosures to population and ω denote the ratio of points to price. Substituting this notation into the market-clearing condition (22) gives:

$$g_H H_t x_m^\gamma \left[V_t/\left(1+\omega\right) P_t\right]^\gamma = \dot{H}_t + \delta^f H_t. \tag{C.9}$$

Dividing through by H_t and recognizing that a constant construction rate means $dH_t/H_t = I_t$ is constant on the BGP, it is apparent that V_t/P_t is also constant. Since V_t grows at rate μ (see the valuation function (C.1)), BGP prices also grow at μ.

It only remains to verify that the foreclosure rate is constant on the BGP. With a constant liquidity shock ι, this will be true if the loan-to-value (LTV) distribution remains stable. Let $M(s,t)$ denote the balance in period s of a buyer who bought in period t and $m(s,t) = M(s,t)/P_s$ the current LTV of that buyer. With initial LTV of ϕ and allowing for generality for a mortgage pay down rate of ς, we have that $m(s,t) = \phi e^{-(\varsigma+\mu)(s-t)}$. This expression can be inverted to find the date t at which someone with LTV m at date s must have bought: $t(m,s) = s - \frac{\ln(\phi/m)}{\varsigma+\mu}$. Let $F(s,t)$ be the cumulative share of mortgages outstanding that bought before date t. Since new mortgages are written at a rate of $I+\iota$ each period, $F(s,t) = e^{-(I+\iota)(s-t)}$. Let $G(m,s)$ denote the share of mortgages outstanding at date s with LTV of less than m. Then:

$$G(m,s) = \left(\frac{\phi}{m}\right)^{-\frac{I+\iota}{\varsigma+\mu}}, \tag{C.10}$$

confirming that the LTV distribution is stable on the BGP.

C.4 Rent Details

We first derive a general user cost expression. To clarify notation, throughout this section we suppress the i subscript for an individual city and let τ index time elapsed since period t, $j = \tau/\Delta$ be the number of periods of length Δ that have elapsed after τ time units (e.g., if Δ is 1 week and τ is in years then at the end of one year when $\tau = 1$ there have been 52 periods of length 1 week), and $t+T$ be the end of time.

With Poisson intensity λ a household may re-optimize the rent-own decision. Let $R_{t+\tau|t}$ denote the rent paid in period $t+\tau$ for a contract signed in period t. An agent must be indifferent between renting and owning, where owning involves an outlay of the down payment $(1-\phi)P_t$ at date t plus the discounted sum of interest payments $i_t\phi P_t$, other costs of owning such as maintenance or property taxes that are assumed to be proportional to the dividend, ζD_t, and expected cash-flow at sale $\mathbb{E}_t^\theta[P_{t+j}] - \phi P_t$, where the notation $\mathbb{E}_t^\theta$ indicates that expectations are taken using the diagnostic measure.[11] We have:

$$\sum_{j=0}^{T/\Delta}\left(\frac{1-\lambda\Delta}{1+\rho\Delta}\right)^{\tau/\Delta}\Delta\mathbb{E}_t^\theta\left[R_{t+\Delta j|t}\right]$$
$$=(1-\phi)P_t+\sum_{j=0}^{T/\Delta}\left(\frac{1-\lambda\Delta}{1+\rho\Delta}\right)^{\tau/\Delta}\left[\phi P_t i_t\Delta+\zeta\Delta\mathbb{E}_t^\theta[D_{t+\Delta j}]-\lambda\Delta\left(\mathbb{E}_t^\theta[P_{t+\Delta j}]-\phi P_t\right)\right].$$

Taking the limit as $\Delta\to 0, T\to\infty$ and solving the integral multiplying P_t gives:

$$\int_0^\infty e^{-(\rho+\lambda)\tau}\mathbb{E}_t^\theta\left[R_{t+\tau|t}\right]d\tau=\left(1+\phi\left(\frac{i_t+\lambda}{\rho+\lambda}-1\right)\right)P_t \\ -\lambda\int_0^\infty e^{-(\rho+\lambda)\tau}\mathbb{E}_t^\theta[P_{t+\tau}]d\tau+c_t\zeta D_t. \tag{C.11}$$

In the continuous time representation, the left hand side is the expected present value of rents paid until the next rent/own decision. On the right hand side, the first term is the price gross of expected discounted interest costs (the interest rate i_t is locked in when the mortgage is signed). The second term is the expected discounted cash flow at sale, which can be written as $\int_0^\infty \lambda e^{-\lambda\tau}\mathbb{E}_t^\theta[e^{-\rho\tau}P_{t+\tau}]d\tau$ to make clear that $\lambda e^{-\lambda\tau}$ is the probability of selling at date $t+\tau$ and $\mathbb{E}_t^\theta[e^{-\rho\tau}P_{t+\tau}]$ is the expected discounted cash flow if the sale occurs at date $t+\tau$. The third term is the expected present value of maintenance costs of owning and is written as $\int_0^\infty e^{-(\rho+\lambda)\tau}\mathbb{E}_t^\theta\zeta D_{t+\tau}d\tau = c_t\zeta D_t$ for a scalar c_t that depends on beliefs of the drift rate and parameters and is given by the right hand side of equation (C.1) with ρ replaced by $\rho+\lambda$. Without uncertainty, $c_t = 1/(\rho+\lambda-\mu)$.

Equation (C.11) involves an indeterminacy since only the expected discounted present value of rents is pinned down by the expected cost of owning. We resolve this indeterminacy by assuming a contract where rents grow at a rate $g_{t|t}$ until the λ reoptimization shock

[11] This derivation involves a slight abuse of notation, as the present value V should subtract these other owning costs. This simply involves a redefinition of ζ.

hits: $R_{t+\tau|t} = e^{g_{t|t}\tau} R_{t|t}$. This assumption captures the empirical regularity that contract rents are sticky but grow at some trend rate. We assume in particular that $g_{t|t} = m_t^{\phi}$, the nowcast of the drift rate, but provide the derivation for a general $g_{t|t}$. Imposing this assumption on equation (C.11), the "reset" rent can then be written as:

$$R_{t|t} = \left(\frac{\rho + \lambda - g_{t|t}}{\rho + \lambda}\right)\left(\left((1-\phi)\,\rho + \phi i_t\right) P_t - \lambda \int_0^{\infty} (\rho+\lambda)\, e^{-(\rho+\lambda)\tau} \left(\mathbb{E}_t^{\theta} P_{t+\tau} - P_t\right) d\tau\right)$$
$$+ \left(\rho + \lambda - g_{t|t}\right) c_t \zeta D_t. \tag{C.12}$$

One can show that in the limit as $\lambda \to \infty$, so that the rent-own decision is re-optimized each instant, this expression collapses to $R_{t|t} = \left((1-\phi)\,\rho + \phi i_t\right) P_t - \mathbb{E}_t^{\theta}\left[\dot{P}_t\right] + \zeta D_t$.

The average rent paid at date t, denoted R_t, evolves according to:

$$\dot{R}_t = g_t R_t + \lambda \left(R_{t|t} - R_t\right), \tag{C.13}$$

$$\text{where: } \dot{g}_t = \left(R_{t|t}/R_t\right) \lambda \left(g_{t|t} - g_t\right). \tag{C.14}$$

Given initial conditions for R_t and g_t, equations (C.12) to (C.14) characterize the path of rents. The initial condition for g_t is $g_0 = \bar{\mu}$, the pre-boom growth rate of house prices and rents. The initial condition for R_0 is chosen to match an average price-rent ratio of 13 over the sample, which we achieve by choosing ζ.

C.5 Rent Growth Acceleration and Fundamentals

Along a BGP with dividend growth of μ, $g_t = \mu$, and $i = \rho$, (C.12) to (C.14) imply:

$$R_t^{\mathrm{BGP}} = (\rho - \mu)\, P_t + \zeta D_t. \tag{C.15}$$

The following lemma shows that a BGP-to-BGP acceleration of rent growth will result from an increase in μ but not from a decline in the discount rate ρ. We refer to this result in Section 2 where we show that rent growth accelerated during the BBR.

Lemma 1 *Suppose up to time* 0*,* $\rho_t = \bar{\rho}$ *and* $\mu_i = \bar{\mu}_i$*. Let* x_{0-} *be the left-limit value of a variable just before time* 0 *and* x_T *the value after convergence to a new balanced growth path.*

1. *Following a change in the discount rate at date* 0 *from* $\bar{\rho}$ *to* ρ_0*, rents continue to growth at* $\bar{\mu}_i$*:* $\log\left(R_{i,T}/R_{i,0-}\right) = \bar{\mu}_i t$*.*

2. *Following a change in the growth rate at date* 0 *from* $\bar{\mu}_i$ *to* $\mu_{i,0}$*, rents grow at the rate* μ_0 *but shift down due to the decline in the price-rent ratio:* $\log\left(R_{i,T}/R_{i,0-}\right) = \log\left(\left(\mu_0/\bar{\mu}\right)^{-1/\gamma}(1-\zeta)+\zeta\right) + \mu_0 t$*.*

Proof: Recall that along a balanced growth path we have that $P_t^{\text{BGP}} = AH_t^{1/\eta}$ and $I_t H_t = g_H H_t x_m^{\gamma}\left(\frac{V_t}{P_t}\right)^{\gamma}$.[12] Using $\dot{V}_t/V_t = \dot{P}_t/P_t = \mu_t$ and $\dot{H}_t/H_t = \eta\mu_t$ and explicitly accounting for the costs of owning ζD_t, the Gordon Growth representation is:

$$P_t^{\text{BGP}} = \left(\frac{g_H}{\eta\mu_t}\right)^{1/\gamma} x_m \frac{D_t(1-\zeta)}{\rho_t - \mu_t}. \tag{C.16}$$

Substituting equation (C.16) into equation (C.15) and grouping terms, we have:

$$R_t^{\text{BGP}} = \left[\left(\frac{g_H}{\eta\mu}\right)^{1/\gamma} x_m(1-\zeta)+\zeta\right] D_t. \tag{C.17}$$

The first claim in the lemma follows immediately, since this expression does not depend on ρ_t. For the second claim, we can normalize $P_{0-} = V_{0-}$, which gives $x_m = \left(\eta\bar{\mu}/g_H\right)^{1/\gamma}$ and hence $\log\left(R_T^{\text{BGP}}/R_{0-}^{\text{BGP}}\right) = \log\left(\left(\mu_0/\bar{\mu}\right)^{-1/\gamma}(1-\zeta)+\zeta\right) + \mu_0 t$.

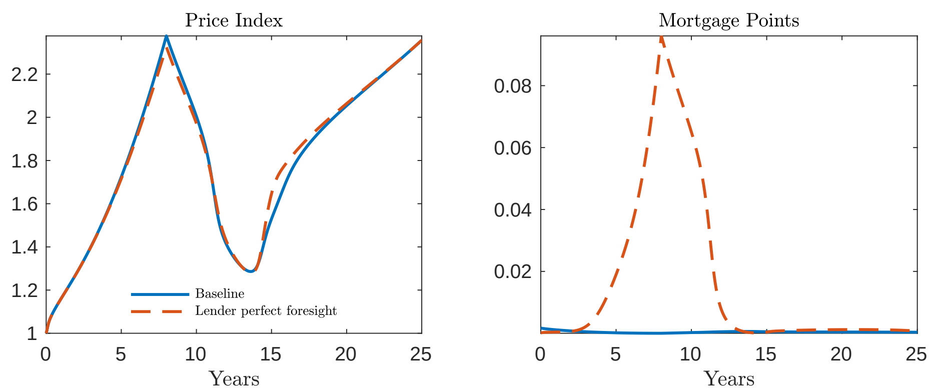
C.6 Lender Perfect Foresight and Role of Credit Markets

Figure C.1 shows the paths of price, P_t, and upfront mortgage cost as a share of the price, W_t/P_t, when lenders have perfect foresight over the path of dividends. Even when lenders perfectly anticipate the peak in buyers' beliefs and hence in prices, the rise in W_t/P_t of 9.6 p.p. has a small impact on prices. This insensitivity reflects the fact that mortgage costs W_t are small relative to the price P_t so that even large changes in W_t shift the demand

[12] Note that the demand equation for $I_t H_t$ coincides with equation (4) in Section 3 for $G = g_H x_m^{\gamma}$. That is, nothing in this proof requires any of the structure of Section 5 not already imposed in Sections 3 and 4. We ignore foreclosures for simplicity and all of what follows holds in the more general case.

curve by only a small amount relative to changes in V_t. Why do perfect foresight lenders not raise W_t by even more so as to choke off the boom-bust? With the double-trigger for default, the estimated liquidity shock frequency of roughly 5% per year, and the empirical recovery rate of roughly 65% on foreclosures, lenders receive substantial cash flows even on mortgages made just prior to a price peak. The 8p.p. rise in W_t/P_t is exactly sufficient to compensate for the anticipated wave of foreclosures.

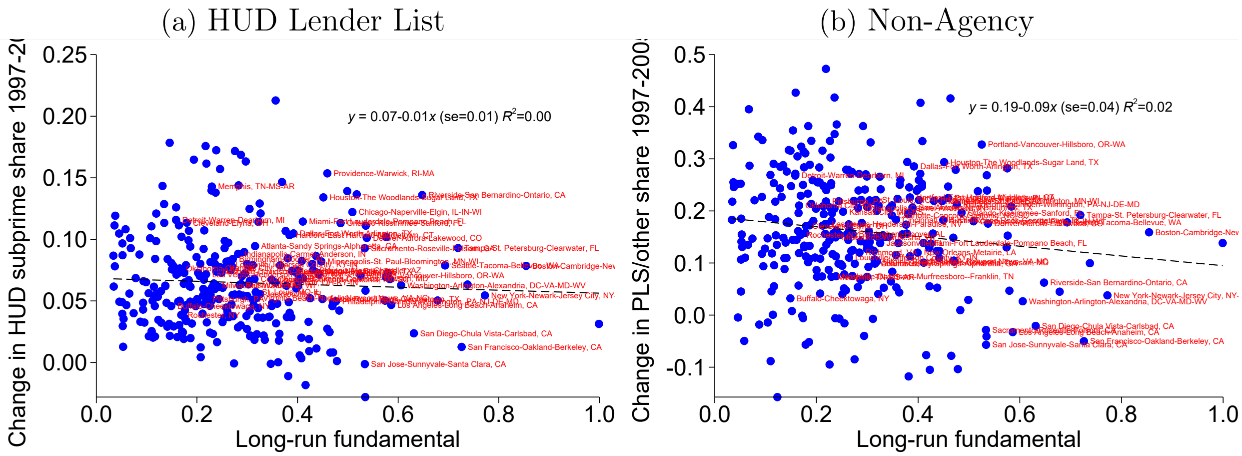
Figure C.1: Prices and Mortgage Costs with Lender Perfect Foresight



Notes: The figure shows the paths of price, P_t, and upfront mortgage cost as a share of the price, W_t/P_t, for the third quartile of CBSAs when lenders have perfect foresight over the path of dividends in the dashed orange line. The baseline model third quartile of CBSAs is shown in the solid blue line for comparison.

Changes in credit that affect approval rates on the extensive margin offer greater potential to impact prices in our model. We consider an extension in which each potential entrant first draws income y from a CDF $G(y)$ and gets approved for a mortgage only if $y > c_t P_t$. The cutoff parameter c_t encompasses a variety of mechanisms including down-payment constraints and payment-to-income constraints (Greenwald, 2018). With this modification, the parameter g_H becomes instead $(1 - G(c_t P_t))\, g_H$. With some abuse of notation, we can therefore accommodate such policies by replacing g_H in equation (17) with a time-varying potential buyer share $g_{H,t}$. In fact, in the presence of an approval constraint $y > c_t P_t$ that binds in at least part of the distribution of y prior to the boom, our

Figure C.2: Non-Prime Credit and Fundamentals

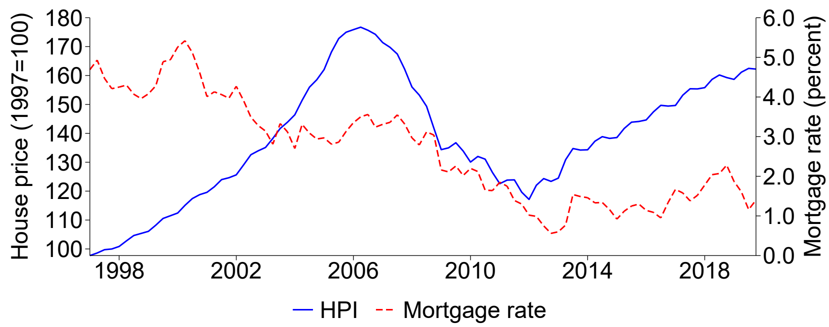


Notes: Panel (a) plots the share of purchase mortgages originated by lenders flagged by the the Department of Housing and Urban Development as subprime lenders against the long-run fundamental. Panel (b) plots the share of purchase mortgages below the jumbo threshold and purchased by non-Agency institutions (private securitization (HMDA code 5), commercial bank, savings bank or savings association (HMDA code 6), life insurance company, credit union, mortgage bank, or finance company (HMDA code 7), affiliate institution (HMDA code 8), and other purchasers (HMDA code 9)) against the long-run fundamental. The data include all first-lien purchase mortgages in HMDA not backed by manufactured housing or buildings with more than four units. CBSAs with more than 1 million persons in 1997 are labeled in red.

calibration with constant g_H *requires* an expansion of credit on the extensive margin (or a rightward shift in the distribution of y), as otherwise an increasing number of potential buyers would get denied mortgage approval as P_t rises (see also Foote et al., 2021). Even so, Figure C.2 shows that the long-run fundamental is essentially uncorrelated with the change in subprime share during the boom, suggesting the role of other types of credit relaxation (e.g. low interest rates that ease payment-to-income constraints) and rising incomes in keeping house prices affordable in high fundamental areas.

Finally, we circumscribe the potential for mortgage rate changes to affect house prices. First, Figure C.3 shows that the timing of rate declines does not generally coincide with the periods of rising prices. We next quantify the impact of the decline in the real mortgage rate from 4.25% in 1998Q1 to 1.4% in 2019Q4. A standard fixed payment mortgage sets a constant dollar payment of $c\Delta$ per time interval Δ and amortizes to 0 after H

Figure C.3: House Prices and Mortgage Rates



Notes: The blue solid line shows the national Case-Shiller index deflated by the GDP price index. The red dashed line shows the Freddie Mac 30 year fixed mortgage rate less median inflation expectations from the Michigan Survey of Consumers.

years. The mortgage balance therefore evolves as $M_{t+h+\Delta} = M_{t+h} - (c\Delta - i_t \Delta M_{t+h}) = (1 + i_t\Delta)\, M_{t+h} - c\Delta$. Taking the limit as $\Delta \to 0$ and using the boundary conditions $M_t = \phi P_t$ and $M_{t+H} = 0$ gives $c = i_t \phi P_t/(1 - e^{-i_t H})$. As most buyers move before final payment, we also allow for early termination after B years. The present value of mortgage costs is therefore $\int_{h=0}^{B} e^{-\rho h} c dh + e^{-\rho B} M_{t+B} = \left(\left(\frac{1-e^{-\rho B}}{1-e^{-i_t H}}\right)\left(\frac{i_t}{\rho}\right) + e^{-\rho B}\left(\frac{1-e^{-i_t(H-B)}}{1-e^{-i_t H}}\right)\right)\phi P_t$. Combining this expression with the down payment of $(1-\phi)P_t$, for a 30 year mortgage with initial LTV of 0.8 and an actual horizon of 15 years (approximately modal numbers for the U.S.), the decline in i causes a decline in the present value of housing costs of 22 log points. This magnitude is not especially sensitive to parameter assumptions.

D Literature Appendix

This Appendix details how other leading models of housing cycles cannot generate a boom-bust-rebound from a single shock.

Burnside et al. (2016) introduce a model in which beliefs spread through epidemiological "social dynamics" about an infrequent, permanent improvement in fundamentals. They consider cases where it is realized (a boom) or not (a boom-bust), but focus most of their attention on intermediate cases where the uncertainty about the fundamental is not realized. They show that if the skeptical agents are most certain (their pdf has the lowest "entroy" in their terminology, which they call Case 1), then the optimism spreads initially but then skeptics take over and one gets a boom-bust in prices. By contrast, if the optimists are most certain (their pdf has lowest entropy, which they call Case 2), then the optimism spreads unchecked and one obtains a boom without a bust, at least until the fundamental uncertainty is resolved. This is most easily seen in the frictionless version of their models in Figures 2 and 3 of their paper (Figures 6 and 7 have the equivalent cases in their search and matching model, which feature smoothed-out versions of these price dynamics). In their model, then, the only way to obtain a boom-bust-rebound is to have two shocks, first an expectation about fundamentals that is not realized (generating a boom-bust) followed by a fundamental shock that is realized, generating a rebound.

The model of Kaplan et al. (2020) produces a boom when agents become optimistic about future growth and a bust when they learn that optimism was misplaced, but no rebound, as can be seen in Figure 3 of their paper. This is driven by aggregate uncertainty over future preferences for housing services, which can be low with a low probability of switching to the high state, low with a high probability of switching to the high state, or high. They simulate a boom by transitioning from the low with low probability to low with high probability and a bust when they switch back (they also change labor productivity and credit conditions simultaneously, but this drives their expectations of fundamentals shock, see page 3310 of their paper for details). Again, one can only obtain a boom-bust-rebound driven by expectations in their model with three shocks – the initial switch from low with low state with low probability of switching to the high state to low state with high probability of switching to the high state, the switch back for the bust, and then a switch back again for the rebound.

Glaeser and Nathanson (2017) introduce a model in which buyers assume past prices reflect only contemporaneous demand rather than both past demand and past beliefs. This leads to a form of extrapolation that leads to persistent oscillations rather than a boom-bust-rebound dynamics. It also leads to overshooting of beliefs in the bust, which is inconsistent with the Case-Shiller-Thompson data. This can be seen in Figure 2 of their paper. This is a numerical simulation that shows the evolution of beliefs after a demand shock. One can see that they oscillate persistently and overshoot the truth on the downside. This then feeds into prices.

We conclude that our model is the only mechanism in the literature to date that can generate a boom-bust-rebound from a single shock.

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