

Do Households Use Homeownership To Insure Themselves? Evidence Across U.S. Cities

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Abstract

Are households more likely to be homeowners when “housing risk” is higher? We show that homeownership 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 confirm this using instruments based on topographic measures. We disentangle the contributions of high price levels from high volatilities by building a life-cycle model of homeownership choices. The model is able to explain much of the cross-city dispersion in homeownership and LTV. We find that higher price levels explain the lower homeownership, while higher risk explains the lower LTV in high land value cities. The relationship between LTV and risk highlights the importance of including other means of incomplete insurance in models of homeownership. Finally, we use the model to show why regression-based inferences about the effect of risk on homeownership are biased.

Keywords: Homeownership, Housing Risk, Land Share, Loan-to-value, Life-Cycle

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1 Introduction

Are households more likely to own their residence when “housing risk” is higher? There is a growing literature on how homeowners use home equity to smooth the transmission of earnings

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shocks into consumption¹. In this paper, we explore how the decision to become a homeowner is influenced by motives for insurance. We argue that, in response to differences in housing risk, households are more likely to adjust their liquid savings than the timing of their ownership decision. Empirically, these savings adjustments manifest themselves in observed variation in mortgage loan-to-value ratios (LTV).

Theoretically, when markets are incomplete there are several reasons why homeownership may be a peculiar and attractive form of insurance against certain risks in the housing market². In Sinai and Souleles (2005), households may use homeownership to insure themselves against the risk of changes to the local rental price (or user-cost) of housing. However, Ortalo-Magne and Rady (2002) suggests that if the household's expected future earnings are more strongly correlated with local house prices, then they already have 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 who 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. This is to partially insure themselves 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 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 homeownership decisions.

This study proceeds in three steps. First, we show that a substantial amount of the cross-city variation in housing risk is systematically related to the cross-city variation in the level of prices, contrary to existing work that had treated these two aspects as independent of each other. We also show that households behave differently in the high-risk, high-price cities: they are less likely to become homeowners and more likely to make a large downpayment (in percentage-of-house-value terms) when they do buy. So, secondly, we use a quantitative life-cycle model with homeownership to disentangle the effects of higher risk from higher price levels on the life-cycle timing

¹Hurst and Stafford (2004); Hryshko et al. (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.

²Formal, direct means to insure against changes in house prices are limited (Caplin et al., 1997) and the correlation between house prices and other financial assets is small (Flavin and Yamashita, 2002).

³Davidoff (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 homeownership.

of homeownership and mortgage decisions. Lastly, we show that typical regression-based inference procedures bias the effects of risk on homeownership because they use the ex-post, realized volatility of prices as their measure of ex-ante housing risk.

We document that both homeownership rates and average household loan-to-value (LTV) ratios at origination at the city level⁴ are strongly negatively correlated with the volatility of house price growth rates in the city⁵, our “ex-ante” measure of housing risk⁶. 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.

When we look at the variation in homeownership rates and LTV by land share (the ratio of local land values to total housing costs), we see the same strong negative correlation. This is true even after instrumenting for possible endogeneity and controlling for differences in demographics. As an instrument for land share we use geographic data on land scarcity collected by Saiz (2010). By this measure, a 10 percentage point increase in land share increases house prices by 20 percent and volatility by 1.7 percentage points. And, it decreases homeownership by 4.9 percentage points and LTV by 2.3 percentage points.

In order to measure the effect of higher volatility on homeownership, we disentangle its impact from that of higher prices by building a life-cycle model of homeownership choice. We account separately for innovations to house prices which are correlated with city wages and those which 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 homeownership: a risk-free bond.

In our setup, households have several potential reasons why they might use homeownership to insure against housing risk. They may use homeownership 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 homeownership are similar to those in Cocco (2005), Li and Yao (2007) and others.

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).

⁵We will sometimes refer to the time-series standard deviation of the annual changes to log house prices within a city as its “volatility”.

⁶“Ex-ante” in the sense that it is our measure of risk before considering the availability of assets that may provide for some degree of partial insurance.

The model is matched to the average city and then used to simulate two sets of cities: one set of cities with low land share and thus low house prices, low risk and slightly higher rent-to-price ratios⁷ and one set of cities with high land share. We find that most of the observed variation in homeownership across cities comes from the observed variation in house price levels and not the variation in risk. However, variation in risk and not prices is important for explaining the variation in LTV.

The weak effect of risk on homeownership is not because the cross-city difference in risk is small. *Each* of the standard deviations of innovations to house prices (both those that are correlated and those that are uncorrelated to innovations in local wages) are 50 percent higher in the high land share cities; about the same as the percentage difference in house price levels across these cities. But in the model, price levels have a much larger effect than risk on homeownership choices through the housing ladder. For example, with a housing ladder, a household in our model must own if it wants to live in a particularly large house. Higher prices in a city decrease housing consumption and can therefore have a large effect on the proportion of households that must own (rent) due to wanting to consume a large (small) amount of housing. Moreover, the household also has an alternative to using homeownership for insurance: it can accumulate precautionary, non-housing savings instead. These extra savings help explain the lower LTV ratios in the high risk cities.

Homeownership 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 helps determine whether a household currently owns or not. Therefore, homeownership rates within the city economy are also a function of the history of prices. In many studies⁸, housing risk is measured using the volatility of area house prices around the time that the homeownership rate is measured. Thus, the volatility variable picks up the history dependence of homeownership on price levels. In the last section of the paper, we show that not accounting for this history dependence in regression-based inferences can lead to biases: specifically, measures of risk are incorrectly found to be important factors in homeownership decisions. The direction of the bias depends on the realized drift in house prices in the sample, with downward “trends” biasing estimates of the effect of volatility upwards.

A key contribution of this paper is that we provide evidence of a systematic cross-city variation in homeownership and LTV using both micro and aggregate (city-level) data. Banks et al. (2010) uses both variation across U.S. states and U.S.-U.K. comparisons on homeownership. Chiuri and

⁷The higher rent-to-price ratios in lower land share cities is due to structural maintenance costs accounting for a higher proportion of the overall user cost of housing.

⁸e.g. Sinai and Souleles (2005); Banks et al. (2010)

Jappelli (2003) looks across developed countries for the effect of financial market imperfections on homeownership. Albouy (2009a,b) look 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 land share and land scarcity across cities to find systematic differences in household choices.

Han (2008) builds a model where homeowners may choose to accumulate more housing in order to hedge against housing risks. Under the assumption of separable utility, she provides conditions for when the hedging motive outweighs the household's normal disinclination to hold riskier assets (as in Rosen et al. (1984)). Our work expands on this contribution by adding the option of renting and looking homeownership and borrowing behavior jointly.

There are a few studies that examine the opposite causal direction - the effect of homeownership and borrowing decisions on prices. Stein (1995) proposes a model where price changes have asymmetric effects on sales due to downpayment constraints. Lamont and Stein (1999) finds 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) finds 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, nor do we deal with issues of regional mobility⁹ 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.

The rest of this paper is as follows: section 2 shows the striking variation in homeownership, 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 section 7 concludes.

2 Homeownership and loan-to-value ratios in the data

A natural first step to answering whether households use homeownership to insure themselves is to look at whether homeownership rates are positively correlated with housing volatility. In this

⁹See Halket and Vasudev (2011) for a model with both, but without the changes in housing supply that we would need here to close the model. Lustig and Nieuwerburgh (2010) looks at inter- and intra-regional risk sharing and home values but not homeownership.

section, we show that homeownership rates are negatively correlated, across cities, with house price *volatilities* (that is, the time-series standard deviations of house price growth within cities). But, we cannot draw causal inference from this result. This is because there is a key omitted variable: homeownership is also negatively correlated with house price *levels*, consistent with the reduced-form results from Banks et al. (2010); Sinai and Souleles (2005). Furthermore, simply controlling for price levels in reduced-form regressions cannot solve this problem, as levels and volatilities are themselves closely correlated.

Price levels and volatilities are closely related because they share the same statistical source: variation in land share, i.e. the share of the average city house price that is attributable to the value of land (as opposed to the value of the structure). We confirm that land share has a large *causal* effect on homeownership, using a suitable instrument based on land scarcity. But, it is impossible to know whether this causal effect is coming through price levels or volatilities through the reduced-form approaches in this section.

Finally, at the end of the section, we show that another variable related to the homeownership decision, the size of the mortgage loan, is also closely negatively correlated with house price volatilities, levels and land share. This result will help guide our discussion of mechanisms below.

2.1 Data

We identify cities with the Metropolitan Statistical Areas (MSAs), of which there are between 270 and 300 in our sample period, depending on the year. However, we focus our analysis on 38 prominent MSAs that form the intersection between the various samples of the data sets we use.

The house price data is taken from Davis and Palumbo (2008)¹⁰. 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 structures cost, respectively, so that:

$$\begin{aligned} housevalue_{j,t} &= landvalue_{j,t} + structurevalue_{j,t} \\ \lambda_{j,t} &= \frac{landvalue_{j,t}}{housevalue_{j,t}} \end{aligned}$$

where $\lambda_{j,t}$ is then the land share for city j at time t . Data on land values from Davis and Palumbo (2008) are actually the residual part of house values within a city that are not explained by structure values.

As a measure of local house price volatility, we take the standard deviation of log annual

¹⁰Their data are available at <http://www.lincolninst.edu/subcenters/land-values>.

changes in the local house price (measured in the first quarter of each year), over the full period of the data, 1985-2010. We do not look at time variation in volatility within cities, because we have a suitable instrument that varies across cities but not over time.

As a supply-side instrument for the share of the price attributable to land, we adopt Albert Saiz's (2010) measure of land scarcity within 50km of the city center, where land scarcity is defined as the proportion of land at an incline over 15%, or on water¹¹. Saiz estimates this variable with GIS data. Homeownership rates are taken from the IPUMS 5% extract of the US 1990 census, organized by Ruggles et al. (2010).

We use the American Housing Survey (AHS) for information on loan-to-value ratios (LTV). The AHS is a longitudinal survey, containing detailed information on housing-related variables. The metropolitan survey covers 41 MSAs, and a further 6 MSAs (the largest) are included in the national survey. These surveys cover different MSAs in different waves, and we therefore rely on four different waves to put together a complete sample: the metropolitan surveys of 1998, 2002 and 2004, and the national survey of 2003. We index observations by year of purchase (rather than survey year), because we have information on the mortgage and home value (to calculate LTV) at the purchase year.¹²

To construct city-specific mean LTVs at purchase year 1990, we use the following method. The AHS samples are not large, and so we use data from *many* purchase years to predict LTVs in 1990. Specifically, using the full sample, we predict the LTV of each household in 1990, by extracting estimated national purchase year effects. The city mean LTVs described below are means over these predicted values. As a check on the quality of the AHS data, we compare AHS estimates of the predicted LTV in 1990 with those from the Federal Housing Finance Agency monthly survey in the same year. Figure 1 plots the FHFA against the AHS estimates in 1990, weighting data points by city size. The two measures appear closely correlated. Still, for the purposes of this study, we use the AHS data. First, it covers more MSAs (47 rather than 26), and second, the AHS contains detailed microdata (which we exploit below).

Several robustness exercises are available in an online appendix at the corresponding author's website. These exercises show that the results presented below are robust to dropping the New

¹¹His data are available at <http://real.wharton.upenn.edu/~saiz/SUPPLYDATA.zip>.

¹²Our sample for the estimation of LTVs is owner occupiers, with mortgages, who purchased their home since 1975, and who took out a mortgage when they purchased their home. The last condition ensures that we measure the loan and price in the same year, to calculate LTV. Unfortunately, there is a large amount of measurement error in the loan and house price variables: over 6% of observations in our data have LTVs of over 1, with some reaching over 100,000. We exclude all observations with LTV greater than 1. The share of truncated observations in each city is uncorrelated with our instrument, the local land scarcity. Of course, there will be issues of attrition, since earlier purchases are less likely to be observed.

York City MSA from the sample, using the extract from the 2000 census instead of the 1990 and using a smaller window for our volatility measure.

2.2 Homeownership and price volatility

Homeownership is negatively correlated across cities with house price volatilities. But, it is also negatively correlated with price levels (see the first two panels of Figure 2). Table 1 shows that these effects are robust to, and are actually reinforced by, the inclusion of household characteristics.¹³

Specifically, column 2 shows that, at the margin, a 1% increase in house prices (evaluated at the mean) is associated with a 0.2 percentage point reduction in homeownership probability¹⁴. And, column 4 shows that a 0.01 increase in the volatility measure (evaluated at the mean) is associated with an 18 percentage point reduction in homeownership probability¹⁵.

However, volatilities and levels are themselves closely correlated. 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 homeownership against these residuals: there is no longer a visible relationship. In the second panel, we plot homeownership against price level residuals (from a regression on volatility): this time, there is relationship, though it is weaker than in Figure 2.

In the final column of Table 1, we include both price levels and volatilities as regressors. Interestingly, all the correlation is absorbed by price levels: the coefficient on volatility is insignificant. Still, this is perhaps unsurprising given that volatility is measured with more error than levels.

2.3 Association between house price volatilities and levels: intuition

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 values. We show that price volatilities and levels are correlated across cities because they share the same statistical source: variation in local land shares.

¹³New York is an outlier in Figure 2. Given the very low homeownership rate, we might expect house price levels and volatilities to be somewhat higher than the figures suggest. However, there is a clear explanation for this: the price data (from Davis and Palumbo (2008)) are based on a sample of single-family, owner-occupied homes. But, many homes in Manhattan, the most expensive (and price-volatile) part of New York, do not fit this description.

¹⁴The estimated effect is 0.14, when New York is excluded.

¹⁵14% when New York is excluded.

Consider first the cross-city variation in price levels. The first panel of Figure 4 shows that there is substantial variation across cities in house price levels (the range covers two log points). Comparing the final two panels of Figure 4, the cross-city variation in structure costs is negligible: it is land values that are driving the large variation in house prices. Clearly then, cities with larger land shares will have higher house prices.

Next, consider the variation in house price volatilities, i.e. the standard deviations over annual growth rates. Like with levels, the first panel of Figure 5 reveals large variation in volatilities, ranging from 0.02 to 0.14. Since the covariance between the growth rates of land and structure values within a city over time is small¹⁶, the standard deviation of house price growth over time within a city can be approximated as follows:

$$\sigma_j(g_{jt}^{hp}) \approx \lambda_j \sigma_j(g_{jt}^{lp}) + (1 - \lambda_j) \sigma_j(g_{jt}^{sp}), \quad (1)$$

where g_{jt}^{lp} , g_{jt}^{sp} , g_{jt}^{hp} are the annual growth rates of land values, structure values and house prices, respectively. Empirically, $\sigma_j(g_{jt}^{hp})$, is uncorrelated with the volatilities of local land values, $\sigma_j(g_{jt}^{lp})$, and structure costs, $\sigma_j(g_{jt}^{sp})$. But, critically, Figure 5 shows that the variation in land value is an order of magnitude larger than the variation in structure values. Therefore, from Equation 1, house price volatility should be strongly positively correlated with land share.

2.4 Association between house price volatilities and levels: evidence

Figure 6 confirms that both local house prices levels and volatilities are increasing in land share, where reported land share is the mean over the 4 quarters of 1990.

A possible criticism of simply studying the correlations is that land share itself may be endogenously determined by local price volatility. For instance, volatility may affect the demand for local housing, and therefore land values. To control for potential endogeneity, we instrument for land share using one of Saiz (2010)'s measure of local housing supply constraints, land scarcity (see above)¹⁷. Unsurprisingly, land value and land share are larger in cities with more scarce land, as reflected in Figure 7.

Table 2 summarizes results from regressions of various price level and volatility variables, on land share and land scarcity. Also included are the 2SLS estimates on land share, instrumented by land scarcity. The OLS and IV coefficients are quite similar. According to the IV results, a

¹⁶The correlation of the within-city growth rates of structures and land values is 0.02.

¹⁷Saiz also has other measures of scarcity which include, e.g., measures of regulation. We use only the geographic measures since the regulatory differences may not be exogenous. However all of our results are robust to including the other measures.

0.1 increase (a 10 percentage point increase) in the land share causes a 20 percent increase in local house prices. This effect is entirely due to variation in land value, rather than structure cost. Also, a 0.1 increase in the land share results in a 0.017 (170 basis point) increase in the standard deviation of annual house price growth. The effect of land share on the volatility of land value is actually weakly negative, while the volatility of structure costs is entirely uncorrelated with land share.

Returning to homeownership, the final panel of Figure 2 confirms that there is a significant negative cross-sectional relationship between homeownership and land share. Table 3 shows that this relationship is robust to the inclusion of household-level controls in probit regressions. Specifically, in the basic specification (column 2), a 0.1 increase in land share (evaluated at the mean) is associated with a 3.5 percentage point fall in the probability of homeownership. When we instrument land share with land scarcity (column 6), the effect is still larger.

2.5 Loan-To-Value Ratios

As with homeownership, average city loan-to-value ratio at origination (LTV) is strongly negatively correlated across cities with both local price volatility and level. This is illustrated in the first two panels of Figure 8, where mean LTV is estimated on the sample of mortgage holders.

These relationships are robust to household-level controls, as illustrated in Table 4. Column 2 shows that a doubling of house prices is associated with a 4 percentage point reduction in LTV, and column 4 shows that a 0.01 increase in the volatility measure is associated with a 0.3 percentage point reduction in LTV. In column 6, where both price levels and volatilities are included in the same regression, the volatility variable loses its significance.

But, as with homeownership, these results are difficult to interpret. Variation in both levels and volatilities are driven by land share. Indeed, there is a strong negative relationship between LTV and land share. This is illustrated in the final panel of Figure 8, and in Table 5, where we control for household characteristics. Table 5 shows that this effect of land share is robust to the inclusion of household controls in the regression, and to using the land scarcity instrument. From column 2, a 10 percentage point increase in land share is associated with a 0.9 percentage point reduction in LTV. The IV effect in column 6, is larger: 1.6 percentage points.

Where do these effects come from? It might be argued that they have a supply-side explanation, due to the intricacies of American mortgage institutions. But, in Appendix A, we show that non-varying conforming loan limits do not drive the observed cross-city variation in LTV. Also, there may be some concern that the variation in LTV is merely arising from cross-city differences in shares of mortgage-holders. Indeed, a third of homeowners (in the 5% census extract of 1990) do not hold mortgages. However, it turns out that mortgage share is uncorrelated with the land scarcity

instrument, so it is not likely to be driving our results. Instead, in the following sections, we argue that this variation in LTV is driven by a precautionary saving motive, on the demand-side.

To summarize, homeownership and LTV are negatively correlated with house price volatility across cities. But volatility is itself positively correlated with house price levels due to a common component, land share. Variations in land share across cities explain a large proportion of the variation in volatility and levels, severely complicating inferences based on reduced-form regressions.

3 Household choice model

Time is discrete, and each period in the economy corresponds to one year in the data. Households are born at age $A = 21$ and live at most to age $T = 75$. The set of ages $a \in A = [A, T]$. A household is indexed by i and lives in a city, indexed by j , for its entire life.

3.1 Preferences

Households have recursive preferences of the Kreps and Porteus (1978) type¹⁸. The household gets instantaneous utility from a non-durable 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, $F : \mathcal{A} \rightarrow \mathbb{R}_{++}$, is exogenous, constant across households of the same age and known to the household at birth.¹⁹ The household's utility at time t , V_t , is then given by the composite of its instantaneous utility and its future expected utility:

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

where future expected utility is given by $\mathcal{R}_t V_{t+1} = (\mathbb{E}_t[V_{t+1}^{1-\gamma}])^{\frac{1}{1-\gamma}}$. γ measures risk aversion while 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, $V_{T+1} = (b_{T+1} + p_{T+1}h_T)^{1-\sigma}$.

¹⁸These preferences nest time-separable preferences but allow for the separate consideration of inter-temporal smoothing (savings) and smoothing across states within a given period (risk-aversion).

¹⁹Attanasio et al. (1999); Gourinchas and Parker (2002); Cagetti (2003); Li and Yao (2007) each let family size affect a household's discount factor. In Gourinchas and Parker (2002); 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); 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).

3.2 Labor Earnings

Households receive labor earnings, Y_t^{20} up until an exogenously set retirement age R , after which they receive a pension. Y_t contains three components: a deterministic life-cycle component, an idiosyncratic component and a city-specific component. The city-specific component follows a geometric random walk. The idiosyncratic component is a geometric random walk with a transitory shock:

$$\begin{aligned} Y_t &= L_t^i Z_t^j \rho_t^i \\ L_t^i &= \exp f(a_t) L_{t-1}^i \psi_t^i \\ Z_t^j &= Z_{t-1}^j v_t^j \end{aligned}$$

where $\ln \psi_t^i \sim \mathcal{N}(-0.5\sigma_\psi^2, \sigma_\psi^2)$, $\ln \rho_t^i \sim \mathcal{N}(-0.5\sigma_\rho^2, \sigma_\rho^2)$ and $\ln v_t^j \sim \mathcal{N}(\mu_v - 0.5\sigma_{v,j}^2, \sigma_{v,j}^2)$. The variance of innovations to the city-specific component, v_t^j , can differ across cities; however all cities have common drifts in earnings. After retirement, the household gets a proportion (adjusted for growth in the city) of its final salary, $Y_t = \zeta L_R^i Z_t^j$. All households' income is taxed at a rate t_y .

3.3 Housing Market

At any time, housing may either be rented ($\tau_t^i = 0$) or owned ($\tau_t^i = 1$), but not both simultaneously. Households may 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:

$$p_t^j = Q_t^j Z_t^j$$

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

An owner pays proportions, t_p and δ_j , of the value of the house each period towards property taxes and maintenance, respectively. The housing maintenance means houses do not depreciate and the maintenance required may vary across cities depending on the land share of the value of

²⁰For ease of notation, we suppress some variables' dependence on the household and city specific labels, i and j respectively, when such dependence is or will become obvious.

the housing in the city. 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 can borrow.

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.²¹ The LTV at the time of purchase is simply the ratio: $-\frac{b_t^i}{p_t^j h_t^i}$.

When purchasing a house, 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. 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 which equals one if the household chooses to move in the period.²²

If the household chooses to sell its house, it must pay off all existing debt, though another loan can be taken out if another house 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 house and will not choose to move in this period.

²¹We also call this a mortgage throughout.

²²This borrowing constraint is different from the more typical one which restricts borrowing to be weakly less than some percentage of the house value ($b_{t+1} \geq -(1-d)\tau_t p_t^j h_t^i$). With risky house prices, for an agent near the typical borrowing constraint, a fall in the value of a house results in a "call on the mortgage principle" - the agent must reduce the amount borrowed. If house price volatility is large enough, the effective down payment constraint (the amount the agent could borrow and still be able to repay in any state of the world next period) may be much tighter than the actual (d).

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 loan²³. This effectively ensures in our calibrated economy that all households reach T 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, Z_t^j (which we do not repeat below) for all variables:

$$V(a_t, L_t, \rho_t, b_t, \tau_{t-1} h_{t-1}; Q_t^j, Z_t^j) = \max_{c_t, h_t, b_{t+1}, \tau_t} [(1 - \beta)u(c_t, h_t, a_t)]^{1-\phi} + \beta (\mathcal{E}V(a_{t+1}, L_{t+1}, \rho_{t+1}, b_{t+1}, \tau_t h_t; Q_{t+1}^j, Z_{t+1}^j))^{1-\phi}]^{\frac{1}{1-\phi}}$$

s.t.

$$c_t + b_{t+1} + h_t((1 - \tau_t)s_t^j + \tau_t p_t^j(\delta_j + t_p + 1 + 1_m \theta_b)) \leq b_t(1 + r) + Y_t(1 - t_y) + h_{t-1} \tau_{t-1} p_t^j$$

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

$$r = \begin{cases} r_l & \text{if } b_t \geq 0 \\ r_b & \text{if } b_t < 0 \end{cases}$$

$$c \geq 0 \quad \tau_t h_t \in \{0, H^o\} \quad (1 - \tau_t)h_t \in \{0, H^r\} \quad \tau_t \in \{0, 1\}$$

4 Parametrization

Parameters that vary across cities in the model are those indexed by j . All other parameters remain constant across cities. We assume each city is in one of three city-sets, $j \in \{base, high, low\}$, which we define below. The key parameters for this exercise are discussed in this section; the calibration of the remainder are discussed in the appendix (see Table 6 for their values). The key parameters are all those that vary across city-sets and the housing ladder parameters in H^r and H^o . These are chosen in three steps.

²³That is, a retired household’s borrowing constraint is $b_{t+1}^j \geq \min\{0, (1 - 1_m)b_t^j\}$.

1. Choose $\sigma_v^j, \sigma_\varepsilon^j, \delta^j$ for each city-set as described below. This can be done without computing the household's problem.
2. Choose a date. We choose 1990 and normalize the house price and wage for all $j \in base$, $p_{1990}^j = 1, w_{1990}^j = 1$. We then calibrate the relative prices and wages in the other city-sets so that they match the data in 1990 (again see below for more detail). We simulate 200,000 households for each city-set. Each household is born at some date at most $T - 1$ years before 1990. For each household we draw realizations of the innovations to prices and wages so that they equal their 1990 relative value in 1990.
3. Choose the parameters in the housing ladder so that specific moments in the model best match those in the data in 1990 in the baseline model (cities in the *base* set). The values of the housing ladder parameters are found by repeatedly computing the household's problem for different values of the parameters and choosing the pair that provided the best match.²⁴

4.1 Housing

We assume that 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

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

For the value of housing, pH , we use non-farm owner-occupied housing from NIPA's *Historical-Cost Net Stock of Residual Fixed Assets* table. Investment in housing is computed using non-farm 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 , $\delta_j = \delta_h(1 - \kappa_j)$, where κ_j is the land share in that city-set. The mean land share in the U.S. is 0.352, which is the value we use in the benchmark city. Note that the rent-to-price ratio in the cities will vary with land share 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 the baseline economy's homeownership rate matches the mean homeownership rate and mean ratio of owner-occupied house sizes to rental house sizes (in square feet) in our data.²⁵

²⁴A simulated method-of-moments computed over a grid of potential parameter values.

²⁵Matching the two moments, the homeownership rate and the relative housing sizes, identifies the two parameters

4.2 Prices

We use the data from Davis and Palumbo (2008) on house prices and BLS data on wages to set the parameters in the price processes. We use the mean growth rate of wages and its variance to calibrate μ_v and σ_v^{base} , respectively.²⁶ We then set $\sigma_\varepsilon^{base}$ so that the variance of house prices in our baseline economy is the same as the mean variance of house prices in the data.

To see if we can replicate the observed cross sectional patterns in loan-to-value and homeownership, we split our sample of cities into two sets - those above the median land scarcity measure (which we denote *high*) and those below it (denoted *low*). We then reparameterize our economy with the measured variances, relative wages, prices and land shares of these sets. Table 7 shows the key parameters.

5 Results

5.1 Moments in models and data

Table 8 shows the results from the baseline model compared to the data. Since the house size parameters were chosen so that the model matched the data on the homeownership rate and relative house sizes, it should not be 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 which, given the model's relatively simple characterization of post-retirement life, is also not surprising. Though no parameters were chosen to match the LTV rates (conditional on taking a loan), the model is able to match the data relatively well. Table 9 shows that the model also matches the profile of homeownership relatively well, though there are too few young and too many middle-aged homeowners.

Table 10 presents the average differences in homeownership and LTV between cities with high land scarcity (i.e. high land shares) and low land scarcity. The model explains the difference in homeownership across cities and appears to just partially explain the difference in LTV. When we look at the differences by age (Table 11), the model matches the increase and then subsequent decrease in the difference between homeownership rates over the life-cycle, though the difference is too sharp for the very oldest. The model explains the difference in LTV over for the younger age

uniquely. We do not have a formal proof but casual introspection and all computation thus far confirms it. If \underline{h}^o increases, then \overline{h}^r must decrease to keep the ownership rate constant, but \overline{h}^r must increase to keep the relative house size ratio constant.

²⁶The covariance of the growth rates of wages and house prices in the data is 0.000248, the same as σ_v^2 , so our assumption that v_t^j affects prices and wages equally appears valid.

groups (actually it matches well up to age 45) but breaks down thereafter. This is perhaps a result of only having one non-housing 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 data. This shortcoming is likely to be more acute for older households that have accrued savings. Late life LTV figures are relatively inconsequential: in the data, 80 percent of new loans are taken by households under 50 and 97 percent by households under 65. 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. The relative lack of convergence in homeownership profiles between high and low land share cities over the life-cycle indicates that motives for earlier “ladder-climbing” on the part of homeowners in high volatility cities is perhaps small.

5.2 Contribution from various elements

High land share cities differ exogenously in several important ways from low land share cities in the model. High land share cities have lower rent-to-price ratios in the model because structural depreciation as a percentage of the house value is smaller (this is also true in the data). High land share cities have higher idiosyncratic house price variance and a higher variance in the innovations to the correlated house price - wages process. These cities also have higher prices but also, as a mitigating factor, higher wages.

To disentangle these different contributions, we simulate five variants on the baseline economy, each time only changing one of the parameters, for both the low land share and high land share cities. Table 12 shows each parameter’s contribution to the cross-city difference. Changes in the variances of innovations to house prices account for most of the change in LTV but little of the change in homeownership. We also simulate two sets of cities with much larger but not quantitatively implausible differences in variances (some of the largest land share cities in the data have standard deviations of price growth as large as 10 percent points). Table 13 contains these results²⁷.

The largest contributor to the cross-city dispersion in homeownership is dispersion in the level of house prices. However, differences in risk explain the differences in LTV. Large changes in risk, such as those shown in Table 13 can have large effects on homeownership. But the results show that higher risk actually reduces homeownership slightly; households, on balance, do not use homeownership to insure themselves against housing risk.

Differences in prices create differences in homeownership through the housing ladder. In both the data and the model, households live in larger houses in cheaper cities and the difference in sizes

²⁷Note that these results do not have to add up to the overall changes in table 10.

is larger for owners than for renters²⁸. 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.

A greatly higher σ_v , the house price risk that covaries with wages, leads to much lower homeownership and LTV (Table 13). A moderately higher σ_v , as in our high-low land share spread (Table 12),²⁹ has little effect on homeownership but does lower LTV. Households rent more in high (co-)variance economies because renting is a better hedge against falls in wages that are correlated with 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 (co-)variance economies: 9 percent more in the outsized counterfactual version. This extra total wealth leads to lower LTVs when the households do decide to purchase a house.

Differences in σ_ε cause several differences in household behavior. Higher σ_ε leads to more mobility and lower expected durations in any given house. Since adjusting owner-occupied housing is costly, this decreases the value to owning and thus homeownership. Thus, the homeownership rate for households under 40 in the $\sigma_\varepsilon = .0324$ economy is 2 percentage points higher than the $\sigma_\varepsilon = .0486$ economy.

Households in cities with higher σ_ε have lower LTVs for two reasons: first, households have higher precautionary savings by the time they buy a house; second, households are less willing to hold little equity in their house as large falls in prices can leave their budget sets particularly small.

Households do own larger houses in the higher variance economy 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. Households in economies with high σ_ε seek to insure themselves against the risk that prices may be high in the future, when they are likely to own, by becoming owners sooner. In our economy however, this potential effect on homeownership rates is subsumed by the offsetting effects that σ_ε has on mobility and because households in our economy have an additional insurance outlet, the bond.

Theoretically, the overall strength of the ladder effect is particularly dependent on the nature

²⁸The square-footage difference in the data between high and low land share cities is 18 percent, while in the model the size difference is 33 percent of the average size house in the high land share city. For owners, the difference is 13 percent and 27 percent in the data and model respectively, while for renters the difference is 11 percent and 21 percent, respectively.

²⁹Note that this “moderate” difference is still a 50 percent change.

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. Moreover, if the ladder effect were large, new homeowners should be willing to buy housing with lower downpayments in order to own sooner in riskier cities. This would make it harder for the model economy to match the higher downpayments (lower LTVs) in riskier cities in the data.

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 share economies makes owner-occupancy relatively more attractive as it increases the tax wedge in the user-cost, leading to very slightly higher homeownership rates and LTV ratios (no difference out to two decimal places). Likewise, the difference in wages across the cities is small, though the rationale for the effect of wages on homeownership is similar to that of prices.

6 History dependence and regression-based inference

A household's decision to become a homeowner is a durable decision. The durability of this decision means that at the aggregate (city) level, homeownership rates are not only a function of contemporaneous prices but also the lagged history of prices. Not accounting for this history dependence in regression-based inference can lead to biases which make measures of volatility appear as important factors in homeownership.

6.1 The history dependence of homeownership rates

To illustrate the history dependence in the model economy, we perform the following experiment. We take four cities (two sets of two) that are each ex-ante identical (all four have the baseline-city parameterization). In the first set, we give one city a positive price shock in period one and a twin city the same positive price shock in period five³⁰, so that prices are identical from year five onwards. In the second set, we apply the same magnitude and timing of shocks, though negative rather than positive.

Figure 9 plots the price path for each city, the implied measured volatility and the path of homeownership in each city. This figure shows two important characteristics. First, homeowner-

³⁰In each case, we use the shock that is correlated with wages, v_t^j .

ship rates do not instantaneously fully incorporate the changes in prices (a “delay effect”). Second, there is an asymmetry in the speed with which a city adjusts to shocks. Positive shocks feed into homeownership rates faster than negative shocks.

The model is homothetic, so a positive shock to prices and wages is equivalent to a shock which proportionally reduces (towards zero) all households’ savings or borrowings. Renters with a lot of financial wealth feel “wealthier” (“poorer”) after a negative (positive) shock to prices and wages and so expect to consume more (less) non-durable and housing goods over the rest of their lives. In particular, they may now expect to cross (or not cross) one of the housing consumption boundaries over their life cycle. In general, households want to turn this new-found wealth into consumption over the rest of their lives. The pivotal change in housing consumption (with respect to the housing ladder constraints) may not be until later in their lives. So homeownership rates take some time to fully react to the change in prices. Wages also go down (up) though, so young, renting households with little financial wealth who are years away from becoming owners are hardly effected by the shock. Eventually, as existing households exit the model and newborn households enter, the ownership rate begins to revert back to its steady-state level.

The shocks have asymmetric effects due to the transactions cost. A negative (positive) shock expands (contracts) the contemporaneous consumption set of the household. In particular, a negative shock means that a household that wanted to presently own but could not due to the borrowing constraint might now be able to (and vice versa). Most households in such a position are young households, as they have much less wealth on average. But younger households also expect to move more often than older households due to higher earnings uncertainty and lower wealth. So they find the transactions cost of buying a house more onerous. So whereas an increase in house prices will strictly prevent some households from becoming a homeowner in the near future and therefore has a more immediate effect on homeownership rates, a decrease in prices merely allows some households to choose to become owners - a choice they may defer for a while due to mobility expectations. Put another way: an increase in prices may bound some households away from owning which means they *must* rent, whereas a decrease can slacken the borrowing constraint for some households which means they *can* own.

6.2 Regression-based inference

The delay effect and the asymmetric effect have important implications for inferences from cross-sectional and panel regressions. The delay effect means that cities with the same prices and same stochastic processes may still have different homeownership rates because their histories of prices differ. This can be clearly seen in the first panel of Figure 9, where after year five, the homeowner-

ship rates differ across cities that received the same shock at different points in time. The asymmetric effect means that if one were to look at absolute price changes (or squared price changes) the delay effect would not average out. The second panel of Figure 9 plots the chosen price sequences and the third panel the realized volatility of prices, for each of the above cities using a five year backward window.

Consider using a panel or cross-section of cities using simulated data from the model to regress homeownership rates on price levels and a risk measure, while controlling for some demographic differences. From the counterfactual analysis in section 5, we know that homeownership rates are functions of the history of prices while only very large differences in ex-ante house price risk matter.

Regression-based measures of the effect of risk typically use an ex-post measure of risk like the realized volatility of house prices over some past period³¹. So there is measurement error in using realized volatility as the proxy for ex-ante risk. However, from the durability and asymmetry effects we know that (1) the history of prices is an important explanatory variable for homeownership rates and that (2) volatility measures, which use squared historical prices, will be correlated with contemporaneous homeownership rates. In other words, while the latent variable, risk, is not important for homeownership rates, the measurement error part of volatility is important.

Lastly, the amount of bias that arises from using historical volatility as a measure of risk can vary a lot. Even the sign can change. There are many possible permutations depending on the window size used for measuring volatility and the difference in the timing of shocks, but an example is helpful.

Take two cities that each receive positive shocks, one in period one and the other in period five (as in the above example). The city that receives the shock in period five is “riskier” (from the perspective of the econometrician) for the years five through nine than the city receiving the shock in period one. A panel regression of homeownership rates on prices and volatility using years 5 through, say, 20 would find a negative coefficient on volatility (and in this case, the coefficient on prices would not be identified as there would be no cross-sectional variation in prices). In other words, a regression with a sample that contained a period of above-trend price growth for many cities, where the timing of this above trend growth differed over cities, could easily have a downwardly biased coefficient on volatility. Likewise, a regression with a sample period with differentially timed, below-trend price growth for many cities would have upwardly biased coefficients on volatility.³²

³¹Sinai and Souleles, 2005 and Banks et al., 2010 use a nine-year window and a five-year window, respectively.

³²For example, in the period 2006-2010, there is a general fall in house prices in the U.S. with cities like Las Vegas experiencing price declines sooner than cities like Seattle.

7 Conclusion

There is significant variation across cities in homeownership, LTV, house prices and housing risk. Much of the variation in house prices and housing risk has a common source - variation in the value or availability of land. This makes regression-based methods of separating the effects of risk from prices on household behavior difficult and inconclusive. Instead, we build a life-cycle model of homeownership which we match to the mean city in our data.

The model is able to explain much of the cross-city variation in homeownership and LTV and matches the variation in the data particularly well for younger households. We find that it is the relatively higher prices in cities with scarce land which causes their lower homeownership 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 to higher reliance on non-housing savings. This result highlights the importance of including other means of imperfect insurance in asset allocation models with incomplete markets.

Logical avenues for further investigation include examining whether any regional variation in mortgage market conditions is systematically related to the data considered here and using a general equilibrium version of the model to examine the different local effects of aggregate (country-wide) shocks. Also, it would be worth exploring whether households in low land share areas (like Las Vegas) are more exposed to changes in land values because of their higher LTV.

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A Robustness to Supply-side effects

A.1 Motivation

It is worth briefly outlining the different types of mortgage available in the United States³³. Mortgage loans may either be conventional or nonconventional. To qualify for a conventional loan, households must pass credit and PITI (income) tests. If they cannot afford a 20% downpayment, they must also purchase PMI (private mortgage insurance) to qualify for a conventional loan. Nonconventional loans are supplied by the government, or guaranteed by the VA. They tend to be more appropriate for households who require a large LTV.

Conventional loans may either be 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.

Now, 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 downpayment (to qualify for the cheaper rates on conforming loans). And, this will yield a negative correlation between land share and LTV. If the conforming loan limit is driving our results, then the effect should be stronger the closer the loan size is 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-land share correlation in samples delineated by the ratio of loan size to loan limit (restricting our attention to households

³³For more detail see, e.g., Caplin et al. (1997).

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.

A.2 Results

The results are reported in Table 14. These regressions are identical to those in the body of the paper, but they are disaggregated into samples delineated by loan-to-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-to-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). For each loan-to-limit ratio sample, we have estimated separately the effect of land scarcity (Panel A) and land share (Panel B) on LTV.

The effect on LTV is negative in all samples for both land scarcity and land share. For land scarcity, the effect is very large for the 0-0.25 sample (0.16) and negligible for the >1.5 sample. But, it is very similar (hovering around 0.05) for all other samples. The fact that the coefficients are similar suggests that the negative effect is not being driven by some interaction with the conforming loan limit. For land share, the effect is declining with the ratio. But, it is everywhere negative, in particular for those loans that fall well before the conforming loan limit: this still indicates that the negative coefficient cannot simply be due to an interaction with the loan limits.

B Parametrization

B.1 Household life-cycle and preferences

We calibrate the discount factor, $\beta = 0.95$, housing's share in the utility function, $\sigma = 0.3$ following Favilukis et al. (2010) and the inverse of the intertemporal elasticity of substitution, $\phi = 5$, following Piazzesi et al. (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 (1989); 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 precautionary savings in our model, we choose $\gamma = 3$, which is well within the more traditional range of two to five that most studies prefer (see Lustig and Nieuwerburgh (2010); Hryshko et al. (2010); Li and Yao (2007)).

B.1.1 Family size equivalence

We collect data from the period 1970-1993 in the CPS. We control for year effects by using year dummies. The family size profile is generated by the following 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 10 shows the profiles of family size from the CPS. Family size increases sharply when the household is young, peaking at age 38.

In order 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 B.4 lists some equivalence scales. L-M stands for Lazear and Michael (1980), US 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 non-integer family sizes, we assume that the adjustment factor is linear within the family sizes specified in Table (B.4). Figure 10 shows the equivalent, normalized family size over the life cycle.

B.2 Assets

We set the downpayment requirement, $d = .1$. We set the transaction cost of buying, $\theta_b = .08$, within the range typically chosen by the literature (Martin (2003); Fisher and Gervais (2011)). We set the interest rates $r_l = .04$. The average difference between a 30 year fixed rate mortgage and the 30 year U.S. Treasury bond is between 1% and 2% for 1977-2010 so we set $r_b = .06$.

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 and 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.

$$\lambda_w = \frac{1}{b_0}$$

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) uses public use micro-files 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 US economy³⁴.

We use data from the Integrated Public Use Microdata Sample (IPUMS) 1990 5% 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 $t_p = 0.01$.

³⁴See Table 1, page 6 in their paper

B.4 Earnings Process

We parametrize the idiosyncratic and age-profile portion of the household's earnings following Halket and Vasudev (2011), who estimate a process similar to Storesletten et al. (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, $\sigma_\psi = .098$ 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 $\sigma_p = .25$, which is within bounds found by Storesletten et al. (2004b); Blundell et al. (2008) We discretize the innovations with a 3-point distribution following Tauchen (1986).

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

Figures and tables

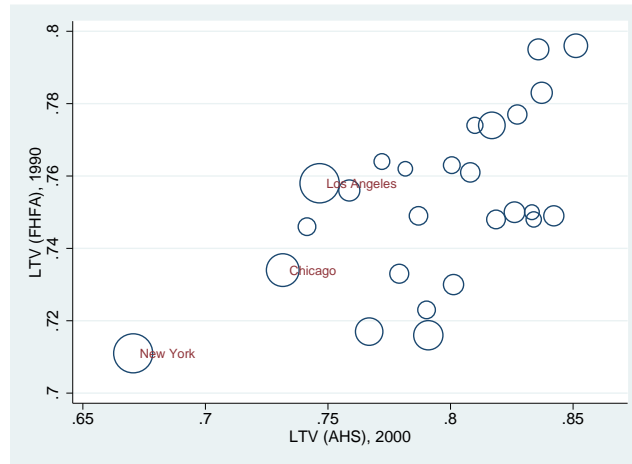


Figure 1: Comparison of LTV estimates from FHFA and AHS in 1990

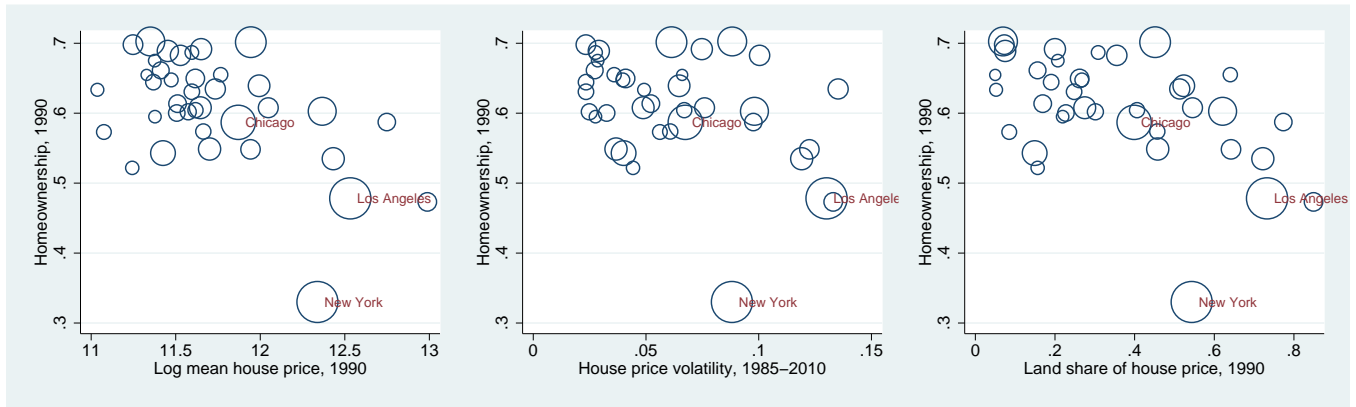


Figure 2: Relationship of homeownership to house price levels, volatilities and land shares

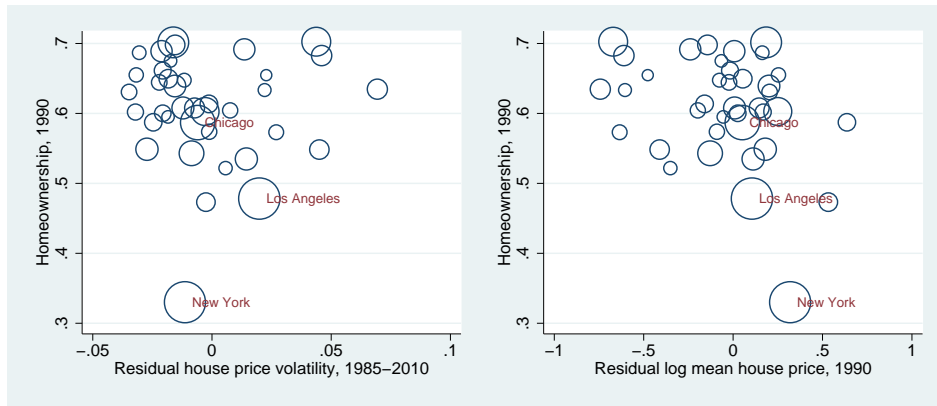


Figure 3: Homeownership and residual price levels and volatilities

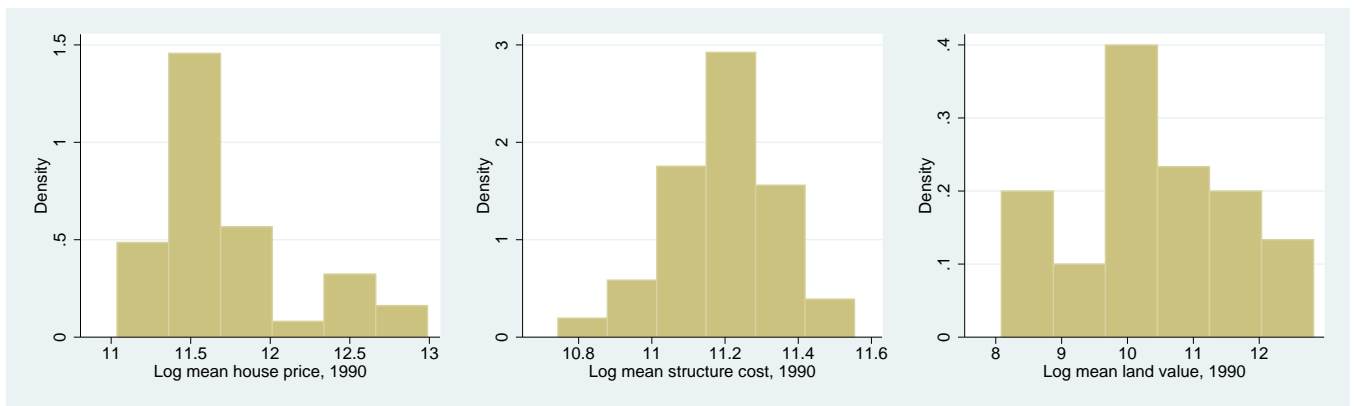


Figure 4: Histograms of city price, structure cost and land value levels

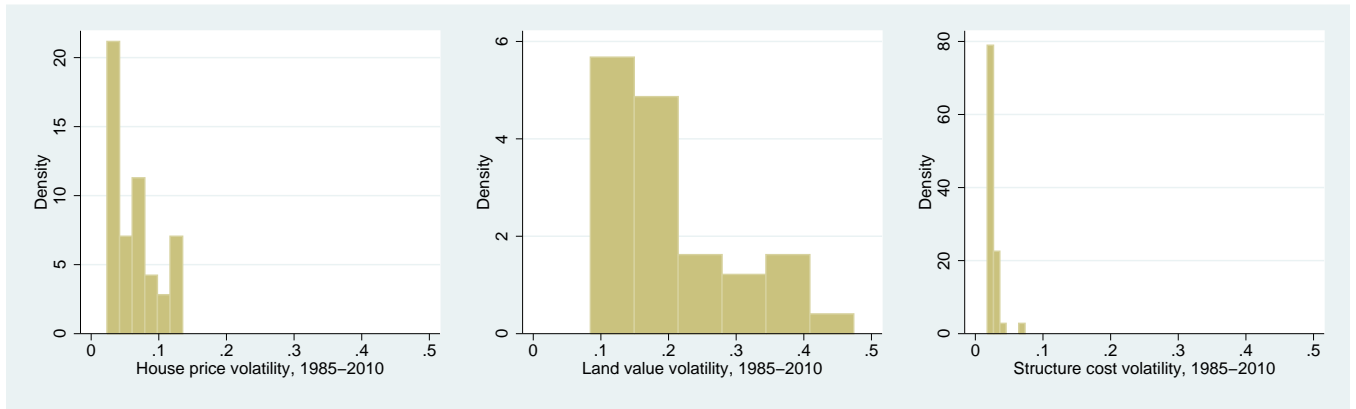


Figure 5: Histograms of city price, structure cost and land value volatilities



Figure 6: Relationship of house price levels and volatilities to land share

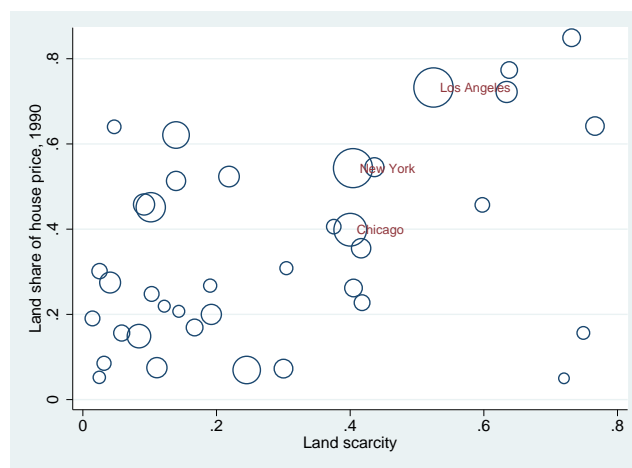


Figure 7: Relationship of land share to land scarcity

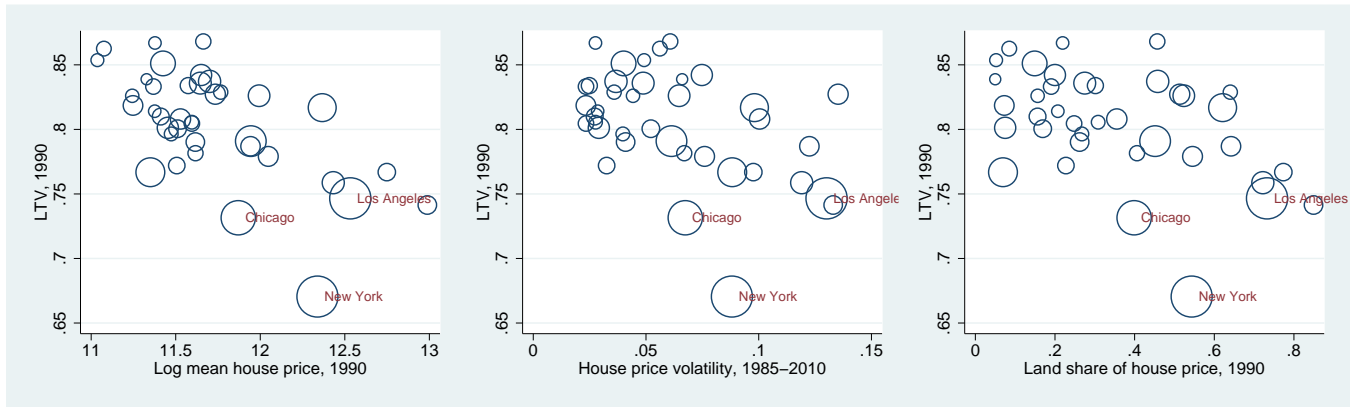


Figure 8: Relationship of LTV to house price levels, volatilities and land shares

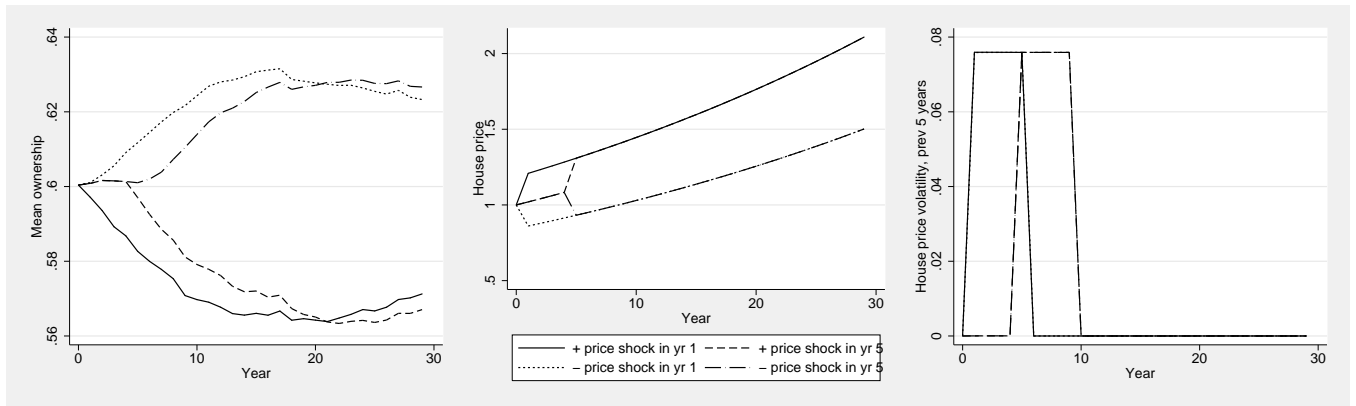


Figure 9: Impulse responses: mean ownership, house price level and volatility

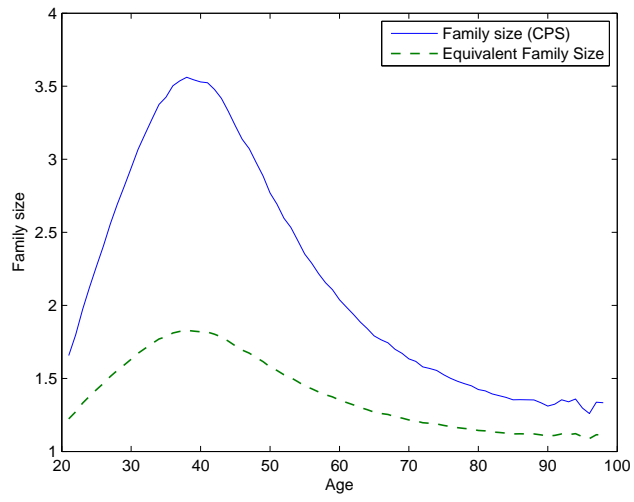


Figure 10: L-M adjusted family size profile (yearly bins)

Table 1: Marginal effects from probit regressions of homeownership on house prices and volatilities

	(1)	(2)	(3)	(4)	(5)	(6)
Log house price	-0.139*** (0.041)	-0.196*** (0.048)			-0.144** (0.063)	-0.210*** (0.073)
House price volatility			-1.321*** (0.397)	-1.762*** (0.468)	0.073 (0.516)	0.246 (0.542)
1 child		0.055*** (0.004)		0.056*** (0.004)		0.055*** (0.004)
2 children		0.097*** (0.006)		0.097*** (0.006)		0.097*** (0.006)
3 children or more		0.051*** (0.008)		0.052*** (0.008)		0.051*** (0.008)
Married		0.250*** (0.006)		0.255*** (0.006)		0.250*** (0.006)
Age		0.035*** (0.001)		0.035*** (0.001)		0.035*** (0.001)
Age ²		-0.000*** (0.000)		-0.000*** (0.000)		-0.000*** (0.000)
Log HH wage		0.133*** (0.003)		0.124*** (0.006)		0.133*** (0.003)
High school grad		0.119*** (0.006)		0.122*** (0.007)		0.119*** (0.006)
Some college		0.162*** (0.013)		0.167*** (0.016)		0.161*** (0.013)
College grad		0.202*** (0.016)		0.199*** (0.018)		0.202*** (0.016)
Observations	1,107,803	1,107,803	1,107,803	1,107,803	1,107,803	1,107,803

Marginal effects are evaluated at the mean of all continuous variables. For binary variables, we report the effect of a 0-1 change. Estimates are based on the sample of all household heads, aged 21-75, from the IPUMS 5 percent US census extract of 1990. Mean ownership in the sample is 0.64. Log house price is log of city mean over four quarters of 1990. Volatility is standard deviation over annual growth rates in prices (measured at first quarter of each year), between 1985 and 2010. Robust SEs, clustered by city, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Explaining cross-city variation in local price levels and volatilities

PANEL A: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Log HP	Log LV	Log SC	Vol HP	Vol LV	Vol SC
Land share	1.895*** (0.122)	5.076*** (0.189)	-0.026 (0.118)	0.113*** (0.017)	-0.181*** (0.058)	-0.015* (0.008)
Constant	11.097*** (0.058)	8.673*** (0.089)	11.269*** (0.056)	0.027*** (0.008)	0.278*** (0.028)	0.032*** (0.004)
Observations	38	38	38	38	38	38
R-squared	0.871	0.952	0.001	0.544	0.211	0.090

PANEL B: Reduced Form

	(1)	(2)	(3)	(4)	(5)	(6)
	Log HP	Log LV	Log SC	Vol HP	Vol LV	Vol SC
Land scarcity	1.213*** (0.304)	2.807*** (0.810)	-0.067 (0.127)	0.102*** (0.022)	-0.071 (0.070)	-0.003 (0.009)
Constant	11.508*** (0.114)	9.913*** (0.303)	11.279*** (0.047)	0.043*** (0.008)	0.224*** (0.026)	0.026*** (0.003)
Observations	38	38	38	38	38	38
R-squared	0.306	0.250	0.008	0.376	0.028	0.003

PANEL C: IV

	(1)	(2)	(3)	(4)	(5)	(6)
	Log HP	Log LV	Log SC	Vol HP	Vol LV	Vol SC
Land share	2.038*** (0.219)	4.713*** (0.351)	-0.113 (0.209)	0.171*** (0.035)	-0.119 (0.105)	-0.005 (0.015)
Constant	11.038*** (0.095)	8.824*** (0.152)	11.306*** (0.091)	0.003 (0.015)	0.252*** (0.045)	0.028*** (0.006)
Observations	38	38	38	38	38	38
R-squared	0.866	0.947	0.000	0.405	0.186	0.048

HP is house price, LV is land value, SC is structure cost. Price levels (Log **) are means over the four quarters of 1990. Volatility ("Vol") is standard deviation over annual growth rates in prices (measured at first quarter of each year), between 1985 and 2010. Instrument in IV columns is land scarcity. Observations are weighted by city size. Robust SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Marginal effects from probit regressions of homeownership on land share

	(1) Basic	(2) Basic	(3) Red. form	(4) Red. form	(5) IV	(6) IV
Land share	-0.259*** (0.066)	-0.345*** (0.074)			-0.377*** (0.125)	-0.493*** (0.141)
Land scarcity			-0.221*** (0.070)	-0.287*** (0.081)		
1 child		0.056*** (0.004)		0.057*** (0.003)		0.054*** (0.004)
2 children		0.097*** (0.006)		0.098*** (0.005)		0.095*** (0.007)
3 children or more		0.049*** (0.008)		0.052*** (0.009)		0.048*** (0.008)
Married		0.254*** (0.006)		0.257*** (0.006)		0.248*** (0.008)
Age		0.035*** (0.001)		0.035*** (0.001)		0.035*** (0.001)
Age^2		-0.000*** (0.000)		-0.000*** (0.000)		-0.000*** (0.000)
Log HH wage		0.128*** (0.005)		0.121*** (0.006)		0.132*** (0.005)
High school grad		0.119*** (0.006)		0.125*** (0.008)		0.113*** (0.008)
Some college		0.162*** (0.015)		0.168*** (0.017)		0.158*** (0.015)
College grad		0.200*** (0.017)		0.200*** (0.018)		0.197*** (0.016)
Observations	1,107,803	1,107,803	1,107,803	1,107,803	1,107,803	1,107,803

Marginal effects are evaluated at the mean of all continuous variables. For binary variables, we report the effect of a 0-1 change. Estimates are based on the sample of all household heads, aged 21-75, from the IPUMS 5 percent US census extract of 1990. Mean ownership in the sample is 0.64. Reported land share is mean over four quarters of 1990. In the IV specifications, land share is instrumented with land scarcity. Robust SEs, clustered by city, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Regressions of LTV on house prices and volatilities

	(1)	(2)	(3)	(4)	(5)	(6)
Log house price	-0.049*** (0.007)	-0.043*** (0.007)			-0.047*** (0.009)	-0.048*** (0.008)
House price volatility			-0.389** (0.145)	-0.278* (0.149)	-0.022 (0.132)	0.095 (0.138)
1 child, at purchase		0.015** (0.006)		0.015** (0.006)		0.016** (0.006)
2 children, at purchase		0.012* (0.006)		0.011* (0.006)		0.012** (0.006)
3 children or more, at purchase		0.013 (0.008)		0.011 (0.009)		0.013 (0.008)
Married		-0.022*** (0.003)		-0.022*** (0.003)		-0.022*** (0.003)
Age, at purchase		-0.003** (0.001)		-0.003*** (0.001)		-0.003** (0.001)
Age^2, at purchase		-0.000** (0.000)		-0.000* (0.000)		-0.000** (0.000)
High school grad		-0.020*** (0.005)		-0.020*** (0.005)		-0.020*** (0.005)
Some college		-0.028*** (0.005)		-0.028*** (0.005)		-0.028*** (0.005)
College grad		-0.056*** (0.006)		-0.059*** (0.006)		-0.055*** (0.006)
Constant	1.402*** (0.086)	1.511*** (0.081)	0.839*** (0.009)	1.014*** (0.021)	1.390*** (0.101)	1.564*** (0.091)
Observations	29,133	29,133	29,133	29,133	29,133	29,133
R-squared	0.010	0.073	0.004	0.067	0.010	0.073

Estimates are based on the sample of all household heads, aged 21-75 (at year of purchase), with mortgages, from the AHS samples described in the data section above. We also restrict the sample to households whose mortgage was taken out simultaneously with their house purchase: this ensures that, when calculating LTV, loan and price are measured at the same time. We truncate LTV observations above 1. And, since homes in the sample were purchased in different years, we recenter all observations by the 1990 purchase year mean. Specifically, we regress LTV on a full set of purchase year dummies, and using these estimates, predict the value for all households in 1990: it is these predicted values that serve as the dependent variable in this table's regressions. Mean LTV in the sample is 0.81. Reported land share is the mean over four quarters of 1990. Number of children (under 18), at purchase date, is predicted. Specifically, we count the number of children currently in the family who would have been under 18 at the purchase date; of course, children born between the purchase and survey years are omitted. In the IV specifications, land share is instrumented with land scarcity. In all regressions, we control for a full set of purchase year fixed effects. Robust SEs, clustered by city, in parentheses. Log house price is log of city mean over four quarters of 1990. Volatility is standard deviation over annual growth rates in prices (measured at first quarter of each year), between 1985 and 2010. Robust SEs, clustered by city, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Regressions of LTV on land share

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	Red. form	Red. form	IV	IV
Land share	-0.104*** (0.023)	-0.086*** (0.024)			-0.164*** (0.048)	-0.159*** (0.044)
Land scarcity			-0.058** (0.027)	-0.057** (0.023)		
1 child, at purchase		0.015** (0.006)		0.016*** (0.005)		0.015** (0.006)
2 children, at purchase		0.011* (0.006)		0.013** (0.005)		0.010 (0.007)
3 children or more, at purchase		0.010 (0.009)		0.015* (0.007)		0.008 (0.010)
Married		-0.022*** (0.003)		-0.022*** (0.003)		-0.022*** (0.003)
Age, at purchase		-0.003*** (0.001)		-0.003*** (0.001)		-0.002** (0.001)
Age^2, at purchase		-0.000** (0.000)		-0.000 (0.000)		-0.000** (0.000)
High school grad		-0.020*** (0.005)		-0.018*** (0.005)		-0.022*** (0.006)
Some college		-0.029*** (0.005)		-0.027*** (0.005)		-0.030*** (0.005)
College grad		-0.058*** (0.006)		-0.059*** (0.005)		-0.057*** (0.006)
Constant	0.870*** (0.010)	1.039*** (0.021)	0.843*** (0.006)	1.025*** (0.021)	0.895*** (0.020)	1.063*** (0.028)
Observations	30,072	30,072	30,072	30,072	30,072	30,072
R-squared	0.008	0.067	0.005	0.067	0.005	0.063

Estimates are based on the sample of all household heads, aged 21-75 (at year of purchase), with mortgages, from the AHS samples described in the data section above. We also restrict the sample to households whose mortgage was taken out simultaneously with their house purchase: this ensures that, when calculating LTV, loan and price are measured at the same time. We truncate LTV observations above 1. And, since homes in the sample were purchased in different years, we recenter all observations by the 1990 purchase year mean. Specifically, we regress LTV on a full set of purchase year dummies, and using these estimates, predict the value for all households in 1990: it is these predicted values that serve as the dependent variable in this table's regressions. Mean LTV in the sample is 0.81. Reported land share is the mean over four quarters of 1990. Number of children (under 18), at purchase date, is predicted. Specifically, we count the number of children currently in the family who would have been under 18 at the purchase date; of course, children born between the purchase and survey years are omitted. In the IV specifications, land share is instrumented with land scarcity. Robust SEs, clustered by city, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Invariant parameters

Parameter	Description	Value
β	Discount factor	0.95
σ	Housing's share in utility	0.30
ϕ	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	Downpayment	0.1
θ_b	Home buyer's transaction cost	0.08
ζ	Replacement rate for pensions	0.6

Table 7: Matched parameters

Parameter	Baseline Value	<i>High</i>	<i>Low</i>
σ_v	0.0158	0.0183	0.0123
σ_ε	0.0417	0.0486	0.0324
$\frac{h^o}{h^r}$	4	4	4
$\frac{h^o}{h^r}$	9	9	9
δ_j	0.0112	0.0101	0.0121
p_1	1	1.1464	0.7947
w_1	1	1.0153	0.9785

The initial price and wage levels can be normalized to one in the baseline model. The units on the house size parameters are median household earnings for 21 year olds and these parameters are not changed across cities.

Table 8: Model fit

	Data	Model
Homeownership rate	0.58	0.60
Homeownership rate under 65	0.56	0.58
Mean loan to value	0.78	0.70
Owner-occupier to renter house size	2.01	2.02

Reported means are taken across city averages, weighted by city populations.

Table 9: Homeownership profile: data and model

age	Data: mean	Model: mean
21-35	0.36	0.22
36-50	0.64	0.67
51-65	0.73	0.87
66-75	0.72	0.68

Reported means are taken across city averages (within age groups), weighted by city populations.

Table 10: Difference between high and low land scarcity

	Data: high-low	Model: high-low
Homeownership rate	-0.08	-0.09
Mean loan to value	-0.07	-0.02

Reported means are taken across city averages, weighted by city populations.

Table 11: Differences in homeownership and LTV profiles from differences in land scarcity: High-Low

age	Own Data	Own Model	LTV Data	LTV Model
21-35	-0.08	-0.08	-0.07	-0.07
36-50	-0.12	-0.11	-0.06	-0.01
51-65	-0.10	-0.04	-0.06	0.06
66-75	-0.10	-0.15	-0.04	NA

The low group of cities contains the 19 in the sample with the lowest shares of unavailable land, and the high group are those 19 with the largest shares. High-low is the difference between the high and low groups. Reported means are taken across city averages, weighted by city populations.

Table 12: Contribution from various elements

Parameter	Homeownership: High-Low	LTV: High-Low
σ_v	-0.00	-0.02
σ_ε	-0.01	-0.01
δ_j	0.00	0.00
p_1	-0.08	0.00
w_1	0.00	0.00

Table 13: High variance economies: Difference from baseline

Parameter	Value	Homeownership: High-Base	LTV: High-Base
σ_v	0.08	-0.16	-0.06
σ_ε	0.09	-0.03	-0.01

Table 14: Regressions of LTV on land scarcity and land share, for samples delineated by loan-limit ratio

PANEL A: LAND SCARCITY							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample: loan/limit	0-0.25	0.25-0.5	0.5-0.75	0.75-1	1-1.25	1.25-1.5	>1.5
Land scarcity	-0.162** (0.062)	-0.055* (0.029)	-0.054* (0.027)	-0.066*** (0.022)	-0.046** (0.022)	-0.062** (0.027)	-0.002 (0.057)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,846	7,336	4,596	2,265	885	470	520
R-squared	0.122	0.134	0.109	0.106	0.065	0.066	0.062

PANEL B: LAND SHARE							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample: loan/limit	0-0.25	0.25-0.5	0.5-0.75	0.75-1	1-1.25	1.25-1.5	>1.5
Land share	-0.506*** (0.087)	-0.147*** (0.052)	-0.115*** (0.032)	-0.077** (0.031)	-0.068* (0.037)	-0.079 (0.049)	-0.023 (0.088)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,846	7,336	4,596	2,265	885	470	520
R-squared	0.163	0.142	0.116	0.102	0.067	0.066	0.063

Regressions are run separately for samples delineated by loan-to-limit ratio (the ratio of loan size to conforming loan limit, reported above each column). For each sample, we separately estimate the effect of land scarcity (in Panel A) and land share (in Panel B). All regressions control for a set of children dummies at purchase year (1, 2, 3+) and characteristics of the head (age, age squared, married, college graduate, some college, high school graduate). All estimates are based on the sample of all household heads, aged 21-75 (at year of purchase), with conventional mortgages, from the AHS samples described in the data section above. We also restrict the sample to households whose mortgage was taken out simultaneously with their home purchase: this ensures that, when calculating LTV, loan and price are measured at the same time. We truncate LTV observations above 1. And, since homes in the sample were purchased in different years, we recenter all observations by the 1990 purchase year mean. Specifically, we regress LTV on a full set of purchase year dummies, and using these estimates, predict the value for all households in 1990: it is these predicted values that serve as the dependent variable in this table's regressions. Reported land share is the mean over four quarters of 1990. Number of children (under 18), at purchase date, is predicted. Specifically, we count the number of children currently in the family who would have been under 18 at the purchase date; of course, children born between the purchase and survey years are omitted. Robust SEs, clustered by city, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Family size equivalence scale

Family Size	L-M	Orshansky (1965)	US 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