House Price Beliefs And Mortgage Leverage Choice*

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Abstract

We study the relationship between homebuyers' beliefs about future house price changes and their mortgage leverage choices. Whether more pessimistic homebuyers choose more or less leverage depends on their willingness to reduce the size of their housing investments. When households primarily maximize the levered return of their property investments, more pessimistic homebuyers reduce their leverage to purchase smaller houses. On the other hand, when considerations such as family size pin down the desired property size, pessimistic homebuyers reduce their financial exposure to the housing market by making smaller downpayments to buy similarly-sized homes. To determine which scenario better describes the data, we investigate the cross-sectional relationship between house price beliefs and mortgage leverage choices in the U.S. housing market. We exploit plausibly exogenous variation in house price beliefs to show that more pessimistic homebuyers make smaller downpayments and choose higher leverage, in particular in states where default costs are relatively low, as well as during periods when house prices are expected to fall on average. Our results highlight the important role of heterogeneous beliefs in explaining households' financial decisions.

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Aggregate leverage ratios in the economy vary substantially over time and play a key role in driving economic fluctuations (see Krishnamurthy and Muir, 2016; Mian, Sufi and Verner, 2016). Understanding the determinants of investors' leverage choices is therefore a question of central economic importance. Leverage choices in the housing market are of particular interest to policy makers (see DeFusco, Johnson and Mondragon, 2017): mortgages are the primary liability on households' balance sheets, and increased household leverage plays a key role in many accounts of the recent Financial Crisis (e.g., Mian and Sufi, 2009). In this paper, we explore the role of homebuyers' beliefs about house price changes as one potential determinant of their mortgage leverage choices.

We first develop a parsimonious model that characterizes the channels through which homebuyers' beliefs about future house price growth can affect their mortgage leverage choices. We show that the direction of the effect of beliefs on leverage choices is ambiguous, and depends on the willingness of relatively pessimistic homebuyers to reduce the size of their housing market investment by either purchasing a cheaper home or deciding to rent instead. We then empirically investigate the relationship between homebuyers' beliefs about future house price growth and their leverage choices, and find that more pessimistic homebuyers take on more leverage.

Our model adapts the portfolio choice framework of Geanakoplos (2010) and Simsek (2013) to the housing market. We consider individuals who optimally choose non-housing consumption in addition to home size and mortgage leverage given a schedule of loan-to-value ratios and interest rates offered by lenders. Introducing consumption as an additional choice margin allows households to separately determine the size of their home and their leverage. House price beliefs affect leverage choices through two forces. The first force works through the perceived expected return on housing investments ("expected return force"). More optimistic agents want to buy larger houses, since they expect each dollar invested in housing to earn a higher return. In order to afford the larger home, they need to further lever up their fixed resources. The second force works through the protection against house price declines offered by the ability to default on mortgages ("downpayment protection force").[1] Holding house size fixed, more pessimistic agents, who perceive a higher probability of defaulting on their mortgage, choose lower downpayments and higher leverage to limit the potential loss of their own funds in case of default.[2]

Our model captures an additional important feature of housing markets. Since owner-occupied housing is both an investment and a consumption good, housing choices are not just determined by homebuyers' investment motives, but also by consumption-driven motives such as family size and neighborhood preferences. This makes homebuyers' property investments less sensitive to changes in house price beliefs than they would be without these consumption considerations. For example, pessimistic homebuyers might not be willing to purchase a home in a cheaper but less-safe neighborhood or live in a smaller home, even if they expect housing prices to decline. Our main theoretical result is to show that the sensitivity of the homebuyers' housing investments to house price beliefs is central to determining the relationship between these house price beliefs and mortgage leverage choices.[3]

We highlight the key mechanisms in our model by considering two polar scenarios for which we can obtain explicit analytical results. We first consider a *variable house size scenario* in which households view home purchases as a pure investment decision, and consumption aspects do not reduce the sensitivity of housing investments to perceived expected returns. This scenario, in which both the expected return force and the downpayment

[1] We show that this force is active independent of whether mortgage default is primarily strategic, with homeowners defaulting as soon as their home is sufficiently "underwater," or whether mortgage default only occurs when households also receive a negative income shock that makes it impossible for them to continue making their monthly mortgage payments.

[2] As will become evident below, an equivalent exposition of the second force describes pessimists as perceiving a lower marginal cost of borrowing, since they expect to repay their loan in fewer states of the world. This makes higher leverage more appealing.

[3] Our examples here focus on the intensive margin of housing investment. In housing markets, renting rather than buying can give individuals the option to separate their decision of what house to live in from the decision of the size of their housing market investment. However, in many cases, the set of properties available for rent is very different from the set of properties available for sale; indeed, large single-family residences are almost exclusively owner-occupied. Therefore, reducing one's housing market exposure through renting will usually also involve a potentially costly adjustment to the type of housing that can be consumed. This force will also reduce the sensitivity of individuals' housing investments to expected housing returns.

protection force are operational, recovers the predictions from the portfolio choice problem in Simsek (2013): under the appropriate definition of optimism, more pessimistic homebuyers reduce their leverage to purchase smaller houses because the expected return force dominates the downpayment protection force.

We then consider a *fixed house size scenario*, in which the size of the housing investment is completely pinned down by factors such as family size, and in which households allocate their resources between consumption and making a downpayment. In this scenario, the expected return force is inactive while the downpayment protection force continues to operate. As a result, more pessimistic agents make smaller downpayments to protect their assets against losses in case of house price declines. In particular, a pessimistic homebuyer might think: "I need at least a 3-bedroom house given my family size, but I think house prices are likely to fall, so I do not want to invest much of my own money to buy the house." Such a borrower would then choose a smaller downpayment and higher leverage. In the paper, we provide extensive evidence for the prevalence of such thinking among homebuyers.

When we move away from these polar cases, whether more pessimistic agents take on more or less leverage depends on the sensitivity of homebuyers' housing investments to their house price beliefs. The empirical contribution of this paper is to investigate which of these forces dominates in the U.S. housing market. This analysis faces a number of challenges. Testing the implications of models with belief heterogeneity is difficult because individuals' beliefs are high-dimensional and hard-to-observe objects. In addition, even if we could cleanly elicit homebuyers' house price beliefs, we rarely observe forces that induce heterogeneity in these beliefs without also inducing variation in other variables that might independently affect those homebuyers' leverage choices.

Our empirical approach builds on Bailey et al. (2017), who document that the recent house price experiences of an individual's geographically distant friends affect her beliefs about the attractiveness of local housing market investments. Indeed, we verify that these experiences can be used as shifters of individuals' beliefs about the distribution of expected future house price changes; we also show that they are unlikely to affect leverage choices through channels other than beliefs. This allows us to explore the causal effect of beliefs on leverage choices by analyzing the cross-sectional relationship between the leverage choices of individuals borrowing from the same lender to purchase homes at the same time and in the same neighborhood, and the house price experiences of these homebuyers' geographically distant friends.

In our data, we observe an anonymized snapshot of U.S. individuals' friendship networks on Facebook, an online social network with over 231 million active users in the U.S. and Canada. Our first empirical step combines these data with responses to a housing market expectation survey that was conducted by Facebook in April 2017. The survey, which targeted Facebook users in Los Angeles through their News Feeds, elicited a distribution of respondents' expectations for future house price changes in their own zip codes. We find that individuals whose friends experienced more recent house price increases expect higher average future house price growth. Quantitatively, a one-percentage-point higher house price appreciation among an individual's friends over the previous 24 months is associated with the individual expecting a 33 basis points higher house price growth over the subsequent year. We also find that individuals whose friends experienced more heterogeneous recent house price changes report a more dispersed distribution of expected future house price growth. This suggests that the house price experiences within an individual's social network do not just affect her beliefs on average, but that other moments of the distribution of friends' experiences affect the corresponding moments of the belief distribution.

To study the role of house price beliefs in shaping mortgage leverage choice, we match anonymized social network data on Facebook users from 2,900 U.S. zip codes to public record housing deeds data, which contain information on both transaction prices and mortgage choices. We observe information on homebuyers' leverage choices for about 1.35 million housing transactions between 2008 and 2014.

We first test the predictions of our model under the assumption that beliefs over future house price changes are normally distributed.[4] We find that individuals whose friends have experienced lower recent house price growth, and who are thus more pessimistic about future house price growth, take on more leverage. Quantitatively, a one-percentage-point decrease in the average house price experiences among an individual's friends over the prior two years is associated with an increase in the loan-to-value ratio of about 11 basis points. Combined with the estimates from the survey, this suggests that a one-percentage-point decrease in the expected house price appreciation over the next twelve months leads individuals to increase their loan-to-value ratio by 33 basis points. These findings are aligned with the corresponding relationship in the fixed house size scenario. Consistent with additional predictions from this scenario, we also find that a higher cross-sectional variance of friends' house price experiences is associated with choosing higher leverage: holding mean beliefs fixed, individuals who have a more dispersed belief distribution perceive a higher probability of default, and thus reduce their downpayment.

We test a number of additional predictions from the model about the relationship between beliefs and leverage choices in the fixed house size scenario. First, the model suggests that the effects of beliefs on leverage choices should be particularly large when the cost of default is relatively small, so that households would consider defaulting in response to declining house prices a less costly proposition. Consistent with this, we find that more pessimistic individuals in non-recourse states, where lenders cannot recover losses on a mortgage by going after borrowers' non-housing assets, are more likely to reduce their downpayments than pessimistic individuals in recourse states, where the ability of lenders to go after non-housing assets translates into a higher cost of default.

Second, in the fixed house size scenario, changes in beliefs have larger effects on leverage choices for individuals that are relatively more pessimistic to begin with. This is because, in this scenario, the perceived probability of default is a key driver of differences in leverage choices among homebuyers. Following large house price increases, even relatively pessimistic individuals assign small probabilities to default states of the world. The quantitative effects of cross-sectional differences in beliefs on optimal leverage are therefore relatively small. Consistent with this, we find the magnitude of the relationship between house price beliefs and leverage choices to be the strongest among individuals who are relatively more pessimistic and during periods of declining house prices.

Third, the relative strength of the downpayment protection force to the expected return force should be increasing in the difficulty of separating the consumption and investment aspects of housing. Consistent with this, we find that pessimists reduce their downpayment more when buying homes in areas with high homeownership rates, where it is harder to reduce their exposure to the housing market by renting instead of buying.

Throughout the analysis, we argue that the house price experiences of a homebuyer's geographically distant friends affect her mortgage leverage choice only through influencing her beliefs about future house price changes. We rule out other channels that could have explained the observed relationship. For example, we show that the results are not driven by wealth effects whereby a higher house price appreciation in areas where an individual has friends increases her resources for making downpayments. Our results are also not explained by correlated shocks to individuals and their friends, or by individuals learning about the cost of default from their friends.

We provide ancillary evidence for the mechanisms described above. First, we show that, in a correlational sense, the negative relationship between optimism and leverage is also found in the New York Fed Survey of Consumer Expectations. Second, we conduct an additional survey on SurveyMonkey in which we present 1,600 individuals with hypothetical house price scenarios, and ask them to recommend a mortgage option to a friend who has already decided to buy a particular house. Survey respondents are more likely to recommend smaller downpayments under scenarios with a higher probability of large house price declines, even though this entails paying higher interest rates. When asked to explain their reasoning, many individuals describe a thought process

[4] By studying the case of normally distributed beliefs, we can derive unambiguous predictions for changes in the mean and standard deviation of beliefs about future house price growth. Our non-parametric results highlight the importance of using the appropriate definitions of optimism to generate unambiguous predictions about the effect of beliefs on leverage.

consistent with the downpayment protection force (e.g., "If he defaults and housing prices decrease so that he cannot sell to recoup his investment, he loses less deposit if he puts less down"). We also document that a similar logic is often described on financial advice websites and blogs that discuss what downpayments individuals should make. We then verify that many individuals do not consider mortgage default particularly costly, another requirement for a strong downpayment protection force. Lastly, we explore Zillow's *Consumer Housing Trends Report 2017* to document that consumption aspects such as location and home size are usually the most important determinants of individuals' property choices, and that potential investment returns are much less important.

Overall, our evidence points to a central role for house price beliefs in determining individuals' mortgage leverage choices. Driven by an important consumption aspect of homeownership, more pessimistic individuals do not buy substantially smaller houses, but instead reduce their exposure to the housing market by making a smaller downpayment, particularly when the costs of mortgage default are relatively small.

Our paper contributes to the theoretical literature on collateralized credit with heterogeneous beliefs developed by Geanakoplos (1997, 2003, 2010) and Fostel and Geanakoplos (2008, 2012, 2015, 2016). Within that literature, which has focused on environments in which investors exclusively make levered purchases of risky assets, our model is most closely related to the baseline environment studied by Simsek (2013). We show that the same theoretical framework can deliver new predictions when (i) an additional margin of adjustment — a consumption-savings decision — is introduced, and (ii) homebuyers' housing choices are not exclusively driven by the perceived pecuniary investment returns on housing. We operationalize the theory by developing implementable tests of how borrowers' beliefs affect their leverage choices. Our results provide support for theories in which investors' beliefs are an important determinant of individual and aggregate behavior, and are complementary to the findings of Koudijs and Voth (2016), who document a positive relation between lenders' optimism and high leverage.

Our theoretical observation that the relationship between borrowers' beliefs and leverage choices depends on the sensitivity of collateral investments to their expected returns is likely to be important in other settings. In the housing market, the consumption aspect of housing reduces households' desire to adjust the size of their housing investments based on their beliefs about future house price growth. In a similar way, firms borrowing against their equipment might not be able to sell any collateral that remains important in the current production process, even if the firms expect the collateral to lose value in the future. Even for pure investment assets, such as stock holdings, an investor's ability to dispose of those assets quickly might be affected by market liquidity, which will effectively determine the return sensitivity of the collateral position in response to changes in beliefs. In these settings, our model predicts that pessimistic agents would engage in significant (non-recourse) collateralized borrowing against any asset that they are unable to sell. To our knowledge, we are the first to *identify* the ability or willingness to adjust collateral positions as the key feature that determines the relationship between borrowers' beliefs and leverage choices, although the primitive forces driving our model are important in many environments.[5]

We also contribute to the growing empirical literature that studies belief formation. Some recent work includes Malmendier and Nagel (2011, 2015), Greenwood and Shleifer (2014), Kuchler and Zafar (2015), and Armona, Fuster and Zafar (2016). Much of this literature has focused on explaining how individuals' own experiences affect their expectations. We expand on the findings in Bailey et al. (2017) to show that various moments of the experiences of individuals' *friends* also affect the corresponding moments of those individuals' belief distributions.

Finally, we provide evidence for the importance of beliefs in determining individuals' housing and mortgage leverage decisions. Our results therefore inform the debate about the extent to which the joint movement in house

[5]For example, the mechanism behind the downpayment protection force is also present in models of sovereign default, such as those described in Aguiar and Amador (2013) and Uribe and Schmitt-Grohé (2017). For instance, a sovereign with pessimistic expectations about the performance of the economy anticipates the possibility of defaulting, which generates an incentive to borrow more. As described in Section 2.2, this effect is modulated by the costs of default, which are endogenous in the sovereign context, as emphasized by Bulow and Rogoff (1989) and Gennaioli, Martin and Rossi (2014), among others.

prices and mortgage leverage during the 2002-2006 housing boom period was the result of homebuyer optimism or other forces in the economy, such as credit supply shocks (Adelino, Schoar and Severino, 2016; Burnside, Eichenbaum and Rebelo, 2016; Case, Shiller and Thompson, 2012; Cheng, Raina and Xiong, 2014; Di Maggio and Kermani, 2016; Foote, Loewenstein and Willen, 2016; Glaeser, Gottlieb and Gyourko, 2012; Glaeser and Nathanson, 2015; Landvoigt, Piazzesi and Schneider, 2015; Mian and Sufi, 2009; Piazzesi and Schneider, 2009; De Stefani, 2017). Our empirical focus on owner-occupiers precludes us from making strong statements about the aggregate correlation between beliefs and leverage. Nevertheless, our findings suggest that, by itself, increased household optimism does not induce higher leverage among individuals that purchase properties to owner-occupy, and that other forces, such as shifts in credit supply, are likely important to understanding these homebuyers' leverage choices during the recent housing cycle. More broadly, our findings provide support for a literature that explores the role of beliefs as drivers of credit and business cycles (see Gennaioli, Shleifer and Vishny, 2012; Xiong, 2012; Angeletos and Lian, 2016; Gennaioli, Ma and Shleifer, 2016, for recent contributions).

1 A Model of Leverage Choice with Heterogeneous Beliefs

In this section, we develop a parsimonious model of leverage choice that allows us to characterize the channels through which homebuyers' beliefs can affect their mortgage leverage decisions.

1.1 Environment

We consider an economy with two dates, $t = \{0, 1\}$, populated by two types of agents: borrowers, indexed by i, and lenders, indexed by L. There is a numeraire consumption good and a housing good.

Borrowers. Borrowers' preferences over initial consumption and future wealth are given by

$$u_i\left(c_{0i}\right) + \beta \mathbb{E}_i\left[w_{1i}\right],$$

where c_{0i} denotes borrowers' date-0 consumption, and $\mathbb{E}_i\left[w_{1i}\right]$ corresponds to borrowers' date-1 expected wealth given their beliefs. We assume that the borrowers' discount factor satisfies $\beta < 1$ and that $u_i(\cdot)$ is a well-behaved increasing and concave function. Our formulation preserves the linearity of borrowers' preferences with respect to future wealth, which allows us to derive sharp results while allowing for a meaningful date-0 consumption decision.

Borrowers are endowed with $n_{0i} > 0$ and $n_{1i} > 0$ dollars at dates 0 and 1, respectively. At date 0, borrowers use their own resources or borrowed funds to either consume c_{0i} or to purchase a house of size h_{0i} at price $p_0 h_{0i}$. They can borrow through a non-contingent non-recourse mortgage that is collateralized exclusively by the value of the house they acquire. Formally, in exchange for receiving $p_0 h_{0i} \Lambda\left(\delta_i\right)$ dollars at date 0, borrowers promise to repay b_{0i} dollars at date 1. The function $\Lambda\left(\delta_i\right)$, which takes as an argument the normalized loan repayment $\delta_i = \frac{b_{0i}}{p_0 h_{0i}}$, denotes borrowers' loan-to-value (LTV) ratio and is determined by lenders as described below. Hence, borrowers' date-0 budget constraint corresponds to

$$c_{0i} + p_0 h_{0i}\left(1 - \Lambda\left(\delta_i\right)\right) = n_{0i}. \tag{1}$$

At date 1, borrowers have the option to default. In case of default, borrowers experience a private loss $\kappa_i h_{0i}$, which scales proportionally with the house size to preserve homogeneity. The default cost parameter $\kappa_i \geq 0$ captures both pecuniary and non-pecuniary losses associated with default. It can also be interpreted as a simple form of allowing for heterogeneity across borrowers regarding future continuation values. For much of the following exposition, we set the default cost $\kappa_i = 0$, allowing us to present the main forces in our model in a parsimonious and tractable way. In the Appendix, we show that our theoretical predictions generalize to a model with non-zero default costs; in Section 2.2, we also explore how the relationship between beliefs and leverage varies with the level of the default cost in such a richer model. The resulting predictions are then verified in our empirical analysis.

We denote house prices at dates 0 and 1 by p_0 and p_1, respectively, and define the growth rate of house prices by $g = \frac{p_1}{p_0}$. Borrowers hold heterogeneous beliefs about this growth rate of house prices. Borrower i's beliefs about the growth rate of house prices are described by a cdf $F_i(\cdot)$:

$$g = \frac{p_1}{p_0}, \text{ where } \quad g \sim_i F_i(\cdot),$$

where g has support in $[\underline{g}, \overline{g}]$, with $\underline{g} \geq 0$ and $\overline{g} \leq \infty$. We express borrowers' future wealth as $w_{1i} = \max\{w_{1i}^{\mathcal{N}}, w_{1i}^{\mathcal{D}}\}$, where $w_{1i}^{\mathcal{N}}$ and $w_{1i}^{\mathcal{D}}$ respectively denote borrowers' wealth in non-default and default states:

$$\begin{aligned} w_{1i}^{\mathcal{N}} &= n_{1i} + p_1 h_{0i} - b_{0i} \\ w_{1i}^{\mathcal{D}} &= n_{1i}. \end{aligned}$$

Finally, we incorporate the possibility of housing collateral choices being "return insensitive" by assuming that borrowers have a minimum desired house size. Formally, borrowers' housing choice h_{0i} must satisfy

$$h_{0i} \geq \underline{h_i}, \tag{2}$$

where $\underline{h_i} \geq 0$ is such that the borrowers' feasible set is non-empty. This specification tractably captures that borrowers' preferences for owner-occupied housing are also affected by the consumption aspect of housing.

When the home size constraint binds, we interpret homebuyers' housing investment decisions as being completely pinned down by consumption aspects of housing, such as the homebuyer's family size, the house quality or location, or the local amenities.[6] This extreme case allows us to study the relationship between beliefs and leverage when homebuyers' housing investments are insensitive to their perceived pecuniary returns. When the home size constraint does not bind, we can analyze the same relationship when homebuyers' housing investments fully respond to the investments' perceived pecuniary returns. These two polar cases, which we study below, provide extreme characterizations that highlight how the relationship between beliefs and leverage choices depends on the sensitivity of a given individuals' housing investment to the perceived pecuniary return of that investment. In the Appendix, we simulate an extension of the model in which homebuyers have conventional CES preferences over consumption and housing. In that extended model, the return sensitivity of housing investments arises endogenously from household preferences rather than being determined by a constraint, as in the stylized model presented here. Depending on the parameterization of the extended model, we can recover the predictions of both polar scenarios about the relationship between beliefs and leverage choices. This motivates our empirical analysis to understand which effects dominate in the data.

Lenders. Lenders are risk neutral and perfectly competitive. They require a predetermined rate of return $1 + r$, potentially different from β^{-1}, and have the ability to offer borrower-specific loan-to-value ratio schedules. For simplicity, we allow the lenders to recover the full value of the collateral upon default. Lenders' perceptions over house price growth, which may be different from those of borrowers, are given by a distribution with cdf $F_L(\cdot)$.

[6] While we model housing as an homogeneous good to maintain tractability, Equation (2) also proxies for households' willingness to adjust their housing choice in other dimensions. For example, it does not just capture households' willingness to buy a smaller house in the same neighborhood, but also their willingness to move to a cheaper neighborhood in order to reduce the fraction of their portfolio allocated to housing.

Equilibrium. An *equilibrium* is defined as consumption, borrowing, and housing choices c_{0i}, b_{0i} (or δ_i), and h_{0i}, as well as default decisions by borrowers, such that borrowers maximize utility given the loan-to-value ratio schedule offered by lenders to break even. Since our goal is to derive testable cross-sectional predictions for changes in borrowers' beliefs, we do not impose market clearing in the housing market, which would not affect our cross-sectional predictions for leverage choices. We work under the presumption that it is optimal for homebuyers to borrow in equilibrium, and relegate a detailed discussion of regularity conditions to the Appendix.

1.2 Equilibrium characterization

We characterize the equilibrium of the model backwards. We first analyze borrowers' default decisions, then characterize the loan-to-value schedules offered by lenders, and finally study the ex-ante choices made by borrowers.

Default decision. At date 1, borrowers default according to the following threshold rule:

$$\text{If} \begin{cases} g \leq \delta_i, & \text{Default} \\ g > \delta_i, & \text{No Default} \end{cases} \qquad \text{where} \quad \delta_i = \frac{b_{0i}}{p_0 h_{0i}},$$

and where g denotes the actual realization of house price growth. Intuitively, borrowers decide to default only when date-1 house prices are sufficiently low. For any realization of house price changes, the probability of default by borrower i increases with the borrower's promised repayment δ_i.

Remark. (Strategic default). A substantial literature investigates the extent to which mortgage defaults represent strategic defaults by households walking away from homes with negative equity despite having the resources to continue making mortgage payments (see Elul et al., 2010; Bhutta, Dokko and Shan, 2017; Ganong and Noel, 2017; Gerardi et al., 2017). This literature generally concludes that default usually happens at levels of negative equity that are larger than what would be predicted by a frictionless default model. Our model can incorporate these findings through the size of the parameter κ_i, which captures other, non-financial default costs (e.g., social stigma). More importantly, though, our theoretical and empirical findings do not depend on whether default is purely strategic or the result of also receiving negative income shocks (the "double trigger hypothesis"). Indeed, our results only require that default is *more likely* when house prices decline; in other words, the results are robust as long as negative equity is a necessary condition for default, even if it is not sufficient.[7]

LTV ratio schedules. Given borrowers' default decisions, competitive lenders offer loan-to-value (LTV) ratio schedules to break even. Equation (3) characterizes the loan-to-value ratio schedule offered by lenders to a borrower of type i for any normalized promised repayment $\delta_i = \frac{b_{0i}}{p_0 h_{0i}}$:

$$\Lambda(\delta_i) = \frac{\int_{\underline{g}}^{\delta_i} g dF_L(g) + \delta_i \int_{\delta_i}^{\overline{g}} dF_L(g)}{1+r}. \tag{3}$$

The first term in the numerator corresponds to the payment received by lenders in default states, normalized by the date-0 value of the house. The second term in the numerator corresponds to the normalized repayment in non-default states. Both terms are discounted at the lenders' risk-free rate, $1 + r$.

[7] This requirement is fulfilled even in the "double trigger" theory, under which negative equity and income shocks are both required before households will default on their mortgage. Importantly, under this theory, when households receive a negative income shock and cannot continue making their mortgage payments, if house prices are high, households can just sell the home, repay the outstanding mortgage, and keep the difference. Only when they are underwater will the negative income shock precipitate mortgage default. We choose to not model income shocks or households' expectations over these shocks. This is driven by a desire to develop the most parsimonious model to understand the mechanisms at the center of our analysis. We also do not observe shifters of households' income expectations that would allow us to test the predictions from such a richer model.

Borrowers' leverage choice. To determine borrowers' leverage choice in an analytically tractable way, we reformulate their problem as a function of δ_i.[8] Formally, borrowers choose c_{0i}, h_{0i}, and δ_i to maximize

$$\max_{c_{0i},h_{0i},\delta_i} u_i\left(c_{0i}\right)+\beta p_0 h_{0i}\int_{\delta_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right), \tag{4}$$

subject to a date-0 budget constraint and the housing constraint (return insensitivity)

$$\begin{aligned} c_{0i}+p_0 h_{0i}\left(1-\Lambda\left(\delta_i\right)\right) &= n_{0i} \qquad (\lambda_{0i}) \\ \underline{h_i} &\leq h_{0i} \qquad (\nu_{0i}). \end{aligned}$$

Borrower i takes into account that $\Lambda\left(\delta_i\right)$ is given by Equation (3), and λ_{0i} and ν_{0i} denote (non-negative) Lagrange multipliers. Note that the integral term in the objective function (4) corresponds to the net return per dollar invested in housing. Borrowers' optimality conditions for consumption, housing, and leverage are given by:

$$c_{0i}: \quad \underbrace{u_i'\left(c_{0i}\right)}_{\text{Marginal Benefit}} - \underbrace{\lambda_{0i}}_{\text{Marginal Cost}} = 0 \tag{5}$$

$$h_{0i}: \quad -\underbrace{\lambda_{0i}p_0\left(1-\Lambda\left(\delta_i\right)\right)}_{\text{Marginal Cost}} + \underbrace{\beta p_0\int_{\delta_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right)}_{\substack{\text{Marginal Benefit} \\ \text{(Expected Return force)}}} + \nu_{0i} = 0 \tag{6}$$

$$\delta_i: \quad \underbrace{\lambda_{0i}p_0 h_{0i}\Lambda'\left(\delta_i\right)}_{\text{Marginal Benefit}} - \underbrace{\beta p_0 h_{0i}\int_{\delta_i}^{\overline{g}}dF_i\left(g\right)}_{\substack{\text{Marginal Cost} \\ \text{(Downpayment protection force)}}} = 0. \tag{7}$$

The optimality condition for consumption equates the marginal benefit of consumption, given by $u_i'\left(c_{0i}\right)$, with the marginal cost of tightening the date-0 budget constraint, given by λ_{0i}.

The optimality condition for housing equates the marginal benefit of buying a larger house with the marginal cost of doing so. The marginal benefit of a housing investment is the net present value of the expected return received at date 1. This is the first channel through which borrower beliefs affect leverage choice, referred to above as the "expected return force." The marginal cost of the investment corresponds to the reduction in available resources at date 0, valued by borrowers according to λ_{0i}. When the housing constraint binds, borrowers' housing corresponds to $h_{0i}=\underline{h_i}$ and Equation (6) simply defines ν_{0i}, the shadow value of relaxing the housing constraint.

The optimality condition for borrowing equates the marginal benefit of increasing the promised repayment, which corresponds to having more resources at date 0, with the marginal cost of doing so. The marginal cost corresponds to the present value of the increased promised repayment in non-default states at date 1. This is the second channel through which borrower beliefs affect leverage choices, referred to above as the "downpayment protection force." Intuitively, a pessimistic borrower that needs a house of a certain size is more inclined to choose a higher LTV ratio, since her perceived probability of repaying the mortgage is low. Equivalently, an optimistic borrower with a similar house size target expects to repay her mortgage in more states of the world. This increase in the perceived marginal cost of borrowing leads more optimistic borrowers to invest more of their own funds by making a larger downpayment to reduce their leverage.

[8] Although we let borrowers choose δ_i, the fact that $\Lambda\left(\cdot\right)$ is a monotone function of δ_i for the relevant range means that our formulation is identical to allowing borrowers to choose loan-to-value ratios (see Appendix A.2).

1.3 Two alternative scenarios

When borrowers have preferences for housing that are not purely driven by investment considerations and they can freely adjust their behavior along consumption, borrowing, and housing margins, it is not generally possible to provide clear analytic characterizations of the effect of changes in beliefs on leverage choices (though we do provide a number of numerical simulations in the Appendix). However, by sequentially studying (i) a scenario in which borrowers freely adjust their housing size, and (ii) a scenario in which borrowers' housing size is fixed due to non-pecuniary forces such as family size, and the borrowers' housing choice is thus return insensitive, we can provide comparative statics on the effects of beliefs shifts on mortgage leverage choices.

We refer to the first case as the *variable house size* scenario. In this case, borrowers choose the size of their house purely based on its return as a levered investment. As a result, their housing choice is maximally sensitive to the investment's perceived pecuniary return. We refer to the second case as the *fixed house size* scenario. This scenario captures an environment where considerations such as family size or locational preferences are the only drivers of borrowers' housing decision, and the size of the housing investment is completely return insensitive. In practice, we expect borrowers' behavior to be a combination of the effects we identify under these polar scenarios. The purpose of our empirical exercise is then to determine which scenario more closely captures the dominant forces driving the relationship between beliefs and leverage in the U.S. housing market. For brevity, we exclusively consider the predictions of our model for loan-to-value ratios, and relegate the study of consumption and housing decisions to the Appendix.

Variable house size. In the variable house size scenario, a borrower's optimal LTV ratio is characterized by:

$$\frac{\Lambda'(\delta_i)}{1-\Lambda(\delta_i)} = \frac{1}{\mathbb{E}_i\left[g\middle|\, g \geq \delta_i\right] - \delta_i}, \quad \text{where} \quad \mathbb{E}_i\left[g\middle|\, g \geq \delta_i\right] = \frac{\int_{\delta_i}^{\overline{g}} g dF_i(g)}{\int_{\delta_i}^{\overline{g}} dF_i(g)}. \tag{8}$$

Equation (8) follows directly from combining borrowers' optimal housing and borrowing choices, given by Equations (6) and (7). The numerator in the definition of $\mathbb{E}_i\left[g\middle|\, g \geq \delta_i\right]$ captures the "expected return force" described above, while the denominator captures the "downpayment protection force." Changes in the distribution of borrowers' beliefs affect leverage choices through the truncated expectation of house price growth, $\mathbb{E}_i\left[g\middle|\, g \geq \delta_i\right]$. Below we characterize conditions under which changes in beliefs shift $\mathbb{E}_i\left[g\middle|\, g \geq \delta_i\right]$ for any $\tilde{\delta}$ (point-wise).[9]

Fixed house size. In the fixed house size scenario, borrowers choose δ_i to solve a consumption smoothing problem.[10] Formally, the optimal LTV ratio is fully characterized by the following equation

$$u_i'\left(n_{0i} - p_0 h_{0i}\left(1 - (\delta_i)\right)\right)\Lambda'(\delta_i) = \beta\left(1 - F_i(\delta_i)\right). \tag{9}$$

Equation (9) follows directly by combining borrowers' optimal consumption and borrowing choices, given by Equations (5) and (7). In this case, only the downpayment protection force is present, through the term $\int_{\delta_i}^{\overline{g}} dF_i(g) = 1 - F_i(\delta_i)$. Therefore, changes in the distribution of borrowers' beliefs only affect leverage choices through changes in the probability of default, $F_i(\delta_i)$. In this scenario, as described below, unambiguous predictions can be found by comparing point-wise shifts in $F_i(\cdot)$.

[9] Throughout the paper, we compare belief distributions along dimensions that allow us to guarantee that truncated expectations and default probabilities, when defined as functions of the default threshold, shift "point-wise." We could establish additional predictions from "local" changes in truncated expectations (starting from a given equilibrium). We do not pursue that route, because our empirical strategy only uses shifts in the distribution $F_i(\cdot)$ and does not use information on actual default thresholds.

[10] In a more general setup, borrowers will also be indifferent at the margin between consuming and investing in other assets. In such a setup, λ_{0i} can be interpreted as the marginal return/utility obtained from investments other than housing. See Cocco (2004) and Chetty, Sándor and Szeidl (2017) for recent work on how housing affects optimal asset allocation problems.

2 Beliefs and Leverage Choice: Equilibrium Outcomes

We next study how changes in the distribution of borrowers' beliefs affect equilibrium outcomes in our model. In the body of the paper, we impose a parametric assumption on the distribution of beliefs and develop comparative statics for changes in the key moments of the belief distribution. Proofs for all Propositions are provided in the Appendix. In Appendix C, we also derive and implement a non-parametric test of how beliefs affect leverage.

2.1 Baseline Parametric Predictions

Throughout this section, we assume that borrowers' beliefs about the expected growth rate of house prices follow a normal distribution with mean μ_i and standard deviation σ_i:

$$g \sim_i N\left(\mu_i, \sigma_i^2\right).$$

We adopt the normal distribution for our parametric predictions based on empirical evidence about the distribution of realized house price changes. In particular, in the Appendix, we show that the distribution of annual house price changes across U.S. counties is unimodal and approximately symmetric, which suggests that the normal distribution is a sensible parametric choice. When needed, we truncate the normal distribution at $\underline{g} = 0$ in all calculations. As we show, one desirable feature of the normal distribution is that shifts in the two moments, mean and variance, have unambiguous predictions for $\mathbb{E}_i\left[g \middle| g \geq \delta_i\right]$ and $F_i\left(\delta_i\right)$, and therefore on the relationship between beliefs and leverage in both the variable house size scenario and the fixed house size scenario.

Proposition 1. (Mean and variance shifts with normally distributed beliefs).

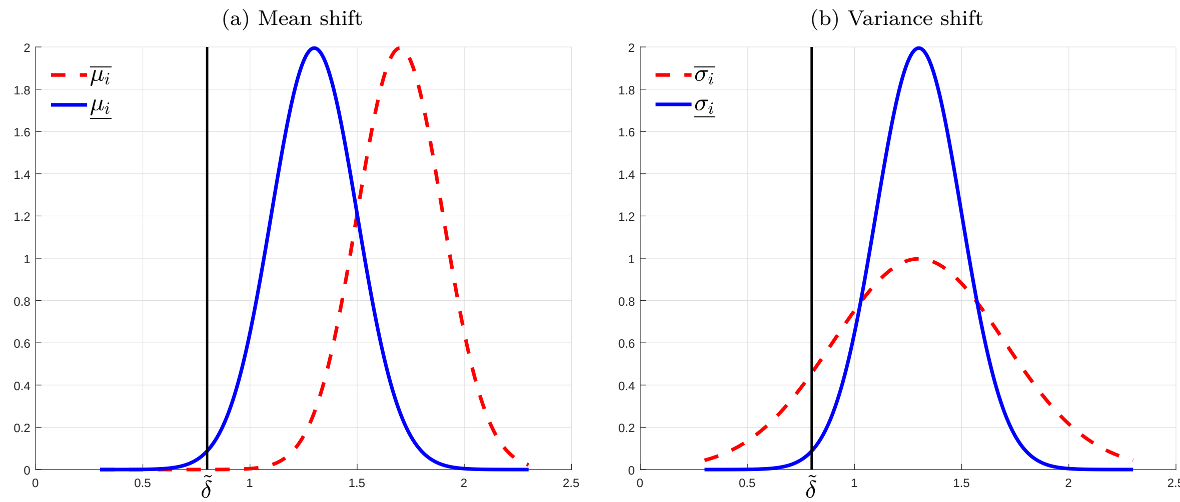
a) **[Variable house size scenario.]** *In the variable house size scenario, holding all else constant, including the belief dispersion σ_i, borrowers with a higher average belief μ_i choose a higher LTV ratio. In the variable house size scenario, holding all else constant, including the average belief μ_i, borrowers with a higher belief dispersion σ_i choose a higher LTV ratio.*

b) **[Fixed house size scenario.]** *In the fixed house size scenario, holding all else constant, including the belief dispersion σ_i, borrowers with a higher average belief μ_i choose a lower LTV ratio. In the fixed house size scenario, holding all else constant, including the average belief μ_i, borrowers with a higher belief dispersion σ_i choose a higher LTV ratio, for a sufficiently low default probability.*

Our model shows that the relationship between beliefs and leverage depends on the margins of adjustment that are active for a given borrower. Indeed, Equation (8) establishes that when borrowers' housing choice is fully sensitive to its pecuniary return (the variable house size scenario), leverage increases when $\mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right]$ is higher for any leverage choice $\tilde{\delta}$. In Figure 1, $\mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right]$ corresponds to the expected value of the house price change conditional on the value being to the right of the default threshold, which is given by the black line. Panel (a) shows that an increase in the average belief increases $\mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right]$ point-wise, inducing borrowers to choose higher leverage and invest more in housing. Panel (b) shows that an increase in σ_i also raises $\mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right]$, which makes housing a more attractive investment for borrowers and induces them to take higher leverage. This is because an increase in the probability of extremely good states of the world is valued by borrowers more than the increase in the probability of extremely bad states of the world, since they expect to default on those states.

On the other hand, Equation (9) highlights that when a borrower finds it optimal not to adjust her housing choice, perhaps because it is determined primarily by family size (fixed house size scenario, with a return insensitive collateral), leverage is decreasing in the perceived probability that the mortgage will be repaid, $1 - F_i\left(\tilde{\delta}\right)$, for a

Figure 1: Illustration of how shifts in μ_i and σ_i affect $\mathbb{E}_i\left[g|\, g \geq \tilde{\delta}\right]$ and $1 - F_i\left(\tilde{\delta}\right)$



Note: Figure 1 illustrates how shifts in μ_i and σ_i modify $\mathbb{E}_i\left[g|\, g \geq \tilde{\delta}\right]$ and $1 - F_i\left(\tilde{\delta}\right)$ for a given threshold $\tilde{\delta}$. The parameters used in Panel (a) are $\underline{\mu} = 1.3$, $\overline{\mu} = 1.7$, and $\sigma = 0.2$. The parameters used in Panel (b) are $\mu = 1.3$, $\underline{\sigma} = 0.2$, and $\overline{\sigma} = 0.4$. In both panels, we set $\tilde{\delta} = 0.78$.

given default threshold $\tilde{\delta}$. In Figure 1, this is given by the probability-mass to the right of the default threshold. Panel (a) shows that a reduction in the average belief is perceived by borrowers as a reduction in the return to their downpayment, since now the resources put down as downpayment are more likely to be lost in case of default. In that case, more pessimistic borrowers optimally decide to make smaller downpayments and borrow more. In addition, Panel (b) highlights that when the probability of default is below the median of the distribution, a higher σ_i increases the probability of default (i.e., it reduces the probability mass to the right of the threshold), reducing the probability of repayment and thus also reducing also the return on borrowers' downpayment. Higher variance of expected house price changes will therefore induce borrowers to increase their leverage.

This discussion highlights that the effect of homebuyer beliefs on leverage choice is theoretically ambiguous. If households are willing to substantially adjust the size of their property in response to changes in expected house price growth, then more pessimistic buyers will buy smaller houses with lower overall leverage. On the other hand, some homebuyers' property choices might be primarily determined by factors related to the consumption aspect of the house, such as family size. This limits the ability of pessimistic homebuyers to reduce their home size, and the only way to minimize their financial exposure to the housing market is to reduce their downpayment. In practice, individuals' behavior will be in between the extreme cases studied above: home size will not be totally insensitive to households' expectations of future house price changes (as documented by Bailey et al., 2017), but it is unlikely to respond as flexibly as investment in purely financial assets. Indeed, our simulations of a more general version of the model in Appendix B study such a world of partial collateral return sensitivity. These simulations show that whether housing choice is sufficiently return insensitive such that more optimistic individuals will choose lower leverage depends on the exact parameter choices, and is thus an inherently empirical question.

2.2 Additional Predictions: Interactions with Cost of Default and Average Beliefs

Proposition 1 establishes that changes in beliefs can have differential implications for borrowers' leverage choices depending on the active margins of adjustment. To ensure maximal parsimony, we focused on the case of zero default costs, while presenting the results from a more general model with non-zero default costs in the Appendix. We now derive additional testable predictions from this more general model. Specifically, we study how the relationship between beliefs and leverage choices characterized in Proposition 1 varies with (a) the magnitude of the default cost, and (b) with the average optimism of homebuyers. In the interest of brevity, we derive these additional predictions in the body of the paper only for the fixed house size scenario, for which we find empirical support. We relegate the formal analysis of the empirically less-relevant variable house size scenario to the Appendix. We will also focus on the intuition behind these predictions, and continue to present formal statements of the propositions and the associated proofs in the Appendix.

Proposition 2. (Additional Predictions).

(a) [**Interaction with cost to default.**] *In the fixed house size scenario, a given increase in the average belief, μ_i, generates a smaller decrease in leverage when borrowers' default cost κ_i is higher, for a sufficiently low default probability and for any default cost. A given increase in belief dispersion, σ_i, generates a smaller increase in leverage when borrowers' default cost κ_i is higher, for a sufficiently low default probability. Hence, high default costs dampen the effects of belief changes on leverage.*

(b) [**Interaction with average beliefs.**] *In the fixed house size scenario, a given increase in the average belief, μ_i, generates a smaller decrease in leverage when borrowers' average belief, μ_i, is higher to begin with, for a sufficiently low default probability and for any default cost. A given increase in belief dispersion, σ_i, generates a smaller increase in leverage when borrowers' average belief, μ_i, is higher to begin with, for a sufficiently low default probability. Hence, high average beliefs dampen the effects of belief changes on leverage.*

Both of these Propositions share the following common intuition: when the probability of default is low to begin with, a given change in μ_i and σ_i shifts only a small mass of the belief distribution from the default to the no-default region, or vice versa. The same changes in beliefs will therefore have a smaller effect on the optimal leverage choice. In Proposition 2a, when default costs are large, the perceived probability of default is low, and the relationship between beliefs and leverage is weaker. In the empirical implementation, we provide evidence for this proposition by using differences across U.S. states in lenders' recourse to borrowers' non-housing assets to provide variation in the default cost. In Proposition 2b, when μ_i is higher to begin with, the perceived probability of default is low. Again, a given change in beliefs therefore moves the probability of repayment by less, and thus has a smaller effect on optimal leverage. In the empirical implementation, we provide both cross-sectional and time-series evidence for Proposition 2b. Cross-sectionally, we will show a stronger relationship between changes in beliefs and leverage for more pessimistic individuals. In the time series, we document a stronger relationship between beliefs and leverage during periods of declining house prices, when individuals on average are likely to be more pessimistic.

3 Beliefs and Leverage Choice: Empirical Investigation

The previous discussion highlights that the relationship between house price beliefs and mortgage leverage choice depends crucially on the return sensitivity of individuals' housing investments. From a theoretical perspective, it is thus ambiguous whether more optimistic individuals end up choosing higher or lower leverage. In this section, we explore the empirical relationship between changes in homebuyer beliefs and changes in mortgage leverage choices in the U.S. housing market.

Our tests use the recent house price experiences of individuals' geographically distant friends as shifters of those individuals' beliefs about the distribution of future house price changes. This approach builds on evidence in Bailey et al. (2017), who show that the recent house price changes experienced within an individual's social network affect that individual's beliefs about the attractiveness of local housing market investments. We expand on these findings, and analyze responses to a new survey that elicits individuals' distribution of beliefs about future house price changes. We document that the mean and standard deviation of the house price experiences across an individual's friends shift the corresponding moments of the distribution of that individual's house price beliefs. Our main empirical exercise is to then compare the leverage choices of otherwise similar individuals purchasing houses at the same point in time and in the same neighborhood, where one individual's friends have experienced more positive or more widely dispersed recent house price growth. To interpret the results, we argue that the house price experiences of an individual's geographically distant friends are likely to only affect her leverage choice through the experiences' effects on beliefs. Indeed, in our empirical analysis we will rule out a number of other initially plausible channels. This empirical approach shows that, in the U.S. housing market, it is the relatively pessimistic individuals that take on more leverage, consistent with the predictions from the fixed house size scenario.

3.1 Data Description and Summary Statistics

Our empirical analysis is based on the combination of two key data sets. First, to measure different individuals' social networks, we use anonymized social network data from Facebook. Facebook was created in 2004 as a college-wide online social networking service for students to maintain a profile and communicate with their friends. It has since grown to over 1.9 billion monthly active users globally and 234 million monthly active users in the U.S. and Canada (Facebook, 2017). Our baseline data include a de-identified snapshot of all U.S.-based active Facebook users from July 1, 2015. For these users, we observe the county of residence as well as the set of other Facebook users that they are connected to. Using the language adopted by the Facebook community, we call these connections "friends." Indeed, in the U.S., Facebook serves primarily as a platform for real-world friends and acquaintances to interact online, and people usually only add connections to individuals on Facebook whom they know in the real world (Jones et al., 2013; Bailey et al., 2018).

To construct a measure of the house price experiences in different individuals' social networks, we combine the data on the county of residence of different individuals' friends with county-level house price indices from Zillow. As we describe below, this allows us to analyze the full distribution of recent house price experiences across any group of Facebook users. For example, we can calculate the standard deviation of house price experiences across every individual's out-of-commuting zone friends.

In order to measure homebuyers' leverage choice, we merge individuals on Facebook with three snapshots from Acxiom InfoBase for July 2010, July 2012, and July 2014 (see Bailey et al., 2017). These data are collected by Acxiom, a leading marketing services and analytics firm, and contain demographic information compiled from a large number of sources. We observe information on age, marital status, education, occupation, income, household size, and homeownership status. For current homeowners, the data also include information on housing transactions after 1993 that led to the ongoing homeownership spell, compiled from public record housing deeds. These data include transaction date, transaction price, and details on any mortgage used to finance the purchase.[11]

Since we can only analyze origination mortgages that have not been refinanced by the time we observe the transaction in an InfoBase snapshot, we focus our analysis on home purchases between 2008 and 2014. There are at most two years between these transactions and the closest InfoBase snapshot, allowing us to observe most of the initial mortgages. We want to study the mortgage choices for home purchases across many geographies, in order to provide us with cross-sectional heterogeneity in the cost of default created by differences in the legal environment across states. To achieve this, we first define a set of eligible geographies as those with complete reporting of house

[11] While the original deeds data contain the precise information on mortgage amount and purchase price, the InfoBase data include these in ranges of $50,000. We take the mid-point of the range as the transaction price and mortgage amount. While the resulting measurement error in LTV ratios does not affect our ability to obtain unbiased estimates in regressions where LTV ratio is the dependent variable, it complicates the interpretation of the R^2 from these regressions.

Table 1: Summary Statistics

	Mean	Standard Deviation	P10	P50	P90
Purchase Characteristics					
Transaction price (k$)	302.3	237.8	125	225	550
Combined Loan-to-Value (CLTV) Ratio	88.5%	16.9%	69.2%	94.7%	100.0%
Network Statistics					
Number of Friends	353.9	408.3	63	241	733
Number of Out-of-Commuting Zone Friends	194.3	272.6	27	114	427
Number of Out-of-State Friends	155.7	241.3	19	83	351
Number of Counties with Friends	74.7	65.5	19	59	144
Neighborhood Statistics					
Homeownership Rate	74.3%	11.7%	58.7%	76.7%	87.2%
Recourse	0.54	0	0	1	1
Δ Friends' House Prices (24m)					
Mean - All Friends	-6.4%	13.3%	-22.6%	-7.7%	12.1%
Mean - Out-of-Commuting Zone Friends	-5.3%	10.3%	-16.3%	-7.4%	10.2%
St.Dev. - All Friends	8.0%	3.3%	4.2%	7.5%	12.5%
St.Dev. - Out-of-Commuting Zone Friends	9.0%	3.1%	5.1%	8.8%	13.2%
Other Friend Experiences					
Δ Friends' County Income (24m) - Mean	3.1%	6.5%	-4.4%	1.7%	11.3%
Δ Friends' County Income (24m) - St.Dev.	5.7%	3.3%	2.8%	5.0%	9.3%
Friends' Foreclosure Rate (24m, Share of Units) - Mean	3.7%	2.3%	1.1%	3.2%	7.1%
Friends' Foreclosure Rate (24m, Share of Units) - St.Dev	2.0%	0.9%	0.9%	1.9%	3.2%
Property Characteristics					
Home Size (sqft)	2,032	12,766	1,056	1,730	3,077
Lot Size (sqft)	12,033	12,549	2,500	7,500	25,000
Property Age (years)	29.0	24.0	3.0	23.0	62.0
SFR	0.82	0	0	1	1
Has Pool	0.19	0	0	0	1
Buyer Characteristics					
Age at Transaction (years)	37.7	12.7	24	35	56
Has Max High School Degree in 2010	0.64	0.48	0	1	1
Has Max College Degree in 2010	0.26	0.44	0	0	1
Has Max Graduate Degree in 2010	0.10	0.30	0	0	0
Income in 2010 ($)	82,116	49,413	25,000	62,500	175,000
Married in 2010	0.41	0.49	0	0	1
Household Size in 2010	2.55	1.51	1	2	5

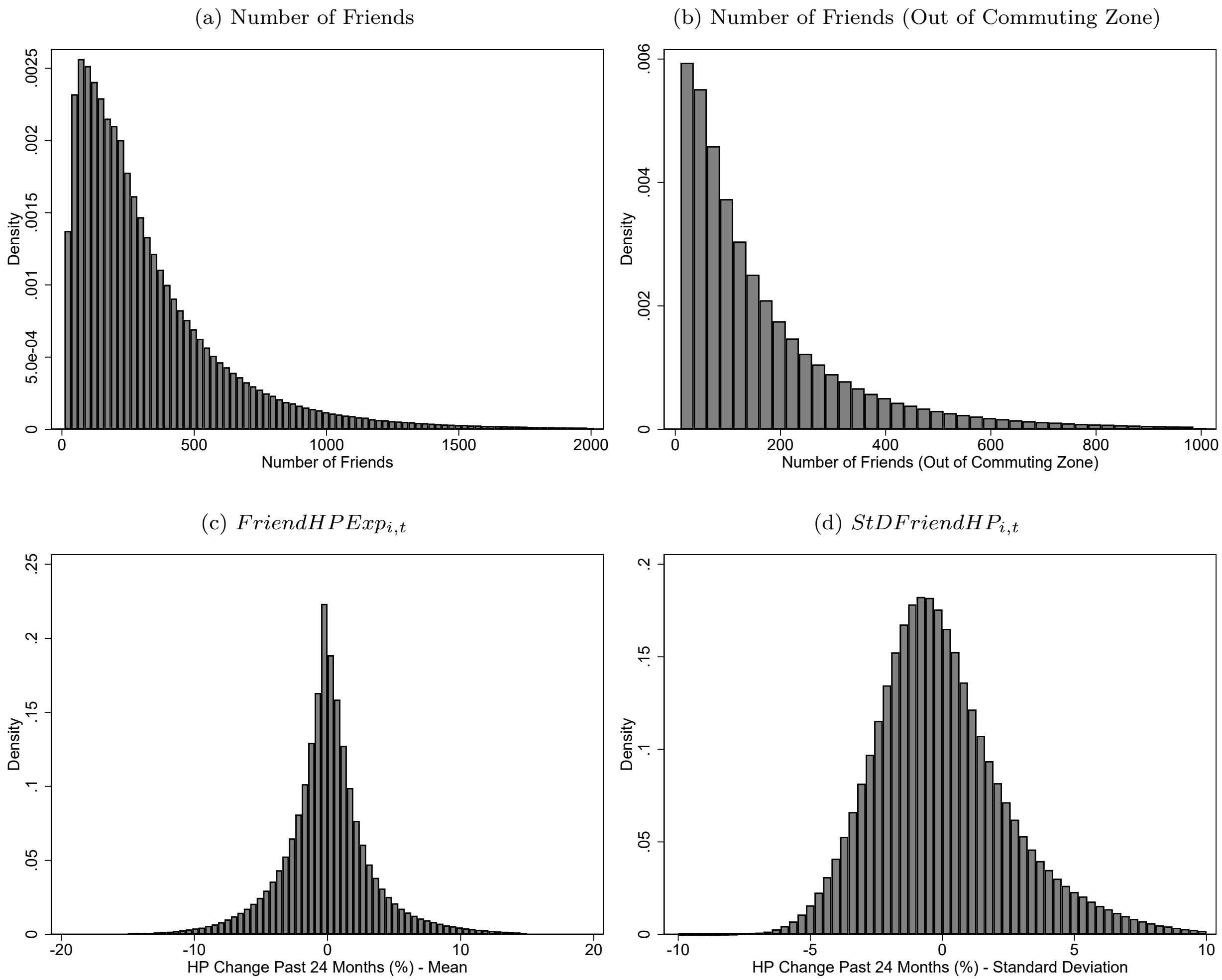
Note: Table shows summary statistics on our matched transaction-Facebook sample. It provides information on the sample mean and standard deviation, as well as the 10th, 50th, and 90th percentiles of the distribution.

prices and mortgage amounts; this excludes, for example, property transactions from non-disclosure states such as Texas, where housing transaction prices are not reported in the public record. We select all transactions in our data since January 2008 from a random sample of 2,900 zip codes from these eligible geographies. This provides us with about 1.35 million housing transactions for which we can match the buyer to Facebook. These transactions come from 33 different states. The most prominently represented states are California (24.6%), Florida (12.4%), and Arizona (9.5%); Ohio, Washington, Nevada, and North Carolina each contribute approximately 5% of all transactions. The Appendix shows how these transactions are distributed over time.

Table 1 shows summary statistics for our sample.[12] The average combined loan-to-value (CLTV) ratio across all mortgages used to finance the transactions in our sample is 88.5%, but there is substantial heterogeneity in this number. The average purchase price is $302,300, while the median purchase price is $225,000. At the point of purchase, the average buyer was 38 years old, but this ranges from 24 years old at the 10th percentile to 56 years old at the 90th percentile of the distribution.

[12] For some of the transactions, the property is purchased by more than one individual, and we can match both individuals to their Facebook accounts. In these cases, we use the characteristics and friends' house price experiences of the head of household, as reported in the InfoBase data. Pooling the sets of friends of both buyers yields very similar results.

Figure 2: Summary Statistics



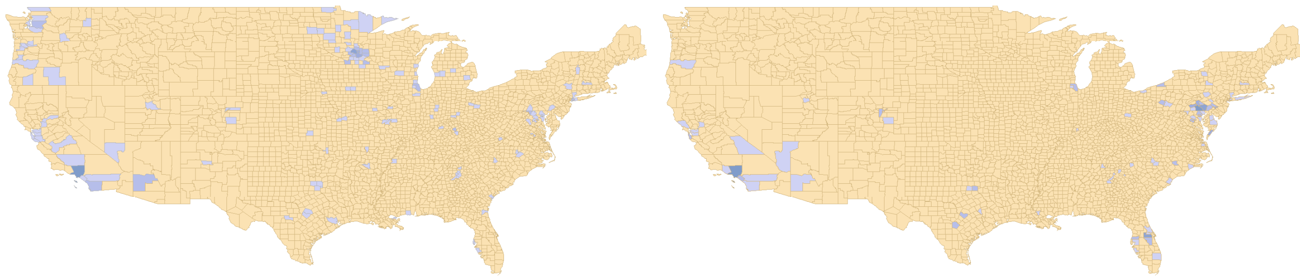
Note: Figure shows summary statistics on our matched transaction-Facebook sample. Panel (a) shows the distribution of the number of friends, Panel (b) shows the distribution of the number of out-of-commuting zone friends. Panel (c) shows the distribution of residuals of a regression of $FriendHPExp_{i,t}$ on zip code by month-of-purchase fixed effects. Panel (d) shows the distribution of residuals from a regression of $StDFriendHP_{i,t}$ on zip code by month-of-purchase fixed effects.

For the average homebuyer, we observe 354 friends, with a 10-90 percentile range of 63 to 733. The average homebuyer has 194 friends that live outside their own commuting zone, and 156 friends that live outside their own state. The top row of Figure 2 shows the full distribution of the number of friends and out-of-commuting zone friends across homebuyers in our sample. Most individuals are exposed to a sizable number of different housing markets through their friends: the average person has friends in over 74 different counties, with individuals at the 90th percentile having friends in 144 different counties.

There is significant heterogeneity across individuals purchasing homes in the same neighborhood in the geographic distribution of their friends. As an example, Figure 3 shows a heatmap of the distribution of the friendship networks of two individuals buying a house at the same time and in the same Los Angeles zip code. Both individuals have a substantial share of their friends who live locally. In addition, the individual in the left panel has many friends in the area around Minneapolis, while the individual in the right panel has many friends in Pennsylvania and Florida.

Such differences in the geographic distribution of friendship networks, combined with time-varying differences in regional house price movements, induce heterogeneity in the average house price movements in the social networks

Figure 3: Geographic Distribution of Friendship Links



Note: Figure shows heatmaps of the friend distributions of two homebuyers in our matched transaction-Facebook sample. The individual in the left panel has a significant number of friends in Minnesota; the individual in the right panel has a significant number of friends in Pennsylvania and Florida.

of different homebuyers purchasing similar properties at the same point in time. We define the average house price movements across homebuyer i's friends in the 24 months prior to purchasing a property at point t as:

$$FriendHPExp_{i,t} = \sum_{c} ShareFriends_{i,c} \times \Delta HP_{c,t-24m,t},$$

where $ShareFriends_{i,c}$ measures the fraction of homebuyer i's friends that live in county c, and $\Delta HP_{c,t-24m,t}$ measures the house price changes in county c in the 24 months prior to time t using the Zillow house price indices.[13] Panel (c) of Figure 2 shows the distribution of the residuals when regressing $FriendHPExp_{i,t}$ on zip code by purchase month fixed effects. The standard deviation of this residual is 3.7%, showing significant variation in friends' house price changes across individuals buying houses in the same place and at the same point in time.

In addition, most homebuyers have friends with relatively heterogeneous house price experiences: the same individuals can have some friends in regions where house prices did relatively well, and other friends in regions where house prices did relatively badly. We define the standard deviation of the house price experiences across homebuyer i's friends in the 24 months prior to time t as:

$$StDFriendHP_{i,t} = \sqrt{\sum_{c} \left(ShareFriends_{i,c} \times \Delta HP_{c,t-24m,t} - FriendHPExp_{i,t}\right)^2}$$

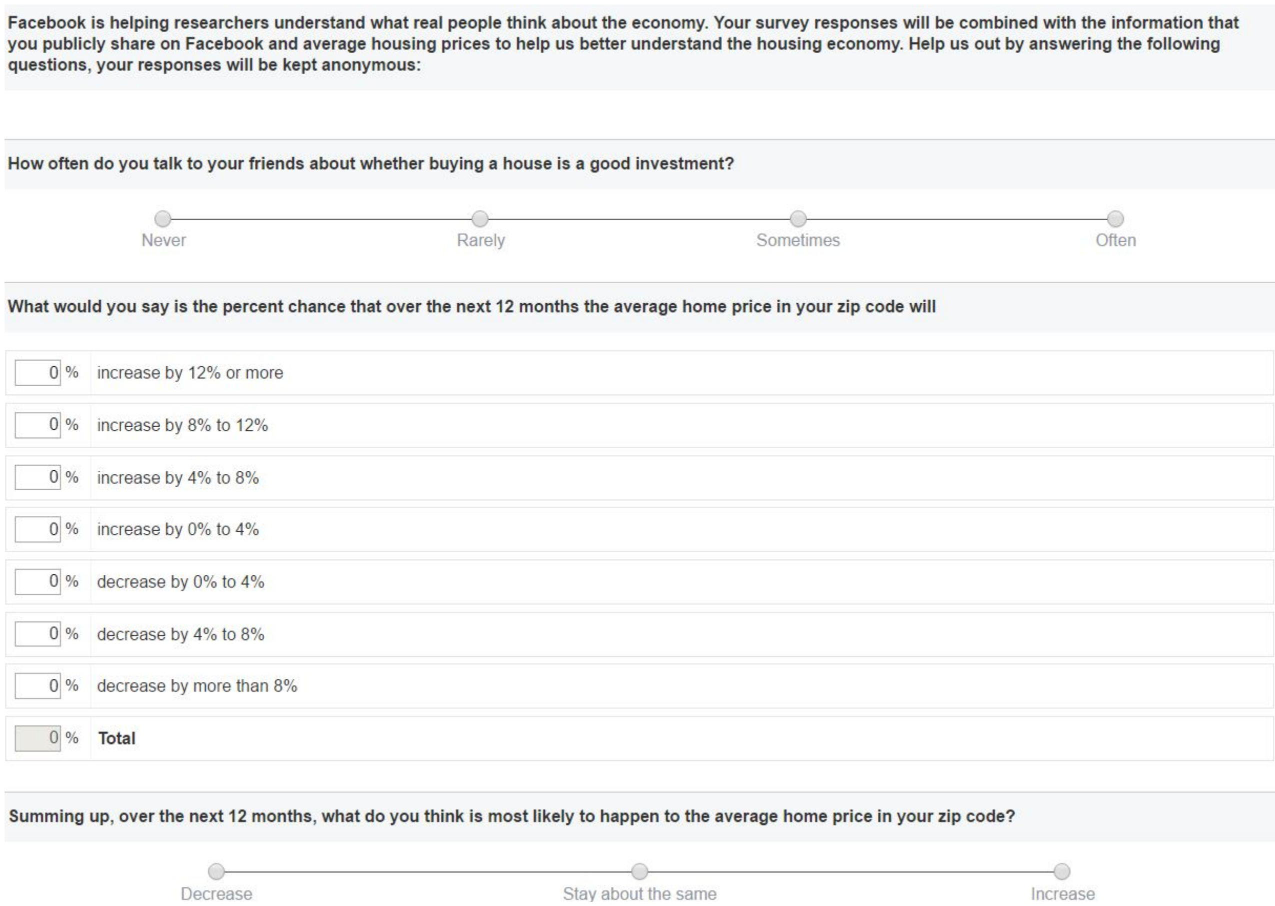
The average value of $StDFriendHP_{i,t}$ across the transactions in our sample is 8.0%, with a 10-90 percentile range of 4.2% to 12.5%. Panel (d) of Figure 2 shows the distribution of the residuals when regressing $StDFriendHP_{i,t}$ on zip code by purchase month fixed effects. The standard deviation of this residual is 2.6%.

3.2 Expectation Survey: Evidence for Belief Shifters

The first step of our empirical analysis is to verify that the moments of the distribution of house price experiences across an individual's friends affect that individual's distribution of beliefs about future house price changes in their own zip code. To do this, we analyze responses to a short survey conducted by Facebook in April 2017. The survey targeted Facebook users living in Los Angeles through a post on their News Feed. Figure 4 shows the survey interface. We observe 504 survey responses. The respondents' average age was 38 years, with a 10-90 percentile range of 23 to 58 years. 62% of respondents are male.

[13] In all of the following analyses, we consider the house price experiences of the homebuyers' friends over the 24 months prior to the purchase. All results are robust to instead considering the experiences over the previous 12, 36, or 48 months.

Figure 4: Survey Interface



Note: Figure shows the interface in a user's News Feed of the expectation survey conducted by Facebook on April 2017.

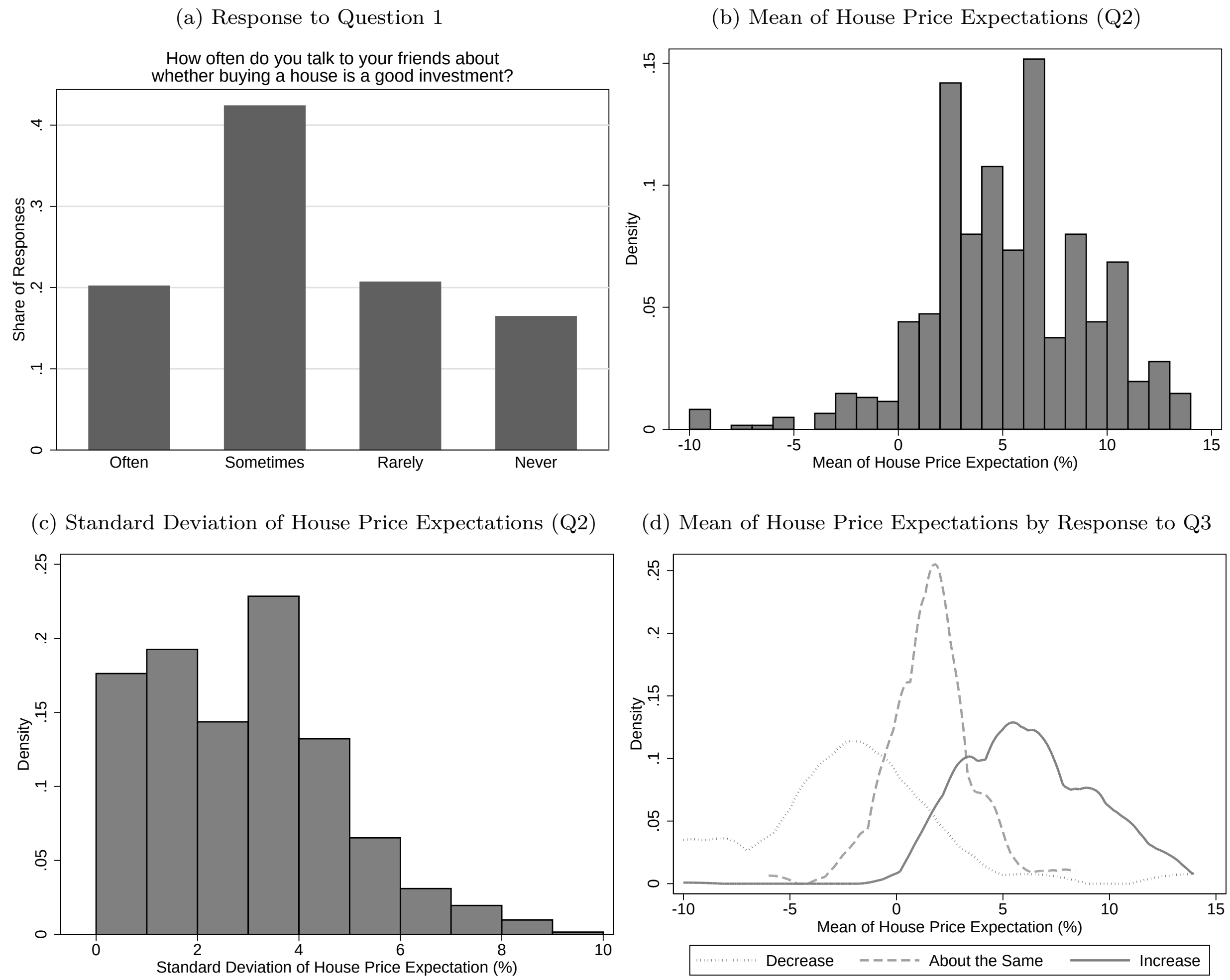
The first survey question elicits how often individuals talk to their friends about whether buying a house is a good investment. Regular conversations with friends about housing investments are important in order for there to be a channel through which the house price experiences of friends can influence an individual's own house price beliefs. Panel (a) of Figure 5 shows the distribution of responses to this question. About 43% of respondents gave the modal answer, "sometimes." The other possible responses were "never" (16% of responses), "rarely" (21% of responses), and "often" (20% of responses).

To measure an individual's beliefs about future house price changes, we use the responses to the second question, which asked individuals to assign probabilities to various scenarios of house price growth in their zip codes over the following 12 months. The survey enforced that the assigned probabilities add up to 100%. We use the responses to determine the mean and standard deviation of the distribution of individuals' house price beliefs.[14] Panels (b) and (c) of Figure 5 show the distribution of these moments across the survey respondents. There is substantial disagreement about expected house price growth among individuals living in the same local housing markets: while the median person expects house prices to increase by 5.3% over the next year, the 10-90 percentile range for this estimate is 0.8% to 10.0%, and the standard deviation is 3.8%.

As a first test for whether individuals provide sensible and consistent responses to the expectation survey, Panel

[14] To do this, we take the mid-point of each bucket, as well as the probabilities that individual respondents assign to that bucket. For the open-ended buckets "Increase by more than 12%" and "Decrease by more than 8%", we use point-estimates of 14% and -10%, respectively, but our results are robust to using different values assigned to these buckets. The roughly 15% of respondents who only assign probabilities to one bucket are assigned a standard deviation of beliefs of 0%.

Figure 5: Summary Statistics - Survey Responses



Note: Figure shows summary statistics on the responses to the housing expectation survey. Panel (a) shows the responses to Question 1. Panels (b) and (c) show the distribution of the mean and standard deviation of the belief distributions derived from individuals' answers to Question 2. Panel (d) shows the distributions of the mean of the belief separately by individuals' answers to Question 3.

(d) of Figure 5 shows the distribution of the means of the belief distributions for individuals separately by their responses to Question 3, which asks if the respondents expect the average home price in their zip code to increase, stay the same, or decrease over the next 12 months. As a response to that question, 79.8% of individuals said they expected house prices in their zip code to increase over the next 12 months, 14.6% said they would expect them to stay about the same, and 5.6% expected them to decline (as a reference point, in the 12 months running up to the survey, Los Angeles house prices increased by 7.4%). Individuals that thought it was most likely that house prices in their zip code would increase over the next twelve months had a median belief about house price growth of 6.0%; the median expected house price growth of respondents who said house prices would stay about the same (decline) was 2.0% (-2.4%). While there are a small number of individuals who indicate they expect house price to fall, yet assign probabilities that imply increasing house prices, the combined evidence documents a substantial degree of consistency across individuals' answers within the same survey.

We next analyze how moments of the distribution of house price changes across individual i's social network in the 24 months prior to answering the survey affect the corresponding moments of the distribution of beliefs about future house price changes. There is significant variation across respondents in both the mean and the standard

Table 2: Regression Results - House Price Expectations

	Dep. Var.: Mean of Belief Distribution			Dep. Var.: Standard Deviation of Belief Distribution		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Friends' House Prices (24m)						
Out-of-CZ Friends - Mean	0.186**					
	(0.082)					
Out-of-CZ Friends - St. D.				0.121**		
				(0.058)		
All Friends - Mean		0.326**	0.322**			-0.024
		(0.144)	(0.148)			(0.055)
All Friends - St. D.			0.027		0.182**	0.184**
			(0.145)		(0.089)	(0.090)
Zip FE and Demographic Controls	Y	Y	Y	Y	Y	Y
Specification Notes	OLS	IV	IV	OLS	IV	IV
N	426	426	426	426	426	426

Note: Table analyzes the determinants of individuals' expectations about house price changes in their own zip codes over the next 12 months. In columns 1 to 3, the dependent variable is the mean of individuals' belief distributions, based on their responses to Question 2 of the expectation survey (see Figure 4); in columns 4 to 6, the dependent variable is the standard deviation of these belief distributions. All specifications include fixed effects for the zip code of the survey respondents; we also control flexibly for age, gender, and the number of friends. Columns 1 and 4 present OLS specifications, while columns 2, 3, 5, and 6 present instrumental variables regressions, where the moments of the house price experiences across an individual's friends are instrumented for by the corresponding moments of the distribution of experiences across their out-of-commuting zone friends. Standard errors are in parentheses. Significance Levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

deviation of the experiences of their friends: indeed, $FriendHPExp_{i,Apr17}$ has a mean of 15.1% and a standard deviation of 1.7% across survey respondents. When measured only among out-of-commuting zone friends, it has a mean of 16.3% and a standard deviation of 2.6%. Similarly, $StDFriendHP_{i,Apr17}$ has a mean of 5.0% and a standard deviation of 1.7% across all friends of the survey respondents; among all out-of-commuting zone friends, the mean and standard deviation of $StDFriendHP_{i,Apr17}$ are 6.9% and 1.7%, respectively.

Table 2 shows results from regressions of moments of the elicited belief distribution on moments of the experience distribution among survey respondents' friends. All specifications control for zip code fixed effects to ensure that we are comparing individuals' assessments of the same local housing markets; it also includes flexible controls for the age, gender, and the number of friends of the respondent. In columns 1 to 3, the dependent variable is the mean of the elicited belief distribution. Since all friends in Los Angeles experience the same recent house price changes, across-individual variation in friends' house price experiences is driven by differences in the experiences of their out-of-commuting zone friends as well as differences in the share of friends that live locally. As we discuss below, we want to isolate variation in friends' experiences coming from the experiences of their out-of-commuting zone friends, since this allows us to address a number of potential alternative interpretations of our findings. Column 1 of Table 2 shows that a one-percentage-point (0.38 standard deviation) increase in the average house price experience of an individual's out-of-commuting zone friends, $FriendHPExp^{Out-CZ}_{i,Apr17}$, is associated with a 0.19 percentage point (0.05 standard deviation) increase in the expected house price growth over the next year.[15] In column 2, the main explanatory variable is the average house price experience of all

[15]The effect of $FriendHPExp^{Out-CZ}_{i,Apr17}$ on the R-squared is relatively modest: conditional on the control variables, the house price experiences of an individual's out-of-commuting zone friends explain an additional 1.1% - 1.6% of the observed variation in the mean of house price beliefs. Specifically, the OLS regression without controlling for out-of-commuting zone friends' average house price experiences, but including all the other control variables, has an R-squared of 0.362; the within-zip code R-squared is 0.074. When we include the out-of-commuting zone friends' house price experiences as an additional control variable, the R-squared increases to 0.373, and the within-zip code R-squared increases to 0.090. However, given the large sample sizes in the leverage choice regressions in Sections 3.3 and 3.4, the belief shifter has sufficient power to identify statistically significant effects of beliefs on leverage. The number of observations in Table 2 is lower than the total number of responses we observe. This is because 78 responses are from individuals who are the only respondents from their own zip code. Their responses are thus fully explained by the zip code fixed effects.

friends, $FriendHPExp_{i,Apr17}$, instrumented for by the average house price experiences of the individuals' out-of-commuting zone friends, $FriendHPExp^{Out-CZ}_{i,Apr17}$. This specification mirrors our baseline regressions in Sections 3.3 and 3.4 below, and will allow us to compare estimates across specifications with different outcome variables. A one-percentage-point increase in the house price experiences of all friends in the previous two years is associated with a 0.33 percentage point increase in individuals' mean belief about house price growth over the coming year. In column 3, we also include the standard deviation of house price experiences across individuals' friends, $StDFriendHP_{i,Apr17}$, instrumented by its out-of-commuting zone counterpart, as an additional control variable; it has no statistically significant effect on individuals' average house price expectations.

The dependent variable in columns 4 to 6 of Table 2 is the standard deviation of the distribution of individuals' beliefs about future house price changes. Column 4 shows that a one-percentage-point (0.38 standard deviation) increase in $StDFriendHP^{Out-CZ}_{i,Apr17}$ is associated with a 0.12 percentage point (0.08 standard deviation) increase in the standard deviation of the belief distribution. In column 5, the main explanatory variable of interest is the standard deviation of house price experiences across all friends, instrumented for by its counterpart among out-of-commuting zone friends. The estimated effect of a one-percentage-point increase in $StDFriendHP_{i,Apr17}$ on the standard deviation of the belief distribution is 0.18 percentage points. In column 6, we also include $FriendHPExp_{i,Apr17}$ as a control variable, but it has no statistically significant effect on the standard deviation of the belief distribution.

Overall, these findings confirm that the mean and standard deviation of the house price experiences across an individual's friends can shift the corresponding moments of the distribution of that individual's house price beliefs. In the following section we will use this insight to analyze the effect of house price beliefs on mortgage leverage choice.

3.3 Main Results

We next test how moments of the distribution of house price experiences across a homebuyer's friends affect that homebuyer's leverage choice in the sample of transactions described in Section 3.1. Based on the evidence in Section 3.2, we argue that these house price experiences provide shifters of individuals' distributions of beliefs about future house price changes. We will also argue below that friends' house price experiences are orthogonal to other factors that might influence a homebuyer's leverage choice.

In our baseline regression specification R1, the unit of observation is a housing transaction. We regress the combined loan-to-value (CLTV) ratio for transaction i at time t in county c and financed by mortgage lender l on moments of the distribution of the house price experiences of the homebuyer's friends. This combined loan-to-value ratio includes all mortgages originated to finance the home purchase. We also control for a rich set of homebuyer characteristics,[16] and include county by purchase month by lender fixed effects, $\psi_{t,c,l}$.[17] This allows us to compare the leverage choices across individuals who borrow from the same lender in the same county and at the same point in time, and who therefore faced the same schedule of loan-to-value ratios and interest rates to choose from.

$$CLTV_{i,t,c,l} = \alpha + \beta_1 MeanFriendHP_{i,t} + \beta_2 StDFriendHP_{i,t} + \beta_3 X_{i,t} + \psi_{t,c,l} + \epsilon_{i,t,z}, \tag{R1}$$

[16] With the exception of age, which can be observed at the point of the transaction, other homebuyer characteristics are observed as of the points of the InfoBase snapshots. We assign the value from the most proximate snapshot. We flexibly control for homebuyer income, age, household size, family status, occupation, and education level. We also control for the number of friends, the number of out-of-commuting zone friends, and the number of counties in which an individual has friends.

[17] Even though Hurst et al. (2016) have shown that most lenders do not vary their mortgage pricing geographically, this choice of fixed effects is conservative, and ensures that we are comparing the leverage choices of individuals facing the same trade-offs between making a smaller downpayment and paying higher interest rates. In the rare cases where the first and second mortgages are by different lenders, we use the identity of the lender of the first mortgage to determine the lender fixed effect.

In order to use estimates of β_1 and β_2 to learn about the relationship between beliefs and leverage, we need to ensure that our key explanatory variables, $MeanFriendHP$ and $StDFriendHP$, only affect leverage choice through their effect on homebuyers' beliefs about the distribution of future house price changes. A first concern is that individuals who have more local friends, and for whom higher local house prices would thus lead to a higher $MeanFriendHP$, might also be more affected by this local house price growth through channels other than the effect on their house price expectations. For example, if individuals with more local friends were more likely to own local property, then they would be more likely to benefit from higher capital gains, allowing them to make a larger downpayment on any subsequent property purchase. To rule out confounding effects through such alternative channels, we estimate regression R1 using an instrumental variables (IV) strategy, where we instrument for the mean and standard deviation of all friends' house price experiences with the mean and standard deviation of the house price experiences of out-of-commuting zone friends (see also the discussion in Section 3.2).[18]

Testing Baseline Predictions. Table 3 shows the results from regression R1. The baseline estimate in column 1, which does not control for homebuyer demographics, suggests that individuals whose friends experienced a one-percentage-point higher house price appreciation over the past 24 months increase their downpayments (and reduce their CLTV ratios) by between 8 and 9 basis points. A one within-zip-code-month standard deviation increase in the house price appreciation experienced by an individual's friends is thus associated with that individual making a 31 basis points larger downpayment. This finding suggests that individuals' house size choice is relatively insensitive to the perceived collateral return, and that these individuals thus behave more like in the fixed house size scenario than in the variable house size scenario.[19] Column 1 also shows that individuals whose friends had more dispersed house price experiences, and who thus expected more variance in future house price changes, chose higher leverage: a one-percentage-point increase in the across-friends standard deviation of house price experiences over the past 24 months is associated with a 35 basis points increase in the combined loan-to-value ratio. This result is also consistent with the predictions from the fixed house size scenario: individuals that expect future house price growth to be more dispersed perceive large house price drops to be more likely. This increases the benefits of not putting all their savings into the house, and therefore increases their optimal leverage choice.

In column 2 of Table 3, we also control flexibly for a large number of homebuyer characteristics. The estimated effects of the house price experiences of a person's friends is remarkably stable with respect to the addition of these observable controls. This provides additional evidence consistent with Bailey et al. (2017) that the house price experiences of a person's friends in a given year are uncorrelated with that person's observable characteristics, and reduces concerns that the results are driven by selection on unobservable buyer characteristics (see Altonji, Elder and Taber, 2005). In column 3, we interact the buyer demographics with year fixed effects. This allows, for example, the effect of having a different education or a different profession on leverage choice to vary by year. This specification provides a first test of whether our findings could be explained by correlated shocks to homebuyers and their friends. For example, one might have worried that less-educated Los Angeles residents have more friends in regions with a relatively less-educated population. In that case, a positive shock to the income prospects of less-educated individuals in a given year might both raise house prices where less-educated buyers have friends, and would increase the ability of these less-educated buyers to make larger downpayments. Our

[18] The instrument has an F-Statistic above 1,500 across all specifications, largely driven by the fact that the set of out-of-commuting zone friends, which is used to construct the instruments, is a subset of the set of all friends, which is used to construct the instrumented variables, $MeanFriendHP_{i,t}$ and $StDFriendHP_{i,t}$.

[19] This does not mean that more pessimistic individuals did not also reduce their housing market investments, as in the polar case with no collateral return sensitivity that we study in Section 1 above. Indeed, Bailey et al. (2017) document that individuals whose friends experienced lower recent house price growth did buy smaller houses: a one-percentage-point smaller friends' house price experience was associated with purchasing a 0.3 percentage points smaller property. Instead, the estimate in column 1 of Table 3 suggests that as individuals got more pessimistic, their desire to reduce their financial exposure to potential house price declines increased faster than the reduction in that exposure that was possible to achieve by buying a smaller house. As a result, they ended up buying (slightly) smaller houses with larger overall leverage (see also the simulations of the more general model in Appendix B).

Table 3: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Friends' House Prices (24m)							
Mean	-0.084***	-0.087***	-0.107***	-0.136***	-0.060***	-0.144***	-0.027**
	(0.005)	(0.005)	(0.006)	(0.008)	(0.012)	(0.008)	(0.012)
St. D.	0.349***	0.318***	0.319***	0.546***	0.276***	0.439***	-0.027
	(0.013)	(0.013)	(0.014)	(0.021)	(0.015)	(0.019)	(0.023)
Mean X Recourse				0.063***			
				(0.011)			
St. D. X Recourse				-0.451***			
				(0.031)			
Mean X Mean					0.0005*		
					(0.0002)		
St. D. X Mean					-0.004***		
					(0.00)		
Mean X Recovery						0.046***	
						(0.012)	
St. D. X Recovery						-0.268***	
						(0.027)	
Mean X HO-Rate							-0.103***
							(0.014)
St. D. X HO-Rate							0.463***
							(0.025)
Month x County x Lender FE	Y	Y	Y	Y	Y	Y	Y
Demographic Controls	N	Y	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year
N	1,350,606	1,350,606	1,350,600	1,350,600	1,350,600	1,350,600	1,350,600
R-Squared	0.242	0.267	0.269	0.269	0.269	0.269	0.270
Mean Dep. Var.	88.38	88.38	88.38	88.38	88.38	88.38	88.38

Note: Table shows results from regression R1. The unit of observation is a housing transaction, the dependent variable is the combined loan-to-value ratio of the mortgages financing the home purchase. All specifications are instrumental variables regressions where we instrument for the moments of the distribution of house price experiences across an individual's friends with the corresponding moments of the distribution of house price experiences across her out-of-commuting zone friends. All specifications control for county $\times$ transaction month $\times$ lender fixed effects. Columns 2-7 also control for homebuyer characteristics (dummy variables for income groups, household size, marriage status, occupation, education levels, age, the number of friends, the number of out-of-commuting zone friends, and the number of unique counties with friends). In columns 3 to 7, we interact all borrower controls with year fixed effects. Column 4 interacts the measures of friends' house price experiences with a dummy variable of whether the transaction was in a recourse state. Column 5 interacts the measures of friends' house price experiences with the mean of friends' house price experiences. Column 6 interacts the measures of friends' house price experiences with a dummy variable capturing zip code - months where the average house price experiences of all buyers' friends were above the sample median, loosely corresponding to a recovery period in the housing market. Column 7 interacts the measures of friends' house price experiences with the homeownership rate in the zip code of the transaction. Standard errors are clustered at the zip code $\times$ transaction-month level. Significance Levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

results are essentially unchanged from our baseline specification, suggesting that such correlated shocks are not a key driver of our results. We provide a large number of additional robustness checks in Section 3.4.

How should one think about the magnitude of these baseline estimates? One option is to use a split-sample IV approach to combine our estimates from column 3 of Table 3 with the estimates from the survey analyzed in Section 3.2. This approach would suggest that individuals who expect a one-percentage-point lower house price growth over the coming twelve months would choose a $\frac{0.107}{0.326} = 33$ basis points lower downpayment. Similarly, one-percentage-point increase in the expected standard deviation of house price growth over the next twelve months would be associated with a $\frac{0.319}{0.182} = 175$ basis points lower downpayment.[20] To judge the plausibility of these magnitudes, it is important to recall that the survey elicits beliefs about house price growth over the coming twelve months, while mortgage leverage choices are affected by individuals' belief distribution about the cumulative house price growth over the expected life-time of the mortgage.[21] Translating the responses to the expectations survey into such cumulative house price changes requires making assumptions on both the time-series properties of the house price growth process as well as the relevant time horizon considered by households when deciding on their mortgage leverage. For example, in Appendix A.4 we show that under a standard AR(1) process for house price changes, with an annual persistence of 0.65 as estimated by Guren (2018), a one-percentage-point increase in the standard deviation of house price changes over the next year translates into a 4.5 percentage point increase in the cumulative standard deviation over the next five years, and an almost 8 percentage point increase in the cumulative standard deviation over the next ten years. When compared against an 8 percentage point increase in the standard deviation of cumulative house price changes over the lifetime of the mortgage, an adjustment of leverage of 175 basis points appears much more reasonable than when compared against a one percentage point increase in the standard deviation of house price changes over the next year.

Testing Additional Predictions. Columns 1 to 3 of Table 3 documented a relationship between beliefs and leverage choices most consistent with the fixed house size scenario. Columns 4 to 6 verify the additional predictions from Section 2.2, which establishes that in the fixed house size scenario, the relationship between beliefs and leverage should be stronger when default is relatively more likely.

Column 4 tests Proposition 2a, which highlights that the downpayment protection force at the heart of the fixed house size scenario should be particularly strong when the cost of mortgage default is low, and default is therefore relatively more likely. We proxy for the cost of default by whether or not the transaction occurred in a recourse state. In recourse states, lenders can collect on debt not covered by the sale of a foreclosed property by going after other assets of the defaulting borrowers. This substantially increases the cost of default for borrowers in recourse states.[22] About half of our transactions come from recourse states. Consistent with Proposition 2a for the fixed house size scenario, the effect of friends' average house price experiences on individuals' leverage choices is about twice as large for transactions in non-recourse states. Similarly, the effect of a higher standard deviation of friends' house price experiences on mortgage leverage choices is over five times as large in non-recourse states as it is in recourse states. This highlights that the downpayment protection force, which is central to the fixed house size scenario, is indeed stronger in legal environments that feature relatively low costs of default.

Columns 5 and 6 of Table 3 test Proposition 2b from Section 2.2, which highlights that, in the fixed house size

[20] These estimates are obtained by using the point estimates from Table 2 (columns 2 and 5) in the denominator. However, given the relatively large standard errors around these estimates, there is also significant uncertainty around these split-sample IV results.

[21] For buyers of single-family residences, the median expected duration of staying in the home is in excess of 10 years.

[22] Ghent and Kudlyak (2011) analyze mortgage default behavior across U.S. states, and find strong evidence that the recourse/non-recourse environment does indeed have significant effects on the default behavior of borrowers, as would be predicted if it induced significant differences in the costs of default. Specifically, the authors find that at the average value of negative equity, the monthly probability of default is 1.3 times higher in non-recourse states than it is in recourse states. All else equal, this means that it takes 8.6% more negative equity to make the probability of default in a recourse state the same as the probability of default in a non-recourse state. See also the discussion in Kuchler and Stroebel (2009).

scenario, the effects of changes in house price beliefs on leverage choice should be smaller if the baseline house price belief is more optimistic, and the default option is thus less important. Column 5 conducts a cross-sectional test, and interacts our belief shifters with the mean of friends' house price experiences. Changes in both the mean and the variance of friends' house price experiences indeed have smaller effects for individuals who are already starting from a higher mean house price expectation, and who thus perceive a lower likelihood of default. Column 6 conducts a time-series text, and interacts the mean and standard deviation of friends' house price experiences with a dummy variable that captures whether or not the average house price experience of all buyers in the purchase zip code-month was above the sample median value. For these transactions, we expect the homebuyers to be relatively more optimistic about future house price changes, and to therefore perceive a lower probability of default (see Case, Shiller and Thompson, 2012, and Kuchler and Zafar, 2015, for evidence on such extrapolative house price expectations). Consistent with the predictions from the fixed house size scenario, the effects of both the mean and standard deviation of friends' house price experiences on leverage choices are significantly larger in absolute terms during the housing bust period than they are during the recovery period.[23] This is consistent with the downpayment protection force being stronger during periods with a higher perceived likelihood of default.

In column 7, we interact the mean and standard deviation of the house price experiences of homebuyers' friends with the homeownership rate in the zip code of the transaction. The homeownership rate is a proxy for the extent to which individuals' home purchase decisions are sensitive to expected house price changes. In markets with high homeownership rates, pessimistic individuals wanting to live in a certain zip code (for example, because of proximity to work or good schools) are less likely to find a suitable rental property as a way of reducing their housing market exposure. Such high-homeownership-rate zip codes are thus a better approximation of the fixed house size scenario, in which reductions in downpayments provide a relatively easier way for households to reduce their housing market exposure. Consistent with this, the estimates show that in regions with high homeownership rates, we see a larger effects of changes in the perceived default probability on leverage choices.

Taken together, the behavior of the homebuyers in our sample corresponds to the predictions from the fixed house size scenario, in which relatively pessimistic homebuyers do not end up renting or purchasing substantially cheaper homes.[24] These pessimistic homebuyers therefore make smaller downpayments in order to reduce their housing market exposures, in particular in states where the cost of default is comparatively smaller, and during time periods when there are concerns about substantial price drops in the housing market.

3.4 Robustness Checks and Ruling Out Alternative Explanations

Our interpretation of the results in Section 3.3 is that the relationship between friends' house price experiences and leverage was driven by the effects of friends' experiences on an individual's belief about future house price growth. In this section, we rule out a number of alternative interpretations of the correlation between friends' house price experiences and individuals' mortgage leverage choice. As we address these alternative interpretations, we note that most of these stories could have potentially explained the effect of friends' average house price experiences on leverage. However, the effect of the dispersion of friends' house price experiences on leverage choices are much harder to rationalize with alternative mechanisms, as are the differential effects across recourse/non-recourse states,

[23] A potential concern when interpreting these differential effects across time comes from the fact that we only observe the friendship network at one point in time, July 2015. This network becomes a noisier measure of individuals' contemporaneous network the further back we go, which could induce increased attenuation bias for measuring friends' house price experiences for buyers in earlier transactions. However, given that the housing bust period preceded the housing recovery period, such an attenuation bias would reduce the measured effect during the housing bust period, and therefore work against producing the effect that we uncover.

[24] One caveat regarding the generalizability of these findings is that our sample is restricted to purchases by owner-occupiers, since we cannot match buyers making investment purchases to their respective Facebook accounts. While we do not have the data to analyze the leverage choices of these investment buyers, our theoretical framework suggests that those individuals' collateral decisions should be more return sensitive. They might therefore respond to increasing optimism by buying more houses with higher leverage.

across periods with relatively high/low average beliefs, and across regions with different homeownership rates.

A first concern we address is that the instruments in our baseline regression, the moments of the house price experiences of out-of-commuting zone friends, might still be correlated with the individuals' own house price experiences, and therefore potentially with their own capital gains, in particular for individuals who have more friends in close-by commuting zones that have house price movements similar to those in their own commuting zone. In column 1 of Table 4, we therefore use moments of the house price experiences of out-of-state friends as instruments. Reassuringly, the magnitudes of the effects in this specification are, if anything, slightly larger than in our baseline specifications.

In column 2 of Table 4, we restrict the sample to purchases by individuals with more than 50 out-of-commuting zone friends; in column 3, we restrict the sample to transactions by individuals with friends in at least 35 counties. These specifications address concerns that the effects of the dispersion of friends' experiences on leverage could be driven by individuals without sufficiently many geographically distant friends to construct powerful shifters of the belief distribution. The magnitude of the estimates are very similar to those in the baseline specification.

Table 4: Robustness Checks I

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Friends' House Prices (24m)							
Mean	-0.112***	-0.094***	-0.093***	-0.080***	-0.090***	-0.084***	-0.114***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.025)	(0.006)	(0.008)
St. D.	0.456***	0.283***	0.278***	0.319***	0.256***	0.273***	0.370***
	(0.019)	(0.016)	(0.017)	(0.014)	(0.065)	(0.014)	(0.023)
Δ Friends' County Income (24m)							
Mean				-8.015***			
				(0.962)			
St. D.				-13.33***			
				(0.910)			
Friends' Foreclosure Rate (24m)							
Mean						40.83***	
						(1.773)	
St. D.						-32.37***	
						(3.479)	
Month x County x Lender FE	Y	Y	Y	Y	Y	Y	Y
Demographic Controls	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year
Specification Notes	Out-of-State Friends' Exp. As Instrument	> 50 Out-Of-Commuting Zone Friends	> 35 Unique Counties		Geographically Non-Clustered Profession		Only Friends in Recourse States
N	1,350,348	996,864	937,075	1,253,013	1,308,731	1,347,592	1,349,396
R-Squared	0.268	0.271	0.280	0.269	0.277	0.270	0.269
Mean Dep. Var.	88.38	88.65	88.86	88.39	88.37	88.38	88.38

Note: Table provides robustness checks to the baseline results presented in Table 3. The unit of observation is a home transaction, the dependent variable is the combined loan-to-value ratio in the transaction. All specifications include controls and fixed effects as in column 3 of Table 3. In column 1, we instrument for moments of the house price experiences of the buyers' total friends with the corresponding moments of the distribution of house price experiences of the buyers' out-of-state friends. In column 2, we restrict the sample to purchases by individuals with at least 50 out-of-commuting zone friends, in column 3 to purchases by individuals with friends in at least 35 unique counties. Column 4 also controls for the average income changes in the counties where an individual has friends. In column 5, we focus on purchases by individuals working in geographically non-clustered professions (e.g., teachers and lawyers). Column 6 also controls for the average foreclosure rate in the counties where an individual has friends. Column 7 only uses the house price experiences of out-of-commuting zone friends in recourse states to instrument for the house price experiences of all friends. Standard errors are clustered at the zip code × transaction-month level. Significance Levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

A further possible concern is that unobserved shocks to an individual's *ability* to make a downpayment in a given year might be correlated with her friends' house price experiences in that year. Such an alternative interpretation requires a shock to an individual's wealth or income that contemporaneously moves house prices in geographically distant regions where she has friends. As discussed above, our baseline regressions already minimize the scope for such potentially confounding effects, by including year-specific controls for a large number of observable characteristics of homebuyers. We next address the one additional potential confounder that we were able to identify. In particular, many people have friends that work in the same sector of the economy. If economic activity in that sector features significant geographic clustering (e.g., tech in Silicon Valley), positive shocks to that sector in a given year might both enable an individual to make a larger downpayment and drive up aggregate house prices in those sector-exposed regions where the individual has friends.

To rule out this explanation of our findings, column 4 includes the average income change in the county where the person has friends as a control, in addition to the average house price change. We measure income annually using data from the Tax Statistics of Income (SOI). In addition, column 5 restricts the sample of transactions to those in which the homebuyer works in geographically non-clustered professions (e.g., lawyers and teachers). Any positive shocks to such professions, which might increase those individuals' ability to make a larger downpayment, should not affect house prices in regions where they have friends. This is because there are no parts of the U.S. where there are so many teachers or lawyers that positive shocks to those professions can shift aggregate house prices. In both specifications the estimates are similar to our baseline estimates, suggesting that common shocks to individuals and their friends that shift house prices in areas where their friends live cannot explain our findings.

A further potential alternative interpretation of our findings is that when house prices decline in counties where an individual has friends, and there are subsequently more foreclosures in those counties, individuals might update both their own house price beliefs as well as their expectations about the cost of default or the benefits of the foreclosure process, both of which might also directly affect their leverage choice. To address such concerns, column 6 also includes measures of the share of all properties in friends' counties that experienced a foreclosure over the previous 24 months, based on data provided by Zillow. While a higher foreclosure rate in friends' locations is associated with larger leverage and a smaller downpayment, the inclusion of this additional control variable does not significantly affect the estimated effect of friends' house price experiences on mortgage leverage choice.[25] In column 7, we only use the house price experiences of friends in recourse states to instrument for the house price experiences of all friends. If most of the effect came through individuals learning about the cost of default when house prices fall where their friends live, then the estimated effect should be smaller when only using variation in house prices in recourse states where a given house price change translate into fewer foreclosures. However, the estimated coefficients are, in fact, almost identical in size to our baseline estimates.

An additional set of potential alternative interpretations for our results comes from constraints on individuals' ability to freely choose their mortgage amount. In particular, imagine that mortgage amounts cannot be increased due to constraints outside of the model. More optimistic individuals would still desire to purchase a larger or more expensive home. As a result, any increase in the value of the property these optimistic individuals purchase will automatically lead to a lower LTV ratio (they increase the "value" without being able to change the "loan" part). However, this decline in the LTV ratios of optimistic individuals would not be due to optimistic borrowers optimally choosing lower LTV ratios (as is the case in the story we tell in the paper), but because of the constraints on their ability to increase their mortgage amount.

We have identified three possible sources of such constraints on borrowers' ability to increase the size of their mortgage, and have verified that these constraints are unlikely to explain our findings. The first possible constraint comes from potentially binding debt-to-income (DTI) or payment-to-income ratios, since banks usually require individual mortgage holders to have sufficient income to afford their monthly mortgage payments. To test whether our estimates are the results of such constraints preventing optimistic borrowers from further increasing their

[25] While the house price experiences and foreclosure rates across friends' counties are naturally correlated, they are far from collinear. Specifically, the extent to which declining house prices translate into more foreclosures depends both on the legal environment across states as well as on the initial level of equity that individuals have in their homes, which, in turn, depends on the entire house price history in the county. In addition, there is a substantial time-lag between the initial house price decline and default/foreclosure activity.

mortgage amounts, column 1 of Table 5 shows our baseline estimates restricted to a sample of individuals with a DTI ratio below the median value of three.[26] The estimates in this sample are similar to those in the full sample, suggesting that binding DTI ratios cannot explain our findings.

Table 5: Robustness Checks II

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Friends' House Prices (24m)						
Mean	-0.089***	-0.106***	-0.100***	-0.099***	-0.105***	-0.094***
	(0.009)	(0.006)	(0.006)	(0.006)	(0.009)	(0.007)
St. D.	0.248***	0.326***	0.304***	0.306***	0.258***	0.324***
	(0.022)	(0.014)	(0.014)	(0.013)	(0.021)	(0.014)
Overpay				-0.067***		
				(0.001)		
Month x County x Lender FE	Y	Y	Y	Y	Y	Y
Demographic Controls	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year
Specification Notes	DTI < Median	Mortgage < (CLL - $10k)	Counties with p75 house price below CLL		"Overpay" < 0	Transactions prior to January 2013
N	588,358	1,206,593	1,246,448	1,334,769	602,461	1,064,658
R-Squared	0.313	0.285	0.265	0.282	0.300	0.265
Mean Dep. Var.	86.81	88.69	88.78	88.40	90.55	88.39

Note: Table provides robustness checks to the baseline results presented in Table 3. The unit of observation is a home transaction, the dependent variable is the combined loan-to-value ratio in the transaction. All specifications include controls and fixed effects as in column 3 of Table 3. In column 1, we restrict the sample to transactions with a debt-to-income (DTI) ratio below the sample median of 3. In column 2, we restrict the sample to transactions with a mortgage of at least $10,000 below the conforming loan limit (CLL). In column 3, we restrict the sample to transactions in counties where the 75th percentile of transaction prices was below the CLL. In column 4, we also control for "Overpay", a variable that was constructed as the differences in the transaction price and a hedonic valuation of the property. In column 5, we restrict the sample to transactions with negative values of "Overpay", where the transaction price was below the property's hedonic valuation. In column 6, we restrict the sample to transactions prior to January 2013, a period with a negative correlation of county-level wealth and county-level house price changes. Standard errors are clustered at the zip code × transaction-month level. Significance Levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

Conforming loan limits might provide a second constraint on the ability of borrowers to increase their mortgage amounts. Indeed, during much of our sample period, obtaining a mortgage with an LTV ratio above 80% required getting a conforming mortgage, which puts an upper bound on the size of the loan. Optimistic individuals who are close to that upper bound would not be able to buy more expensive homes without also reducing their final LTV ratios. To show that such constraints do not explain our results, column 2 of Table 5 focuses the sample on individuals who take out a mortgage that is at least $10,000 lower than the conforming loan limit in their county, and who thus would have been able to further increase their LTV ratios if they had chosen to do so. The estimates in this sample are very similar to those in the baseline sample, suggesting that our results are unlikely to be driven by constraints coming from the conforming loan limit. In addition, in column 3 we repeat the analysis only for counties where at least 75% of properties transact at values below the conforming loan limit, and where such properties could thus have been purchased and fully financed with a conforming mortgage. In these counties, where few buyers are constrained by conforming loan limits, we see a similar relationship between house price beliefs and mortgage leverage choice as in the full sample, again confirming that constraints on borrowers' ability to increase their mortgage above the conforming loan limit cannot explain our findings.

A third constraint on an optimistic buyer's ability to increase her mortgage could come from the assessed value of the property: banks might determine the allowable mortgage as a fraction of their own assessed property

[26]Our data do not include information on the monthly payments for each mortgage, so we cannot calculate the mortgages' payment-to-income ratios. However, given the limited heterogeneity in interest rates, individuals with a below-median debt-to-income ratio are unlikely to be constrained by a payment-to-income ratio.

value (based, for example, on automated valuation models) instead of basing it on the transaction price. To the extent that more optimistic people end up paying more for otherwise identical properties, as suggested by Bailey et al. (2017), both optimistic and pessimistic people might end up with the same loan amount, but optimistic people would pay more for the same house, and would therefore have a lower observed LTV ratio. At first sight, the potential for such a mechanism to drive our results seems limited, given the extensive evidence in the literature that the vast majority of appraised property values are at or above the transaction price (e.g., Cho and Megbolugbe, 1996). We also show that, empirically, such constraints are unlikely to explain our results. To do this, we construct a measure of "overpaying" for a property as the difference between the transaction price and a predicted property price based on a hedonic valuation model (see Appendix D.3 for details). We then include that measure of overpaying as an additional regressor in column 4 of Table 5. The relationship between beliefs and leverage is unaffected by the addition of this further control variable. In column 5, we restrict the sample to transactions where the transaction price was below the predicted value from our hedonic valuation. In this sample, the effects of beliefs on leverage are very similar as in the full sample, providing further evidence that constraints due to assessed property values are unlikely to explain our findings.

An additional challenge to our interpretation comes from our inability to directly control for wealth in regression R1. If wealthy individuals have friends in richer counties, and if these richer counties experienced higher house price appreciation, then our estimates of β_1 might just be picking up that wealthy people make larger downpayments. There are two reasons why we think that such a story is unlikely to explain our results. First, while we cannot control for wealth directly, we do control for a number of demographic characteristics that are likely to be correlated with wealth, such as income and occupation. The fact that the addition of these control variables does not affect our estimates of β_1 suggests that the coefficient is unlikely to pick up any demographic characteristics that correlate with having friends in areas with higher house price growth (see columns 1 and 2 of Table 3). Second, there are no fixed demographic characteristics that are consistently correlated with having friends in areas with higher house price appreciation, since counties that experienced above-average house price appreciation in the beginning of our sample generally had below-average house price growth towards the end of our sample. Indeed, in the period prior to January 2013, richer counties actually experienced *below-average* house price changes (see Appendix D.4). Yet, column 6 of Table 5 shows that there remains a negative relationship between friends' house price experiences and homebuyers' leverage choice during this period, suggesting that our inability to directly control for wealth does not explain our findings.

Wealth effects might also operate through a bequest channel that is not yet ruled out by the evidence presented above: if an individual has family members that live in those areas where she has friends, and if those family members own real estate, then house price increases in those areas might increase her expected bequest. This wealth channel could then provide an alternative explanation for why individuals make larger downpayments when their geographically distant friends have experienced higher house price increases. We rule out such an explanation in a number of ways. First, columns 1 to 6 of Table 6 separately explore the house price experiences across an individual's social network of work friends, family friends, and college friends. Since not all individuals report their family member, their employer, or their college on Facebook, these regressions have fewer observations than our baseline estimates. In columns 1, 3, and 5, we run our baseline regression (corresponding to column 3 of Table 3), but only on the set of individuals for whom we can identify at least ten work friends, ten family friends, or ten college friends, respectively. In columns 2, 4, and 6, we then run the same regression, but only use the house price experiences among out-of-commuting zone work friends, family friends, and college friends, respectively, to instrument for all friends' house price experiences.[27] While one might expect to inherit a house from a family

[27] Bailey et al. (2017) documented that the average house price experiences across these three separate out-of-commuting zone networks are relatively uncorrelated. This suggests that homebuyers' family friends do not, in general, live in the same parts of the

Table 6: Robustness Checks III

	Same Employer		Same College		Family		All Friends
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Friends' House Prices (24m)							
Mean	-0.126***	-0.191***	-0.121***	-0.133***	-0.089***	-0.086***	-0.362***
	(0.014)	(0.030)	(0.012)	(0.018)	(0.017)	(0.033)	(0.027)
St. D.	0.366***	0.629***	0.254***	0.333***	0.222***	0.118	0.776***
	(0.035)	(0.119)	(0.029)	(0.074)	(0.039)	(0.091)	(0.051)
Month x County x Lender FE	Y	Y	Y	Y	Y	Y	Y
Demographic Controls	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year	Y, x Year
Specification Notes	All Friends	Same Employer	All Friends	Same College	All Friends	Family	Purchase in Home State, Out-of-State Friends for Instrument
N	257,450	257,450	368,612	368,612	167,587	167,587	485,031
R-Squared	0.323	0.324	0.297	0.298	0.343	0.340	0.300
Mean Dep. Var.	89.72	89.70	88.22	88.20	91.11	91.10	88.96

Note: Table provides robustness checks to the baseline results presented in Table 3. The unit of observation is a home transaction, the dependent variable is the combined loan-to-value ratio in the transaction. All specifications include controls and fixed effects as in column 3 of Table 3. In columns 1 and 2, we focus on purchases by people for whom we can identify at least ten work friends, in columns 3 and 4 on purchases by people for whom we can identify at least ten college friends, and in columns 5 and 6 on purchases by people for whom we can identify at least ten family members. In columns 1, 3, and 5, we repeat our baseline specification on the restricted sample for comparability. In columns 2, 4, and 6, we use the house price experiences of an individual's geographically distant work friends, college friends, and family members, respectively, to instrument the corresponding moments of the house price experiences among all friends. In column 7, we only include transactions of individuals who report a hometown, and who purchase a property in their home state. We use these buyers' out-of-state friends' house price experiences to instrument for the house price experiences of all friends. Standard errors are clustered at the zip code × transaction-month level. Significance Levels: * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$).

member, this is much less likely for a colleague or college friend. Yet, our results are very similar when exploiting variation in house price experiences across these three networks, suggesting that wealth effects are not a key driver of our findings. Finally, column 7 restricts the sample to individuals who report their hometown on Facebook, and who purchase a property in their home state. We use the house price experiences of their out-of-state friends as an instrument. For those individuals, the exposure of their expected bequest to out-of-state house price movements is smaller, since the properties they might inherit are likely to be located in their home state. Yet, we find a somewhat larger correlation between the house price experiences of their geographically distant friends and their leverage choices, providing additional evidence against important bequest effects.

A final concern with our interpretation comes from the fact that we focus on exploring the intensive margin choices among homeowners. Bailey et al. (2017) show that more optimistic individuals are more likely to become homeowners, raising concerns that optimistic and pessimistic homeowners might differ on other characteristics that could affect their downpayment decisions. However, such a selection story would, if quantitatively important, push against our findings. In particular, the selection story would suggest that pessimistic homebuyers obtain larger non-financial benefits from homeownership, for example because they purchase a home that is a great match with their consumption preferences. As a result, they would perceive defaulting and moving to be more costly. This would reduce the strength of the downpayment protection force, and push more pessimistic individuals to make larger downpayments, not smaller ones, as we see in the data.

country as their work or college friends.

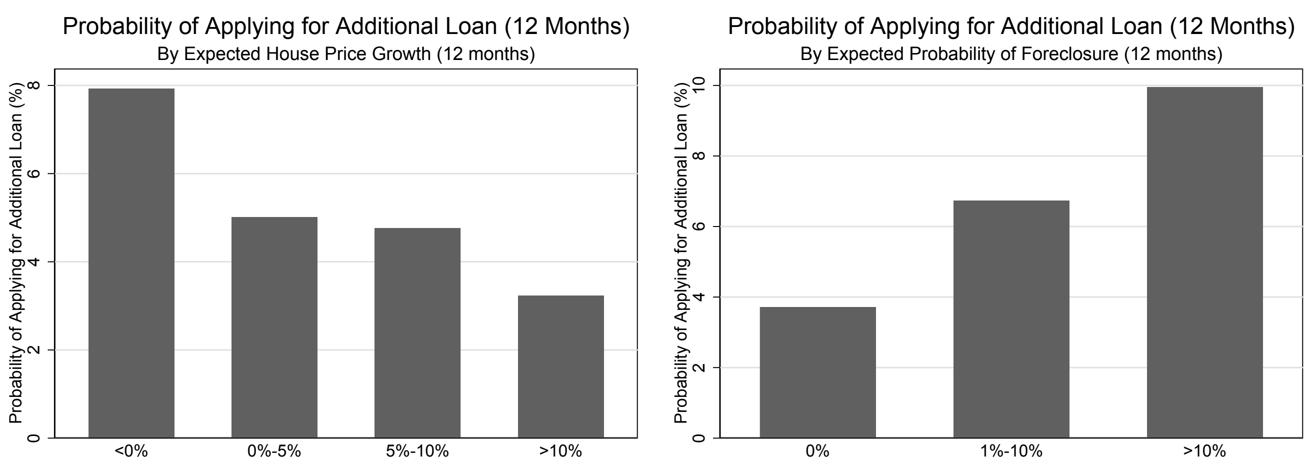
4 Beliefs and Leverage Choice: Ancillary Evidence

The previous section documented that more optimistic individuals make larger downpayments, consistent with the directional predictions from the fixed house size scenario. In this section, we show that this relationship between house price beliefs and mortgage leverage choice is consistent with various additional survey data. We also provide additional evidence for the importance of the downpayment protection force that is central to the predictions from the fixed house size scenario.

4.1 NY Fed Survey of Consumer Expectations.

We first analyze survey data from the 2014 Real Estate and Housing Module of the New York Fed Survey of Consumer Expectations (SCE).[28] Within these data, we consider the determinants of individuals' (anticipated) leverage choices. Our key outcome variable is the answer to the following question asked of current homeowners: "What is the percent chance that over the next 12 months you will apply for an additional loan on your primary residence?" In Figure 6, we explore how the answer to this question differs with respondents' expectations. In the left panel, we sort respondents by their beliefs about house price growth in their neighborhood over the coming 12 months, which was also elicited in the SCE. In the right panel, we sort respondents by their answer to the following question: "What is the percent chance that over the next 12 months you will enter foreclosure or lose your home through a repossession?"

Figure 6: Expectation of Applying for Additional Loan



Note: Figure shows summary statistics based on data from the FRBNY SCE. The left panel shows the average probability that survey respondents assign to applying for an additional loan on their property over the next 12 months, in percent, separately by groups of expected house price growth over the next 12 months. The right panel shows the average probability of applying for an additional loan separately by the probability that individuals assign to having their house foreclosed over the next 12 months.

In both panels, there is evidence that individuals who are more pessimistic are more likely to want to increase leverage, thereby reducing their financial exposure to the housing market. However, while these results are highly consistent with the downpayment protection force that is central to the predictions of the fixed house size scenario, there are other possible explanations for the observed correlations. For example, in regions where the economy is

[28]The Survey of Consumer Expectations is a monthly online survey of a rotating panel of nationally representative household heads launched by the Federal Reserve Bank of New York in 2013. New respondents are drawn monthly to match demographic targets from the American Community Survey (ACS), and stay on the panel for up to twelve months before rotating out. The Housing Module is an annual 30-minute add-on to the SCE conducted in February; the set of questions varies by year. In the 2014 implementation, 85% of SCE household heads completed the module, for a sample size of 1,213.

doing badly, individuals might expect house prices to decline and might also fear they have to tap into home equity to smooth out income shocks. Such possibly confounding stories highlight the value of the quasi-orthogonal belief shifters in our main empirical analysis for identifying causal relationships between beliefs and leverage choice.

4.2 Downpayment Motivation Survey

To provide direct evidence on the motivations behind individuals' mortgage leverage choices, we designed a short Downpayment Motivation Survey (DMS) to elicit how and why individuals' mortgage leverage choices depend on their beliefs about future house price changes. The most important purpose of this survey is to provide direct evidence that the mechanism behind the fixed house size scenario, in particular the downpayment protection force, features regularly in the narratives that individuals have about their own leverage choice process.

The DMS was administered to current homeowners via SurveyMonkey in September 2017. The demographics of the survey respondents are described in the Appendix. The survey presented individuals with different scenarios about future house price growth, and asked them to recommend one of three possible downpayment choices to a friend. Specifically, the first wave of the survey, administered to 826 respondents, was designed as follows:[29]

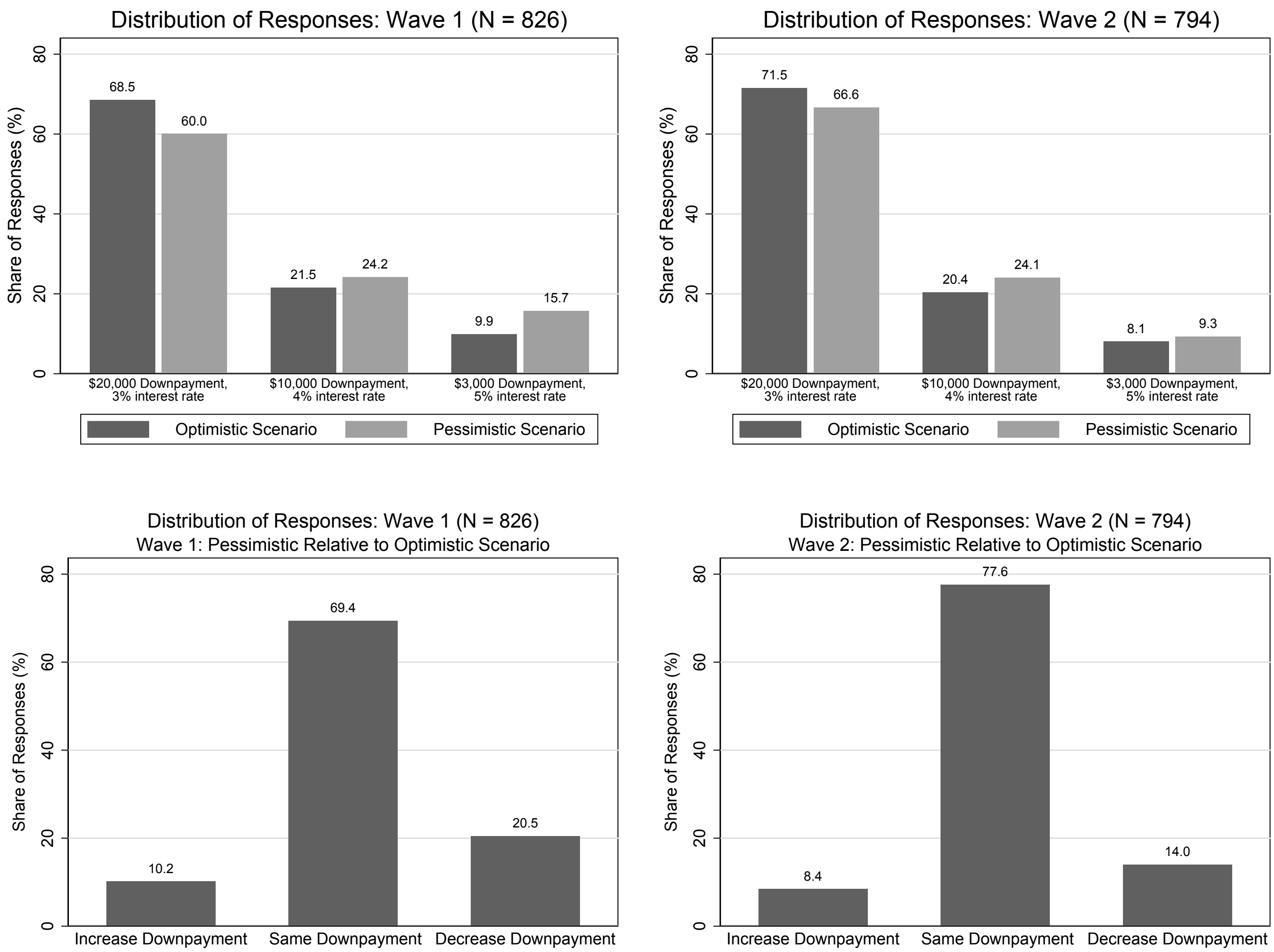
> Your friend is buying a house, and is asking you for advice on what downpayment to choose. The house costs $100,000, and your friend has a total of $30,000 in savings.
>
> [**OPTIMISTIC SCENARIO.**] Your friend believes that over the next few years there is an equal 50% chance that house prices will either *stay the same* or *increase* by 25%. If the bank offers him the following three 30-year mortgages, which mortgage would you advise your friend to take?
>
> (i) Downpayment of $20,000, interest rate of 3%
>
> (ii) Downpayment of $10,000, interest rate of 4%
>
> (iii) Downpayment of $3,000, interest rate of 5%
>
> [**PESSIMISTIC SCENARIO.**] If your friend instead believes that over the next few years there is an equal 50% chance that house prices will either *stay the same* or *decrease* by 25%, which of the following 30-year mortgages would you advise him to take?
>
> (i) Downpayment of $20,000, interest rate of 3%
>
> (ii) Downpayment of $10,000, interest rate of 4%
>
> (iii) Downpayment of $3,000, interest rate of 5%

The order of the mortgage options and the order of the optimistic and pessimistic scenarios were randomized across respondents. If the respondent did not change the downpayment recommendation across the two house price scenarios, we asked the following free-text question: "Why did you decide not to change the mortgage recommendation for your friend?"; if the respondent did change the downpayment recommendation, we asked: "Why did you change the mortgage recommendation for your friend?".

The second wave of the survey, which had 794 respondents, presented different house price scenarios. In that wave, the optimistic scenario was house prices that stayed flat with certainty, while the pessimistic scenario involved an equal probability each of a 25% increase and a 25% decrease in house prices. We call this second scenario, which involves a mean-preserving increase in the spread, more pessimistic, because it entails a higher probability of substantial house price declines.

[29] The actual survey design did not include the terms in square brackets ("Optimistic Scenario" and "Pessimistic Scenario").

Figure 7: Downpayment Motivation Survey – Responses



Note: Figure shows summary statistics on the responses to the Downpayment Motivation Survey. In the left panels, we show responses from survey wave 1, where the optimistic scenario was a 50% probability of constant house prices and a 50% probability of a 25% increase in house prices, and the pessimistic scenario was a 50% probability of constant house prices and a 50% probability of a 25% house price decrease. In the right panels, we show responses from survey wave 2, where the optimistic scenario was house prices that stayed flat, while the pessimistic scenario was a 50% chance each of a 25% house price increase and a 25% house price decrease. In the top row we show the share of respondents that make each downpayment recommendation in both the optimistic and the pessimistic scenario. In the bottom row, we show the share of respondents that either increase, do not change, or decrease their recommended downpayment in the pessimistic relative to the optimistic scenario.

For each of the two survey waves, we begin by exploring if and how individuals changed their leverage choices across the two house price scenarios. The left column of Figure 7 analyzes responses to the first survey wave, the right column to the second wave. The top row of Figure 7 shows the share of respondents that make each of the three downpayment recommendations, both in the optimistic and the pessimistic house price scenarios. The bottom row shows the share of individuals that either increase, do not change, or decrease their recommended downpayment in the pessimistic relative to the optimistic scenario.

Consistent with the findings in Section 3.3, and consistent with the predictions from the fixed house size scenario, there is a noticeable shift in the distribution of recommendations towards lower downpayments in the more pessimistic house price scenarios.[30] The bottom row confirms this finding: across the two survey waves, there

[30] Across all house price scenarios and survey waves, the most common recommendation is to make a downpayment of 20%. In addition, the majority of respondents did not change their downpayment recommendation in response to changes in house price

are twice as many people that recommend making a smaller downpayment in the relatively more pessimistic house price scenario than there are people that recommend making a larger downpayment. In Appendix D.6, we explore how changes in downpayment recommendations across the two scenarios differ with demographic characteristics. We find that individuals across all gender, income, and location groups are more likely to recommend reduced downpayments in response to the more pessimistic house price scenario.

Table 7: Stated Reasons for Recommending Smaller Downpayment Under Pessimistic Scenario

	Wave 1	**Wave 2**
Optimistic First	• Less money at risk when the chance of a decline in value increases • Less money invested in potential loss • No need to put more for a down payment if the value will drop. • If he defaults and housing prices decrease so that he cannot sell to recoup his investment, he loses less deposit if he puts less down. • Because the house MAY be worth less I would rather have cash on hand than tied up in the house	• Put down less money in case house prices go down. • Risk of losing equity with house devaluation. • Because I am anticipating that the friend may need to file for a bankruptcy and would want to be sure to be able to shield his or her equity in the property. • If the value of the home decreases substantially, he wouldn't have as much invested in the asset which is losing value, yet will still have a better interest rate than the first option.
Pessimistic First	• Cheaper rate so total cost is lower and down payment is not in jeopardy • Could be a chance he defaults on the loan in the first case to get out from under a mortgage. • If the house is not going to appreciate in value I wouldn't put too much money in	• Because if they think they are going to lose money, they shouldn't risk much. • So he would put less money/savings down on a house that could quickly decrease in value. • As long as the housing market (and his investment in the house) stays stable, he should go for the smaller monthly payments he'd have with the smaller interest rate.

Note: Table shows comments from the free-text question in the Downpayment Motivation Survey among those individuals who recommended a smaller downpayment in the more pessimistic house price scenario. The free-text question asked respondents to explain their decision for changing the mortgage recommendation. In the left panels, we show responses from survey wave 1, where the optimistic scenario was a 50% probability of constant house prices, and a 50% probability of a 25% increase in house prices, and the pessimistic scenario was a 50% probability of constant house prices and a 50% probability of a 25% house price decrease. In the right panels, we show responses from survey wave 2, where the optimistic scenario was house prices that stayed flat, while the pessimistic scenario was a 50% chance each of a 25% house price increase and a 25% house price decrease. The top row shows responses from individuals who were first shown the optimistic scenario, and then recommended a smaller downpayment for the more pessimistic scenario. The bottom row shows responses from individuals who were first shown the pessimistic scenario, and then recommended a larger downpayment for the more optimistic scenario.

While it is reassuring to find the same directional relationship between house price beliefs and mortgage leverage choices in the DMS as in the detailed empirical analysis in Section 3.3,[31] the primary benefit of the DMS is our ability to investigate the mechanism behind this relationship, by directly asking individuals to explain why they suggested a smaller downpayment in the more pessimistic house price scenario. Table 7 presents a number of representative explanations by the survey respondents. Importantly, many of the explanations reflect a desire to

expectations. This is consistent with other factors besides beliefs playing an important role in determining individuals' leverage choices, as well as the wide buckets offered. The "free text" responses of those individuals who did not change their recommendation provide some insights into what these reasons are. Very common explanations for keeping the downpayment recommendation fixed, usually at 20%, are a desire to reduce the interest rate as much as possible (e.g., "Choice is based on objective to reduce interest as much as possible"; "No matter what, better to have lower interest rate on smaller mortgage") or to borrow as little as possible (e.g., "Debt, even mortgage debt, makes me uncomfortable."; "Proverbs 22:7, Romans 13:8"; "Debt is a four-letter word. Don't borrow one penny more than you need to. Most people live in their homes for more than a few years, anyway."). Consistent with this last response, a second set of responses suggested that house price beliefs didn't matter so much for households that did not plan on selling/moving any time soon (e.g., "Because the interest rate makes the biggest difference to savings over time. Nothing indicated the friend might want to sell in the near future."; "Because it did not state whether or not he would be staying in the house long term.") Finally, a number of individuals explicitly recommend at least a 20% downpayment, if at all possible, in order to avoid having to pay private mortgage insurance ("By putting down 20% they eliminate the required mortgage insurance"; "with 20% down you do not have to have mortgage insurance, which is a great savings").

[31] Given the vague wording of the time horizon over which we presented house price scenarios in the DMS, we do not believe that it is possible to compare the implied magnitudes of the relationship between belief changes and leverage choices from the DMS to the split-sample IV estimates discussed in Section 2.1.

reduce the financial exposure to the housing asset in case of higher expected default probabilities, which maps directly into the downpayment protection force, the central mechanism behind the fixed house size scenario.[32] Indeed, a number of individuals explicitly mention that through bankruptcy or default a smaller downpayment can allow individuals to avoid the potential capital loss coming from declining house prices.

4.3 Financial Advice Websites

Many homebuyers turn to the internet for help in the home purchase and mortgage choice process (see Piazzesi, Schneider and Stroebel, 2015). Indeed, financial advice websites and blogs regularly discuss the tradeoffs behind choosing the size of the downpayment, and therefore offer another window into how considerations about future house price changes affect leverage choices. In surveying these financial advice websites, we came across many instances of financial advisors highlighting the risk-shifting benefits of taking out smaller mortgages that are at the heart of the downpayment protection force. For example, Ric Edelman (2014), the number-one independent financial adviser as ranked by Barron's in 2009, 2010, and 2012, described the following benefits of a large mortgage:

> Have you noticed that your home is worth much more than it was 10 years ago? You might be worried that your home's value will fall. If you're afraid that your home's value might decline, you should sell the house before that happens. But you don't want to do that! It's your home, after all. You have roots in the community. Uproot the kids? And where would you move? No, selling is not a practical idea. Still, you fret that your home's equity is at risk. Can you protect it without having to sell? Yes! Simply get a new mortgage, and pull the equity out of the house. It's the same thing as selling, except that you don't have to sell!

In the language of our model: pessimistic homebuyers with a return-insensitive collateral choices can reduce their exposure to house price changes by taking on higher leverage. Similarly, the following discussion on The Mortgage Reports (2017) highlights that making a 20% downpayment may not be the ideal choice, since "you're at risk when [your] home value drops. A down payment protects the bank, not the home buyer:"

> Home values are tied to the U.S. economy. Most of the time, the economy is making incremental gains, and home prices rise. But sometimes, the economy falters. This usually happens after extended periods of too-hot growth. That happened in the late 2000s. In this situation, consider two home buyers:
>
> - Buyer A: Puts 20% down on a $300,000 home
>
> - Buyer B: Uses FHA to put 3.5% down on a $300,000 home
>
> Buyer A, thinking he is being "conservative" puts $60,000 down on a home. Buyer B puts down just $10,500. If home values fall 20% neither Buyer A nor Buyer B have any equity in their homes. However, Buyer A lost a much bigger amount. Plus, Buyer B carries less risk of being foreclosed on if she can no longer make her payments. This is because banks know they will take a bigger loss repossessing a home with a larger outstanding loan balance. So, really, which home buyer is more conservative? The one who puts the least amount down.

[32] While respondents usually provided a reasonable explanation for why they did or did not change their mortgage recommendation, there is a fair amount of noise in the responses (e.g., respondents posting random YouTube links). In addition, some individuals responded with comments along the lines of "no clue," "not sure," and "just a feeling." The presence of such responses is unsurprising given the non-incentivized nature of the survey. Also, when asked why they changed their mortgage recommendation, a small number of individuals responded "I did not." Investigating these cases suggests that they were most likely responses from individuals who had picked the answer in the same "position" as their previous one, but which, due to the randomization of the downpayment choices presented to respondents, now corresponded to a different downpayment recommendation.

Appendix D.1 shows additional examples of financial advice websites and blogs highlighting that one benefit of small downpayments is the limited exposure to potential house price declines. This evidence, combined with the responses to the Downpayment Motivation Survey analyzed in Section 4.2, highlights the channel through which concerns about falling house prices can induce individuals to make smaller downpayments. Importantly, we do not want to suggest that house beliefs are the only or even the most important determinant of mortgage leverage choice. However, to the extent that beliefs do affect households' leverage decisions, there is strong support for the role of the downpayment protection force in explaining why more pessimistic individuals choose lower downpayments.

4.4 Beliefs about Default Costs

One reason why more pessimistic individuals make smaller downpayments in the fixed house size scenario is their perception that walking away from an underwater mortgage is not overly costly, either financially or socially. This is very consistent with some of the responses from the Downpayment Motivation Survey presented in Table 7. In this section, we explore additional data to investigate households' beliefs about the cost of mortgage default. In particular, we analyze responses to the following question from the SCE described in Section 4.1: "If somebody with a mortgage like yours and living in your state went through foreclosure, do you think their lender could legally go after some of their other assets (e.g. bank accounts, cars, other property, etc.) to cover the remaining amount they owe?" 55% of respondents said that the bank could legally go after other assets, 45% responded that the bank could not.[33] However, only 77% of respondents who said that the bank could go after other assets (which corresponds to 42% of all respondents) believed that the bank *would* actually do this.[34] This suggests that most respondents believe that walking away from an underwater mortgage would allow them to discard any negative equity without putting other assets at risk, a belief that would strengthen the downpayment protection force.

4.5 Perceived Housing Returns and Property Choice

The behavior of households documented in Section 3 implies the presence of significant collateral return insensitivity. As discussed above, this unwillingness of households to adjust property size based purely on their expected housing returns captures that individuals' decisions about which house to buy are also shaped by their consumption motives. Collateral return insensitivity means that more pessimistic homebuyers do not reduce their exposure to house price movements by buying a smaller property or moving to a different neighborhood, since this would generate a substantial decline in their utility from living in the house. Instead, these pessimistic households chose to reduce their downpayment to minimize their housing market exposure.

In this section, we analyze data from Zillow's "Consumer Housing Trends Report 2017" to provide direct evidence for the importance of these consumption aspects in explaining property choice. In the survey, a sample of about 3,000 representative homebuyers were asked about the criteria in the selection of their property. With respect to location, 71% of buyers required the home to be in a safe neighborhood, 40% required off-street parking, 39% required that the house was in their preferred neighborhood, and 29% required that the house was in their preferred school district. Other neighborhood requirements were proximity to shopping (29% of respondents), proximity to work (28%), proximity to family and friends (26%) and proximity to public transportation (18%).

[33] As discussed above, the legal ability of banks to go after non-housing assets depends on state-level recourse laws. Unfortunately, the public release data from the SCE do not contain state identifiers that would allow us to explore whether individuals' perceptions of banks' legal authority are correlated with banks' true legal authority. These numbers are consistent with evidence from Guiso, Sapienza and Zingales (2013), who conducted a quarterly survey on the mortgage default beliefs and attitudes of a representative sample of U.S. households between December 2008 and September 2010. Consistent with the evidence from the SCE, respondents reported an average probability of 53.4% that lenders would go after other assets of defaulters.

[34] The precise question from the SCE is: "If somebody with a mortgage like yours and living in your state went through foreclosure, do you think their lender actually would go after some of their other assets (e.g. bank accounts, cars, other property, etc.) to cover the remaining amount they owe?"

With respect to the actual property, 67% of respondents required the home to be within their initial price range, 62% required that the property had air conditioning, 62% required that it had their preferred number of bedrooms, and 53% that it had the preferred number of bathrooms. Other requirements were that the property had private outdoor space (48% of respondents), that it had the preferred square footage (47%), that it had a layout that fit the buyers' preferences (47%), that it had ample storage (41%), and that it had the buyers' preferred utilities (40%). Only 40% of respondents required that the property had good potential to increase in value. This suggests that, consistent with significant collateral return insensitivity, homebuyers regularly perceive the consumption aspect of the property to be more important than the investment aspect.

5 Conclusion

We develop a parsimonious model of mortgage leverage choice in the presence of heterogeneous beliefs to show that the relationship between homebuyers' optimism and leverage crucially depends on the degree of collateral return sensitivity of homebuyers. When households primarily maximize the levered return of their property investment (high collateral return sensitivity), more pessimistic homebuyers reduce their leverage to purchase smaller houses. However, when other considerations such as family size pin down the desired property size, and collateral investments are therefore much less sensitive to expected returns, the only way for pessimistic homebuyers to reduce the size of their housing market exposure is by reducing their downpayment and increasing their leverage. Our empirical findings show that borrowers' beliefs indeed play an important role in determining borrowers' leverage decisions: more pessimistic homebuyers take on more leverage, in particular during periods of declining house prices, and in particular in states with a relatively low cost of default.

Our paper also highlights the increasing role that data from online services, such as Facebook, LinkedIn, Twitter, eBay, Mint, Trulia, and Zillow, can have in helping researchers overcome important measurement challenges across the social sciences (see, for example, Baker, 2018; Giglio et al., 2015; Einav et al., 2015; Piazzesi, Schneider and Stroebel, 2015). Specifically, we expect that the increasing availability of data from online social networking services, such as the Social Connectedness Index described in Bailey et al. (2018), will substantially increase our understanding of the role of social interactions on social, political, and economic outcomes.

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Appendix

A Theoretical Derivations

A.1 Proofs

We first provide proofs for the simplified model considered in Sections 1 and 2 of the paper. We then study a more general environment with non-zero default costs. At times we rely on auxiliary mathematical results collected in Section A.3.

Proof of Proposition 1. (Mean and variance shifts with normally distributed beliefs).

Variable House Size. In the variable house size scenario, given Equation (8), it is sufficient to establish the behavior of $\Psi_{VHS}\left(\tilde{\delta}\right) \equiv \mathbb{E}_i\left[g|\, g \geq \tilde{\delta}\right]$ to characterize the effect of beliefs on leverage. Under standard regularity conditions, any change in parameters associated with an upwards point-wise shift in $\Psi_{VHS}(\cdot)$ for a range of $\tilde{\delta}$ implies a higher equilibrium level of δ_i. We respectively denote the pdf and cdf of the standard normal distribution by $\phi(\cdot)$ and $\Phi(\cdot)$. Under the assumption that $g \sim N\left(\mu_i, \sigma_i^2\right)$, we can express $\Psi_{VHS}\left(\tilde{\delta}\right)$ as follows

$$\Psi_{VHS}\left(\tilde{\delta}\right) = \mathbb{E}_i\left[g|g \geq \tilde{\delta}\right] = \mu_i + \sigma_i \lambda(\alpha_i)$$

where $\lambda(\alpha_i) = \frac{\phi(\alpha_i)}{1-\Phi(\alpha_i)}$ and $\alpha_i = \frac{\tilde{\delta}-\mu_i}{\sigma_i}$. The relevant comparative statics in μ_i and σ_i are given by

$$\frac{\partial \Psi_{VHS}\left(\tilde{\delta}\right)}{\partial \mu_i} = 1 - \lambda'(\alpha_i) > 0$$
$$\frac{\partial \Psi_{VHS}\left(\tilde{\delta}\right)}{\partial \sigma_i} = \lambda(\alpha_i) - \lambda'(\alpha_i)\alpha_i = \lambda(\alpha_i)\left(1 - \left(\lambda(\alpha_i) - \alpha_i\right)\alpha_i\right) > 0,$$

where we have used the properties of the Normal hazard rate from Fact 2 in Section A.3. These results establish the conclusions for the variable house size scenario.

Fixed House Size. In the fixed house size scenario, given Equation (9), it is sufficient to establish the behavior of

$$\Psi_{FHS}\left(\tilde{\delta}\right) \equiv 1 - F_i\left(\tilde{\delta}\right) = 1 - \Phi(\alpha_i),$$

where $\alpha_i = \frac{\tilde{\delta}-\mu_i}{\sigma_i}$, to characterize the effect of beliefs on leverage. Any change in parameters associated with an upwards point-wise shift in $\Psi_{FHS}(\cdot)$ for a range of $\tilde{\delta}$ implies a lower equilibrium level of δ_i. The relevant comparative statics in μ_i and σ_i are given by

$$\frac{\partial \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \mu_i} = \frac{1}{\sigma_i}\phi(\alpha_i) > 0$$
$$\frac{\partial \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \sigma_i} = \phi(\alpha_i)\frac{\alpha_i}{\sigma_i} = -\frac{\phi'(\alpha_i)}{\sigma_i},$$

which is negative when the probability of default is less than 50% (sufficiently low default probability), that is, when $\alpha_i < 0$ or, equivalently, when $\tilde{\delta} < \mu_i$.

Summary. Formally, we can summarize both sets of predictions as follows:

$$\frac{\partial \mathbb{E}_i\left[g|\, g \geq \tilde{\delta}\right]}{\partial \mu_i} > 0,\ \forall \tilde{\delta} \quad \Rightarrow \quad \frac{\partial \delta_i}{\partial \mu_i} > 0, \qquad \frac{\partial F_i\left(\tilde{\delta}\right)}{\partial \mu_i} < 0,\ \forall \tilde{\delta} \quad \Rightarrow \quad \frac{\partial \delta_i}{\partial \mu_i} < 0,$$
$$\frac{\partial \mathbb{E}_i\left[g|\, g \geq \tilde{\delta}\right]}{\partial \sigma_i} > 0,\ \forall \tilde{\delta} \quad \Rightarrow \quad \frac{\partial \delta_i}{\partial \sigma_i} > 0, \qquad \frac{\partial F_i\left(\tilde{\delta}\right)}{\partial \sigma_i} > 0,\ \forall \tilde{\delta} \quad \Rightarrow \quad \frac{\partial \delta_i}{\partial \sigma_i} > 0, \quad \text{if } \tilde{\delta} < \mu_i.$$

Proof of Proposition 2. (Additional predictions)

To be able to meaningfully study to impact of changes on the cost of default we must consider a model with non-zero default costs, so we provide the proof of part (a) of the proposition in the next section. We also refer to our derivations in the context of the more general model below regarding the part (b) results concerning the variable house size scenario.

In the fixed house size scenario, in which $\Psi_{FHS}\left(\tilde{\delta}\right) \equiv 1 - F_i\left(\tilde{\delta}\right) = 1 - \Phi\left(\alpha_i\right)$, we can find that

$$\frac{\partial^2 \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \mu_i^2} = -\frac{1}{\sigma_i^2}\phi'\left(\alpha_i\right),$$

which is negative when the probability of default is less than 50%, that is, when $\tilde{\delta} < \mu_i$. We also find that

$$\begin{aligned}
\frac{\partial^2 \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \sigma_i \partial \mu_i} &= \frac{1}{\sigma_i}\left[-\frac{1}{\sigma_i}\phi'\left(\alpha_i\right)\alpha_i - \phi\left(\alpha_i\right)\frac{1}{\sigma_i}\right] \\
&= \frac{\phi\left(\alpha_i\right)}{\sigma_i^2}\left[\alpha_i^2 - 1\right] \\
&= \frac{\phi\left(\alpha_i\right)}{\sigma_i^2}\left[\left(\frac{\tilde{\delta} - \mu_i}{\sigma_i}\right)^2 - 1\right],
\end{aligned}$$

which is positive as long as $\left|\tilde{\delta} - \mu_i\right| > \sigma_i$. Hence, it is needed that $\tilde{\delta} < \mu_i - \sigma_i$, which is valid whenever the probability of default is less than 16%. Note that the characterization of Proposition 2 exclusively focuses on the direct effects of changes in the default cost and average beliefs. As we describe in more detail below, when formally characterizing the more general environment, second-order comparative statics exercises are determined by both direct effects and curvature effects. Our focus is on the former set of effects.

A.2 General Environment: Non-zero default costs

We now proceed to systematically study a more general model in which default costs are non-zero. The goal of this section is to show that the results derived in Propositions 1 and 2 extend to the case of non-zero default costs, while providing a more detailed formal analysis of the environment that we consider in the body of the paper.[35]

Borrowers' Problem and Default Decision

When borrowers face non-zero default costs, they solve the following optimization problem

$$\max_{c_{0i}, b_{0i}, h_{0i}} u_i\left(c_{0i}\right) + \beta \mathbb{E}_i\left[\max\left\{w_{1i}^{\mathcal{N}}, w_{1i}^{\mathcal{D}}\right\}\right],$$

subject to Equation (1), where $w_{1i}^{\mathcal{N}}$ and $w_{1i}^{\mathcal{D}}$ denote borrowers' wealth in non-default and default states, given by

$$\begin{aligned}
w_{1i}^{\mathcal{N}} &= n_{1i} + p_1 h_{0i} - b_{0i} \\
w_{1i}^{\mathcal{D}} &= n_{1i} - \kappa_i h_{0i},
\end{aligned}$$

where $\kappa_i \geq 0$. Assuming that the default cost is proportional to the house size preserves the homogeneity of the borrowers' problem. This assumption can be relaxed without affecting our insights, though we believe that it is reasonable to assume that individual default costs are larger for homeowners with larger properties. At date 1, borrowers default according to the following threshold rule,

$$\text{if} \begin{cases} g \leq \delta_i - \chi_i, & \text{Default} \\ g > \delta_i - \chi_i, & \text{No Default} \end{cases} \qquad \text{where} \quad \chi_i = \frac{\kappa_i}{p_0} \quad \text{and} \quad \delta_i = \frac{b_{0i}}{p_0 h_{0i}},$$

and where g denotes the actual realization of house price growth. Note that $\chi_i \geq 0$ is simply a rescaled version of the default cost, so that $\chi_i = 0$ when $\kappa_i = 0$. Intuitively, borrowers decide to default only when date-1 house prices are sufficiently low. For any realization of house price changes, the probability of default by borrower i increases with the borrower's promised repayment δ_i and decreases with the magnitude of default costs κ_i.

[35] Throughout the paper, we present our results in a principal-agent formulation in which borrowers and lenders have predetermined roles. A common theme in existing work is that optimists endogenously become asset buyers and borrowers while pessimists become asset sellers and lenders. This type of sorting is natural if belief disagreement is the single source of heterogeneity. However, in housing markets, additional dimensions of heterogeneity (e.g., life-cycle motives, wealth, risk preferences, access to credit markets, etc.) also determine which agents become buyers and borrowers in equilibrium.

Properties of $\Lambda_i(\delta_i)$

When allowing for non-zero default costs, we also allow for the possibility of loan-to-value ratios to vary with the identity of the borrower, so we denote them by $\Lambda_i(\delta_i)$. The loan-to-value ratio offered to borrower i for a given promised repayment δ_i corresponds to

$$\Lambda_i(\delta_i) = \frac{\eta \int_{\underline{g}}^{\delta_i - \chi_i} g dF_L(g) + \delta_i \int_{\delta_i - \chi_i}^{\overline{g}} dF_L(g)}{1+r},$$

which can be alternatively written in terms of default and non-default probabilities and truncated expectations as $\Lambda_i(\delta_i) = \frac{\eta F_L(\delta_i - \chi_i) \mathbb{E}[g | g \leq \delta_i - \chi_i] + (1 - F_L(\delta_i - \chi_i))\delta_i}{1+r}$. Note that $\Lambda_i(\delta_i)$ is strictly positive and that $\Lambda_i'(\delta_i)$ can be expressed as

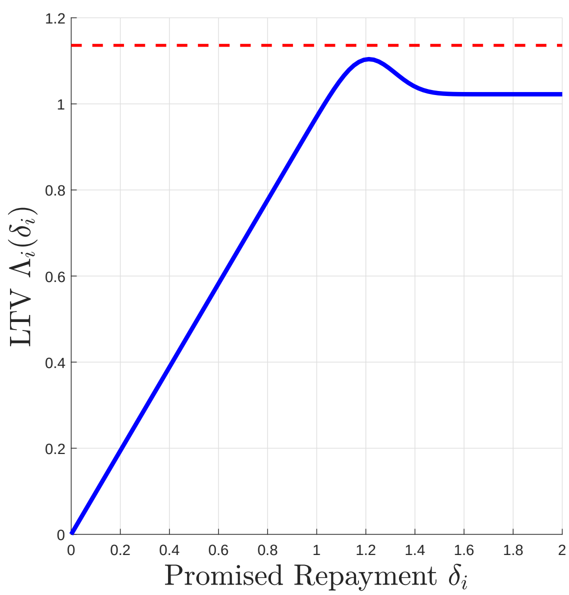
$$\Lambda_i'(\delta_i) = (1 - (\eta\chi_i + (1-\eta)\delta_i)\lambda_L(\delta_i - \chi_i)) \frac{1 - F_L(\delta_i - \chi_i)}{1+r},$$

where $\lambda_L(\delta_i - \chi_i) = \frac{f_L(\delta_i - \chi_i)}{1 - F_L(\delta_i - \chi_i)}$. In general, $\Lambda_i'(\delta_i)$ can take positive or negative values, depending on the sign of $1 - (\eta\chi_i + (1-\eta)\delta_i)\lambda_L(\delta_i - \chi_i)$. When $\eta < 1$ or $\chi_i > 0$, the function $\Lambda_i(\delta_i)$ has a well-defined maximum. Note that, whenever $\delta_i > 0$, it is the case that $\Lambda_i'(\delta_i) < 1$. At any interior optimum for leverage there exists a positive relation between $\Lambda_i(\delta_i)$ and δ_i. Alternatively, we could have formulated homebuyers' choices in terms of the margin/haircut/downpayment, which is equal to $1 - \Lambda_i(\delta_i)$, or the leverage ratio, which is equal to $\frac{1}{1-\Lambda_i(\delta_i)}$, since there exists a one-to-one relation among these variables. For instance, if a borrower pays \$100k dollars for a house, borrowing \$75k and paying \$25k in cash, the borrower's loan-to-value ratio is 0.75, his downpayment is 25%, and his leverage ratio is 4. Note that the limits of the LTV schedule offered by lenders correspond to

$$\lim_{\delta_i \to \infty} \Lambda_i(\delta_i) = \frac{\eta \int_{\underline{g}}^{\overline{g}} g dF_L(g)}{1+r} = \frac{\eta \mathbb{E}_L[g]}{1+r} \quad \text{and} \quad \lim_{\delta_i \to 0} \Lambda_i(\delta_i) = 0.$$

Figure A1 illustrates the behavior of $\Lambda_i(\delta_i)$ when lenders' beliefs are normally distributed.

Figure A1: LTV schedule $\Lambda_i(\delta_i)$



Note: Figure shows the LTV schedule $\Lambda_i(\delta_i)$ offered by lenders with normally distributed beliefs with mean $\mu_L = 1.17$ and standard deviation $\sigma_L = 0.1$, for a recovery rate after default of $\eta = 0.9$ and a default cost that corresponds to $\chi_i = 0.1$. The red dashed line corresponds to the maximum LTV ratio with full recovery, which corresponds to $\frac{\mu_L}{1+r}$.

Note that our results remain valid under weaker assumptions on the determination of credit supply. For instance, our results are unchanged if lenders are restricted to offering a single loan-to-value schedule to all borrowers. A correct interpretation of our empirical findings requires that potentially unobserved characteristics used by lenders' to offer loan-to-value schedules to borrowers must be orthogonal to the recent house price experiences of a borrower's geographically distant friends.

Borrowers' Leverage Choice

The specification of the housing constraint in Equation (2) guarantees equilibrium existence provided that $n_{0i} > p_0 \underline{h_i}$, which guarantees that the feasible choice set is non-empty. Exploiting homogeneity, the problem solved by borrowers to determine their optimal leverage choice can be expressed in terms of the following Lagrangian:

$$\max_{c_{0i},\delta_i,h_{0i}} u_i\left(c_{0i}\right)+\beta p_0 h_{0i}\left[-\chi_i \int_{\underline{g}}^{\delta_i-\chi_i} dF_i\left(g\right)+\int_{\delta_i-\chi_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right)\right]$$
$$-\lambda_{0i}\left(c_{0i}+p_0 h_{0i}\left(1-\Lambda_i\left(\delta_i\right)\right)-n_{0i}\right)+\nu_{0i}\left(h_{0i}-\underline{h_i}\right).$$

The optimality conditions of this problem regarding consumption, promised repayment, and housing choice, are the counterparts to Equations (5) to (7) in the text. The derivation of Equation (7) uses the envelope theorem. Even though borrowers take into account that adjusting their leverage choice affects their probability of default ex-post — formally, varying δ_i modifies the limits of integration — no additional terms appear in Equation (7) to account for this effect, since borrowers make default decisions optimally. Intuitively, because borrowers are indifferent between defaulting and repaying at the default threshold, a small change in the default threshold has no first-order effects on borrowers' welfare. The same logic applies to the derivation of Equation (6).

Formally, when borrowers can adjust housing freely, the following relation must hold at the optimum:

$$\underbrace{u_i'\left(c_{0i}\right)}_{\substack{\text{Marginal Benefit}\\ \text{of Consumption}}}=\underbrace{\frac{\beta\int_{\delta_i-\chi_i}^{\overline{g}} dF_i\left(g\right)}{\Lambda_i'\left(\delta_i\right)}}_{\substack{\text{Return on Larger}\\ \text{Downpayment}}}=\underbrace{\frac{\beta\left[-\chi_i\int_{\underline{g}}^{\delta_i-\chi_i} dF_i\left(g\right)+\int_{\delta_i-\chi_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right)\right]}{1-\Lambda_i\left(\delta_i\right)}}_{\text{Return on Leveraged House Purchase}}. \tag{A1}$$

Intuitively, at an optimum in which the housing constraint is slack, a borrower is indifferent between (i) consuming a dollar, (ii) using a dollar to increasing today's downpayment, and (iii) leveraging the dollar to make a larger housing investment. The second and third terms in Equation (A1) have an intuitive interpretation. A dollar of extra downpayment at date 0 allows borrowers to reduce their future per-dollar of housing repayment by $\frac{\partial\delta_i}{\partial\Lambda_i}=\frac{1}{\Lambda_i'(\delta_i)}>1$ dollars. The per-dollar net present value of such a reduction corresponds to $\beta\int_{\delta_i-\chi_i}^{\overline{g}} dF_i\left(g\right)$, since borrowers only repay in states of the world in which they do not default. Said differently, pessimistic borrowers who think they are quite likely to default in the future perceive a very small benefit of reducing the promised payment tomorrow, and will therefore make small downpayments and take on larger leverage. Alternatively, a dollar invested in housing at date 0 can be levered $\frac{1}{1-\Lambda_i(\delta_i)}$ times, while the per-dollar net present value of a housing investment corresponds to $\beta\left[-\chi_i\int_{\underline{g}}^{\delta_i-\chi_i} dF_i\left(g\right)+\int_{\delta_i-\chi_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right)\right]$.

In the variable house size scenario, the borrowers' problem simplifies to

$$\max_{c_{0i}} J\left(c_{0i}\right),\quad \text{where}\quad J\left(c_{0i}\right)=u_i\left(c_{0i}\right)+\left(n_{0i}-c_{0i}\right)\beta\rho_i,$$

and

$$\rho_i=\max_{\delta_i}\frac{-\chi_i\int_{\underline{g}}^{\delta_i-\chi_i} dF_i\left(g\right)+\int_{\delta_i-\chi_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right)}{1-\Lambda_i\left(\delta_i\right)}. \tag{A2}$$

With a solution is given by

$$\frac{\Lambda_i'\left(\delta_i\right)}{1-\Lambda_i\left(\delta_i\right)}=\frac{\int_{\delta_i-\chi_i}^{\overline{g}} dF_i\left(g\right)}{-\chi_i\int_{\underline{g}}^{\delta_i-\chi_i} dF_i\left(g\right)+\int_{\delta_i-\chi_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right)}. \tag{A3}$$

Equation (A3) determines borrowers' optimal leverage choice independently of the choices of consumption and housing. Once δ_i is determined, borrowers choose initial consumption by equalizing the marginal benefit of investing in housing with the marginal utility of consumption, that is, setting $u_i'\left(c_{0i}\right)=\rho_i$, where ρ_i, defined in (A2), is the maximized levered return on a housing investment. Finally, given δ_i and c_{0i}, borrowers choose h_{0i} to satisfy their budget constraint, defined in Equation (1). Note that when $\kappa_i=\chi_i=0$, Equation (A3) can be mapped to Equation (12) in Simsek (2013). The upshot of introducing a consumption margin in our formulation is that it highlights that borrowers' optimism only increases leverage indirectly – through Equation (6), not Equation (7) – through the fact that more optimistic borrowers need to lever up a given amount of resources to buy larger properties.

We derive all regularity conditions for the leading case $\kappa_i=\chi_i=0$. Similar conditions apply to the general case. Given c_{0i} and δ_i, borrowers' housing choice satisfies $h_{0i}=\frac{1}{p_0}\frac{n_{0i}-c_{0i}}{1-\Lambda_i(\delta_i)}$. Note that the problem solved by borrowers can be decoupled into two problems. First, borrowers maximize the levered return on a housing investment. Second, borrowers solve a consumption savings problem. Therefore, introducing a consumption margin per se does not affect borrowers' leverage choice. If $\kappa_i = \chi_i = 0$ and $\eta = 1$, then the borrowers' leverage choice has a unique optimum if borrowers' beliefs dominate lenders' beliefs in a hazard rate sense, as in Simsek (2013). That condition is not necessary when $\eta < 1$ or $\chi_i > 0$, which we assume throughout. In that case, the problem that maximizes the levered return on a housing investment always has a well defined interior solution, since $\Lambda_i'(\delta_i)$ has to be strictly positive at the optimum, implying that an optimum is reached before the maximum feasible LTV level. The consumption-savings problem is equally well defined, since $\frac{\partial J}{\partial c_{0i}} = u_i'(c_{0i}) - \beta\rho_i = 0$ and $\frac{\partial^2 J}{\partial c_{0i}^2} = u_i''(c_{0i}) < 0$.

In the fixed house size scenario, the problem solved by borrowers can be expressed as

$$\max_{\delta_i} J(\delta_i), \quad \text{where} \quad J(\delta_i) = u_i(n_{0i} - p_0 h_{0i}(1 - \Lambda_i(\delta_i))) + \beta p_0 h_{0i} \left[-\chi_i \int_{\underline{g}}^{\delta_i - \chi_i} dF_i(g) + \int_{\delta_i - \chi_i}^{\overline{g}} (g - \delta_i)\, dF_i(g) \right],$$

where $h_{0i} = \underline{h_i}$. Borrowers' first order condition corresponds to

$$\frac{\partial J}{\partial \delta_i} = p_0 h_{0i} \left(u_i'(n_{0i} - p_0 h_{0i}(1 - \Lambda_i(\delta_i))) \Lambda_i'(\delta_i) - \beta(1 - F_i(\delta_i - \chi_i)) \right) = 0. \tag{A4}$$

Borrowers' second order condition satisfies

$$\begin{aligned}
\frac{\partial^2 J}{\partial \delta_i^2} &= p_0 h_{0i} \left(u_i''(c_{0i}) \left(\Lambda_i'(\delta_i)\right)^2 p_0 h_{0i} + u_i'(c_{0i}) \Lambda_i''(\delta_i) + \beta f_i(\delta_i - \chi_i) \right) \\
&= p_0 h_{0i} \left(u_i''(c_{0i}) \left(\Lambda_i'(\delta_i)\right)^2 p_0 h_{0i} + \beta \int_{\delta_i - \chi_i}^{\overline{g}} dF_i(g) \left(\frac{\Lambda_i''(\delta_i)}{\Lambda_i'(\delta_i)} + \frac{f_i(\delta_i - \chi_i)}{1 - F_i(\delta_i - \chi_i)} \right) \right) \\
&= p_0 h_{0i} \left(u_i''(c_{0i}) \left(\Lambda_i'(\delta_i)\right)^2 p_0 h_{0i} + \beta \int_{\delta_i - \chi_i}^{\overline{g}} dF_i(g) \left(M - \frac{f_L(\delta_i - \chi_i)}{1 - F_L(\delta_i - \chi_i)} + \frac{f_i(\delta_i - \chi_i)}{1 - F_i(\delta_i - \chi_i)} \right) \right),
\end{aligned}$$

where the second line is valid at an optimum and $M \equiv \frac{-\left((1-\eta)\lambda_L(\delta_i - \chi_i) + (\eta\chi_i + (1-\eta)\delta_i)\lambda_L'(\delta_i - \chi_i)\right)}{(1 - (\eta\chi_i + (1-\eta)\delta_i)\lambda_L(\delta_i - \chi_i))} < 0$. Hence, sufficient conditions that guarantee that borrowers' first order condition corresponds to an optimum are a) a non-decreasing lenders' hazard rate, and b) that borrowers' beliefs dominate lenders' beliefs in a hazard rate sense. Once δ_i is determined, borrowers choose initial consumption to satisfy their budget constraint, defined in Equation (1), where $h_{0i} = \underline{h_i}$.

Proof of Generalized Proposition 1. (Mean and variance shifts with normally distributed beliefs and non-zero default costs)

In the variable house size scenario, given Equation (A3) and the sustained regularity conditions, it is sufficient to establish the behavior of

$$\Psi_{VHS}\left(\tilde{\delta}\right) \equiv -\chi_i \frac{F_i\left(\tilde{\delta} - \chi_i\right)}{1 - F_i\left(\tilde{\delta} - \chi_i\right)} + \mathbb{E}_i\left[g \middle| g \geq \tilde{\delta} - \chi_i\right]$$

to characterize the effect of beliefs on leverage. Any change in parameters associated with an upwards point-wise shift in $\Psi_{VHS}(\cdot)$ for a range of $\tilde{\delta}$ implies a higher equilibrium level of δ_i. Under the assumption that $g \sim N\left(\mu_i, \sigma_i^2\right)$, we can express $\mathbb{E}_i\left[g | g \geq \tilde{\delta} - \chi_i\right]$ and $F_i\left(\tilde{\delta} - \chi_i\right)$ as follows

$$\begin{aligned}
\mathbb{E}_i\left[g | g \geq \tilde{\delta} - \chi_i\right] &= \mu_i + \sigma_i \lambda(\alpha_i) \\
F_i\left(\tilde{\delta} - \chi_i\right) &= \Phi(\alpha_i),
\end{aligned}$$

where $\lambda(\alpha_i) = \frac{\phi(\alpha_i)}{1 - \Phi(\alpha_i)}$ and $\alpha_i = \frac{\tilde{\delta} - \chi_i - \mu_i}{\sigma_i}$, which allows us to express $\Psi_{VHS}\left(\tilde{\delta}\right)$ as

$$\Psi_{VHS}\left(\tilde{\delta}\right) = -\chi_i \frac{\Phi(\alpha_i)}{1 - \Phi(\alpha_i)} + \mu_i + \sigma_i \lambda(\alpha_i).$$

The relevant comparative statics in μ_i and σ_i are given by

$$\frac{\partial \Psi_{VHS}\left(\tilde{\delta}\right)}{\partial \mu_i} = \chi_i \frac{\phi\left(\alpha_i\right)\frac{1}{\sigma_i}}{\left(1-\Phi\left(\alpha_i\right)\right)^2} + 1 - \lambda'\left(\alpha_i\right) > 0$$
$$\frac{\partial \Psi_{VHS}\left(\tilde{\delta}\right)}{\partial \sigma_i} = \chi_i \frac{\phi\left(\alpha_i\right)\frac{1}{\sigma_i}\alpha_i}{\left(1-\Phi\left(\alpha_i\right)\right)^2} + \lambda\left(\alpha_i\right) - \lambda'\left(\alpha_i\right)\alpha_i = \underbrace{\chi_i \frac{\lambda\left(\alpha_i\right)}{1-\Phi\left(\alpha_i\right)}\frac{\alpha_i}{\sigma_i}}_{\gtreqless 0} + \underbrace{\lambda\left(\alpha_i\right)\left(1-\left(\lambda\left(\alpha_i\right)-\alpha_i\right)\alpha_i\right)}_{>0},$$

where we have used the properties of the Normal hazard rate from Fact 2. Note that the sign of the comparative statics on σ_i is strictly positive for low or moderate values of χ_i, since $\lim_{\chi_i \to 0} \chi_i \frac{\lambda(\alpha_i)}{1-\Phi(\alpha_i)}\frac{\alpha_i}{\sigma_i} = 0$, so the variance result remains valid in this case for sufficiently low default costs. Importantly, sufficiently low default costs is only a sufficient condition, not a necessary one. These results establish the conclusions for the variable house size scenario.

In the fixed house size scenario, given Equation (A4) and the sustained regularity conditions, it is sufficient to establish the behavior of

$$\Psi_{FHS}\left(\tilde{\delta}\right) \equiv 1 - F_i\left(\tilde{\delta}-\chi_i\right) = 1 - \Phi\left(\alpha_i\right), \tag{A5}$$

where $\alpha_i = \frac{\tilde{\delta}-\chi_i-\mu_i}{\sigma_i}$, to characterize the effect of beliefs on leverage. Any change in parameters associated with an upwards point-wise shift in $\Psi_{FHS}(\cdot)$ for a range of $\tilde{\delta}$ implies a lower equilibrium level of δ_i.

The relevant comparative statics in μ_i and σ_i are given by

$$\frac{\partial \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \mu_i} = \frac{1}{\sigma_i}\phi\left(\alpha_i\right) > 0$$
$$\frac{\partial \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \sigma_i} = \phi\left(\alpha_i\right)\frac{\alpha_i}{\sigma_i} = -\frac{\phi'\left(\alpha_i\right)}{\sigma_i},$$

which is negative when the probability of default is less than 50%, that is, when $\alpha_i < 0$ or, equivalently, when $\tilde{\delta} < \mu_i + \chi_i$.

Proof of Generalized Proposition 2(a) (Interaction with cost of default)

Note that we exclusively focus on the direct effects of how changes in χ_i affect the sensitivity of leverage choices to beliefs. Abstractly, in an optimization problem in which agents choose x to solve $\max_x F(x;\theta,\alpha)$, where θ are parameters and where an interior optimum $x^\star$ is characterized by $F_x(x^\star;\theta,\alpha) = 0$ and $F_{xx} \leq 0$, we can characterize first-order comparative statics by $\frac{dx^\star}{d\theta} = \frac{F_{x\theta}}{-F_{xx}}$ and second-order comparative statics by $\frac{d\left(\frac{dx^\star}{d\theta}\right)}{d\alpha} = \frac{d^2x^\star}{d\theta d\alpha} = \frac{F_{xxx}\frac{dx^\star}{d\alpha}\frac{dx^\star}{d\theta} + F_{xx\alpha}\frac{dx^\star}{d\theta} + F_{x\theta x}\frac{dx^\star}{d\alpha} + F_{x\theta\alpha}}{-F_{xx}}$. When we state that we characterize the direct effect of recourse, we refer to the term of the form $F_{x\theta\alpha}$, which does not rely directly on assumptions about the curvature of the model, as F_{xxx} and $F_{xx\alpha}$ do.

In the fixed house size scenario, where $\Psi_{FHS}(\cdot)$ is defined in Equation (A5),

$$\frac{\partial^2 \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \mu_i \partial \chi_i} = -\frac{1}{\sigma_i^2}\phi'\left(\alpha_i\right),$$

which is negative when the probability of default is less than 50%. The marginal cost of borrowing goes up by less when the cost of default is higher.

$$\frac{\partial^2 \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \sigma_i \partial \chi_i} = \frac{1}{\sigma_i^2}\phi''\left(\alpha_i\right),$$

which is positive as long as $\left|\tilde{\delta}-\mu_i-\chi_i\right| > \sigma_i$. Hence, it is needed that $\tilde{\delta} < \mu_i + \chi_i - \sigma_i$, which is valid whenever the probability of default is less than 16%.

In the variable house size scenario, to be able to derive unambiguous predictions, we focus for simplicity on the case in which $\chi_i \to 0$. In that case,

$$\frac{\partial^2 \Psi_{VHS}\left(\tilde{\delta}\right)}{\partial \mu_i \partial \chi_i} = \frac{1}{\sigma_i}\lambda''\left(\alpha_i\right) + \frac{\phi\left(\alpha_i\right)\frac{1}{\sigma_i}}{\left(1-\Phi\left(\alpha_i\right)\right)^2} > 0$$
$$\frac{\partial^2 \Psi_{VHS}\left(\tilde{\delta}\right)}{\partial \sigma_i \partial \chi_i} = -\frac{1}{\sigma_i}\lambda'\left(\alpha_i\right) + \frac{\alpha_i}{\sigma_i}\lambda''\left(\alpha_i\right) + \frac{1}{\sigma_i}\lambda'\left(\alpha_i\right) + \frac{\phi\left(\alpha_i\right)\frac{\alpha_i}{\sigma_i}}{\left(1-\Phi\left(\alpha_i\right)\right)^2} = \frac{\alpha_i}{\sigma_i}\lambda''\left(\alpha_i\right) + \frac{\phi\left(\alpha_i\right)\frac{\alpha_i}{\sigma_i}}{\left(1-\Phi\left(\alpha_i\right)\right)^2},$$

which is negative when the probability of default is less than 50%, that is, when $\alpha_i < 0$ or, equivalently, when $\tilde{\delta} < \mu_i + \chi_i$.

Proof of Generalized Proposition 2(b) (Interaction with average beliefs)

In the fixed house size scenario, where $\Psi_{FHS}(\cdot)$ is defined in Equation (A5),

$$\frac{\partial^2 \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \mu_i^2} = -\frac{1}{\sigma_i^2}\phi'(\alpha_i),$$

which is negative when the probability of default is less than 50%, that is, when $\tilde{\delta} < \mu_i$. We also find that

$$\begin{aligned}
\frac{\partial^2 \Psi_{FHS}\left(\tilde{\delta}\right)}{\partial \sigma_i \partial \mu_i} &= \frac{1}{\sigma_i}\left[-\frac{1}{\sigma_i}\phi'(\alpha_i)\alpha_i - \phi(\alpha_i)\frac{1}{\sigma_i}\right] \\
&= \frac{\phi(\alpha_i)}{\sigma_i^2}\left[\alpha_i^2 - 1\right] \\
&= \frac{\phi(\alpha_i)}{\sigma_i^2}\left[\left(\frac{\tilde{\delta} - \chi_i - \mu_i}{\sigma_i}\right)^2 - 1\right],
\end{aligned}$$

which is positive as long as $\left|\tilde{\delta} - \chi_i - \mu_i\right| > \sigma_i$. Hence, it is needed that $\tilde{\delta} < \mu_i + \chi_i - \sigma_i$, which is valid whenever the probability of default is less than 16%.

In the variable house size scenario, to be able to derive unambiguous predictions, we focus for simplicity in the case in which $\chi_i \to 0$. In that case,

$$\begin{aligned}
\frac{\partial^2 \mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right]}{\partial \mu_i^2} &= \lambda''(\alpha_i)\frac{1}{\sigma_i} > 0, \ \forall \tilde{\delta} \\
\frac{\partial^2 \mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right]}{\partial \sigma_i \partial \mu_i} &= -\lambda'(\alpha_i)\frac{1}{\sigma_i} + \frac{1}{\sigma_i}\lambda''(\alpha_i)\alpha_i + \frac{1}{\sigma_i}\lambda'(\alpha_i) = \frac{\alpha_i}{\sigma_i}\lambda''(\alpha_i),
\end{aligned}$$

which is negative when the probability of default is less than 50%, that is, when $\tilde{\delta} < \mu_i$.

A.3 Auxiliary results

Facts 1 and 2 follow from Greene (2003). Fact 3 follows from Krishna (2010). When needed, we respectively denote the pdf and cdf of the standard normal distribution by $\phi(\cdot)$ and $\Phi(\cdot)$.

Fact 1. (Truncated expectation of a normal distribution) *If $X \sim N\left(\mu, \sigma^2\right)$, then*

$$\begin{aligned}
\mathbb{E}\left[X \middle| X > a\right] &= \mu + \sigma\lambda(\alpha), \quad \textit{where} \quad \lambda(\alpha) = \frac{\phi(\alpha)}{1 - \Phi(\alpha)} \quad \textit{and} \quad \alpha = \frac{a-\mu}{\sigma} \\
\mathbb{E}\left[X \middle| X < b\right] &= \mu - \sigma\frac{\phi(\beta)}{\Phi(\beta)}, \quad \textit{where} \quad \beta = \frac{b-\mu}{\sigma}.
\end{aligned}$$

More generally, $\mathbb{E}\left[X \middle| a < X < b\right] = \mu + \sigma\frac{\phi(\alpha)-\phi(\beta)}{\Phi(\beta)-\Phi(a)}$*, where α and β are defined above.*

Fact 2. (Properties of normal hazard function) *The function $\lambda(\cdot)$, which corresponds to the hazard rate of the normal distribution, is also known as the Inverse Mills Ratio. It satisfies the following properties:*

1. $\lambda(0) = \sqrt{\frac{2}{\pi}}$, $\lambda(\alpha) \geq 0$, $\lambda(\alpha) > \alpha$, $\lambda'(\alpha) > 0$, and $\lambda''(\alpha) > 0$.
2. $\lim_{\alpha \to -\infty}\lambda(\alpha) = \lim_{\alpha \to -\infty}\lambda'(\alpha) = 0$, and $\lim_{\alpha \to \infty}\lambda'(\alpha) = 1$.
3. $\lambda(\alpha) < \frac{1}{\alpha} + \alpha$, $\lambda'(\alpha) = \frac{\phi'(\alpha_i)}{1-\Phi(\alpha_i)} + (\lambda(\alpha_i))^2 = \lambda(\alpha)(\lambda(\alpha) - \alpha) > 0$, $\lambda'(\alpha) < 1$, and $\lambda''(\alpha) \geq 0$.

Fact 3. (Hazard rate dominance implies first-order stochastic dominance) *The hazard rate of a distribution with cdf $F(\cdot)$ is defined by $\lambda(x) = \frac{f(x)}{1-F(x)} = -\frac{d\ln(1-F(x))}{dx}$, so $F(x) = 1 - e^{-\int_0^x \lambda(t)dt}$. If $\lambda_i(g) > \lambda_j(g)$, $\forall g$, then it trivially follows that $F_i(\cdot) > F_j(\cdot)$.*

At times, we use the fact that $\phi'(\alpha) = -\alpha\phi(\alpha)$. The following results are also relevant for our derivations:

$$\frac{\partial\left(\frac{\Phi(\alpha)}{1-\Phi(\alpha)}\right)}{\partial \mu} = \frac{-\phi(\alpha)\frac{1}{\sigma}}{(1-\Phi(\alpha))^2} \quad \text{and} \quad \frac{\partial\left(\frac{\Phi(\alpha)}{1-\Phi(\alpha)}\right)}{\partial \sigma_i} = \frac{-\phi(\alpha)\frac{\alpha}{\sigma}}{(1-\Phi(\alpha))^2},$$

as well as

$$\frac{\partial \alpha}{\partial \mu} = \frac{\partial \alpha}{\partial \chi} = -\frac{1}{\sigma} \quad \text{and} \quad \frac{\partial \alpha}{\partial \sigma} = -\frac{\alpha}{\sigma}.$$

A.4 AR(1) Mathematics

Let us assume that investors perceive the following law of motion for house prices:

$$\Delta p_{t+1} = \mu + \rho \Delta p_t + \varepsilon_{t+1}, \tag{A6}$$

where $\epsilon_{t+1} \sim \mathcal{N}\left(0, \sigma_\epsilon^2\right)$ and $\Delta p_{t+1} \equiv p_{t+1} - p_t$. Equivalently, this process can be expressed as a non-stationary AR(2) process: $p_{t+1} = \mu + (1+\rho)\, p_t - \rho p_{t-1} + \varepsilon_{t+1}$, where we define an agent's information set by $\mathcal{I}_t = \{p_t, p_{t-1}\}$.

Perception of Future Prices: Analytical Results

First, we can analytically characterize the distribution of individual perceptions over house prices k-period forward, given by p_{t+k}. We analytically characterize up to to $k=5$, but illustrate our results for higher k in Figure A2. Note that, from the perspective of date t, any statistical moment of the perceived distribution of p_{t+k} translates one-for-one into moments of the distribution of $p_{t+k} - p_t$. Note also that $p_{t+k} - p_t = \sum_{m=1}^{k} \Delta p_{t+m}$, so we can refer in the text to the distribution of cumulative price changes.

One and two periods forward, we can write

$$\begin{aligned} p_{t+1} | \mathcal{I}_t &\sim N\left(\mu + (1+\rho)\, p_t - \rho p_{t-1}, \sigma_\varepsilon^2\right). \\ p_{t+2} | \mathcal{I}_t &\sim \mathcal{N}\left((1 + (1+\rho))\, \mu + \left((1+\rho)^2 - \rho\right) p_t - (1+\rho)\, \rho p_{t-1}, \left(1 + (1+\rho)^2\right) \sigma_\epsilon^2\right). \end{aligned}$$

Three periods forward, we can show that $p_{t+3}|\mathcal{I}_t$ is normally distributed with the following moments:

$$\begin{aligned} \mathbb{E}\left[p_{t+3}|\mathcal{I}_t\right] &= \left(2 + (1+\rho)^2\right) \mu + \left((1+\rho)^3 - 2\rho\,(1+\rho)\right) p_t + \left(\rho^2 - (1+\rho)^2 \rho\right) p_{t-1} \\ \mathbb{V}ar\left[p_{t+3}|\mathcal{I}_t\right] &= \left(1 + (1+\rho)^2 + \left((1+\rho)^2 - \rho\right)^2\right) \sigma_\varepsilon^2. \end{aligned}$$

Four periods forward, we can show that $p_{t+4}|\mathcal{I}_t$ is normally distributed with the following moments:

$$\begin{aligned} \mathbb{E}\left[p_{t+4}|\mathcal{I}_t\right] &= \mu\left[1 + (1+\rho)\left(2 + (1+\rho)^2\right) - \rho\,(2+\rho)\right] + p_t\left[(1+\rho)^4 - 3\rho\,(1+\rho)^2 + \rho^2\right] + p_{t-1}\left[2\rho^2\,(1+\rho) - \rho\,(1+\rho)^3\right] \\ \mathbb{V}ar\left[p_{t+4}|\mathcal{I}_t\right] &= \left[1 + (1+\rho)^2 + \left((1+\rho)^2 - \rho\right)^2 + \left((1+\rho)^3 - 2\rho\,(1+\rho)\right)^2\right] \sigma_\varepsilon^2. \end{aligned}$$

Finally, we can show that $p_{t+5}|\mathcal{I}_t$ is normally distributed with the following moments:

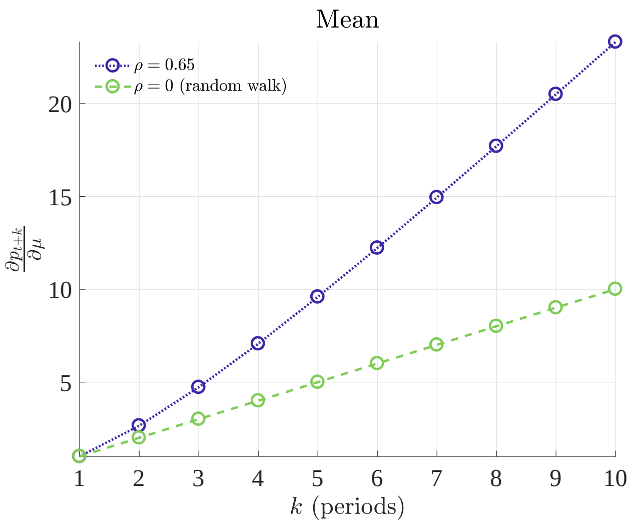
$$\begin{aligned} \mathbb{E}\left[p_{t+5}|\mathcal{I}_t\right] &= \mu\left[1 - 2\rho + (1+\rho) + (2-\rho)\,(1+\rho)^2 + (1+\rho)^4 - \rho\,(1+\rho)\,(2+\rho)\right] \\ &\quad + p_t\left[(1+\rho)\left[(1+\rho)^4 - 3\rho\,(1+\rho)^2 + \rho^2\right] - \rho\left((1+\rho)^3 - 2\rho\,(1+\rho)\right)\right] \\ &\quad + p_{t-1}\left[(1+\rho)\left[2\rho^2\,(1+\rho) - \rho\,(1+\rho)^3\right] - \rho\left(\rho^2 - (1+\rho)^2 \rho\right)\right] \\ \mathbb{V}ar\left[p_{t+5}|\mathcal{I}_t\right] &= \left[1 + (1+\rho)^2 + \left((1+\rho)^2 - \rho\right)^2 + \left((1+\rho)^3 - 2\rho\,(1+\rho)\right)^2 + \left((1+\rho)^4 - 3\rho\,(1+\rho)^2 + \rho^2\right)^2\right] \sigma_\varepsilon^2. \end{aligned}$$

Perception of Future Prices: Simulation

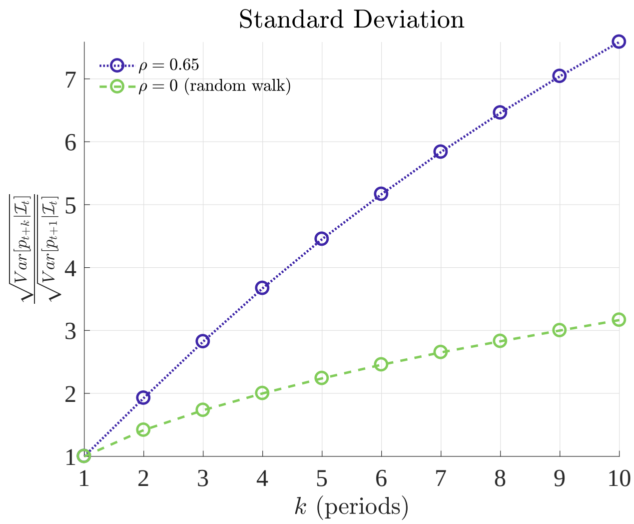
Given our assumption about the behavior of beliefs in Equation (A6), when we elicit information about house price growth one-period forward, the average belief reported by an individual must be mapped to $\mu + \rho \Delta p_t$ and the standard deviation reported by an individual must be mapped to σ_ε.

Figure A2a shows the sensitivity of the expected house price k periods forward to a change in the parameter μ as of date t. This exercise corresponds to attributing the reported expected house price growth by an individual over the next twelve months to a change in μ: hence, the values in Figure A2a provide an upper bound for the impact that an increase of $\mathbb{E}\left[p_{t+1}|\mathcal{I}_t\right]$ may have on $\mathbb{E}\left[p_{t+k}|\mathcal{I}_t\right]$. Figure A2b shows the sensitivity of the standard deviation of the house price k periods forward to a change in the parameter σ_ε as of date t. Because there is a one-to-one mapping between $\mathbb{V}ar\left[p_{t+k}|\mathcal{I}_t\right]$ and σ_ε^2, these values are exact within the context of the process, and not only a bound.

Our results map a unit change in μ into roughly a twenty-fold increase for the expected price ten periods forward. Our results map a unit change in σ_ε into a roughly seven-fold increase for the standard deviation of house prices ten periods



(a) Sensitivity of $\mathbb{E}\left[p_{t+k}|\mathcal{I}_t\right]$ to a change in μ



(b) Sensitivity of $\sqrt{\mathbb{V}ar\left[p_{t+k}|\mathcal{I}_t\right]}$ to a change in σ_ε.

Note: Figure A2a illustrates the path of expected values for the house price k-periods forward induced by a change in μ. In other words, it shows how a unit change in μ propagates over individual expectations of house prices. Figure A2b illustrates the path of standard deviations induced by a unit change in σ_ε, that is, it shows how a change in σ_ε affects future perceived house price volatility. Both figures correspond to the stochastic process $\Delta p_{t+1} = \mu + \rho \Delta p_t + \varepsilon_{t+1}$. The blue dotted line is drawn for $\rho = 0.65$, while the green dashed line is drawn for a random walk ($\rho = 0$), for comparison.

Figure A2: Expectation and Standard Deviation of p_{t+k}

forward.

A.5 Further Extensions

Two assumptions crucially allow us to derive tractable analytical results: the risk neutrality of borrowers, common in existing work on leverage cycles, and our formulation for housing preferences. Here, we show how our framework can be extended to incorporate curvature in borrowers' date-1 utility and smooth preferences for housing. Our theoretical results can be interpreted as a first-order approximation to the more general case.

It is conceptually easy to make borrowers in our model risk averse. We assume that, at date 1, borrowers derive a continuation utility of wealth $v_i(\cdot)$. We also assume that their date-0 flow utility corresponds to a sufficiently regular $u_i(c_{0i}, h_{0i})$, so

$$\max_{\delta_i, h_{0i}} u_i\left(n_{0i} - p_0 h_{0i}\left(1 - \Lambda_i\left(\delta_i\right)\right), h_{0i}\right) + \beta\left[\int_{\underline{g}}^{\delta_i - \chi_i} v_i\left(w_{1i}^{\mathcal{D}}\right) dF_i(g) + \int_{\delta_i - \chi_i}^{\overline{g}} v_i\left(w_{1i}^{\mathcal{N}}\right) dF_i(g)\right],$$

where $w_{1i}^{\mathcal{N}} = n_{1i} + p_1 h_{0i} - b_{0i} = n_{1i} + p_0 h_{0i}(g - \delta_i)$ and $w_{1i}^{\mathcal{D}} = n_{1i} - \kappa_i h_{0i} = n_{1i} - \chi_i p_0 h_{0i}$.

Borrowers' optimality conditions in this case correspond to

$$\frac{\partial u_i}{\partial c_{0i}}\left(1 - \Lambda_i\left(\delta_i\right)\right) = \frac{\frac{\partial u_i}{\partial h_{0i}}}{p_0} \underbrace{- \chi_i \beta \int_{\underline{g}}^{\delta_i - \chi_i} v_i'\left(w_{1i}^{\mathcal{D}}\right) dF_i(g) + \beta \int_{\delta_i - \chi_i}^{\overline{g}} \left(g - \delta_i\right) v_i'\left(w_{1i}^{\mathcal{N}}\right) dF_i(g)}_{\text{Expected Return}},$$

$$\frac{\partial u_i}{\partial c_{0i}} \Lambda_i'\left(\delta_i\right) = \underbrace{\beta \int_{\delta_i - \chi_i}^{\overline{g}} v_i'\left(w_{1i}^{\mathcal{N}}\right) dF_i(g)}_{\text{Mg. Cost of Borrowing}},$$

which are the counterparts of Equations (6) and (7) in the main text. We highlight the terms through which the expected return and downpayment protection channels materialize. Equation (A1) corresponds in this case to

$$\frac{\partial u_i}{\partial c_{0i}} = \beta \frac{\int_{\delta_i - \chi_i}^{\overline{g}} v_i'\left(w_{1i}^{\mathcal{N}}\right) dF_i(g)}{\Lambda_i'(\delta_i)} = \frac{\frac{\partial u_i}{\partial h_{0i}}}{p_0\left(1-\Lambda_i(\delta_i)\right)} + \beta \frac{\left(-\chi_i \int_{\underline{g}}^{\delta_i - \chi_i} v_i'\left(w_{1i}^{\mathcal{D}}\right) dF_i(g) + \int_{\delta_i - \chi_i}^{\overline{g}} (g-\delta_i) v_i'\left(w_{1i}^{\mathcal{N}}\right) dF_i(g)\right)}{1-\Lambda_i(\delta_i)}.$$

In this more general scenario, changes in borrowers' beliefs only affect borrowers' decisions insofar as they affect the expected return and downpayment protection terms, which now include marginal utilities. We now sequentially study the impact of several alternative modeling assumptions.

Final date risk aversion

We now assume that housing does not enter borrowers' utility directly. In that case, we can combine borrowers' optimality conditions for housing and leverage to find a condition that generalizes (8). In particular, assuming $\kappa_i = 0$ for simplicity,

$$\frac{\Lambda_i'(\delta_i)}{1-\Lambda_i(\delta_i)} = \frac{1}{\frac{\mathbb{E}_i\left[(g-\delta_i) v_i'\left(w_{1i}^{\mathcal{N}}\right) \middle| g \geq \delta_i\right]}{\mathbb{E}_i\left[v_i'\left(w_{1i}^{\mathcal{N}}\right) \middle| g \geq \delta_i\right]}},$$

where

$$\frac{\mathbb{E}_i\left[(g-\delta_i) v_i'\left(w_{1i}^{\mathcal{N}}\right) \middle| g \geq \delta_i\right]}{\mathbb{E}_i\left[v_i'\left(w_{1i}^{\mathcal{N}}\right) \middle| g \geq \delta_i\right]} = \mathbb{E}_i\left[g-\delta_i \middle| g \geq \delta_i\right] + \frac{\mathbb{C}ov_i\left[g-\delta_i, v_i'\left(w_{1i}^{\mathcal{N}}\right) | g \geq \delta_i\right]}{\mathbb{E}_i\left[v_i'\left(w_{1i}^{\mathcal{N}}\right) \middle| g \geq \delta_i\right]}.$$

This more general expression includes a new term that separately affects borrowers' leverage choices. Unfortunately, it is not possible to analytically characterize how a change on borrowers' beliefs affects the new term.

In the fixed house size scenario, a simple result can be found when borrowers are prevented from defaulting. In that case, the first-order condition for borrowing corresponds to

$$\frac{\partial u_i}{\partial c_{0i}} \Lambda_i'(\delta_i) = \beta \int_{\underline{g}}^{\overline{g}} v_i'\left(n_{1i} + p_0 h_{0i}(g-\delta_i)\right) dF_i(g).$$

In this case, it is easy to show that more optimistic borrowers, in a first-order stochastic dominance sense, decide to borrow more. Intuitively, optimism is associated with a desire to transfer resources from the future and lower precautionary savings, both of which are associated with higher borrowing.

Smooth preferences for housing

In this case, we preserve borrowers' risk neutrality and focus on the case in which preferences for housing are separable, so $u_i(c_{0i}, h_{0i}) = v_i(c_0) + \frac{\alpha}{2}\left(h_{0i} - \bar{h}\right)^2$ and $\frac{\frac{\partial u_i}{\partial h_{0i}}}{p_0} = \alpha \frac{h_{0i} - \bar{h}}{p_0}$. Setting again $\kappa_i = 0$ for simplicity, we can express borrowers' optimality condition for housing as

$$h_{0i} = \bar{h} + \frac{p_0}{\alpha}\left(\frac{\partial u_i}{\partial c_{0i}}\left(1-\Lambda_i(\delta_i)\right) - \beta \int_{\delta_i}^{\overline{g}} (g-\delta_i) dF_i(g)\right).$$

In the limit in which $\alpha \to \infty$, it must be that $h_{0i} \to \bar{h}$, so changes in borrowers' beliefs do not affect housing choices. In that case, borrowers' make leverage choices according to

$$\frac{\partial u_i}{\partial c_{0i}} \Lambda_i'(\delta_i) = \beta \int_{\delta_i}^{\overline{g}} dF_i(g),$$

as in the fixed house size scenario.

Alternative savings opportunities

Finally, although we have introduced consumption at date 0 as homebuyers' alternative use of funds, they could be indifferent at the margin between their investment return on housing and alternative investment opportunities. If we assume that households have access to a savings opportunity with a constant gross returns R_s, their date 0 budget constraint becomes

$$n_{0i} = p_0 h_{0i}\left(1-\Lambda_i(\delta_i)\right) + s, \tag{A7}$$

where s denotes savings. Therefore, at the optimum, the counterpart of Equation (A1) corresponds to

$$R_s = \frac{\beta \int_{\delta_i - \chi_i}^{\overline{g}} dF_i(g)}{\Lambda_i'(\delta_i)} = \frac{\beta \left[-\chi_i \int_{\underline{g}}^{\delta_i - \chi_i} dF_i(g) + \int_{\delta_i - \chi_i}^{\overline{g}} (g - \delta_i) dF_i(g) \right]}{1 - \Lambda_i(\delta_i)}. \tag{A8}$$

Homebuyers' housing and borrowing decisions must at the margin yield a return R_s, so every argument in the paper remains valid. We adopt the formulation with consumption in the paper because for this alternative formulation to be well-behaved in the variable house size case, we would need to impose some curvature in the return R_s. By slightly changing the default formulation, one can allow for borrowers to save at date 0 to use some of those funds to avoid default at date 1. In that case, Equations (A7) and (A8) still determine the equilibrium after accounting for the different default behavior.

Role of Lenders' Beliefs

Although our empirical findings build on cross-sectional variation on homebuyers' beliefs, it may be valuable to separately characterize the effect of changes in lenders' beliefs on the equilibrium leverage choices of borrowers. We show that an increase in lenders' optimism can increase equilibrium leverage in both the fixed house size and the variable house size scenarios. We assume that lenders have normally distributed beliefs with mean μ_L.

Proposition. (Parametric predictions of lenders' beliefs.) *In the variable house size scenario and the fixed house size scenario, higher optimism by lenders, in the form of a higher average belief μ_L, holding all else constant, including borrowers' beliefs, can be associated with higher leverage.*

We now formally show that a change in the average belief of lenders μ_L is associated with point-wise shifts in $\Lambda_i(\cdot)$ and $\Lambda_i'(\cdot)$. Intuitively, when lenders become more optimistic, borrowers have access to cheaper funding. In the variable house size scenario, we show that access to cheaper credit increases the maximum levered return that a borrower can achieve, generating a substitution effect towards higher leverage in equilibrium. In the fixed house size scenario, in addition to the substitution effect, there is an income effect that works in the opposite direction: lower interest rates make borrowers feel richer, which generates a force towards higher consumption and lower leverage. Therefore, our results show that shifts in the beliefs of borrowers and lenders, when considered in isolation, can have opposite predictions for equilibrium leverage.

To provide comparative statics in the case of lenders' beliefs, we must characterize the behavior of $\frac{\partial \Lambda_i(\delta_i)}{\partial \mu_L}$ and $\frac{\partial \Lambda_i'(\delta_i)}{\partial \mu_L}$.[36] Formally, we find that both the LTV schedule offered by lenders and its derivative with respect to δ_i shift pointwise with changes in μ_L:

$$\begin{aligned}
\frac{\partial \Lambda_i(\delta_i)}{\partial \mu_L} &= \frac{\eta \Phi_L\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right) - \frac{(\eta\mu_L - \delta_i)}{\sigma_L}\phi_L\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right) + \eta \phi_L'\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)}{1+r} > 0, \\
\frac{\partial \Lambda_i'(\delta_i)}{\partial \mu_L} &= (\eta\chi_i + (1-\eta)\delta_i)\left(\lambda\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right) - \frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)\frac{1}{\sigma_L}\frac{\phi\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)}{1+r} \\
&\quad + \left[1 - (\eta\chi_i + (1-\eta)\delta_i)\lambda\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)\right]\frac{1}{\sigma_L}\frac{\phi\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)}{1+r} > 0,
\end{aligned}$$

where we use the fact that the pdf of the Normal distribution satisfies $\phi'(x) = -x\phi(x)$ and that $1 > (\eta\chi_i + (1-\eta)\delta_i)\lambda\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)$ at any interior solution. Both results, when combined, imply that

$$\frac{d\left(\frac{\Lambda_i'(\delta_i)}{1-\Lambda_i(\delta_i)}\right)}{d\mu_L} > 0.$$

In the variable house size scenario, Equation (A3) directly implies that upward point-wise shifts on $\frac{\Lambda_i'(\delta_i)}{1-\Lambda_i(\delta_i)}$ are associated with a higher equilibrium leverage choice δ_i. Hence, a higher μ_L is associated with a higher equilibrium

[36] Note that we can express LTV schedules as

$$\begin{aligned}
\Lambda_i(\delta_i) &= \frac{\eta \Phi_L\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)\left(\mu_L - \sigma_L \frac{\phi_L\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)}{\Phi_L\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)}\right) + \left(1 - \Phi_L\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)\right)\delta_i}{1+r} \\
&= \frac{\delta_i + (\eta\mu_L - \delta_i)\Phi_L\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right) - \eta\sigma_L\phi_L\left(\frac{\delta_i - \chi_i - \mu_L}{\sigma_L}\right)}{1+r}
\end{aligned}$$

leverage choice δ_i. In the fixed house size scenario, Equation (A4) directly implies that upward point-wise shifts on $u_i'(n_{0i} - p_0 h_{0i}(1 - \Lambda_i(\delta_i)))\Lambda_i'(\delta_i)$ are associated with a higher equilibrium leverage choice δ_i. In this case,

$$\frac{\partial\left(u_i'(\cdot)\Lambda_i'(\delta_i)\right)}{\partial\mu_L} = u_i'(n_{0i} - p_0 h_{0i}(1 - \Lambda_i(\delta_i)))\frac{\partial\Lambda_i'(\delta_i)}{\partial\mu_L} + p_0 h_{0i} u_i''(n_{0i} - p_0 h_{0i}(1 - \Lambda_i(\delta_i)))\frac{\partial\Lambda_i(\delta_i)}{\partial\mu_L}\Lambda_i'(\delta_i),$$

whose sign is ambiguous. An increase in μ_L generates both a substitution and an income effect. More optimistic lenders offer more attractive LTV schedules at the margin, so borrowers substitute towards higher leverage. More optimistic lenders offer more attractive schedule, which makes borrowers effectively richer at date 0, reducing their need to borrow, which reduces their equilibrium leverage.

B Numerical Simulation

Although we have derived our analytical results in the context of two polar scenarios, we now simulate an extension of the model in which homebuyers have conventional CES preferences over consumption and housing (see, for example, Piazzesi, Schneider and Tuzel, 2007). In that case, the return sensitivity of housing investments is not determined by a potentially-binding housing size constraint, but instead arises endogenously from household preferences.

Our goal with this simulation is twofold. First, we show that we can recover the predictions of both polar scenarios for the relationship between beliefs and leverage choices when employing more conventional preferences for housing. The fact that we can generate opposite predictions reinforces our motivation for the empirical analysis, which seeks to understand which effects dominate in the data. At the same time, we can provide a sense of the parameters that are consistent with the predictions of the fixed house size scenario that we find in the data. Second, the extended model allows us to formally reconcile the findings of this paper with the findings of Bailey et al. (2017), who document that more optimistic individuals purchase larger homes. Specifically, we show that in a world with partial collateral return sensitivity, it is possible to have more optimistic individuals purchasing larger houses with lower LTV ratios.

Environment. We consider the same environment as in Section 3, except that we drop the housing constraint, given by Equation (2), and instead introduce standard CES preferences between consumption and housing at date 0. Formally, homebuyers solve the following problem:

$$\max_{c_{0i},\delta_i,h_{0i}} J\left(c_{0i},\delta_i,h_{0i}\right)$$

where

$$J\left(c_{0i},\delta_i,h_{0i}\right)=U\left(c_{0i},h_{0i}\right)+\beta p_0 h_{0i}\int_{\delta_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right)-\lambda_{0i}\left(c_{0i}+p_0h_{0i}\left(1-\Lambda\left(\delta_i\right)\right)-n_{0i}\right),$$

and where

$$U\left(c_{0i},h_{0i}\right)=\frac{\left(u_i\left(c_{0i},h_{0i}\right)\right)^{1-\gamma}}{1-\gamma}\quad\text{and}\quad u_i\left(c_{0i},h_{0i}\right)=\left[\alpha c_{0i}^{\frac{\varepsilon-1}{\varepsilon}}+\left(1-\alpha\right)h_{0i}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$$

where σ corresponds to the elasticity of substitution between consumption and housing.[37] The lenders' LTV schedule is given by

$$\Lambda_i\left(\delta_i\right)=\frac{\eta\int_{\underline{g}}^{\delta_i}gdF_L\left(g\right)+\delta_i\int_{\delta_i}^{\overline{g}}dF_L\left(g\right)}{1+r},$$

with $F_L\left(\cdot\right)$ normally distributed. Using the fact that $c_{0i}=n_{0i}-p_0h_{0i}\left(1-\Lambda\left(\delta_i\right)\right)$, the solution of the model can be found by solving the following system of two equations and two unknowns, δ_i and h_{0i}:

$$\frac{\partial u_i\left(c_{0i},h_{0i}\right)}{\partial h_{0i}}=p_0\beta\left(1-F_i\left(\delta_i\right)\right)\left(\frac{1-\Lambda\left(\delta_i\right)}{\Lambda'\left(\delta_i\right)}-\frac{\int_{\delta_i}^{\overline{g}}\left(g-\delta_i\right)dF_i\left(g\right)}{\int_{\delta_i}^{\overline{g}}dF_i\left(g\right)}\right)$$

$$\frac{\partial u_i\left(c_{0i},h_{0i}\right)}{\partial c_{0i}}=\beta\frac{1-F_i\left(\delta_i\right)}{\Lambda'\left(\delta_i\right)}$$

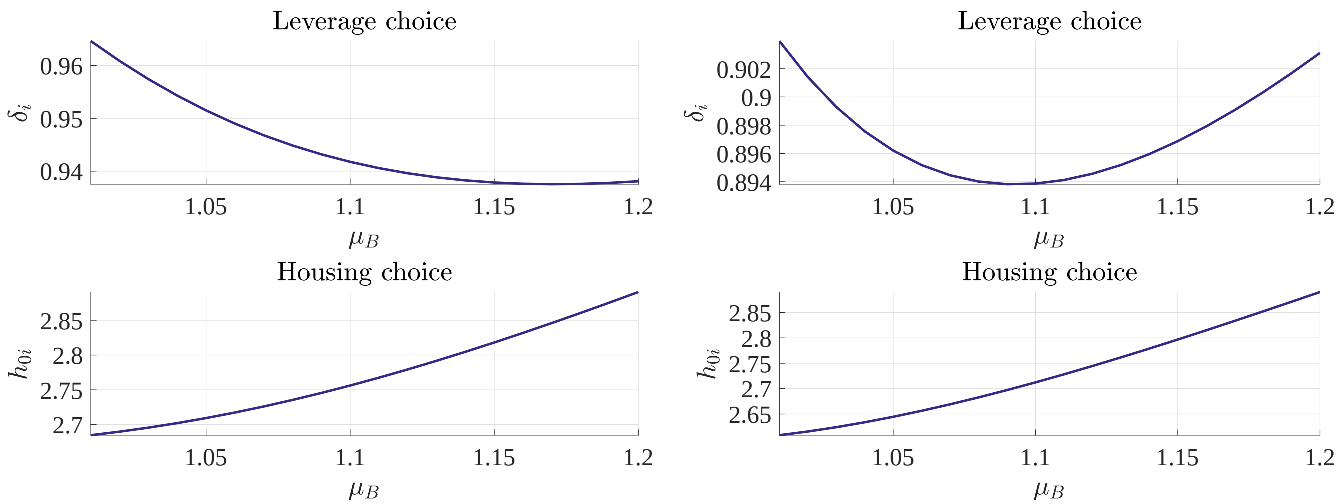
Parameters. Although our model is highly stylized, we stay close to existing quantitative models with housing when selecting parameters for our simulation. We interpret the single period in the model as five years. Our choices for preference parameters build on Piazzesi, Schneider and Tuzel (2007). We select a static elasticity of substitution between consumption and housing of $\varepsilon=1.25$, an EIS/Risk Aversion parameter of $\gamma=1$ (corresponding to log-utility), and $\alpha=0.5$, which would imply equal shares of consumption and housing services in a static setup. We use a recovery rate for lenders of $\eta=0.75$ after default, consistent with Campbell, Giglio and Pathak (2011). We normalize $p_0=n_{0i}=1$, so that lenders' date-0 resources are equal to unity. We assume that lenders' average belief is $\mu_L=1.1$ and that both homebuyers and lenders have the same standard deviation of beliefs, $\sigma_B=\sigma_L=0.25$. We assume that $r=1.15\approx1.03^5$ and consider two scenarios: one with patient homebuyers/borrowers ($\beta=0.95\approx0.99^5$), and one with impatient homebuyers/borrowers ($\beta=0.7\approx0.94^5$). We set (effectively non-binding) upper and lower thresholds for all distributions $\underline{g}=0.1$ and $\overline{g}=2$.

Results. We illustrate the results of our simulation in Figure A3. The left panels show the relationship between impatient borrowers' beliefs and choices for LTV ratio and house size. Over almost the entire range of beliefs considered, $\mu_B\in[1,1.2]$, we find a negative relationship between borrowers' beliefs and leverage choices, consistent with the empirical results in Section 3. Only when borrowers are very optimistic, we find that LTV ratios are increasing in borrowers' beliefs. In

[37] This preference specification implies that $U_c=\alpha u_i^{\frac{1}{\varepsilon}-\gamma}c_{0i}^{-\frac{1}{\varepsilon}}$ and $U_h=\left(1-\alpha\right)u_i^{\frac{1}{\varepsilon}-\gamma}h_{0i}^{-\frac{1}{\varepsilon}}$.

Figure A3: Simulation

(a) Relatively Impatient Homebuyers (b) Relatively Patient Homebuyers



Note: Both panels show homebuyers' optimal leverage and housing decisions for different values of homebuyers' average belief. Both panels share the following parameters: $\varepsilon = 1.25$, $\gamma = 1$, $\alpha = 0.5$, $\eta = 0.75$, $r = 0.12$, $n_{0i} = 1$, $p_0 = 1$, $\mu_L = 1.1$, $\sigma_L = 0.25$, and $\sigma_B = 0.22$. The left panel corresponds to impatient homebuyers, with $\beta = 0.7$. The right panel corresponds to patient homebuyers, with $\beta = 0.95$.

addition, over the entire range of beliefs considered, more optimistic borrowers purchase bigger houses. This suggests that for reasonable parameters, the predictions from our model are consistent with both our empirical results and the findings in Bailey et al. (2017).

Which parameters are important for the model to generate both observed relationships? To explore this question, the right panels show simulations of these relationships for impatient homebuyers. For relatively pessimistic borrowers we continue to observe house size to increase and leverage to decrease with optimism. However, the relationship between changes in optimism and changes in leverage turns positive at lower baseline levels of optimism. This suggests that homebuyer impatience is helpful in generating the empirical findings within our model. The intuition is that, all else equal, more impatient homebuyers choose to borrow more, and are therefore closer to the default threshold. More generally, assumptions on primitives that generate high perceived probabilities of default are likely to generate the negative link between optimism and leverage that we identify in this paper.

C Non-Parametric Predictions

C.1 Theoretical results

While the parametric assumption underlying Propositions 1 and 2 are natural, given that the distribution of g is unimodal and symmetric in the data, these results impose a priori unnecessary distributional restrictions. An alternative approach is to consider cross-sectional comparisons among borrowers that do not rely on parametric assumptions. This approach uses the ability to potentially observe shifts of the whole distribution of beliefs, which is a unique feature of our empirical setup.

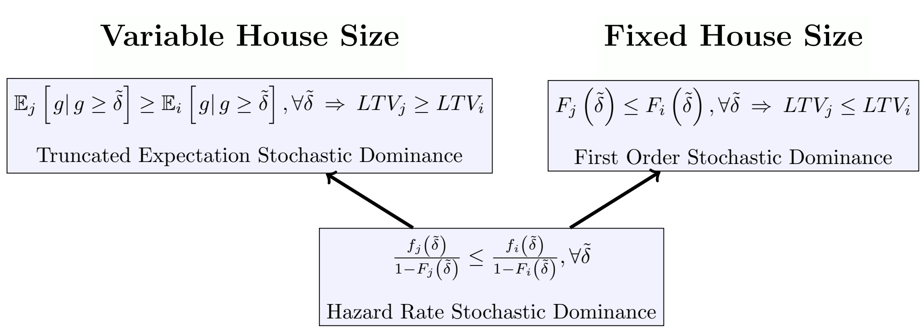
In general, there are numerous ways in which one borrower may be "more optimistic" than another in a non-parametric sense. For example, two borrowers could disagree primarily about the probability of very large declines or very large increases in house prices. In this section, we identify the appropriate definition of stochastic dominance that allows us to provide unambiguous directional predictions for borrowers' leverage choices across both the fixed house size and variable house size scenarios. Because of the inherent difficulties with establishing general comparisons between infinite-dimensional distributions, our non-parametric results only provide a partial order when comparing borrowers in the data — there are many pairwise comparisons of borrowers' distributions that cannot be ranked according to the appropriate dominance notion.

We use three different stochastic orders to define optimism. Given two distributions with cumulative distribution functions $F_j(\cdot)$ and $F_i(\cdot)$ with support $\left[\underline{g}, \overline{g}\right]$, we define truncated expectation stochastic dominance, first-order stochastic dominance and hazard rate dominance as follows:

1. **Truncated expectation stochastic dominance:** F_j stochastically dominates F_i (borrower j is more optimistic than i) in a truncated expectation sense if
$$\mathbb{E}_j\left[g \mid g \geq \delta\right] \geq \mathbb{E}_i\left[g \mid g \geq \delta\right], \quad \forall \delta \in \left[\underline{g}, \overline{g}\right].$$
2. **First-order stochastic dominance:** F_j stochastically dominates F_i (borrower j is more optimistic than i) in a first-order sense if
$$F_j(\delta) \leq F_i(\delta), \quad \forall \delta \in \left[\underline{g}, \overline{g}\right].$$
3. **Hazard rate stochastic dominance**: F_j stochastically dominates F_i (borrower j is more optimistic than i) in a hazard rate sense if
$$\frac{f_j(\delta)}{1-F_j(\delta)} \leq \frac{f_i(\delta)}{1-F_i(\delta)}, \quad \forall \delta \in \left[\underline{g}, \overline{g}\right].$$

All three definitions capture different notions of optimism. We show in Appendix A.3 that if $F_j(\cdot)$ dominates $F_i(\cdot)$ in a hazard rate sense, then $F_j(\cdot)$ also dominates $F_i(\cdot)$ in a first-order and a truncated expectation sense. The converse is not true: first-order stochastic dominance and truncated expectation dominance do not imply hazard rate dominance. Figure A4 illustrates the relation between the different orders. Hazard rate dominance is equivalent to saying that $\frac{1-F_j(g)}{1-F_i(g)}$ is increasing on g. It captures the idea that optimists are increasingly optimistic about higher house price growth realizations.

Figure A4: Relation Between Stochastic Orders



We have shown that in the variable house size scenario, when $\kappa_i = 0$, there are clear predictions for the leverage choices across two borrowers whose belief distributions could be ranked according to truncated-expectation stochastic dominance. We also showed that in the fixed house size scenario, clear predictions were obtained for belief distributions that could be ranked according to first-order stochastic dominance. However, neither of these dominance concepts implies the other, so it is unclear how to compare belief distributions if we are ex-ante agnostic about whether the fixed house size or the variable house size scenario applies. Therefore, we adopt hazard rate dominance as the appropriate definition of optimism that allows to test non-parametrically for the effect of beliefs on leverage regardless of the underlying scenario, as formalized in Proposition 3.

Proposition 3. (Non-parametric predictions.) *Compare two borrowers i and j with different distributions $F_i(\cdot)$ and $F_j(\cdot)$ about the growth rate of house prices changes.*
a) In the variable house size scenario, if $F_j(\cdot)$ dominates $F_i(\cdot)$ in a hazard rate sense (or in a truncated expectation sense when $\kappa_i = 0$), all else equal, borrower j chooses a higher LTV ratio and a larger house than borrower i.
b) In the fixed house size scenario, if $F_j(\cdot)$ dominates $F_i(\cdot)$ in a hazard rate sense (or in a first-order sense), all else equal, borrower j chooses a lower LTV ratio and lower consumption than borrower i.

Proposition 3 shows that borrowers' optimism, measured as hazard rate dominance, has opposite predictions in the polar scenarios we consider for any value of κ_i. More optimistic borrowers take on more leverage in the variable house size scenario, but they take on less leverage in the fixed house size scenario. These results generalize the insights from the case with normally distributed beliefs, but they are not exactly identical. We show here that, when beliefs are normally distributed, a distribution with a higher mean dominates in a hazard rate sense a distribution with a lower mean (holding its variance constant). Hence, when comparing means in the normal case, the results of Proposition 1 are implied by those of Proposition 3. However, we also show that, in the normal context, a distribution with a higher variance does not dominate in a hazard rate sense a distribution with a lower variance (holding its mean constant). This illustrates that hazard rate dominance is only a sufficient (not a necessary) condition to derive unambiguous predictions for the relationships between beliefs and leverage choice.

Proof of Proposition 3. (Non-parametric predictions)

In the variable house size scenario, it follows that an upward pointwise shift in $1 - F_i\left(\tilde{\delta}\right)$, $\forall \tilde{\delta}$, is associated with a lower equilibrium value of δ_i. If the beliefs of borrower j first-order stochastically dominate the beliefs of borrower i (borrower j is more optimistic), then $F_j\left(\tilde{\delta}\right) < F_i\left(\tilde{\delta}\right)$ and $1 - F_j\left(\tilde{\delta}\right) > 1 - F_i\left(\tilde{\delta}\right)$, which implies that borrower j takes on more leverage on equilibrium.

In the variable house size scenario, from Equation (8), it follows that an upward pointwise shift in $-\chi_i \frac{F_i\left(\tilde{\delta}-\chi_i\right)}{1-F_i\left(\tilde{\delta}-\chi_i\right)} + \mathbb{E}_i\left[g \middle| g \geq \tilde{\delta} - \chi_i\right]$, $\forall \tilde{\delta}$ is associated with a higher equilibrium value of δ_i. To compare the leverage choices of two different borrowers i and j, it is thus sufficient to show that $F_j \succ_{HRD} F_i$ implies that

$$\mathbb{E}_j\left[g \middle| g \geq \tilde{\delta}\right] - \mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right] > 0, \quad \forall \tilde{\delta},$$

to conclude that the more optimistic borrower j takes on more leverage, since hazard-rate dominance implies first order stochastic dominance, which trivially implies that $\frac{F_j\left(\tilde{\delta}-\chi_i\right)}{1-F_j\left(\tilde{\delta}-\chi_i\right)} < \frac{F_i\left(\tilde{\delta}-\chi_i\right)}{1-F_i\left(\tilde{\delta}-\chi_i\right)}$. To this purpose, we can define $h(\delta)$ as

$$h\left(\tilde{\delta}\right) = \mathbb{E}_j\left[g \middle| g \geq \tilde{\delta}\right] - \mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right].$$

We can express the derivative of $h\left(\tilde{\delta}\right)$ as

$$\begin{aligned} h'\left(\tilde{\delta}\right) &= \frac{\partial \mathbb{E}_j\left[g \middle| g \geq \tilde{\delta}\right]}{\partial \delta} - \frac{\partial \mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right]}{\partial \delta} \\ &= \frac{f_j\left(\tilde{\delta}\right)}{1 - F_j\left(\tilde{\delta}\right)}\left[\mathbb{E}_j\left[g \middle| g \geq \tilde{\delta}\right] - \tilde{\delta}\right] - \frac{f_i\left(\tilde{\delta}\right)}{1 - F_i\left(\tilde{\delta}\right)}\left[\mathbb{E}_i\left[g \middle| g \geq \tilde{\delta}\right] - \tilde{\delta}\right] \\ &= \underbrace{\left(\frac{f_j\left(\tilde{\delta}\right)}{1 - F_j\left(\tilde{\delta}\right)} - \frac{f\left(\tilde{\delta}\right)}{1 - F\left(\tilde{\delta}\right)}\right)}_{>0}\mathbb{E}_j\left[g \middle| g \geq \tilde{\delta}\right] + \frac{f_i\left(\tilde{\delta}\right)}{1 - F_i\left(\tilde{\delta}\right)} h\left(\tilde{\delta}\right). \end{aligned} \tag{A9}$$

When $\tilde{\delta} \to 0$, it follows from hazard-rate dominance that $\mathbb{E}_j[g] - \mathbb{E}_i[g] > 0$. Note that all elements in (A9) are strictly positive under hazard rate dominance, which implies that the solution to the ordinary differential equation for $h\left(\tilde{\delta}\right)$ must be weakly positive everywhere, implying that $h\left(\tilde{\delta}\right)$ is positive, which shows our claim.

C.2 Non-Parametric Test

The empirical results presented in Sections 3.3 and 3.4 test the predictions from our model under the assumption that individuals' beliefs about future house price changes are normally distributed. We argued that this is a realistic approximation, given the shape of the distribution of actual house price changes. In Section C.1, we also derived non-parametric predictions on the relative mortgage leverage choices of individuals with arbitrary belief distributions. In particular, we showed that an individual whose belief distribution dominated that of an otherwise identical individual in the sense of hazard rate dominance would choose higher leverage in the variable house size scenario, but lower leverage in the fixed house size scenario.

While we are not able to measure the full belief distribution of each individual, we can compare how the leverage choices of individuals vary with the full distribution of the house price experiences of their friends.[38] Specifically, we conduct pairwise comparisons of the distributions of the house price experiences of all friends (and all out-of-commuting zone friends) of individuals purchasing houses in the same county in the same month, and who borrow from the same lender. We then test whether one distribution dominates the other in a hazard rate dominance sense. We only focus on county-month-lender combinations with at least three mortgage originations: at the average (median) such combination, we have 9.8 (5) mortgage originations. Of all the pairwise comparisons across these originations, we can rank the distribution of all friends' house price experiences in a hazard rate sense for 3.5% of transaction pairs, and the distributions of out-of-commuting zone friends' house price experiences for 8.1% of transaction pairs. When comparing the mortgage leverage choices across the individuals with a clear ranking using the experience distribution of all friends, we find that individuals with an experience distribution that is hazard rate dominant will choose 90 basis points lower leverage; this difference is highly statistically significant. When comparing the experience distribution of individuals' out-of-commuting zone friends, those with a hazard rate dominant distribution choose a 68 basis points lower leverage. Both of these results provide additional evidence that the fixed house size scenario, in which collateral choices are return insensitive, is dominant in the data.

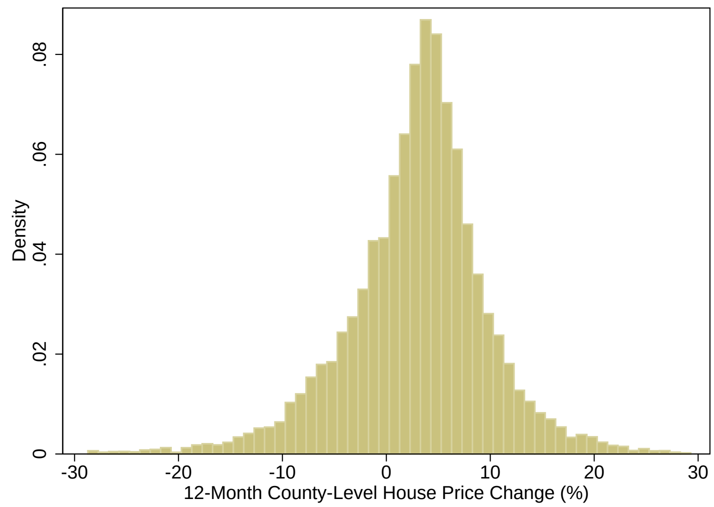
[38]This test builds on the survey evidence in Section 3.2, which showed that, on average, the first and second moments of the house price experiences of an individual's friends affect the corresponding moments of her belief distribution about future house price changes. The assumption underlying the test in this section is that additional moments of the distribution of individuals' friends' house price experiences will also shift the corresponding moments of those individuals' belief distribution.

D Additional Evidence

D.1 Distribution of County-Level House Price Changes

Figure A5 shows the distribution of county-year level annual house price changes in the United States between 1993 and 2017, as measured by Zillow. The distribution is unimodal and approximately symmetric, motivating our choice of modeling beliefs about house price changes to follow a normal distribution.

Figure A5: Distribution of House Price Changes (1993-2017)

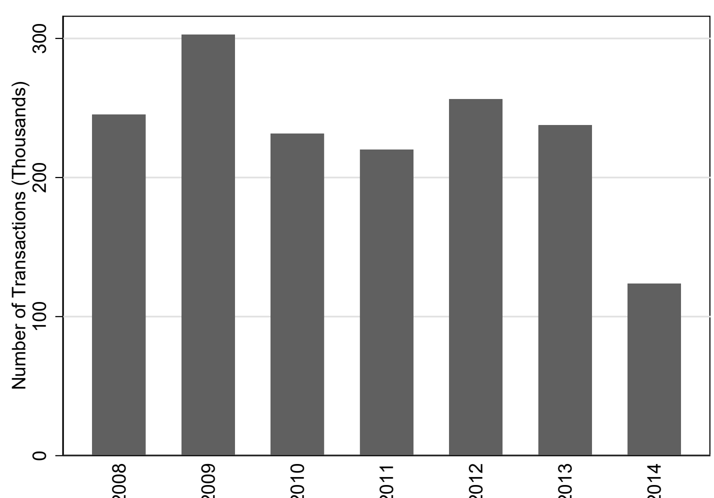


Note: Figure shows the distribution of annual county-level house price changes in the United States since 1993, as measured by Zillow.

D.2 Transactions Over Time

Figure A6 shows the number of transactions per calendar year in the baseline sample studied in Section 2.1.

Figure A6: Number of Transactions



Note: Figure shows the number of transactions by purchase year in our matched transaction-Facebook sample.

D.3 Hedonic Valuation Model

In Section 3.4, we address the concern that the relationship between optimism and leverage is the result of more optimistic individuals not being able to increase their mortgage amount. The concern is that these optimistic individuals overpay for their properties, yet banks determine maximal mortgage amounts based on their own assessed value of the property. To rule out such concerns, we control for the extent of overpayment by individual homebuyers in column 4 of Table 5. In column 5 of that Table, we restrict the sample to transactions where the homebuyer paid less for the property than its predicted value. In this Appendix, we discuss our procedure of arriving at the automated valuation of the property, and describe how we construct our measure of overpayment. Specifically, we begin by running a hedonic regression of the log of the transaction price on observable characteristics of the property (see Giglio, Maggiori and Stroebel, 2015; Stroebel, 2015, for similar hedonic pricing approaches):

$$\log\left(Price_{i,t}\right) = \alpha + \beta X_{i,t} + \psi_{zip_i,t} + \varepsilon_{i,t}.$$

We control flexibly for the property characteristics that are observable in our data set: property size, lot size, property age, property type, and whether the property has a pool. For property size and lot size, we include year-specific dummy variables for 50 quantiles of the distribution. For the other variables, we include year-specific dummy variables for each of the possible values. In addition, we include zip code by month fixed effects, to control for localized time-trends in house prices. This regression has an R-Squared of 83.6%, which is high, particularly given the fact that we observe prices in buckets. We then calculate, for each property, the predicted price based on this hedonic pricing model. We then construct a measure of whether a particular buyer "overpaid" relative to the predicted value as:

$$Overpay = 100 \times \frac{TransactionPrice - PredictedPrice}{PredictedPrice}.$$

D.4 County Wealth vs. County House Price Changes

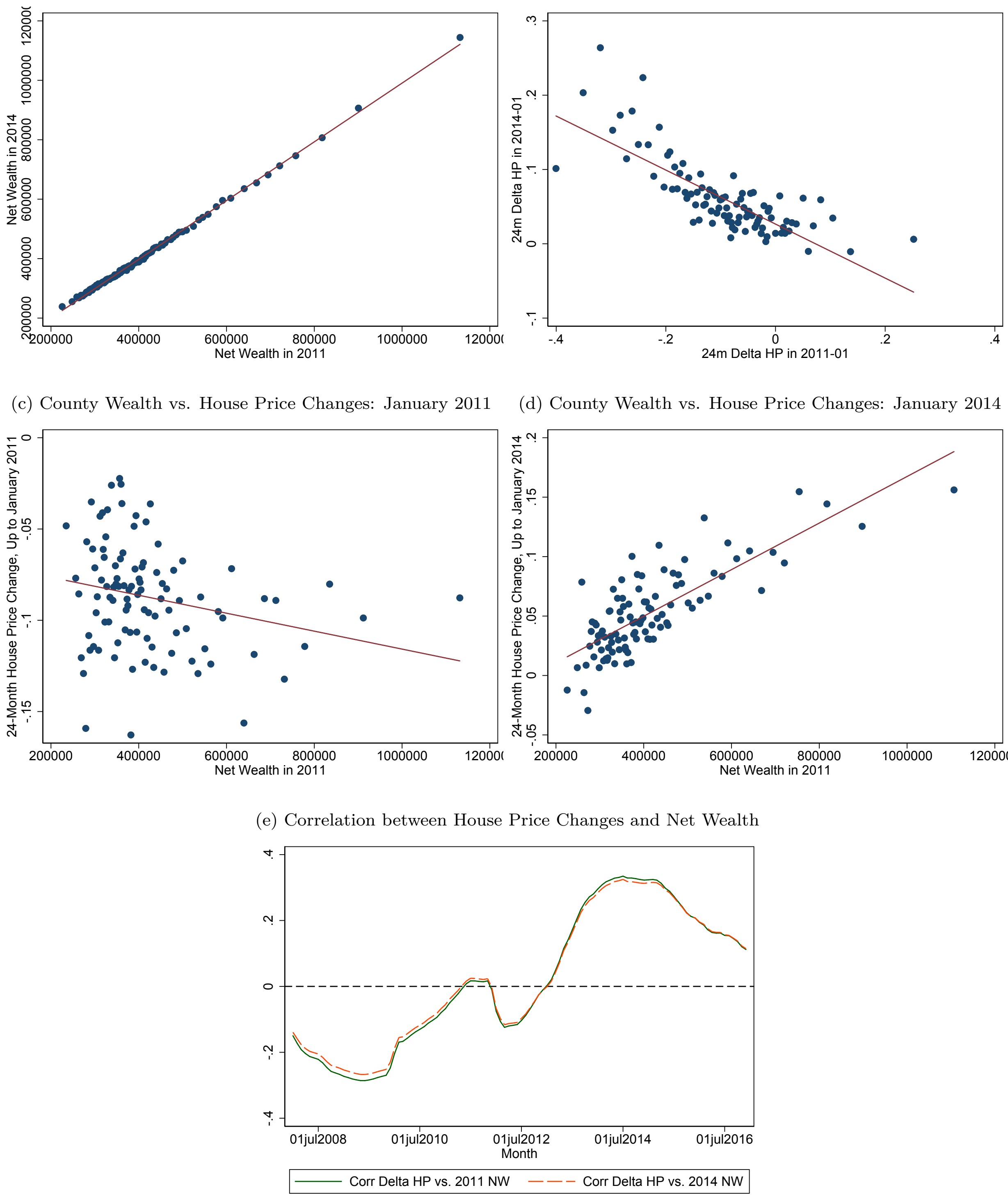
One concern addressed in Section 3.4 was that wealthier people would have friends in wealthier counties. If these wealthier counties also experienced house price appreciation, then the estimates of β_1 in Equation R1 might be picking up that wealthier people make larger downpayments. We argued that this is unlikely to be the explanation of our results, since no persons' friend experience consistently higher or lower house price experiences. Specifically, we argued that it was not the case that wealthier regions always have higher house price growth — in some years, wealthier counties see larger house price increases, in other years they see smaller house price increases. In this Appendix, we provide the evidence for these claims.

Specifically, to measure household wealth at the county level, we use county-level measures of average household net wealth constructed by Applied Geographic Solutions for the years 2011 to 2016.[39] The ranking of counties in their net wealth is stable over time: counties that were relatively wealthy in 2011 were generally relatively wealthy in 2014 — see Panel (a) of Figure A7. However, house price changes over the prior 24 months were quite different between 2011 and 2014: counties that had a relatively positive house price experience in the 24 months leading up to January 2011 had a relatively negative house price experience in the 24 months leading up to January 2014 – see Panel (b) of Figure A7. As a result, the relationship between county-level wealth and house price growth depends on time horizon considered. For example, Panel (c) shows that in January 2011, wealthier counties had experienced relatively larger house price declines over the previous 24 months while Panel (d) shows that in January 2014, wealthier counties had seen larger relative house price increases.

The instability of the relationship between county wealth and house price experiences is a persistent pattern in our data. To document this, we calculate, for every month between January 2008 and December 2016, the correlation between net wealth and house price changes over the previous 24 months. Panel (e) of Figure A7 plots that correlation over time. One can see that the correlation between wealth and past house price experiences is zero or negative until January 2013, after which it becomes positive. Due to the strong persistence in county net wealth over time, this pattern is unaffected by when we measure of county level net wealth.

[39] Applied Geographic Solutions defines net worth as the difference between assets and debts of households at the county level, where assets include transactions accounts, life insurance with cash value, primary residence value, and debts include mortgage and credit card debt. This measure is constructed using a number of data sets, including from the American Community Survey, the U.S. Census, IRS statistics, and credit bureau data.

Figure A7: County Level Wealth and House Price Changes



(a) Correlation in County-Level Net Wealth

(b) County Wealth vs. House Price Changes

(c) County Wealth vs. House Price Changes: January 2011

(d) County Wealth vs. House Price Changes: January 2014

(e) Correlation between House Price Changes and Net Wealth

Note: Panel (a) shows a binned scatter plot of counties' average net wealth in 2011 and 2014. Panel (b) shows a binned scatter plot of counties' house price changes in the 24 months up to January 2011 and the 24 months up to January 2014. Panels (c) and (d) show binned scatter plots of county-level wealth in 2011 and county-level house price changes in the 24 months prior to January 2011 and prior to January 2014, respectively. Panel (e) shows a monthly time-series in the correlation between county-level net wealth (either measured in 2011 or in 2014) and the counties' house price changes over the previous 24 months.

D.5 Downpayments and Expected Default

As discussed in Section 4, many personal financial advice websites and blogs discuss the tradeoffs between making larger and smaller downpayments. Many of these highlight explicitly the tradeoffs that we formally model in Section 1. For example, the real estate brokerage website Home Point Real Estate describes one of the benefits of high leverage as follows:

> This last reason for putting down a small down payment is kind of twisted, but sadly practical. I doubt we are going to have any down turn in the market soon, and I really doubt it will be like the one we just came through if it does come; but the less you put down the less you lose. Yet, if you are upside down on your home and have to walk away (or lose to foreclosure) the less down payment you put into it the less you lose.

Reuters (2011) outlines similar reasons for making a smaller downpayment:

> Even if you have the money for a bigger down payment, there can be good reasons to save your cash. Mortgage rates continue to skirt all-time lows: Why not put your money to work for yourself and borrow as much as you can reasonably afford, on a monthly basis, at today's rates? You can put the money you're not paying into a down payment to work elsewhere. If home values rise, you will have done your best to leverage a small down payment into bigger equity. If they fall, you'll have less skin in the game, and that could put more pressure on your banker to improve your loan terms lest you walk away.

US News (2017) described the benefits of a smaller downpayment as follows:

> The last major housing crash scared some people away from low down payments after many homeowners found themselves owing more than their homes were worth when values plummeted. But even a 20 percent down payment won't protect you against a 50 percent drop in home values. In fact, if you lost your home to foreclosure or did a short sale, you may have lost less money if you made a small down payment.

MK Real Estate (2016) describes why making smaller downpayments is the more conservative choice for home buyers worried about potential house price drops.

> The link between the economy and home prices is the third reason to consider a small down payment. In general, as the U.S. economy improves, home values rise. When the U.S. economy sags, home values sink. Buyers with large down payments find themselves over-exposed to economic downturns compared to buyers whose down payments are small.
>
> Consider the purchase of a $400,000 home and two home buyers, each with different ideas about how to buy a home. One buyer makes a 20% down payment to avoid Private Mortgage Insurance (PMI). The other buyer wants to stay as liquid as possible, and puts down just 3.5%. The first buyer takes $80,000 from the bank and converts it to illiquid home equity. The second buyer puts $14,000 into the home.
>
> Over the next few years, the economy falters. Our two buyers lose 20% of the value of each of their homes, bringing their values down to $320,000. Neither buyer has any equity left. Our first buyer lost all $80,000 of their money. That money is lost and cannot be recouped except through the housing market's recovery. The second buyer lost only $14,000. While the second buyer's home is "underwater," with more money owed on the home than the home is worth, the bank has the risk of loss and not the borrower.
>
> Let's say that both borrowers default and no longer make their payments. Which homeowner will the bank be more likely to foreclose upon? It's counter-intuitive, but the buyer who made a large down payment is less likely to get relief during a time of crisis and is more likely to face foreclosure. A bank's losses are limited to when the home is sold at foreclosure. The homeowner's twenty percent home equity is already gone, so the remaining losses (legal and home prep costs) are easily absorbed by the bank. Foreclosing on an underwater home will lead to great losses. All of the borrower's money is already lost. The bank will not only have legal and home prep costs, but will also have to write down $66,000 in lost value.
>
> Conservative borrowers recognize that risk increases with the size of the down payment. The smaller your down payment, the smaller your risk.

D.6 Downpayment Motivation Survey

In Section 4.2, we described results from our Downpayment Motivation Survey. In this Appendix, we provide additional information on the respondent demographics, and more details on how the responses vary with these demographics. For complete disclosure, the full data set is available from the authors upon request.

We ran two waves of the survey between September 19, 2017, and September 21, 2017. The survey was designed using the SurveyMonkey survey platform. Each wave was targeted at approximately 800 homeowners, and no additional filters for the target audience were selected. In each wave, respondents were presented with two different house price growth scenarios, and asked to select one of three different mortgage choices for each house price scenario. In Table A1, we show the changes in the downpayment recommendation between the optimistic and the pessimistic scenario ("Decreased Downpayment" represents individuals who suggested a smaller downpayment in the more pessimistic house price scenario).

Table A1: Downpayment Motivation Survey - Results by Demographics

	Wave 1				**Wave 2**			
	Total	Decreased DP	Same DP	Increased DP	Total	Decreased DP	Same DP	Increased DP
All	826	20.5%	69.4%	10.2%	794	14.0%	77.6%	8.4%
Income								
$0 to $9,999	17	11.8%	82.3%	5.9%	12	8.3%	91.7%	0.0%
$10,000 to $24,999	38	13.2%	63.2%	23.7%	37	10.8%	62.2%	27.0%
$25,000 to $49,999	92	14.1%	76.1%	9.8%	84	8.3%	88.1%	3.6%
$50,000 to $74,999	56	23.2%	73.2%	3.6%	46	15.2%	60.9%	23.9%
$75,000 to $99,999	35	20.0%	71.4%	8.6%	40	17.5%	80.0%	2.5%
$100,000 to $124,999	15	6.7%	86.7%	6.7%	18	16.7%	83.3%	0.0%
$125,000 to $149,999	50	26.0%	66.0%	8.0%	51	7.8%	84.3%	7.8%
$150,000 to $174,999	103	28.2%	59.2%	12.6%	88	13.6%	77.3%	9.1%
$175,000 to $199,999	122	22.1%	68.0%	9.8%	122	13.1%	80.3%	6.6%
$200,000 and up	117	18.0%	75.2%	6.8%	108	16.7%	74.1%	9.3%
Prefer not to answer	125	16.0%	76.8%	7.2%	137	16.8%	77.4%	5.8%
Age								
18-29	51	23.5%	62.8%	13.7%	42	14.3%	78.6%	7.1%
30-44	168	18.5%	68.4%	13.1%	154	11.7%	76.6%	11.7%
45-59	215	16.7%	76.3%	7.0%	216	16.2%	76.4%	7.4%
60+	336	21.4%	70.5%	8.0%	331	13.0%	79.2%	7.8%
Gender								
Male	324	19.4%	67.9%	12.6%	294	14.3%	77.2%	8.5%
Female	446	21.5%	70.8%	7.7%	449	9.2%	83.1%	7.7%
Region								
East North Central	130	21.5%	70.8%	7.7%	130	9.2%	83.1%	7.7%
East South Central	46	15.2%	73.9%	10.9%	41	9.8%	82.9%	7.3%
Middle Atlantic	94	18.1%	73.4%	8.5%	90	16.7%	75.6%	7.8%
Mountain	58	13.8%	82.8%	3.5%	63	14.3%	74.6%	11.1%
New England	44	13.6%	77.3%	9.1%	47	12.8%	78.7%	8.5%
Pacific	133	23.3%	65.4%	11.3%	111	10.8%	79.3%	9.9%
South Atlantic	131	22.1%	64.1%	13.7%	134	18.7%	72.4%	9.0%
West North Central	59	17.0%	78.0%	5.1%	55	18.2%	76.4%	5.4%
West South Central	74	20.3%	71.6%	8.1%	68	11.8%	79.4%	8.8%

Note: Table shows responses in the Downpayment Motivation Survey separately by the reported demographic of the respondents. The results show how the downpayment recommendation changes in the pessimistic house price scenario relative to the optimistic house price scenario.