

Do households use home-ownership to insure themselves? Evidence across U.S. cities

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Are households more likely to be homeowners when “housing risk” is higher? We show that home-ownership rates and loan-to-value (LTV) ratios at the city level are strongly negatively correlated with local house price volatility. However, causal inference is confounded by house price levels, which are systematically correlated with housing risk in an intuitive way: in cities where the land value is larger relative to the local cost of structures, house prices are higher and more volatile. We disentangle the contributions of high price levels from high volatilities by building a life-cycle model of home-ownership choices. We find that higher price levels can explain most of the lower home-ownership. Higher risk in the model leads to slightly lower home-ownership and LTV ratios in high land value cities. The relationship between LTV and risk is corroborated by LTV’s negative correlation with price volatility in the data and highlights the importance of including other means of incomplete insurance in models of home-ownership.

KEYWORDS. Home-ownership, housing risk, land share, loan-to-value, life-cycle.

JEL CLASSIFICATION. D91, E21, R21, R31.

1. INTRODUCTION

Are households more likely to own their home when “housing risk” is higher? There is a large literature on how homeowners use home equity to smooth the transmission of earnings shocks into consumption.¹ In this paper, we explore how the decision to be-

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¹Hurst and Stafford (2004) and Hryshko, Luengo-Prado, and Sorensen (2010) look at how households use mortgage refinancing decisions and home equity, respectively, to smooth unemployment shocks and earnings shocks. Leth-Petersen (2010) finds that household expenditure increases moderately after credit constraints are relaxed. Paciorek and Sinai (2012) find that the cross-sectional variance of housing consumption is lower for homeowners who have moved between cities whose house prices are strongly correlated.

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come a homeowner is influenced by exposure to housing market risk and motives for insurance.

Some people have argued that households may bring forward their home purchase as a hedge against future house price fluctuations (e.g., [Sinai and Souleles \(2005\)](#), [Banks, Blundell, Oldfield, and Smith \(2010\)](#)). But an earlier purchase would often necessitate a larger mortgage and increased risk to consumption. Using a life-cycle model, we argue that in response to differences in housing risk, otherwise similar households are more likely to differ in their liquid savings than the timing of their ownership decision. Empirically, these savings differences manifest themselves in observed variation in loan-to-value ratios (LTV). In other words, in response to higher price risk, households do not bring forward ownership decisions (nor do households that never own choose to become homeowners)—but rather, conditional on owning, they may instead reduce their LTV.

Theoretically, when markets are incomplete, there are several reasons why home-ownership may be a peculiar and attractive form of insurance against certain risks in the housing market.² In [Ben-Shahar \(1998\)](#), [Nordvik \(2001\)](#), [Sinai and Souleles \(2005\)](#), and [Ortalo-Magne and Prat \(2010\)](#), households may use home-ownership to insure themselves against the risk of changes to the local rental price (or user cost) of housing. However, [Ortalo-Magne and Rady \(2002\)](#) suggest that if a household's expected future earnings are more strongly correlated with local house prices, then it already has partial insurance through their labor earnings.³ [Ortalo-Magne and Rady \(2006\)](#) and [Banks et al. \(2010\)](#) propose and find supporting evidence for a housing-ladder theory in which households that plan on eventually owning a large house (in part because larger houses may not be available on the rental market) are more likely to own a smaller home (rather than rent) first if they live in a risky area. In this case, home-ownership partially insures young households against increases in the price of a good in their future consumption bundle (the larger house).

If financial constraints prevent some households from insuring themselves through owning, there may be important welfare improvements from policies designed to make ownership “accessible.” However, measuring the size or even the overall sign of the insurance motive on home-ownership is challenging, in part because it is difficult to isolate differences in households' exposure to housing risks that are independent from other factors that affect their home-ownership decisions.

This study proceeds in two steps. First, we present some empirical facts based on cross-city⁴ variation. As documented by [Banks et al. \(2010\)](#), households in high-risk cities are less likely to become homeowners. We also find that they are more likely

²Formal, direct means to insure against changes in house prices are limited ([Caplin, Chan, Freeman, and Tracy \(1997\)](#)), and the correlation between house prices and other financial assets is small ([Flavin and Yamashita \(2002\)](#)).

³[Davidoff \(2006\)](#) finds that households purchase less housing when they work in an industry whose workers' income are relatively more correlated with local house prices. However, he finds very small effects of the same on the probability of home-ownership.

⁴Throughout we refer to Metropolitan Statistical Areas as cities and LTV always refers to the loan-to-value at origination (that is, at the time of purchase). We will sometimes refer to the time-series standard deviation of the annual changes to log house prices within a city as its volatility.

to make a large down payment (in percentage-of-house-value terms) when they do buy. These relationships hold when controlling for household characteristics. However, causal inference is confounded by house price levels, which are systematically correlated with housing volatility in an intuitive way: in cities where the land value is larger relative to the local cost of structures, house prices are higher and more volatile. When we look at the variation in home-ownership rates and LTV by land share (the ratio of local land values to total housing costs), we see the same strong negative relationship. This is true even after instrumenting for possible endogeneity, using a measure of physical local land scarcity constructed by [Saiz \(2010\)](#). So, second, we use a quantitative life-cycle model with home-ownership to disentangle the effects of higher risk from higher price levels on the life-cycle timing of home-ownership and mortgage decisions.

We focus on the cross-sectional dimension in our empirical work, rather than the time-series, for several reasons. For one, in the data, the amount of heterogeneity both in household and price behavior is much larger across cities than within cities over time. For another, the land scarcity instrument offers a way to measure the effect of higher price levels and risk (jointly) on household behavior in the cross section. However, we cannot use it to control for endogeneity within a city over time. In this sense, our work is complementary to much of the previous literature (e.g., [Sinai and Souleles \(2005\)](#)), which exploits within-city variation in volatility (controlling for prices) to measure the insurance motive.

To measure the effect of higher volatility on home-ownership, we disentangle its impact from that of higher prices by building a life-cycle model of home-ownership choice. We account separately for innovations to house prices that are correlated with city wages and those that are not. The model has a flexible housing ladder where medium-sized housing can either be rented or owned, which enables the model to match the relative consumption of owner-occupied to rental housing in the average city according to land scarcity. Importantly, households have another means of imperfectly insuring themselves in addition to home-ownership: a risk-free bond.

In our setup, households have several potential reasons why they might use home-ownership to insure against housing risk. They may use home-ownership to insure themselves against the risk of changes to the rental price of housing, though their labor earnings will provide some partial insurance. Also, the housing-ladder assumption forces households that wish to live in large houses to own them so that the model nests the theories of [Banks et al. \(2010\)](#) and [Ortalo-Magne and Rady \(2006\)](#). Otherwise, the basic elements of our life-cycle model of home-ownership are similar to those in [Cocco \(2005\)](#), [Li and Yao \(2007\)](#), and others.

Key model parameters are chosen to match moments from the average city based on land scarcity. Cities in the model differ ex ante only in their land scarcity and, through land scarcity, their stochastic processes for house prices and wages. The model endogenously captures most of the variation by land scarcity in household behavior. Given that, we then perform counterfactual analyses where we vary one element at a time (e.g., vary the level of prices, keeping volatility constant). We find that most of the observed variation in home-ownership across cities comes from the observed variation in house price

levels and not the variation in risk. Instead, higher risk leads to slightly lower LTVs and home-ownership rates in the model.

The weak effect of risk on home-ownership comes despite the large dispersion across cities in the local volatility of house prices, which is as large as the dispersion in price levels. Furthermore, absent other factors, more risk would lead to more home-ownership in the model (and as in [Ortalo-Magne and Prat \(2010\)](#)); home-ownership is the only asset available for purchase in the model that has returns correlated with any shock. However, in our model, home-ownership also has many extra costs that potentially increase with more price volatility (such as the transactions costs for buying a house). Moreover, households also have an alternative to using home-ownership for insurance: they can accumulate precautionary, nonhousing savings instead. We find that, given the extra costs to home-ownership, young households with rising income profiles would rather save a little in liquid precautionary savings than save a lot to afford a down payment. These extra savings help explain the lower LTV ratios in the high-risk cities. The precautionary savings motive is not sufficient in our model to generate the same magnitude of LTV dispersion as in the data, so it is likely that there are other explanations beyond those discussed here that are also important in explaining the dispersion in mortgage behavior. The qualitative concurrence of volatility and LTV in the model and data should then be treated as corroborating our other, more definitive evidence that higher housing risk does not lead to more home-ownership.

In the model, dispersion in price levels has a much larger effect than risk on home-ownership choices due to the housing ladder. With a housing ladder, a household in our model must own (rent) if it wants to live in a particularly large (small) house. Higher prices in a city decrease housing consumption and, therefore, reduce home-ownership rates.

Patterns in the data corroborate our conclusions that differences in price levels cause differences in home-ownership rates through housing-ladder effects, while differences in LTV are independent of housing-ladder effects and are instead due to risk. In the data, once we condition on whether a household lives in an apartment or a house (a proxy for the housing ladder in the model), the negative correlation between home-ownership rates and price levels disappears. However, the negative relationship between LTV and volatility does not disappear after conditioning.

In the last section of the paper, we discuss why regression-based inferences of risk's effect on home-ownership may be biased. Home-ownership decisions in economies with transaction costs are durable decisions. Unsurprisingly for an (S, s) -type model, not only contemporaneous prices but also the past history of prices help determine whether a household currently owns or not. Therefore, home-ownership rates within the city economy are also a function of the history of prices. In many studies, expected housing risk is measured using the volatility of area house prices around the time that the home-ownership rate is measured.⁵ Thus, the volatility variable picks up the history dependence of home-ownership on price levels, leading to potential bias.

⁵For example, [Sinai and Souleles \(2005\)](#), [Banks et al. \(2010\)](#). [Han \(2010, 2013\)](#) looks at the variance of house price forecasts instead of house prices, where prices are forecasted using an AR(1) process and the variance of innovations is forecasted using a GARCH(1, 1) process.

1.1 *Related literature*

A key contribution of this paper is that we document systematic cross-city variation in home-ownership and LTV using both micro- and aggregate (city-level) data. [Banks et al. \(2010\)](#) use both variation within and across U.S. states and United States–United Kingdom comparisons on home-ownership. [Chiuri and Jappelli \(2003\)](#) look across developed countries for the effect of financial market imperfections on home-ownership. [Albouy \(2009a, 2009b\)](#) looks at the effects of cross-city variation in taxes and amenities. [Han \(2010\)](#) looks at the effects of housing risks on housing demand and homeowners' propensity to move, using cross-city and time variation. City-level data is appealing, since it is more plausible to assume, as we do, that financial market conditions are similar across the areas, in contrast to cross-country comparisons. But there is still enough plausibly exogenous, observable variation in price levels and risk across cities to find systematic differences in household choices.

[Han \(2008\)](#) builds a model where homeowners may choose to accumulate more housing so as to hedge against housing risks. Under the assumption of separable utility and no income risk, she provides conditions for when the hedging motive outweighs the household's normal disinclination to hold riskier assets (as in [Rosen, Rosen, and Holtz-Eakin \(1984\)](#)). [Han \(2013\)](#) finds evidence that the hedging motive may be priced into housing risk premia in markets where housing supply is constrained. Our work expands on this contribution by adding the option of renting and looking at home-ownership and borrowing behavior jointly.

There are a few studies that examine the opposite causal direction—the effect of home-ownership and borrowing decisions on prices. [Stein \(1995\)](#) proposes a model where price changes have asymmetric effects on sales due to down payment constraints. [Lamont and Stein \(1999\)](#) find that cities with high LTVs have higher rather than lower elasticities of house prices with respect to changes in income, but the instrument they use turns out to be weak. [Genesove and Mayer \(1997\)](#) find that within a specific market (the Boston condominium market), sellers with higher LTVs have higher expected time on the market and receive higher prices.

We do not offer a general equilibrium model of housing; neither do we deal with issues of regional mobility⁶ or time variation in the stochastic process for prices. By using the time-invariant differences in land scarcity across cities to calibrate the different price processes, we largely sidestep issues of endogeneity that may normally arise from examining only one side of a market. Providing structural explanations for the relationship between land values and house prices and for the existence of a housing ladder are interesting explorations that we hope the facts presented here will encourage.

The rest of this paper is as follows: Section 2 shows the striking variation in home-ownership, LTV, house prices, and housing risk across U.S. cities, Section 3 presents the model, and Section 4 discusses its parametrization. Section 5 presents our results. Section 6 discusses bias in regressions and concludes. We include an appendix here with

⁶See [Halket and Vasudev \(2014\)](#) for a model with both, but without the changes in housing supply that we would need here to close our model. [Paciorek \(2012\)](#) has a model of housing supply where the elasticities differ according to factors like land scarcity. [Lustig and Van Nieuwerburgh \(2010\)](#) look at inter- and intraregional risk sharing and home values but not home-ownership.

many further details on our empirics and model parametrization, while an additional appendix, available in a supplementary file on the journal website, <http://qeconomics.org/supp/346/supplement.pdf>, contains some further regression results and robustness exercises. Additional resources are also available in a supplementary file on the journal website, http://qeconomics.org/supp/346/code_and_data.zip.

2. HOME-OWNERSHIP AND LOAN-TO-VALUE RATIOS IN THE DATA

In this section, we present some basic facts from cross-city data. First, we show that local home-ownership rates are decreasing in price volatility (as Banks et al. (2010) document). But we cannot draw causal inference from this result, because local price volatilities are themselves closely correlated with local price levels. And indeed, home-ownership is also strongly negatively correlated with price levels across cities.

We then show that cities with high and volatile prices are also characterized by low LTV ratios. So households in these cities are less likely to own, and when they do choose to own, their purchases are less leveraged. But, again, it is not clear solely from the data whether these outcomes are insurance-type responses to local price volatility, local price levels, or something else entirely.

Local price levels and volatilities are closely related for a simple intuitive reason. They share the same statistical source: variation in land share, that is, the share of the price of the city's typical house that is attributable to the value of land (as opposed to the cost of the structure). As a result, it is not possible to empirically disentangle the impact of price volatilities from that of price levels without the use of behavioral models and counterfactuals.

2.1 Data

This study is based on a number of data sources, with our analysis restricted to the cross section of 2000 for simplicity.⁷ Ownership rates and local mean price levels (based on reported values of owned dwellings) are constructed from the Integrated Public Use Microdata Series (IPUMS) 5 percent extract of the U.S. 2000 census, organized by Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010). We use two different measures of LTV ratios, taken from the American Housing Survey (AHS) and the Monthly Interest Rate Survey (MIRS);⁸ the latter is maintained by the Federal Housing Finance Agency (FHFA). Quarterly metropolitan house price indices are also taken from the FHFA⁹ to estimate local price volatilities. Our metropolitan-level average earnings series come from the Bureau of Economic Analysis (BEA) regional program.¹⁰ Finally, we use data on local land scarcity from Saiz (2010) and land share from Davis and Palumbo

⁷In the supplementary appendix, we show that the general patterns also hold for 1990, with the exception of the systematic patterns of LTV discussed below, which have become considerably stronger since 1990.

⁸<http://www.fhfa.gov/DataTools/Downloads/Pages/Monthly-Interest-Rate-Data.aspx>.

⁹All-transactions index; <http://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx>. The Case-Shiller indices distributed by Standard & Poor's (which is the other popular publicly available data set) cover a much smaller sample of cities.

¹⁰http://www.bea.gov/iTable/index_regional.cfm.

(2008); we discuss these further below. Where survey data are used, we restrict our sample to households with heads aged 21–75,¹¹ living in houses or apartments. Throughout this study, we weight all city-level regressions and scatter plots; our weights correspond to the local sample of households with heads aged 21–75, living in houses or flats (as estimated from the census extract).

We identify cities with the set of (primary¹²) metropolitan statistical areas (MSAs), of which there are 297 in the census data in 2000. However, we restrict our sample to the 221 MSAs for which FHFA price data, BEA wage data, and the land scarcity instrument are available. Of these, 42 cities are available in the AHS (for the estimation of local LTV ratios) and in the Davis–Palumbo (2008) data on land shares (itself based on the AHS) and just 25 are available in the metropolitan MIRS LTV data, although these tend to be the most prominent cities. Further details on the city sample can be found in Appendix A.

Our measure of local house price volatility is the standard deviation of log annual changes in the FHFA local price index (measured in the first quarter of each year) over the previous 5 years (1995–2000).¹³ This approach is based on Banks et al. (2010). We estimate wage volatility in the same way using annual BEA data.

We present much of the evidence on cross-city correlations between ownership rates/LTV and price levels/volatilities graphically. But there are of course concerns that any observed effects will simply be driven by differences in local household composition. Therefore, in all cross-city analyses (including graphs), we use local ownership rates and LTV that condition on local household characteristics and household income in particular. See Section A.1 for more details.

There are concerns of large measurement error in the LTV data estimated from the AHS (Lam and Kaul (2003)), so we also present our analysis using MIRS data. The MIRS reports (among other statistics) mean LTV ratios for conventional (i.e., excluding federally guaranteed Federal Housing Authority (FHA) and Veterans Administration (VA) loans; see Appendix A for description of loan types) single-family loans in 25 cities, based on a monthly survey of mortgage lenders. However, the AHS does have a number of advantages for our purposes: it covers more cities, it covers nonconventional loans, and (being a household survey) it allows us to control for household characteristics.

Our data on land shares are taken from Davis and Palumbo (2008).¹⁴ They construct a data set containing, by city and quarter, the average local house price as well as the share of the local price that is attributable to land value and structure cost, respectively, so that

$$\text{house value}_{j,t} = \text{land value}_{j,t} + \text{structure value}_{j,t},$$

$$l_{j,t} = \frac{\text{land value}_{j,t}}{\text{house value}_{j,t}},$$

¹¹In the case of the AHS, age is calculated at purchase year.

¹²We do not aggregate these into “consolidated” areas.

¹³The supplementary file contains robustness results for alternative volatility window lengths.

¹⁴Their data are available at <http://www.lincolnst.edu/subcenters/land-values>.

where $l_{j,t}$ is then the land share for city j at time t . Their land value estimates are the residual part of house values within a city that is not explained by structure costs. Since it is partially based on the AHS, these data are only available for 42 MSAs in our sample.

As a supply-side instrument for the share of the price attributable to land, we adopt Saiz's (2010) measure of local land scarcity, based on physical constraints on housing supply. For each city, this is the share of a circle around the city center, of 50 km radius, that is either steeply inclined land (at an incline of over 15%) or water.¹⁵ Saiz estimates this variable with satellite data.

2.2 Home-ownership and LTV

As the first panel of Figure 1 shows, the local home-ownership rate (conditional on household income and other characteristics) is negatively correlated across cities with house price volatility. The predicted (ordinary least squares (OLS)) effect shows ownership rates ranging from about 0.7 (for the least volatile cities) to 0.4 (for the most), with an R squared of 41 percent. But, as the second panel shows, it is also strongly negatively correlated with price levels (see the first two panels of Figure 1): here, the correlation is 60 percent. It should be noted that New York appears to be an important outlier in these home-ownership figures; however, we argue in Section 5 that this relates to the local abundance of apartments and, anyway, the results presented here are robust to excluding it.

Unsurprisingly, volatilities and levels are themselves closely related, with a correlation of 38 percent (see Figure 2). Consequently, it is difficult to disentangle their respective effects. To see this graphically, we isolate the portion of variation in volatilities that is uncorrelated with price levels (i.e., the residuals from an OLS regression of volatilities on levels). In the first panel of Figure 3, we plot home-ownership against these volatility residuals: the effect is much weaker than before, with less than half the coefficient and

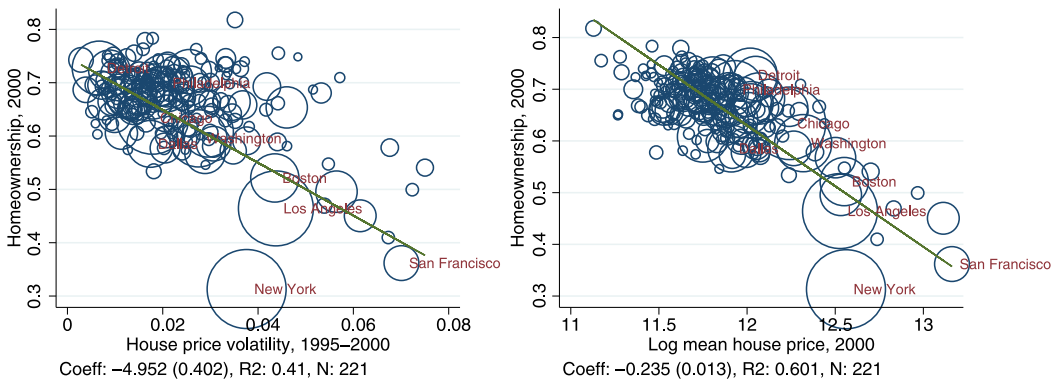


FIGURE 1. Home-ownership, price risk, and price levels.

¹⁵Mian and Sufi (2011) and Chaney, Sraer, and Thesmar (2012) similarly use this data to instrument for elasticities of supply, while Paciorek (2012) builds a model of housing supply that directly connects Saiz's measure of land scarcity to the theoretical elasticity.

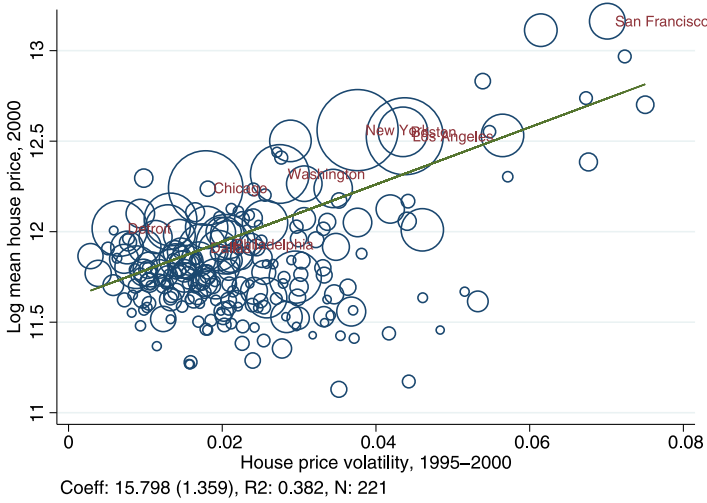


FIGURE 2. Price levels and risk.

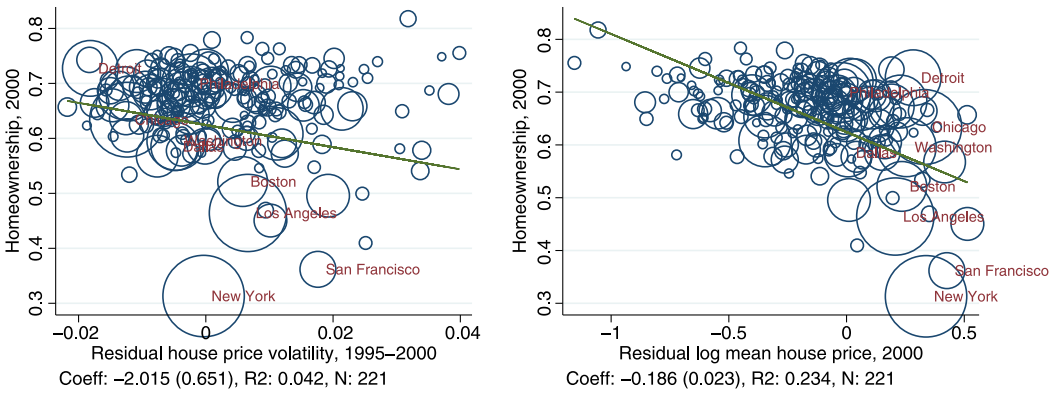


FIGURE 3. Home-ownership and residual price levels against volatilities.

an *R* squared of under 5 percent. In the second panel, we plot home-ownership against price level residuals (from a regression on volatility). The relationship is stronger than the one from the volatility residuals,¹⁶ though still much weaker than in Figure 1: the correlation is 23 percent.

As with home-ownership, average city loan-to-value ratio at origination (LTV), as measured by the AHS (controlling for household characteristics including income), is strongly negatively correlated with both local price volatility and level (Figure 4). In the first panel, moving from the lowest to highest price volatilities in the MSA sample, following the OLS-predicted line, LTV falls from 0.85 to 0.79, with an *R* squared of 19 percent. But again, unsurprisingly, the second panel shows a strong negative correlation between LTV and price levels of 46%.

¹⁶This is perhaps unsurprising given that volatility is measured with more error than levels.

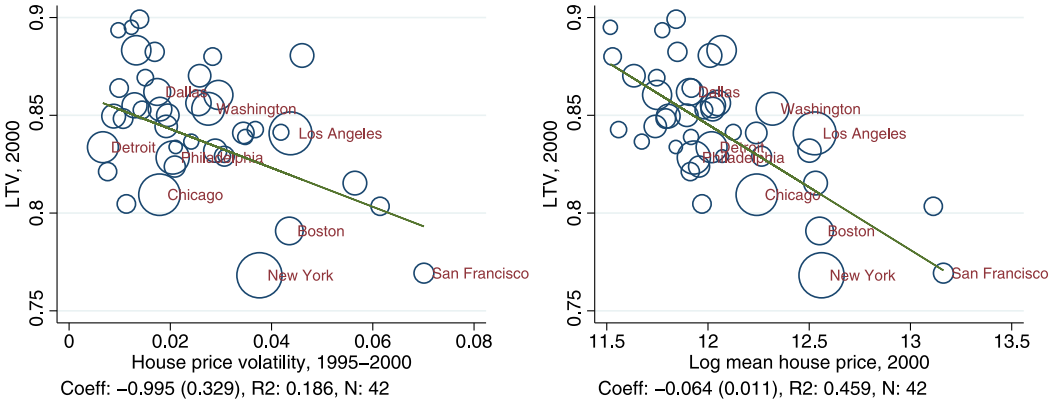


FIGURE 4. LTV (AHS), price risk, and price levels.

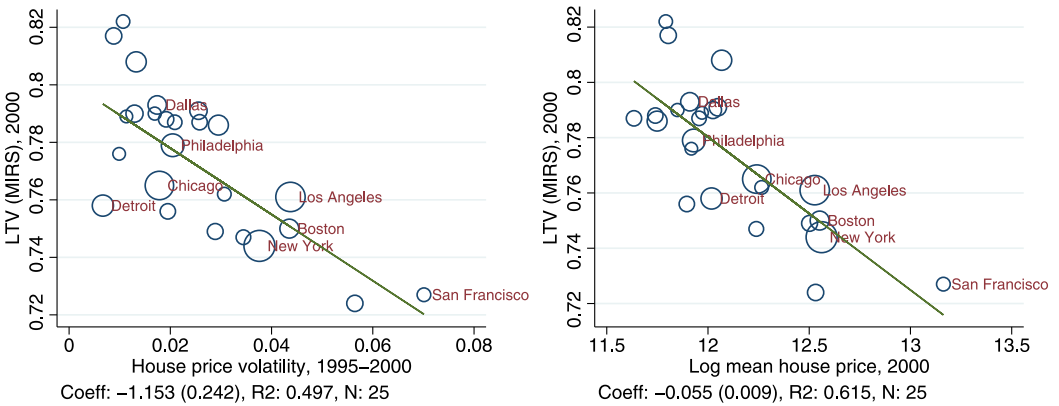


FIGURE 5. LTV (MIRS), price risk, and price levels.

These relationships also exist for the MIRS data, as Figure 5 shows. The correlation is much tighter than for the AHS data: the AHS is likely to be subject to substantial sampling and reporting error. But the magnitudes of the effects on LTV are very similar for the two data sets: for example, for volatility, the MIRS effect is -1.2 compared to -1.0 for the AHS. Notice that the mean LTV is lower for the MIRS (0.77) than for the AHS (0.84) estimates. This is in part because the MIRS sample is restricted to conventional loans only: the AHS mean for conventional loans is 0.80.

It might be argued that these LTV patterns have a supply-side explanation, due to the intricacies of American mortgage institutions. But in Appendix A, we show that geographically non-varying conforming loan limits do not drive the observed cross-city variation in LTV and neither do differences in local mortgage interest rates. It is unlikely then that any potential geographic differences in default propensities are causing the observed variation in LTV via differences in default risk premia. So in the model, we abstract from default.

Also, there may be concern that the variation in LTV is merely arising from cross-city differences in shares of mortgage holders. Indeed, almost a quarter of homeowners (in

the 5 percent census extract of 2000) do not hold mortgages. However, it turns out that the local mortgage share (among homeowners) is uncorrelated with the ownership rate itself, so it is not likely to be driving our results. Last, we also show in Appendix A that the LTV patterns are equally strong for first-time buyers as for repeat buyers, so our results are unlikely to arise from existing homeowners trading up after periods of high price growth.

To summarize, expensive and price-volatile cities tend to be characterized by low ownership rates, but also low LTV ratios. Households in these cities are less likely to own, and when they do buy a house, they take a bigger equity stake. But we cannot make causal statements based on this evidence, given the close association between local price volatility and levels.

2.3 Association between house price volatility and levels

To understand the close link between volatilities and levels, it is necessary to view house prices as the sum of two components: land values and structure costs. Price volatilities and levels are correlated across cities because they share the same statistical source: variation in local land shares, as demonstrated in Figure 6.¹⁷ The intuition is simple: compared to structure costs, the price of land tends to vary much more both across cities and within cities over time; as a result, due to a simple composition effect, cities with large land shares tend to have higher and more volatile prices. We elaborate on this in Appendix A.5.

Given the strong empirical connection between price volatility and levels, we have to disentangle their effects on household choices with a model. One approach would be to simulate ownership and LTV decisions in cities with different land shares. These cities are characterized by different local price volatilities and levels (this is what matters for the simulation), and these can be estimated from the data (by reference to their empirical relationship with land share).

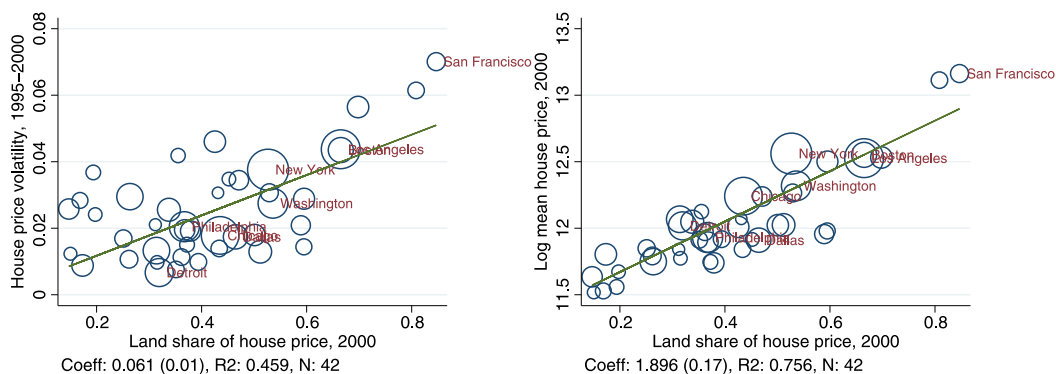


FIGURE 6. Price risk and levels, and land share.

¹⁷To ensure comparability, all data (including house prices) for this figure are taken from Davis and Palumbo (2008) for 42 MSAs.

The problem is that the correlation between land share and ownership or LTV cannot be considered causal a priori. Omitted variation in local productivity or housing demand should not be a concern, because we are controlling for household income in our estimates of ownership and LTV. But we are worried about reverse causation from ownership/LTV to price levels/volatilities and land share.

There are two ways to address this issue. The first is to simulate a general equilibrium model, where land share, price levels, and volatilities are all determined endogenously. However, the determination of these housing market outcomes is not the focus of this paper, and the equilibrium conditions would significantly complicate computation.

The second approach, which we choose, is to find a suitable instrument for land share that will only affect ownership and LTV indirectly, that is, via local price levels and volatilities. We opt for a measure of local land scarcity, described in the data section above. It is based on local geographical features, namely inclined land and water. Conditional on household income, this instrument is unlikely to affect tenure and LTV in a significant way *directly*; the effect should only come through local housing conditions (captured by price levels and volatility). The first stage is sufficiently powerful. Figure 7 shows a strong relationship between land scarcity and land share: a 1 percentage point increase in land scarcity is associated with a 0.5 percentage point increase in land share. Unsurprisingly, Figure 8 shows there is a strong positive relationship between land scarcity and price volatilities/levels as well, with correlations of 28 and 30 percent, respectively. Finally, Figures 9 and 10 show the relationships between home-ownership and LTV, and land share/scarcity.

As with land *share*, we confirm in the supplementary appendix that the entire effect of land *scarcity* on price levels comes through the land value component (and not structure costs). And the effect on price volatility is entirely a composition effect: land-scarce cities have larger land shares, and local land values are more volatile than structure costs.

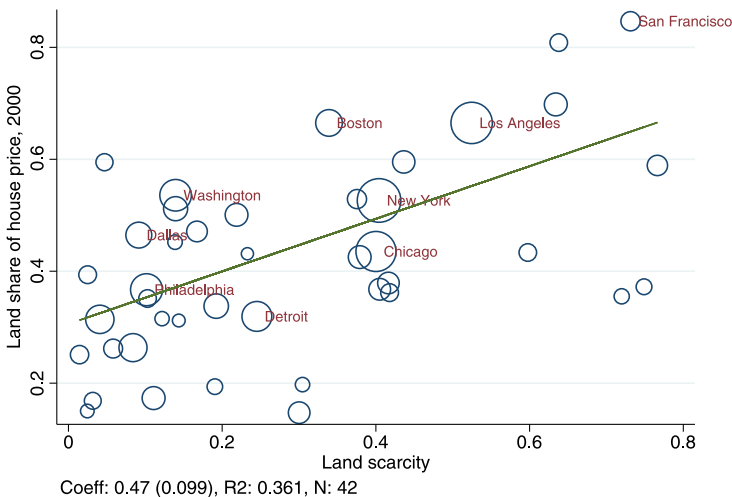


FIGURE 7. Land share and land scarcity.

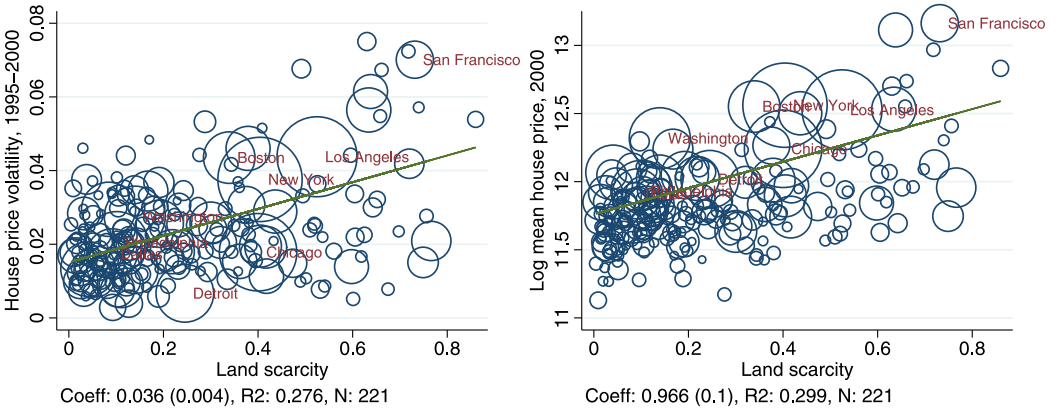


FIGURE 8. Price risk and levels, and land scarcity.

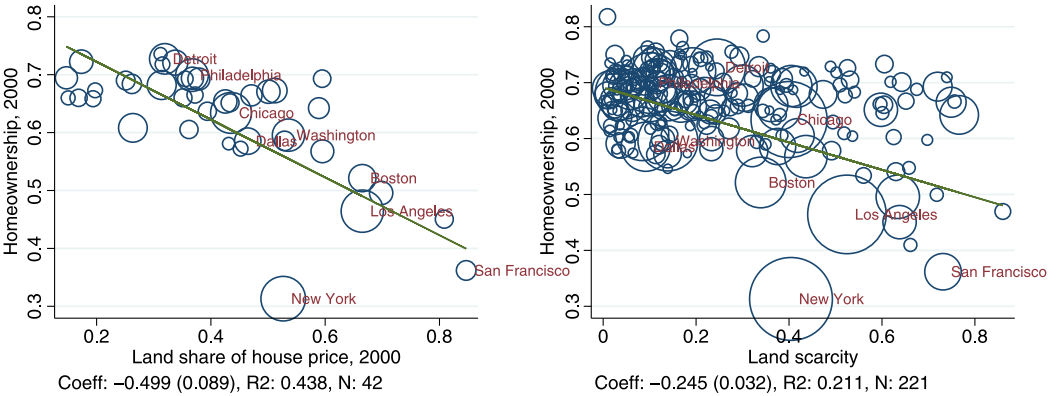


FIGURE 9. Home-ownership, land share, and land scarcity.

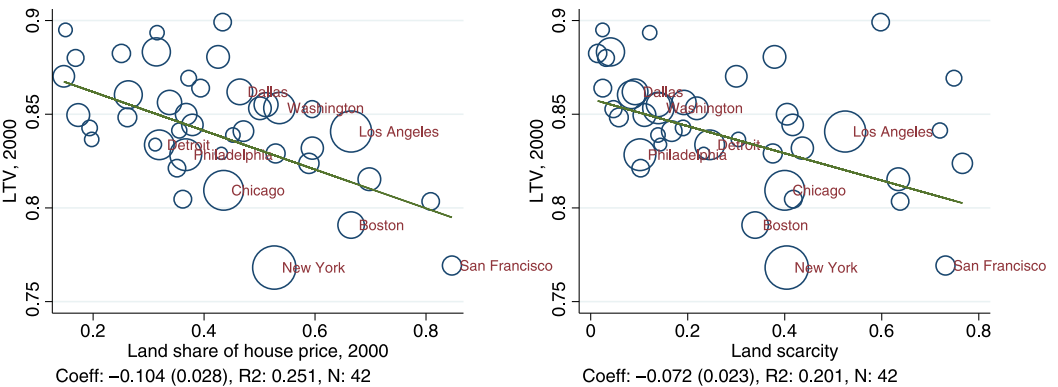


FIGURE 10. LTV, land share, and land scarcity.

3. HOUSEHOLD CHOICE MODEL

In this section, we build a life-cycle model of households that work and consume in a particular city for their entire lives. Several of the assumptions we make deserve extra attention.

We severely limit households' access to insurance in a way that should bias the model *in favor* of using home-ownership as insurance: we do not allow for intercity migration, so households cannot use moving away from the city as a source of insurance against house price changes;¹⁸ the only asset besides a house is a risk-free bond.

Though the model is "partial equilibrium," rental prices are tied to sale prices through an implied equilibrium relationship that leads to counterfactually high rental volatility. In the model, rents will be as volatile as house prices, while in the data they are clearly lower.¹⁹ Excess volatility in rents as compared to prices will again bias the model in favor of home-ownership as insurance. Also, all house price changes are common to all houses within a city; we abstract away from house-level idiosyncratic changes in prices and rents. This too favors the home-ownership-as-insurance hypothesis as idiosyncratic volatility would fall more heavily on homeowners in the model (a renter could easily move to an alternative house if she gets an idiosyncratic increase in rent).

Time is discrete and each period in the economy corresponds to 1 year in the data. Households are born at age $a = 21$ and live at most to age $a = 75$. A household is indexed by i and lives in a city, indexed by j , for its entire life. The city has a time-invariant land scarcity λ_j .

3.1 Preferences

Households have recursive preferences of the [Kreps and Porteus \(1978\)](#) type.²⁰ The household gets instantaneous utility from a nondurable consumption good c and a durable housing good h according to

$$u(c_t, h_t, a_t) = (c_t^{1-\sigma} h_t^\sigma) / F(a_t).$$

The path for the family size adjustment factor, $F: \{21, 22, \dots, 75\} \rightarrow \mathbb{R}_{++}$, is exogenous, constant across households of the same age, and known to the household at birth.²¹ The

¹⁸See [Sinai and Souleles \(2009\)](#) for a model where owning can hedge moving risk. There the risk is that a household moves to a market whose house prices are highly correlated with the household's previous market. In our model, all moves will be within-city moves and so this risk is maximized.

¹⁹For instance, see [Campbell, Davis, Gallin, and Martin \(2009\)](#) and [Verbrugge \(2008\)](#).

²⁰These preferences nest time-separable preferences but allow for the separate consideration of intertemporal smoothing (savings) and smoothing across states within a given period (risk aversion).

²¹[Attanasio, Banks, Meghir, and Weber \(1999\)](#), [Gourinchas and Parker \(2002\)](#), [Cagetti \(2003\)](#), and [Li and Yao \(2007\)](#) each let family size affect a household's discount factor. In [Gourinchas and Parker \(2002\)](#) and [Li and Yao \(2007\)](#), the life-cycle profile for family size is deterministic and homogeneous across households of the same age. [Attanasio et al. \(1999\)](#) and [Cagetti \(2003\)](#) let the profiles vary by education. [Browning and Lusardi \(1996\)](#) have a stochastic process for family size (see their paper for more references). [Gervais \(2002\)](#), [Campbell and Cocco \(2003\)](#), [Li and Yao \(2007\)](#), and [Diaz and Luengo-Prado \(2008\)](#) all use Cobb–Douglas preferences over nondurable consumption and housing that are consistent with evidence from [Davis and Ortalo-Magne \(2011\)](#) that housing expenditure shares are approximately constant across cities.

household's utility at time t , V_t , is then given by the composite of its instantaneous utility and its future expected utility,

$$V_t = [(1 - \beta)u(c_t, h_t, a_t)^{1-\phi} + \beta(\mathcal{R}_t V_{t+1})^{1-\phi}]^{1/(1-\phi)},$$

where future expected utility is given by $\mathcal{R}_t V_{t+1} = (\mathbb{E}_t[V_{t+1}^{1-\gamma}])^{1/1-\gamma}$. γ measures risk aversion, and ϕ is the inverse of the intertemporal elasticity of substitution. Additive utility is a special case where $\phi = \gamma$.

Households get utility at death from bequeathing wealth, $V_{t+1}(\cdot, a_t = 75) = (b_{t+1} + p_{t+1}^j h_t)^{1-\sigma}$.

3.2 Labor earnings

Households receive labor earnings Y_t^{ij} until an exogenously set retirement age R , after which they receive a pension. Y_t^{ij} contains two parts: idiosyncratic components and a city-specific component. The city-specific component W_t^j , which we call wages, follows a geometric random walk. The idiosyncratic components are L_t^i , a geometric random walk with deterministic age-dependent drift, and a transitory shock ρ_t^j as in, for example, Storesletten, Telmer, and Yaron (2004a):

$$\begin{aligned} Y_t &= L_t^i W_t^j \varrho_t^i, \\ L_t^i &= \exp f(a_t) L_{t-1}^i \psi_t^i, \\ W_t^j &= W_{t-1}^j \nu_t^j, \end{aligned}$$

where $\ln \psi_t^i \sim \mathcal{N}(-0.5\sigma_\psi^2, \sigma_\psi^2)$, $\ln \varrho_t^i \sim \mathcal{N}(-0.5\sigma_\varrho^2, \sigma_\varrho^2)$, and $\ln \nu_t^j \sim \mathcal{N}(\mu_\nu - 0.5\sigma_\nu^2(\lambda_j), \sigma_\nu^2(\lambda_j))$. The variance of innovations to wages, ν_t^j , can differ across cities according to their land scarcity; however, all cities have common drifts. After retirement, the household gets a proportion (adjusted for growth in the city) of its final salary, $Y_t = \zeta L_R^i W_t^j$. All households' income is taxed at a rate t_y .

3.3 Housing market

At any time, homes may either be rented ($\tau_t^i = 0$) or owned ($\tau_t^i = 1$), but not both simultaneously. There is a housing ladder that forces households to choose rented housing from the set H^r and owner-occupied housing from the set H^o .

Housing can be bought at a unit price p_t^j , which contains two components: one correlated with labor earnings and one uncorrelated with labor earnings,

$$p_t^j = Q_t^j W_t^j,$$

where $Q_t^j = Q_{t-1}^j \varepsilon_t^j$ and $\ln \varepsilon_t^j \sim \mathcal{N}(-0.5\sigma_\varepsilon^2(\lambda_j), \sigma_\varepsilon^2(\lambda_j))$. The variance of innovations to the uncorrelated component, ε_t^j , like those of the correlated component, differs across cities; city-specific drifts remain common.²²

²²There is an extensive literature (e.g., Case and Shiller (1989)) that documents a small predictable component in house prices, and Han (2010, 2013) uses price processes with some predictability. For computa-

An owner pays proportions t_p and δ_j of the value of the house each period toward property taxes and maintenance, respectively. The housing maintenance means houses do not depreciate and the maintenance required may vary across cities. A household may not “build on” to its house; to adjust the size of an owner-occupied house, it must sell its current one and buy a new house. Each time a household buys a house, it pays a fraction θ_b of the value of the house as a transaction cost.

A renter pays only the spot rental price per unit of housing s_t^j , which we set so that a risk-neutral landlord would be indifferent between renting or selling the house, subject to paying income tax on its rental income,

$$s_t^j = \frac{t_p + \delta_j + \frac{r_b - \mu_v}{1 + r_b}}{1 - t_y} p_t^j,$$

where r_b is the risk-free interest rate at which households and landlords can borrow.

Households have three potential motives for owning: the cost of renting exceeds the user cost of owning due to the taxation of rental income, the housing ladder restricts the size of rental housing, and several insurance motives.

3.4 Assets

Besides housing, the only other financial asset for the household is a risk-free one period bond, b_{t+1}^i , which pays r_l to savers but costs (net) $r_b > r_l$ to borrow. Households may borrow at this rate, subject to a borrowing constraint. Housing is the sole form of collateral. We model this by giving households a home equity line of credit.²³ The LTV at the time of purchase is simply the ratio $-\frac{b_{t+1}^i}{p_t^j h_t^i}$.

When purchasing a home, households can borrow up to $(1 - d)$ of the value of the house, where d is the down payment constraint. Thereafter, as long as they continue to be homeowners, agents may borrow up to $(1 - d)$ of the value of the house. They may also choose to roll over their debt after making an interest payment. So at any time, the borrowing constraint is

$$b_{t+1}^i \geq \min\{-(1 - d)\tau_t^i p_t^j h_t^i, (1 - 1_m)b_t^i\},$$

where 1_m is an indicator variable that equals 1 if the household chooses to move in the period.²⁴

For additional reasons, we follow Flavin and Yamashita (2002), Campbell and Cocco (2003), Cocco (2005), Yao and Zhang (2005), Li and Yao (2007), and Diaz and Luengo-Prado (2008) and assume shocks to house prices are permanent.

²³We also call this a mortgage throughout. It is worth reiterating that there is only one asset in the model, the risk-free bond; households are not allowed to simultaneously hold “savings” and a “mortgage.” Such an alternative, if allowed, would generally be unattractive due to the higher interest rate on debt. However, because of the borrowing constraints in the model, some households might find it slightly attractive. Modeling both assets separately would require an extra state variable though.

²⁴This borrowing constraint is different from the more typical one that restricts borrowing to be weakly less than some percentage of the house value ($b_{t+1}^i \geq -(1 - d)\tau_t^i p_t^j h_t^i$). With risky house prices, for a house-

If the household chooses to sell its home, it must pay off all existing debt, though another loan can be taken out if another home is purchased. A household that does not have positive total cash-in-hand (housing wealth plus financial wealth plus current income) will not be able to pay off the mortgage it has (the debt it owes) on its home and will not choose to move in this period. We do not allow the household to choose to default (see [Jeske and Krueger \(2005\)](#) for a model with mortgage default), but households can default implicitly by dying. After retirement, we do not allow households to take out new loans, but they may continue with their old loan.²⁵ This effectively ensures in our calibrated economy that all households reach age 75 debt-free.

Newborn households are “born” with no housing, but they draw their initial wealth from a distribution Π_b , which is a probability distribution on \mathbb{R}_+ .

3.5 Household's problem

The problem of the household is to choose consumption, house size and ownership, and savings, given its permanent and transitory earnings components, housing and assets at the beginning of the period, and prices, subject to budget, borrowing, and choice-set constraints, and the initial condition and laws of motion for Q_t^j , W_t^j (which we do not repeat below) for all variables:²⁶

$$\begin{aligned}
 & V(a_t, L_t, \varrho_t, b_t, \tau_{t-1}h_{t-1}; Q_t^j, W_t^j, \lambda_j) \\
 &= \max_{c_t, h_t, b_{t+1}, \tau_t} [(1 - \beta)u(c_t, h_t, a_t)]^{1-\phi} \\
 &\quad + \beta(\mathcal{R}V(a_{t+1}, L_{t+1}, \varrho_{t+1}, b_{t+1}, \tau_t h_t; Q_{t+1}^j, W_{t+1}^j, \lambda_j))^{1-\phi}]^{1/(1-\phi)} \\
 \text{s.t. } & c_t + b_{t+1} + h_t((1 - \tau_t)s_t^j + \tau_t p_t^j(\delta_j + t_p + 1 + 1_m \theta_b)) \\
 &\quad \leq b_t(1 + r) + Y_t(1 - t_y) + h_{t-1}\tau_{t-1}p_t^j, \\
 & b_{t+1}^i \geq \begin{cases} \min\{-(1 - d)\tau_t^i p_t^i h_t^i, (1 - 1_m)b_t^i\}, & \text{if } a_t \leq 65, \\ \min\{0, (1 - 1_m)b_t^i\}, & \text{else,} \end{cases} \\
 & r = \begin{cases} r_l, & \text{if } b_t \geq 0, \\ r_b, & \text{if } b_t < 0, \end{cases} \\
 & c \geq 0, \quad \tau_t h_t \in \{0, H^o\}, \quad (1 - \tau_t)h_t \in \{0, H^r\}, \quad \tau_t \in \{0, 1\}.
 \end{aligned}$$

4. PARAMETRIZATION

In Section 5, we will compare how households that live in cities with different expected prices and volatilities behave differently in both the model and the data. Since our model

hold near the typical borrowing constraint, a fall in the value of a house means the household must reduce the amount borrowed. If house price volatility is large enough, the effective down payment constraint (the amount the household could borrow and still be able to repay in any state of the world next period) may be much tighter than the actual (d).

²⁵That is, a retired household's borrowing constraint is $b_{t+1}^i \geq \min\{0, (1 - 1_m)b_t^i\}$.

²⁶Variable superscripts are dropped where obvious.

TABLE 1. Invariant parameters.

Parameter	Description	Value
β	Discount factor	0.95
σ	Housing's share in utility	0.30
ϕ	Inverse intertemporal elasticity of substitution (IIES)	5
γ	Risk aversion	3
t_y	Income tax	0.20
t_p	Property tax	0.01
σ_ϱ	Std. dev. of the idiosyncratic transitory shock	0.25
σ_ψ	Std. dev. of the idiosyncratic permanent shock	0.098
r_b	Interest rate on loans	6%
r_l	Interest rate on savings	4%
d	Down payment	0.1
θ_b	Home buyer's transaction cost	0.08
ζ	Replacement rate for pensions	0.6

is partial equilibrium and we have argued that differences in land scarcity are plausibly exogenous to differences in home-ownership rates and LTV except through the cross-city variation in price behavior, the cities that we simulate with our model will differ ex ante only by their land scarcity. Parameters indexed by j vary ex ante across cities according to their land scarcity, λ_j . All other parameters remain constant across cities.

In this section, we discuss the calibration/estimation of some key parameters; the calibration of the remainder are discussed in Appendix B (see Table 1 for their values). These key parameters are all those that vary across cities and the housing-ladder parameters in H' and H^o . These are estimated in three steps.

Step 1. We initialize the model so that the cross section of relative prices and wages in a particular year, 2000, is the same in the model as in the data. We assume σ_ν^j , σ_ε^j , p_{2000}^j , W_{2000}^j , and δ^j vary across cities in the model with respect to land scarcity according to the same (linear) relationship estimated in the data:

$$\sigma_\nu^j = \alpha_\nu + \beta_\nu \lambda_j, \quad (1)$$

$$\sigma_\varepsilon^j = \alpha_\varepsilon + \beta_\varepsilon \lambda_j, \quad (2)$$

$$p_{2000}^j = \alpha_p + \beta_p \lambda_j, \quad (3)$$

$$W_{2000}^j = \alpha_w + \beta_w \lambda_j, \quad (4)$$

$$\delta^j = (1 - \alpha_\delta - \beta_\delta \lambda_j) \delta_h. \quad (5)$$

We run OLS regressions on equations (1)–(4), with land scarcity as the independent variable and a range of dependent variables: local price volatility (the standard deviation over annual growth rates, 1995–2000), wage volatility, price level, and wage level. We take local wage levels from the BEA data of 2000, and estimate price levels (as discussed

above) from the 5 percent census extract of 2000.²⁷ The δ^j are set using the relationship between land share and maintenance described below. This entire step can be done without computing the household's problem.

Step 2. We simulate a set of cities with different land scarcities, each with 200,000 households. Each household is born at some date at most 54 years before 2000. For each city, we draw realizations of the annual innovations to prices and wages so that they equal their 2000 relative value in 2000.

Step 3. We choose the parameters in the housing ladder so that specific moments in the simulated model data best match those in the data in 2000. The values of the housing-ladder parameters are found by repeatedly computing the household's problem for different values of the parameters (and repeating Step 2) and choosing the pair that provides the best match.²⁸

4.1 Housing

We assume that a city's housing supply is fixed and that homeowners pay a maintenance cost to replace depreciated housing capital. So the (growth-adjusted) relationship between housing depreciation and housing investment is (abusing notation)

$$\delta_h = \frac{I_h - \Delta(pH)}{pH}.$$

For the aggregate value of housing, pH , we use nonfarm owner-occupied housing from the National Income and Product Accounts' (NIPA's) *Historical-Cost Net Stock of Residual Fixed Assets* table. Investment in housing is computed using nonfarm owner-occupied housing from NIPA's *Historical-Cost Investment in Residential Fixed Assets*. This gives $\delta_h = 0.017$. These values from NIPA are the value of the structures and do not include the value of land. For any city, j , $1 - \alpha_\delta - \beta_\delta \lambda_j$ is the share of structure costs in house value. So for each city, we set $\delta_j = (1 - \alpha_\delta - \beta_\delta \lambda_j) \delta_h$, where $\alpha_\delta = 0.306$ and $\beta_\delta = 0.470$ are the intercept and slope, respectively, of the linear relationship estimated between land share and land scarcity (see the supplementary appendix for further details). The rent-to-price ratio in the cities will therefore vary slightly with land scarcity due to changes in δ_j .

We allow households to choose any size rental up to a maximum: $H^r = (0, \bar{h}^r]$. We impose a minimum owner-occupied house size but no other restriction: $H^o = [\underline{h}^o, \infty)$. We use the model to set \underline{h}^o and \bar{h}^r so that (i) cities with the mean land scarcity in the model have an average home-ownership rate that matches the fitted home-ownership rate at the mean land scarcity in the data and (ii) the mean ratio of owner-occupied house sizes to rental house sizes in the model matches the fitted ratio (in square feet) in the data. Matching the two moments, the home-ownership rate and the relative housing sizes, identifies the two parameters uniquely. We do not have a formal proof, but

²⁷Further details about the estimates of the α and β coefficients as well as estimates using alternative windows for measuring volatility can be found in the supplementary appendix.

²⁸A simulated method of moments computed over a grid of potential parameter values.

casual introspection (if \bar{h}^o increases, then \bar{h}^r must decrease to keep the ownership rate constant, but \bar{h}^r must increase to keep the relative house size ratio constant) and all computation thus far confirm it.

4.2 Prices

To estimate the parameters in the price processes, we match year/city panels of house prices (from the FHFA) and average wages (from the BEA). These data are used to calculate, for each city, a covariance matrix of annual growth rates of wages and house prices over 1995–2000.²⁹ We have assumed in the model that ν_j^i affects prices and wages equally. So we could use either wage growth variance or price–wage growth covariance as alternative estimates for $\sigma_\nu^2(\lambda_j)$. The mean (across cities) wage growth variance (0.00021) is almost twice as large as the mean price–wage growth covariance (0.00011). However, if we restrict our attention to the 30 largest cities in the sample, the two statistics do match (they are both 0.00015). We choose to use the wage growth variances to estimate α_ν and β_ν .

Conditional on α_ν and β_ν , house prices are used to estimate α_ε , β_ε , and β_p . Due to the homogeneity in our model and since we only set the housing-ladder parameters in a later step, we are free to normalize α_w and α_p . Table 2 shows some moments for the key parameters. The results from the instrumental variable regressions are available in the supplementary appendix.

5. RESULTS

5.1 Moments in models and data

Table 3 shows the results from the average city by land scarcity compared to the data. Since the house size parameters were chosen so that the model matched the data on the

TABLE 2. Matched parameters.

Parameter	Description	Mean Value	Interquartile Range
σ_ν	Std. dev of shock to wages (corr with house prices)	0.012	0.010–0.013
σ_ε	Std. dev of idiosyncratic shock to house prices	0.022	0.015–0.025
\bar{h}^o	Min owner-occupied house size	4	4–4
\bar{h}^r	Max rental house size	8.25	8.25–8.25
δ_j	Housing maintenance	0.0112	0.012–0.010
P_{2000}	Price level in 2000	1	0.81–1.09
W_{2000}	Wage level in 2000	1	0.96–1.02

Note: Price and wage levels are normalized so that prices and wages are equal to 1 for all cities with the average level of land scarcity in the year 2000. The units on the house size parameters are median household earnings for 21 year olds, and these parameters are not changed across cities. The “interquartile range” is the difference in the predicted value of the parameter (as predicted from an OLS regression on land scarcity) between the city at the 25th and 75th percentile of the land scarcity distribution.

²⁹Results are mostly robust to changes in sample dates with the exception that β_ε would go up if the post-2007 data are used and α_ε would go up if the data included either the recent bust or the late 1980’s bust.

TABLE 3. Model fit.

	Data Source	City Sample	Data	Model
Home-ownership rate	Census	221	0.62	0.63
Home-ownership rate under 65	Census	221	0.61	0.61
Owned/rented home size ratio	AHS	42	2.07	2.05
LTV	AHS	42	0.84	0.71
LTV (conventional loans only)	AHS	42	0.80	0.71
LTV (conventional loans only)	MIRS	25	0.77	0.71

Note: This table compares key parameters in the data with the model. The third column shows the number of cities on which the data estimates are based (see Appendix A for further details). The fourth column gives the mean (weighted by census sample size) for the relevant variable across those cities (NB: restricting the larger samples to 25 cities has only a negligible effect on the estimated means). The AHS LTV estimates are conditional on household characteristics; see Appendix A for further details and the estimation procedure. We also report the mean LTV across cities for the sample of conventional loans in the AHS. This makes it more comparable with the LTV estimate from the MIRS (the final row), whose sample excludes nonconventional loans.

TABLE 4. Home-ownership profile: data and model.

Age	Data Source	City Sample	Data: Mean	Model: Mean
21–35	Census	221	0.38	0.25
36–50	Census	221	0.67	0.72
51–65	Census	221	0.76	0.88
66–75	Census	221	0.78	0.68

Note: See notes under Table 3. This table reports mean ownership rates by age group.

home-ownership rate and relative house sizes, it is not surprising that we attain a very good fit along these lines. The model also matches the data well if we consider only those households 65 years old and younger. Given the model's relatively simple characterization of post-retirement life, this is also not surprising. Table 4 shows that the model also matches the profile of home-ownership relatively well, though there are too few young and too many middle-aged homeowners. We conjecture that additional heterogeneity, particularly in family size (which here does not vary within age), would cure the excess steepness.

Though no parameters were chosen to match the LTV rates (conditional on taking a loan), the model is able to match the data from the AHS relatively well; however, it is somewhat lower. This is perhaps a result of only having one nonhousing asset in the model. In the data, we do not observe the mortgage net of other financial assets, which is the relevant variable in the model.

Table 5 shows the slopes of linear regressions of city-level home-ownership and LTV on land scarcity in the data and in the model. The model is able to explain much of the difference in home-ownership and LTV across cities. A 10 percentage point increase in land scarcity implies a decrease in home-ownership of 2.5 and 2.0 percentage points in the data and model, respectively. Likewise, the same increase in land scarcity implies a decrease in LTV of 0.7 and 0.6 percentage points in the data and model, respec-

TABLE 5. Slopes with respect to land scarcity.

Age	Own: Data	Own: Model	LTV: Data (AHS)	LTV: Data (MIRS)	LTV: Model
All ages	-0.25**	-0.20 [†]	-0.07**	-0.08**	-0.06 [†]
21-35	-0.23**	-0.32	-0.09**	N/A	-0.16
36-50	-0.24**	-0.22 [†]	-0.05**	N/A	0.04
51-65	-0.18**	-0.09	-0.08	N/A	0.22
66-75	-0.17**	-0.13 [†]	0.02	N/A	0.00 [†]

Note: This table compares cross-city slopes of ownership rates and LTV with respect to land scarcity, for both the data and model. For the data, reported coefficients are taken from cross-city OLS regressions (weighted by census sample size) of mean ownership or LTV (for the age group in question) on land scarcity. The local ownership and AHS LTV estimates are conditional on observed household characteristics (see Appendix A for the estimation procedure), but not the MIRS. Also, there is no available disaggregation of the MIRS data by age group. Cross-city OLS regressions on simulated data weight all cities equally and do not control for household characteristics (since the sample of households in each city is the same). ** signifies that the estimate from the data is significant at the 95 percent confidence level. [†] signifies that the model estimate falls within the 95 percent confidence interval of the data.

tively. Generally speaking, the difference in home-ownership rates across land scarcity declines with age, a pattern that the model matches.³⁰

As in the data, the relationship between LTV and land scarcity for the most part becomes less negative with age, turning positive for the older ages (although the coefficients are not significant for these ages). The shortcoming of not being able to observe net financial assets in the data is likely to be more acute for older households that have accrued savings, and perhaps explains why the increase in the coefficients is sharper in the model than in the data. Fortunately, late-life LTV figures are relatively inconsequential for the cross-city dispersion: in the data, 80 percent of new loans are taken by households under 50 years old and 97 percent by households under 65 years old. Thus the restriction that, in the model, households over 65 are not allowed to take new loans is probably not important for the LTV results.

5.2 Counterfactuals

In the data and the model, cities with high price volatility have lower home-ownership rates and LTVs, but they also have high price levels and high wages, among other differences. To disentangle these different contributions, we simulate five variations to the baseline model economy, each time allowing only one of the parameters to vary and keeping the other parameters at their mean land scarcity values. Since the parameters have different implicit units, for comparability we again look at slopes with respect to land scarcity. In two of the counterfactuals, we allow the variances to vary by land scarcity according to equations (1) and (2), respectively. In a third and fourth, we simulate cities with different land scarcities so that they have relative prices or wages in the year 2000 that vary according to equations (3) and (4), respectively. In the final counterfactual, we vary the maintenance in cities according to equation (5). Table 6 shows the coefficient from regressing home-ownership and LTV on land scarcity from each of the

³⁰This may explain why Sinai and Souleles (2005) find a positive effect on ownership from the interaction between mobility (which is negatively correlated with age) and rent volatility (which is positively correlated with land scarcity).

TABLE 6. Contribution from various elements: slopes with respect to land scarcity.

Parameter	Home-Ownership: Slopes	LTV: Slopes
σ_v	-0.02	-0.01
σ_ε	-0.03	-0.01
δ_j	-0.01	0.01
p_{2000}	-0.23	0.02
W_{2000}	0.04	0.00

counterfactual economies, so highlighting each parameter's contribution to the cross-city differences generated by the model.

The largest contributor to the cross-city dispersion in home-ownership is dispersion in the *level* of house prices. Changes in risk do affect home-ownership slightly, but the results show that higher risk reduces home-ownership; households, on balance, do not use home-ownership to insure themselves against housing risk. Instead, the model suggests higher risk leads to lower LTVs.

5.2.1 Differences in price levels and home-ownership Differences in prices create differences in home-ownership through the housing ladder. In both the data and the model, households live in larger houses when they live in cheaper cities, and the difference in sizes is larger for owners than for renters.³¹ So, households in cheaper cities, living in larger houses, are more likely to choose to own due to a binding maximum rental constraint, while households in the expensive cities are more likely to rent due to a binding minimum owner-occupied house size constraint. Likewise, differences in wages work similarly, though the total effect is smaller. Everything else equal, higher wages in the land-scarce cities lead to higher housing consumption and, due to the housing ladder, higher home-ownership (consistent with findings from [Coulson and Fisher \(2009\)](#)).

In our simulations, households respond to lower prices by increasing housing consumption, which leads to higher home-ownership due to the housing ladder. Therefore, households that adjust their tenure decision in response to local prices are likely doing so to adjust their housing consumption. And so, holding housing consumption fixed, we should expect to see no effect of price on tenure decisions. In other words, prices affect tenure choices only through the price's effect on housing consumption.

In the data, a critical margin of adjustment in housing consumption is between apartments and houses.³² According to our census sample, almost all houses (85 percent) are owned and almost all apartments (87 percent) are rented. Interestingly though,

³¹The square-footage difference in the data (using the AHS, all reported differences statistically significant) between the 75th percentile and the 25th percentile city by land scarcity is 21 percent, while in the model, the size difference is 19 percent of the average size house. For owners, the difference in house size is 15 percent and 17 percent in the data and the model, respectively. For renters, the difference is 13 percent and 9 percent, respectively.

³²Based on U.S. census data, we have defined an "apartment" as a housing unit that shares its structure with one or more other housing units; a "house" is a single-unit structure. Note that "houses" need not be entirely detached from other structures: a housing unit attached to another unit by a full-height dividing wall, that goes from ground to roof, is here defined as a house.

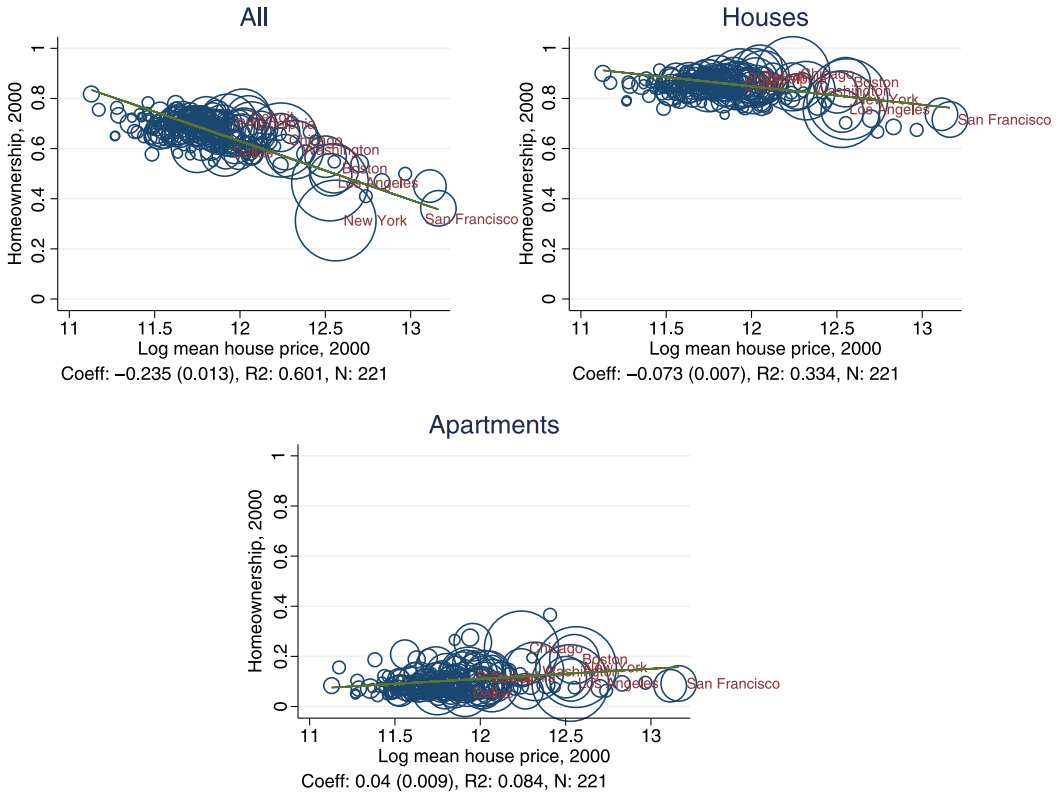


FIGURE 11. Home-ownership–price relationship by dwelling type.

among owned properties, LTV ratios (predicted for 2000 from the AHS) are almost identical across dwelling types: 0.84 for houses and 0.86 for apartments.³³

In Figure 11, we plot the relationship between conditional home-ownership rates and prices across MSAs by dwelling type: full sample, houses only, and apartments only. The estimated effect of prices on ownership rates is more than three times as large for the full sample as for the houses-only sample, and the relationship for apartments is actually slightly positive. Clearly then, adjustments in housing consumption (in this case, between dwelling types) play an important part in driving the overall price–ownership relationship. Also, Figure 11 suggests that New York City is an outlier in Figure 1 because it has more apartments per unit of housing than the typical city with its land scarcity.

In contrast to the tenure choice, the LTV decision (conditional on ownership) is not strongly related to housing consumption. This suggests the mechanism driving these LTV results is independent of the housing ladder (instead, we argue below that insurance motives are important). In Figure 12, we plot LTV–price relationships for the full sample, and separately for houses and apartments. This time, the effects of log prices are negative for *both* dwelling types; they are also very similar in magnitude: -0.060 for

³³These two statistics are means of local conditional LTVs across the 42 cities in our sample (for houses and apartments respectively), where the conditional LTVs are estimated as described in Appendix A.

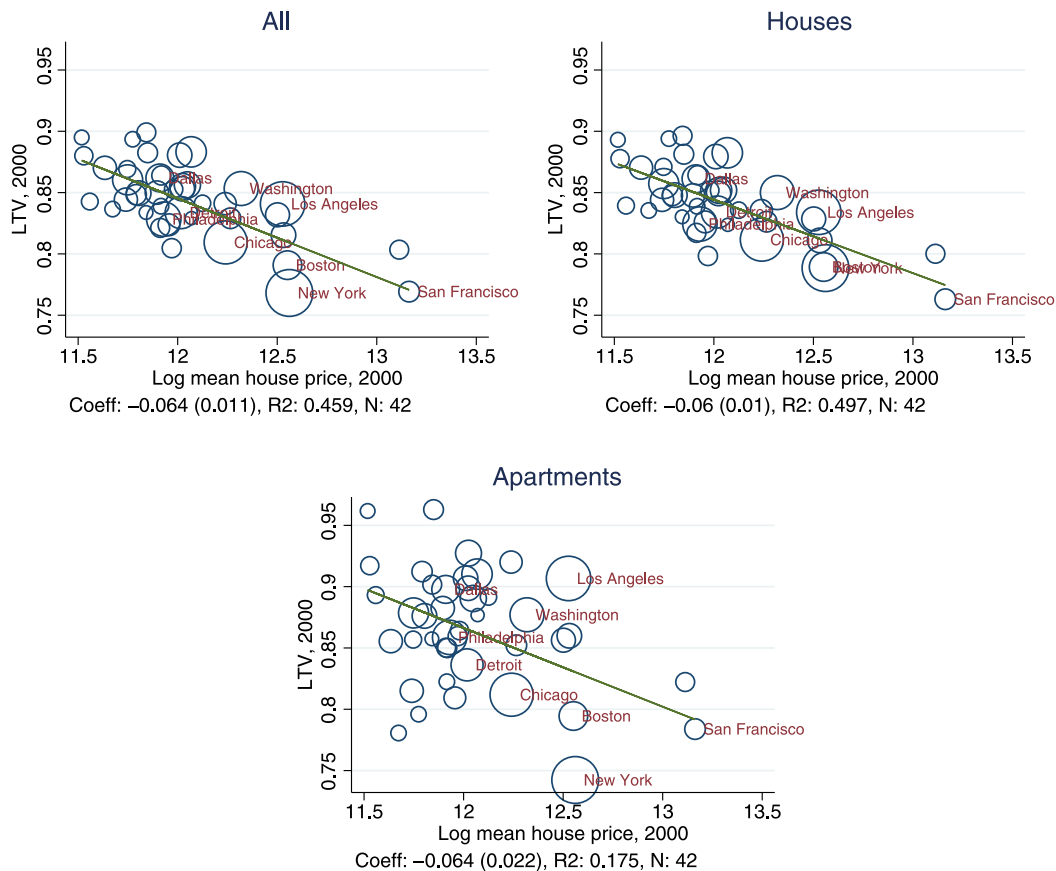


FIGURE 12. LTV-price relationship by dwelling type.

houses and -0.064 for apartments. It is clear that composition effects are not driving the relationship for LTV.

5.2.2 Home-ownership and within-city differences In a general equilibrium model, the home-ownership-as-insurance effect may lead to higher price-to-rent ratios (as in Nordvik (2001), Sinai and Souleles (2005), Han (2013)) rather than higher home-ownership rates in cities with high price volatility.³⁴ So Sinai and Souleles (2005) look at how differences in rental volatility across cities tilts the home-ownership-by-age profile within cities. They find that riskier cities have steeper profiles, increasing faster before age 60 and then decreasing faster afterward.³⁵ This evidence is consistent with

³⁴Ortalo-Magne and Prat (2010) build a model where insurance effects imply that home-ownership and price-to-rent ratios are positively correlated.

³⁵More exactly, they impute a household's expected duration in a home using the proportion of households within the same age-occupation-education cell in an MSA that did not move the previous year. They find that propensities to own are increasing in this proxy interacted with rental volatility (see Table II, columns 2 and 3 from their paper). Halket and Vasudev (2014) show that differences in expected duration vary substantially by age—in part due to endogenous differences in tenure. Sinai and Souleles's (2005) interaction result implies a steeper age profile in riskier cities (see Figure I from their paper).

TABLE 7. Ownership slopes with respect to land scarcity for select counterfactuals.

Age	σ_v	σ_ε	P_{2000}
21–35	–0.035	–0.046	–0.23
36–50	–0.026	–0.049	–0.19
51–65	–0.005	–0.010	–0.14
66–75	0.003	–0.007	–0.39

the hypothesis that households use home-ownership as insurance: younger households (which are more likely to move shortly) are more likely to rent when volatility is high, whereas older households are more likely to own.

In our data and model, we too find a steeper profile in cities with high land scarcity and thus high volatility.³⁶ So we can use our counterfactuals to find the cause of the change in the steepness of the profiles. Table 7 shows that the age profiles of home-ownership are steeper in riskier cities and in more expensive cities. Higher risk leads to lower home-ownership for all age levels. However, the change in steepness due to changes in the volatilities is consistent with the insurance hypothesis: both the σ_v and the σ_ε slopes increase by about 0.03 from the age 21–35 cell to the age 51–65 cell. If, like Sinai and Souleles (2005), we used only the change in the steepness of the profiles to identify the effect of risk on home-ownership, we would find that more risk leads to more home-ownership. Quantitatively though, the change in steepness due to changes in price levels is almost three times as large as either change from the volatility parameters, implying that a sizable proportion of the effect that Sinai and Souleles (2005) find may not be due to risk. Instead, our model finds that most of the observed large change in age profiles is because the housing ladder is more relevant at earlier ages.

5.2.3 Differences in risk and LTV Higher risk has a small effect on home-ownership, but accounts for all of land-scarce cities' lower LTVs. This is for two reasons. First, households save more in the high variance cities, in part due to higher price volatility, but also due to high wage volatility. Renting is a partial hedge against falls in wages that are correlated with rents and prices. However, households will not completely insure themselves against falls in wages through rental housing, since doing so would distort their housing consumption greatly. So households also hold more total wealth in the high covariance economies. This extra total wealth leads to lower LTVs when the households do decide to purchase a house.

Model households do view home-ownership as a potential source of insurance, but it is a highly imperfect variety of insurance. Housing comprises about 25–30 percent of expenditures in the model, so households would like home-ownership to comprise about the same amount in their total wealth portfolio (including human capital) for insurance purposes. However, most renters would have to leverage their financial wealth greatly to buy a home, leaving them near the borrowing constraint and particularly exposed to

³⁶From Table 5, home-ownership rates decline with land scarcity faster earlier in the life cycle. Our data do not show a significant steepening after age 65, however.

large falls in house prices, which are more likely in risky cities. Large falls in prices can leave their budget sets particularly small. So households in riskier cities defer housing purchases until they can afford to buy the house with lower leverage.³⁷ This is consistent with our finding that the share of homeowners that purchase their house without a mortgage is not correlated with risk (or land scarcity) in the data: households with this much financial wealth in the model are not troubled by the borrowing constraint.

There are also transactions costs: more risk leads to more mobility and lower expected durations in any given house. Since adjusting owner-occupied housing is costly, this decreases the value of owning and thus the ownership rate. For instance, in the σ_ε counterfactual, the home-ownership rate for households under 35 in a typical low land scarcity city (25th percentile) economy is 2 percentage points higher than its counterpart at the 75th percentile. If we eliminate transactions costs, the (negative) slope of home-ownership with respect to land scarcity halves in both risk counterfactuals. In other words, households optimally prefer to self-insure with a risk-free bond, which does not have transaction costs, does not distort the intratemporal consumption bundle, and does not compel asset-poor households (which young would-be homeowners largely are) to overleverage themselves, rather than insure with housing even though housing is the only asset whose return is correlated with some of the risks the household faces.

Households do own slightly larger houses in the higher variance economies, but there is little evidence of a housing-ladder effect as discussed in [Banks et al. \(2010\)](#). Their theory is that households that expect to consume more housing than a rental can provide later in life anticipate owning later in life and, therefore, households in economies with high risk will seek to insure themselves against the risk that prices may be high in the future, when they are likely to own a large house, by purchasing (rather than renting) a small house earlier.

Theoretically, the overall strength of the “ladder effect” is particularly dependent on the nature of the housing-ladder assumptions. A very rigid ladder (where, say, the minimum owner-occupied size equaled the maximum rental available, such as in [Banks et al. \(2010\)](#)) can potentially have large average effects early in the life cycle. However, a rigid ladder with a low maximum rental size would not enable our model to match the relative housing consumption of renting versus owning households seen in the data. More importantly, if the ladder effect were large, new homeowners should be willing to buy housing with lower down payments so as to own sooner in riskier cities. From the price level counterfactual, we do see that households would opt for higher leverage purchases in expensive cities so as to climb the housing ladder. If more risk also led households to try and climb the ladder faster via larger loans, the model would not be able to match the higher down payments (lower LTVs) in land-scarce cities in the data.

Finally, the effect of differing maintenance costs is small: maintenance after all is only part of the cost of housing. Relatively high maintenance in low land scarcity economies makes owner-occupancy relatively more attractive as it increases the tax wedge in the user-cost formula, leading to very slightly higher home-ownership rates and LTV ratios.

³⁷These are two sides of similar coins: households worry about the risk that their house will be expensive at the time of purchase and also the risk that their house falls in value after buying it.

6. REGRESSION-BASED INFERENCES

We use a life-cycle model of home-ownership to ask whether households are more likely to own when housing market volatility is higher. Our approach has been to document stylised facts based on a cross-section of cities, which we interpret using a calibrated model. Other studies on this topic have exploited variation in price or rent volatility within cities over time to empirically identify the effect on ownership. Before concluding, we wish to use the language of our model to caution against such an approach.

A household's decision to become a homeowner is a durable decision. The durability of this decision means that at the aggregate (city) level, home-ownership rates are not only a function of contemporaneous prices, but also of lagged prices. For instance, take a city in the model that has high prices today but had low prices in previous years (with constant wages) and compare it to another city with the same high prices today but that also had high prices in the past. Let these two cities be otherwise identical in that households in the two cities have the same expectations with regard to price levels and volatilities going forward (i.e., these two cities have the same land scarcity value). In other words, households with the same current state values today will make the same choices in each of the two cities today. Note, however, that an econometrician using historical prices to measure current expected housing volatility³⁸ will regard the first city as having higher expected volatility relative to the second city.

In this case, the city that is measured by the econometrician as "riskier" today will also have a higher home-ownership rate today relative to the second city. This is because prices in the first city were lower in the past, which led some households then to want to live in bigger houses, which meant they were more likely to own (due to the housing-ladder constraints). When prices rise to their current level, many households will not choose to immediately downsize, so ownership rates remain high relative to the second city. Therefore, there is error in the measurement of expected price volatility that is correlated with variables that do explain differences in home-ownership rates (historical price *levels*), and so estimates of the effect of expected volatility on home-ownership may be biased.

Two particular attributes of this bias are worth mentioning. First, the direction of the bias will generally depend on the direction of price movements: in the above example, the bias is positive; if the first city instead had prices that fell to the same level as the second city, then the bias would be negative. Second, the magnitudes of the bias are not generally symmetric: positive shocks to prices lead to tighter borrowing constraints and so some households are unable to own, whereas negative shocks relax borrowing constraints and so some households are now able (but not required) to own.

6.1 Conclusion

Our model is able to explain much of the cross-city variation in home-ownership and LTV, and matches the variation in the data for younger households. We find that it is the

³⁸Sinai and Souleles (2005) and Banks et al. (2010) measure volatility using a 9-year window and a 5-year rolling window of realized volatilities, respectively, in their regressions. Han (2010, 2013) use an AR(1)-GARCH(1, 1) process to model expectations.

relatively higher prices in cities with scarce land that causes their lower home-ownership rates, while it is their relatively higher volatility that causes homeowners in these cities to borrow less. So we do not find that more risk leads households to own more. Instead, more risk leads perhaps to a higher reliance on nonhousing savings. This result highlights the importance of including other means of imperfect insurance in asset allocation models with incomplete markets. Land scarcity has a larger effect on LTV in the data than in the model. So it is probable that there are other channels through which risk may affect LTV that are precluded in our model. For instance, it is possible that households in risky cities hold the same amount of wealth but take smaller mortgages due to, perhaps, higher propensities to move and the presence of prepayment penalties that are proportional to the mortgage balance.

The main question explored in this paper concerns home-ownership and insurance. Several of the facts developed in this paper—the relationships between land values, land scarcity, and house prices, and between housing availability (the housing ladder) and home-ownership—beg further examination and a full structural explanation. It would also be worth using a general equilibrium version of the model to examine the different local effects of aggregate (countrywide) shocks. Finally, it would be useful to explore whether land scarcity, via LTV, can help explain any recent geographical patterns in mortgage defaults. If our model allowed for default, households may perhaps be more likely to own in volatile cities (though this would then perhaps also imply that households would borrow more in these cities). This of course depends on the particulars of the contracting problem between lenders and households.³⁹

APPENDIX A: DATA CONSTRUCTION AND ROBUSTNESS CHECKS

A.1 *Construction of conditional ownership rates and LTVs*

Here, we describe the construction of the conditional measures of local ownership rates and mean LTV used in cross-city analysis. For home-ownership, we first run a probit-level regression (using the full national sample) of an ownership dummy on various characteristics of the household head,⁴⁰ together with a full set of MSA effects. Then, for each MSA, we use the regression estimates to predict the ownership rate corresponding to a household with the mean characteristics in each dimension.⁴¹ To estimate conditional local ownership rates for a particular demographic group (e.g., an age category), we follow exactly the same procedure, but from the beginning (i.e., even before the probit regression) restrict the sample to the relevant demographic group.

As described above, we have two alternative sources of city-specific LTV data: the AHS and MIRS. The AHS is a longitudinal survey, containing detailed information on

³⁹See Chatterjee and Eyigungor (2011), Corbae and Quintin (2013), Garriga and Schlagenhauf (2009), Guler (2010), and Jeske, Krueger, and Mitman (2011) for various models of default and home-ownership.

⁴⁰Quadratic in age, education dummies (high school graduate, 1–3 years of college, 4 years + of college), gender, marital status, dummies for number of children under 18 (1, 2, 3+), ethnicity dummies (black, Hispanic), and log household income.

⁴¹Because the regression is nonlinear, the mean of our “conditional” ownership rates will not equal the mean unconditional rate. Therefore, we re-center all observations by a constant to correct for this.

housing-related variables. The Metropolitan Survey covers 41 MSAs, and booster samples of a further 6 MSAs (the largest) are included in the national survey.⁴² Of these 47 cities, we have land scarcity data on 42, and, we base our AHS analysis on this set of 42. The AHS surveys cover different MSAs in different waves, and we, therefore, rely on four different waves to put together a complete sample for cross-city analysis: the metropolitan surveys of 1998, 2002, and 2004, and the national survey of 2001. We index observations by year of purchase (rather than survey year), because we have information on the loan amount and home price (to calculate LTV) at the purchase year. We restrict our sample to households with mortgages, and we only study details of mortgages that were taken out when the home was purchased. The last condition ensures that we measure the loan and price in the same year to calculate LTV.

As with the ownership rates, all reported local LTVs from the AHS are conditional on characteristics of the household head.⁴³ Also, since the AHS samples are not large, we include all households that purchased their home up to 5 years prior to the survey year (so the full data set spans purchase years 1993–2004) to predict LTVs in 2000. The consequent overlapping (in terms of purchase year) of the different waves allows us to identify MSA effects. Specifically, we run an OLS regression of LTV on household characteristics, purchase year dummies, and MSA dummies,⁴⁴ and we predict LTV in each MSA for a household with the mean characteristics in each dimension⁴⁵ that purchased their home in 2000. To estimate “conditional” LTV for a particular group (e.g., an age category or loan type), we follow exactly the same procedure, but from the beginning (i.e., even before the predicting regression) restrict the sample to the relevant group.

⁴²In the national survey, the samples for cities other than these 6 are insufficient to derive reliable city-specific statistics.

⁴³Quadratic in age (at purchase year), education dummies (high school graduate, 1–3 years of college, 4 years + of college), gender, marital status, dummies for number of children under 18 at purchase year (1, 2, 3+), ethnicity dummies (black, Hispanic), and log household income (deflated by the consumer price index (CPI) to 2000 dollars). To predict number of children at purchase year, we count the number of children currently in the family who would have been under 18 at the purchase year; of course, children born between the purchase and survey years are not included.

⁴⁴In this regression, we exclude a number of observations that have suspect LTV values. First, we exclude observations with home purchase prices and loans below \$5000 and LTV ratios above 1.2. Second, the AHS includes a number of imputed values for mortgage size; we exclude these observations, because the imputations are not conditional on MSA. There is also a problem with top-coding, discussed in Davis and Palumbo (2008). In the metropolitan surveys, the top-coded values for house price and loan amount are calculated *by city* (as the mean value of the top-coded observations), which is ideal for our purposes. But this is not the case for the (relatively expensive) cities with booster samples in the national survey: there, a *national* top code is used. In our sample, 10% of observations in New York City are top-coded, 9% in Los Angeles, and 5% in Chicago. Our approach is to exclude all top-coded observations in the national survey from the regression. However, we take some assurance from the fact that we control in the regression for household characteristics that are correlated with top codes (e.g., household income, education); see the following footnote.

⁴⁵When estimating the means of household characteristics, we include in our sample all excluded observations detailed in the previous footnote. This should partially address the problem of omitted top codes in the national survey (we essentially predict the LTV of the top-coded observations, based on their observed characteristics).

A.2 Conforming and nonconforming loans

Here, we consider the impact of conforming loan limits.⁴⁶ The existence of this nationally uniform loan limit may well be responsible for our LTV result. In more expensive cities, the conforming loan limit is more likely to bind. As a result, households will be forced to make a larger down payment (to qualify for the cheaper rates on conforming loans), and this will yield a negative correlation between price and LTV (and, consequently, between price risk and LTV too). If the conforming loan limit is driving our results, then the effect should be stronger the closer is the loan size to the conforming loan limit: increases in land value would be less likely to lead to increases in loan value if that means the household will go over the conforming loan size limit.

To test whether the loan limit is driving this effect, we check the LTV–price level/volatility correlation in samples delineated by the ratio of loan size to loan limit (restricting our attention to households with conventional mortgages). It turns out, though, that the correlation is strongly negative (especially) for loans well below the limit and less so for loans close to the limit. So we conclude that the loan limit cannot be responsible for the correlation.

The results are reported in Table 8. In each case, observations are at the household level and the dependent variable is LTV. The regressor of interest is price volatility in Panel A and log house price in Panel B. Also included are a range of household-level controls (see the table notes) and a full set of purchase year fixed effects (we only include households that purchased their home between 1993 and 2004).

Regressions are disaggregated into samples delineated by the loan-limit ratio. Also, the sample is restricted to households with conventional mortgages (we are interested in the impact of the conforming loan limit). The loan-limit ratio for each sample is reported at the top of the columns (0–0.25, 0.25–0.5, 0.5–0.75, 0.75–1, 1–1.25, 1.25–1.5, and >1.5).

The effect on LTV is negative in all samples for both price volatility and levels. For volatility (Panel A), the effect is very large and statistically significant for the 0–0.25 sample (–4.9) and the 0.25–0.5 sample (–1.6), but the effects for all the other samples fall below 0.8 and are statistically insignificant. The effects around the conforming loan limit (0.75–1 and 1–1.25) actually tend to be *smaller* than elsewhere. This suggests that the negative effect is not being driven by some interaction with the conforming loan limit. The patterns are very similar for price level in Panel B, though more of the samples are statistically significant.

⁴⁶Mortgages in the United States fall into different categories. Mortgage loans may either be conventional or nonconventional. To qualify for a conventional loan, households must pass credit and income tests (known as PITI tests: principal–interest–taxes–insurance). If they cannot afford a threshold down payment (often as high as 20%), they will also have to purchase PMI (private mortgage insurance) to qualify for a conventional loan. Nonconventional loans are guaranteed by the government, through the Federal Housing Administration (FHA) or Department of Veteran Affairs (VA). They tend to be more appropriate for households that require a large LTV. Conventional loans may be either conforming or nonconforming. Loans are conforming if they fall below a dollar threshold, which varies with time. Until 2008, this threshold was nationally uniform (our sample excludes years after 2008). Conforming loans are subject to cheaper rates, because they are more liquid: Fannie Mae or Freddie Mac will provide guarantees enabling a lender to sell them to the secondary market. See, for example, [Caplin et al. \(1997\)](#) for further detail.

TABLE 8. Regressions of LTV on price volatilities and levels for samples delineated by the loan-limit ratio.

Sample: Loan Limit	(1) 0–0.25	(2) 0.25–0.5	(3) 0.5–0.75	(4) 0.75–1	(5) 1–1.25	(6) 1.25–1.5	(7) >1.5
Panel A: Price Volatilities							
House price volatility	−4.882*** (1.653)	−1.593*** (0.586)	−0.587 (0.392)	−0.223 (0.483)	−0.552 (0.380)	−0.767 (0.455)	−0.474 (0.863)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purchase year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1360	4566	3285	1506	550	275	304
MSAs	42	42	42	42	42	42	42
R-squared	0.051	0.020	0.007	0.008	0.055	0.099	0.169
Panel B: Price Levels							
Log house price	−0.388*** (0.051)	−0.116*** (0.017)	−0.042*** (0.014)	−0.005 (0.021)	−0.031* (0.017)	−0.042** (0.019)	−0.055 (0.033)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purchase year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1360	4566	3285	1506	550	275	304
MSAs	42	42	42	42	42	42	42
R-squared	0.119	0.037	0.012	0.008	0.060	0.108	0.189

Note: Regressions are run separately for samples delineated by the loan-limit ratio (the ratio of loan size to conforming loan limit, reported above each column). For each sample, we separately estimate the effect of price volatility (in Panel A) and log price level (in Panel B) on household-level LTV. All regressions control for the household characteristics listed earlier in Appendix A (i.e., those used to condition the local LTV estimates) as well as a full set of purchase year effects. We use the composite sample described earlier in Appendix A, though we exclude all household with nonconventional mortgages. There are 42 MSAs in the sample. Standard errors (SEs), clustered by city, are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.3 Local variation in effective interest rates

An alternative hypothesis is that banks subject households in riskier cities to higher mortgage interest rates—and this could explain the lower ownership rate in these cities. Similarly, it could explain why households in these cities choose to take out smaller loans (relative to home value). Interest rates may also vary across cities because of differences in state-level regulation.

However, it turns out that effective interest rates⁴⁷ are actually *lower* in expensive/risky/land-scarce cities. This is illustrated by Figure 13, using data from the MIRS on 25 major cities. There is a strong negative correlation across cities between the interest rate, and both price risk and level (R squared is 40–50 percent in each case). The interest rate varies from 7 percent in the most expensive/risky/land-scarce cities to 8 percent in the least. And so this cannot explain why ownership rates and LTV ratios are also lower in expensive cities.

A.4 Dynamic wealth explanations

The lower LTVs in land-scarce cities might also be explained by the contemporaneous emergence of significant local wealth, allowing home-buyers to put down large deposits

⁴⁷“Effective” because it accounts for any up-front fees.

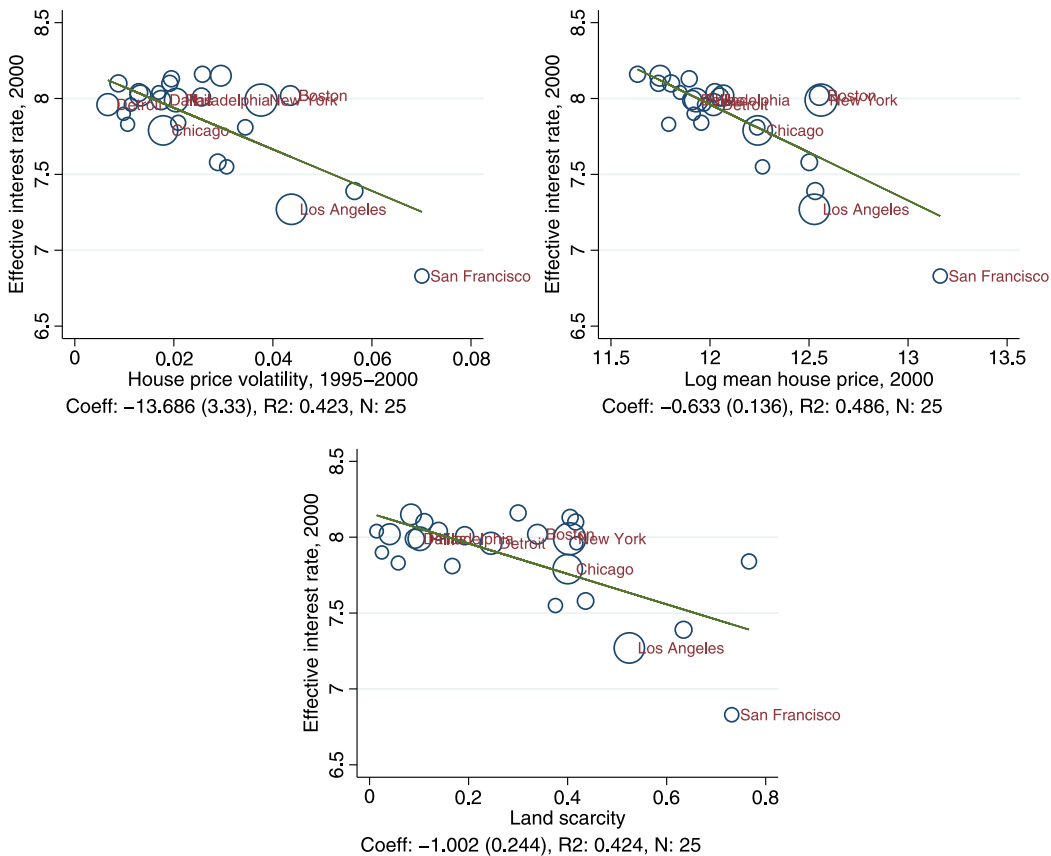


FIGURE 13. Effective mortgage interest rate, price risk, and price levels.

(with more modest loan requirements). In particular, this wealth may originate from recent local house price growth: as argued above, land-scarce cities tend to experience larger price booms (and busts). In Figure 14, we plot local house price growth separately for recent decades (1980s, 1990s, 2000s) against land scarcity.⁴⁸ Prices grew significantly faster in land-scarce cities in the 1980s and 2000s.

If wealth effects from house price trends are responsible for the LTV results, we should find that the patterns are driven by purchases by previous homeowners rather than first-time buyers. Fortunately, the AHS data allow us to estimate conditional LTV separately for each of these buyer types. In Figure 15, we plot conditional LTV (in 2000) on land scarcity, separately for previous homeowners and first-time buyers. Reassuringly, the coefficient of the OLS-estimated slope is identical in each case (0.09). This suggests that housing wealth effects are not driving the results.

⁴⁸Local price growth is estimated from the IPUMS census extracts of 1980, 1990, and 2000 and the American Community Survey of 2010. The sample size in these plots varies across periods because the sample of MSAs is not identical in each census cross section. Note that the geographical definitions of these MSAs has also changed over time, as the cities have expanded.

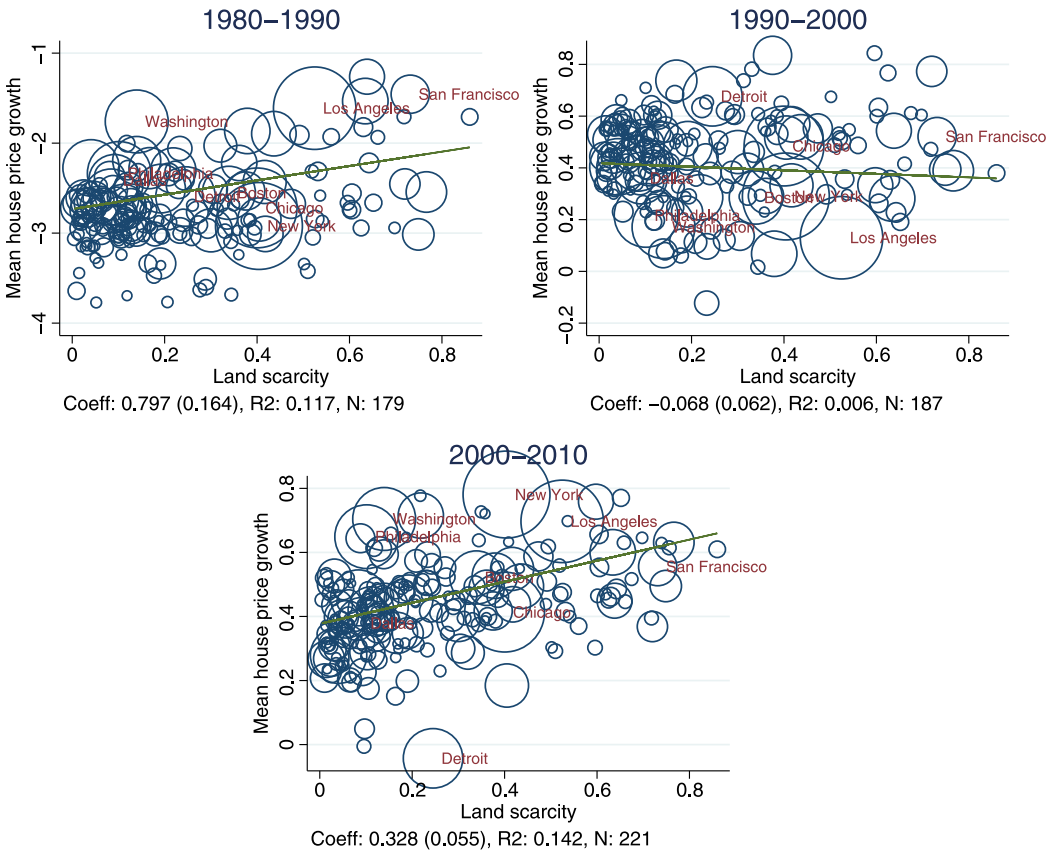


FIGURE 14. House price growth and land scarcity by decade.

It is true that the down payments of first-time buyers may be funded by relatives, who have benefited from growing local housing wealth. However, only a small fraction of households (5 percent in our sample) report that the main source of their down payment was an inheritance or gift. Reestimating the results without these households makes only a negligible difference to these results.

An alternative source of expanding local wealth is contemporaneous wage growth. However, Figure 16 shows that the growth of average wages in the 1980s, 1990s, and 2000s is uncorrelated with the land scarcity instrument.⁴⁹

A.5 Land share, price levels, and volatilities

In this section, we explain why land share is an important factor for both house price levels and volatilities. Consider first the cross-city variation in price levels. The first panel of Figure 17 shows that there is substantial variation across cities in house price levels (the range covers 2 log points). But, comparing the final two panels of Figure 17, the cross-city variation in structure costs is negligible: it is land values that are driving the large

⁴⁹Local wage growth is estimated from the IPUMS census extracts of 1980, 1990, and 2000 and the American Community Survey of 2010.

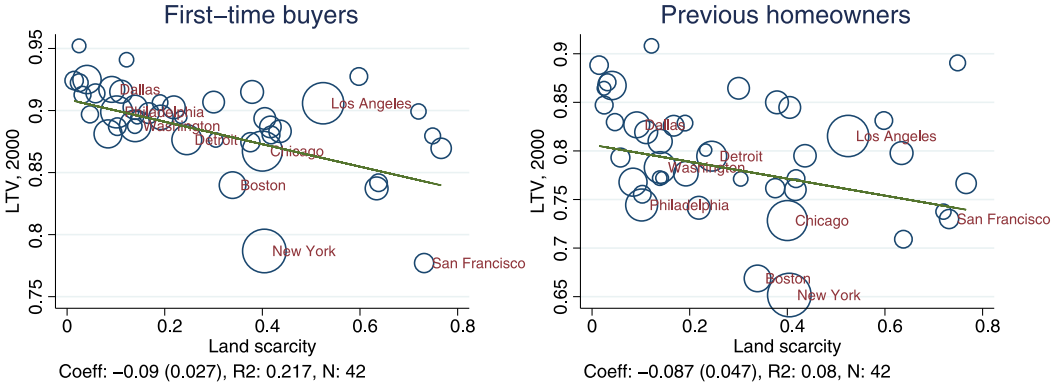


FIGURE 15. LTV and land scarcity by buyer type.

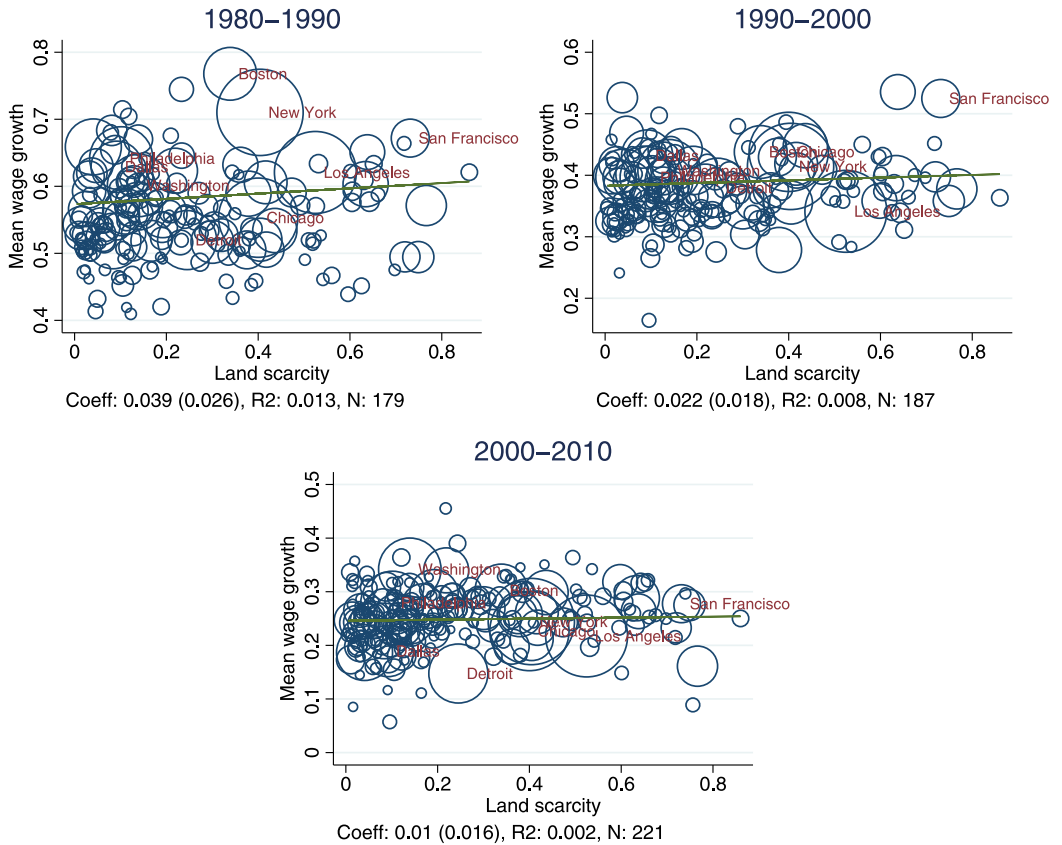


FIGURE 16. Wage growth and land scarcity by decade.

variation in house prices. Clearly then, cities with larger land shares will have higher house prices. In further results in the supplementary appendix, we confirm that the effect on price levels comes entirely through the land value component (structure costs are uncorrelated with land share).

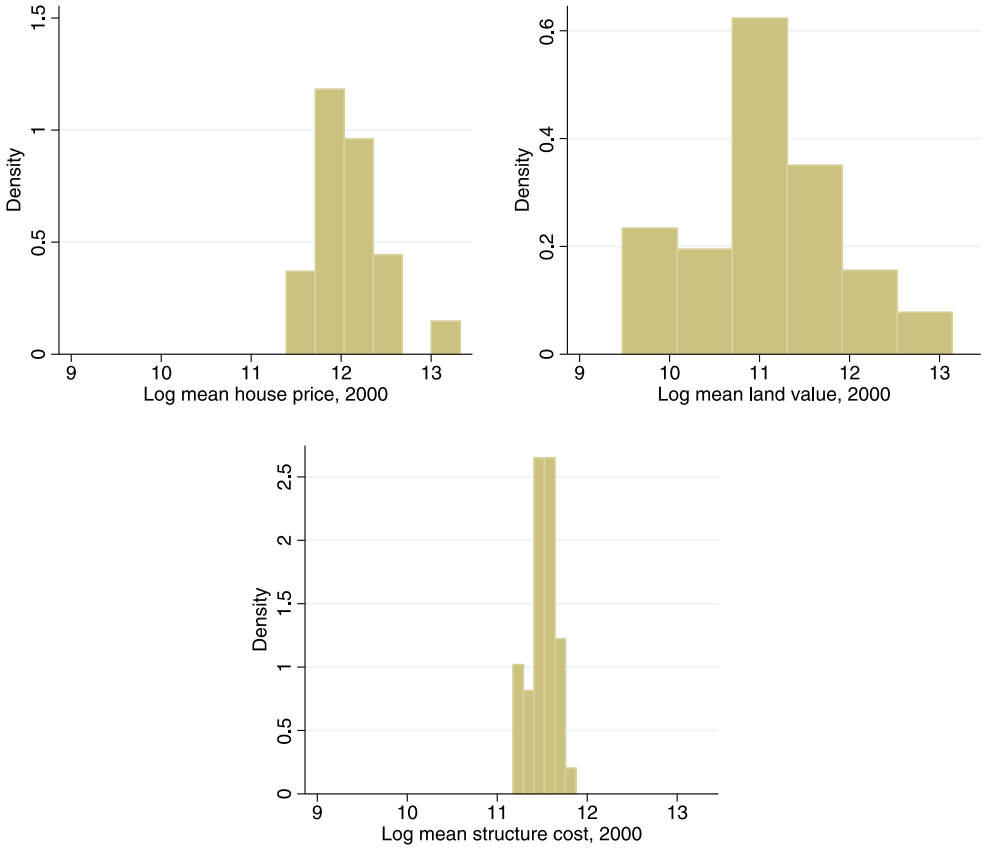


FIGURE 17. Histograms of city price, structure cost, and land value levels.

Next, consider the variation in house price volatilities, that is, the standard deviations over annual growth rates. As with the price levels, the first panel of Figure 18 reveals large variation in volatilities, ranging from 0.006 to 0.075. It turns out that the covariance between the growth rates of land and structure costs within a city over time is, on average, negligible. And so the standard deviation of house price growth over time within a city can be approximated as

$$\sigma_j(g_{jt}^{hp}) \approx l_{j,t} \sigma_j(g_{jt}^{lv}) + (1 - l_{j,t}) \sigma_j(g_{jt}^{sc}), \quad (6)$$

where l_{jt} is land share, and g_{jt}^{lv} , g_{jt}^{sc} , and g_{jt}^{hp} are the annual growth rates of land values, structure costs, and house prices, respectively. In the supplementary appendix, we show that the volatilities of land values and structure costs are individually uncorrelated with land shares. And, as can be seen in Figure 18, the volatility of land value is an order of magnitude larger than the volatility of structure costs. Therefore, according to equation (6), house price volatility will be strongly positively correlated with land share

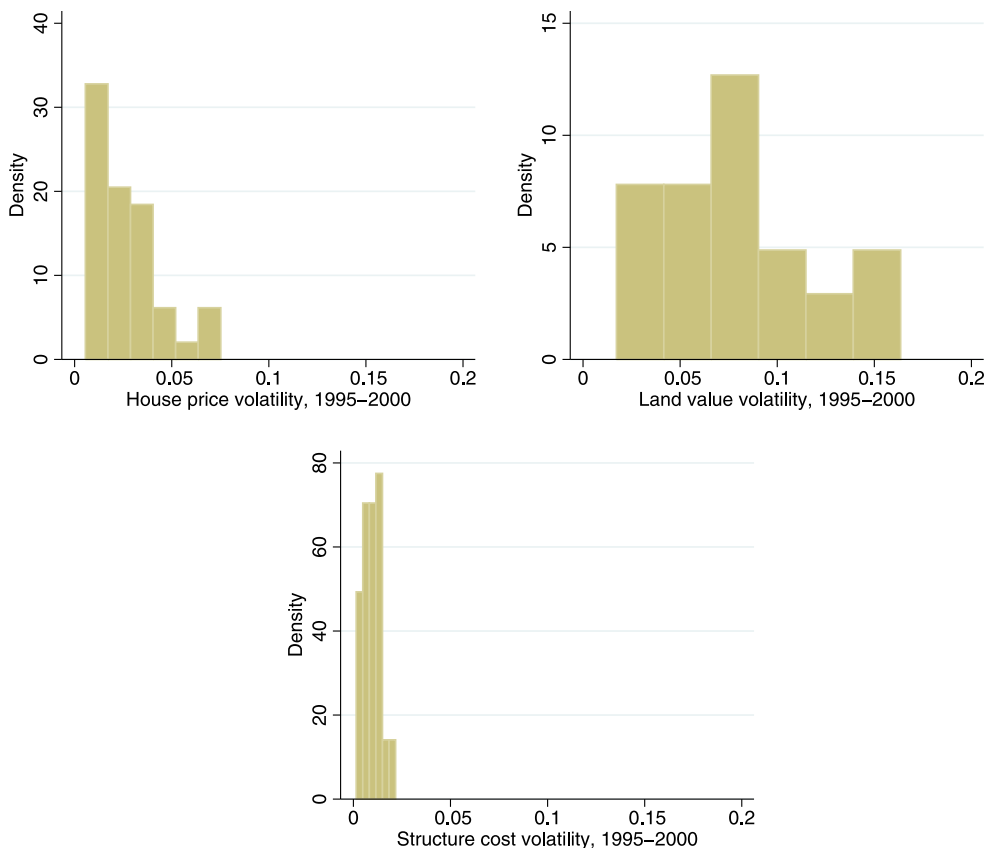


FIGURE 18. Histograms of city price, structure cost, and land value volatilities.

through a composition effect. And indeed, Figure 6 confirms that both local house prices levels and volatilities are increasing in land share.⁵⁰

APPENDIX B: PARAMETRIZATION

B.1 Household life cycle and preferences

We calibrate the discount factor, $\beta = 0.95$, and housing's share in the utility function, $\sigma = 0.3$ following Favilukis, Ludvigson, and Van Nieuwerburgh (2010), and the inverse of the intertemporal elasticity of substitution, $\phi = 5$, following Piazzesi, Schneider, and Tuzel (2007). Estimates of risk aversion vary widely, particularly when the parameter is separately identified from the intertemporal elasticity of substitution. Some studies have point estimates with $\gamma = 20$ or higher but with equally large confidence intervals (see Attanasio and Weber (2010), Vissing-Jorgensen and Attanasio (2003), and, for values over 100, Yogo (2006)). Since such a large value of γ would imply an outlandish level of

⁵⁰Reported land share is the mean over the four quarters of 2000, based on estimates from Davis and Palumbo (2008).

TABLE 9. Family size equivalence scale.

Family Size	L-M	Orshansky (1965)	U.S. Dept. of Commerce	F-V&K
1	100	100	100	100
2	106	126	128	134
3	128	151	157	165
4	147	189	201	197
5	169	223	237	227

precautionary savings in our model, we choose $\gamma = 3$, which is well within the more traditional range of 2–5 that most studies prefer (see Lustig and Van Nieuwerburgh (2010), Hryshko, Luengo-Prado, and Sorensen (2010), Li and Yao (2007)).

B.1.1 Family size equivalence We collect data from the period 1970–1993 in the Current Population Survey (CPS). We control for year effects by using year dummies. The family size profile is generated by the regression

$$F_{iat} = \sum_{k=21}^{81} \beta_k 1_k + \sum_{t'=1970}^{1993} \beta_{t'} 1_{t'} + \varepsilon_{iat},$$

where 1_k is a year dummy, which takes on value 1 when $a = k$, and $1_{t'}$ is the year dummy that takes on value 1 when $t' = t$.

Figure 19 shows the profiles of family size from the CPS. Family size increases sharply when the household is young, peaking at age 39.

To adjust the household's housing and consumption stream, we use a household equivalence scale. The objective of an equivalence scale is to measure the change in consumption needed to keep the welfare of the family constant as the family size varies. Note that using per capita consumption assumes that the family converts consumption expenditure into utility flow following constant returns to scale. Lazear and Michael (1980) point to the existence of family goods, economies of scale, and complementarities, which are all factors that they show to be significant. We therefore use a household equivalence scale that is not constant returns to scale. Table 9 lists some equivalence scales. L-M stands for Lazear and Michael (1980), U.S. Dept. of Commerce refers to US Department of Commerce (1991), and F-V&K stands for Fernandez-Villaverde and Krueger (2007). Lazear and Michael's scale takes greater account of common or public goods, so that the impact of family size is less than other equivalence scales (compare, for instance, Orshansky (1965)). We use the housing equivalence scale used by Fernandez-Villaverde and Krueger (2007).

All households in the model economy have the same life-cycle profile of family size, which is set to the average family size at each age in the CPS. To account for noninteger family sizes, we assume that the adjustment factor is linear within the family sizes specified in Table 9. Figure 19 shows the equivalent, normalized family size over the life cycle.

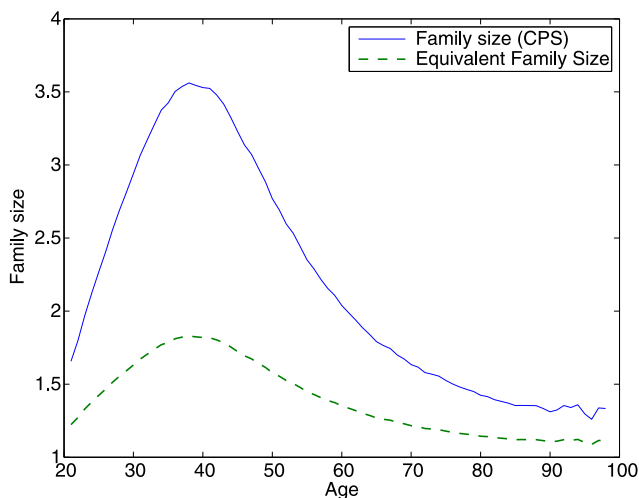


FIGURE 19. L-M adjusted family size profile (yearly bins).

B.2 Assets

We set the down payment requirement, $d = 0.1$. We set the transaction cost of buying, $\theta_b = 0.08$, within the range typically chosen in the literature (Martin (2003), Fisher and Gervais (2011)). We set the interest rates at $r_l = 0.04$. The average difference between a 30 year fixed rate mortgage and the 30 year U.S. Treasury bond is between 1 percent and 2 percent for 1977–2010, so we set $r_b = 0.06$.

B.2.1 Initial wealth distribution We calibrate the wealth distribution of newborns using the distribution of wealth among 21–25 year olds in the Survey of Consumer Finances (SCF) waves from 1989–2001. We drop top-coded observations, households with negative wealth, and students from the sample, and use the sample weights provided by the SCF. We parametrize the initial wealth distribution as an exponential distribution. That gives us one parameter that we have to match,

$$f(b_0) = \lambda_w e^{-\lambda_w b_0},$$

where b_0 is the initial wealth and λ_w is the parameter to estimate in the exponential distribution. We estimate λ_w by matching the mean of the initial wealth distribution:

$$\lambda_w = \frac{1}{\bar{b}_0}.$$

This gives us $\lambda_w = 0.00589$. We convert the initial wealth distribution in the data to model terms by scaling by the ratio of average labor earnings at age 21 in the model to average labor earnings at age 21 in the data.

B.3 Taxes

There are two forms of taxes in the model economy—income tax, t_y , and property tax, t_p . Piketty and Saez (2007) use public use microfiles of tax return data from the Internal

Revenue Service, which have the advantage of being aggregated to the household level already. The income tax rate we choose, $t_y = 0.2$, is in the same range that they compute for the U.S. economy.⁵¹

We use data from the IPUMS 1990 5 percent sample. The variables used are the amount of property tax paid and the estimated value of the house. We remove top-coded variables from the sample and consider only owner-occupiers. Sample observations are weighted using the household weights given in the data set. The weighted average of the ratio of the amount of property tax paid to the estimated value of the house is 0.012. In the model, we set $t_p = 0.01$.

B.4 Earnings process

We parametrize the idiosyncratic and age-profile portion of the household's earnings following Halket and Vasudev (2014), who estimate a process similar to Storesletten, Telmer, and Yaron (2004a) but also control for regional variability (in their case, at the U.S. state level) in earnings rather than just national variability. We set the standard deviation of idiosyncratic innovations, $\sigma_\psi = 0.098$, and let the initial (fixed effect) distribution have a standard deviation of 0.5 (since the persistent component of earning follows a random walk, a fixed effect is equivalent to households entering at age 21 with a value ψ_{21}^i drawn from normal distribution with standard deviation 0.5). As is well known, the variance of the transitory shock is not separately easily identified from the variance of measurement error in these approaches to estimation. We set $\sigma_\varrho = 0.25$, which is within bounds found by Storesletten, Telmer, and Yaron (2004b), Blundell, Pistaferri, and Preston (2008). We discretize the innovations with a three-point distribution following Tauchen (1986).

We set the pension at 60 percent of final earnings, $\zeta = 0.6$.

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⁵¹See Table 1, page 6 in their paper.

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