

House Price Beliefs And Mortgage Leverage Choice

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We study the relationship between homebuyers' beliefs about future house price changes and their mortgage leverage choices. Whether more pessimistic homebuyers choose higher or lower leverage depends on their willingness and ability to reduce the size of their housing market 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 use 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.

Key words: Leverage, Mortgage choice, Disagreement, Heterogeneous beliefs, Collateralized credit.

JEL Codes: E44, G12, D12, D84, R21

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 et al., 2016](#)). Understanding the determinants of households' 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 et al., 2017](#)): mortgages are the primary liability on households' balance sheets,

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and increased household leverage plays a key role in many accounts of the recent Financial Crisis (e.g. Mian and Sufi, 2009). In this article, we explore the role of homebuyers' beliefs about future 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 choice is ambiguous, and depends on the willingness and ability 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 U.S. 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 neighbourhood 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 neighbourhood or live in a smaller home, even if they expect housing prices to decline. The presence of consumption motives for home purchases can thus dampen the expected return force. Our main theoretical result is to show that the remaining sensitivity of homebuyers' housing investments to house price beliefs is central to determining the relationship between these house price beliefs and mortgage leverage choices.³

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 (the "double trigger" hypothesis).

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 belief sensitivity of the intensive margin of housing investments. 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 investments. However, in many cases, the set of properties available for rent is very different from the set of properties available for sale. For example, 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. Consumption motives will thus also reduce the sensitivity of the extensive margin of housing investments to expected housing returns.

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 protection force are fully 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 a downpayment. In this scenario, the expected return force is completely 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 when default costs are low. For example, 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 article, we provide extensive evidence that U.S. homebuyers frequently consider and respond to such risk-shifting incentives.

When we move away from these polar cases, whether more pessimistic agents take on higher or lower leverage depends on the sensitivity of homebuyers’ housing investments to their house price beliefs, which modulates the strength of the expected return force, as well as the cost of default, which modulates the strength of the downpayment protection force. The empirical contribution of this article 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 measure 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. We verify that these experiences can indeed be used as shifters of individuals’ beliefs about the distribution of expected 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 analysing the cross-sectional relationship between the leverage choices of individuals borrowing from the same lender to purchase similar homes at the same time, and the house price experiences of these homebuyers’ far-away friends.

In our data, we observe an anonymized snapshot of U.S. individuals’ friendship networks on Facebook, an online social network with over 241 million active users in the U.S. and Canada ([Facebook, 2018](#)). 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 invited Los Angeles-based Facebook users to participate, and was designed to measure the distribution of respondents’ expectations for local house price changes. We find that individuals whose friends experienced larger recent house price increases expect higher average local 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 local 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 can affect the corresponding moments of the belief distribution.

To study the role of house price beliefs in shaping mortgage leverage choices, 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 local 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 12 months leads individuals to increase their loan-to-value ratios by about 33 basis points, though this number is not estimated with a high degree of precision. 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 our 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 perceive defaulting in response to declining house prices to be a less costly proposition. Consistent with this, we find that 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 more pessimistic to begin with. This is because, in this scenario, the perceived probability of default is the key driver of differences in leverage choices among homebuyers. Following large house price increases, even relatively pessimistic individuals assign only 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

4. By studying the case of normally distributed beliefs, we can derive unambiguous predictions for the effect of changes in the mean and standard deviation of beliefs about future house price growth on leverage. 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.

buying homes in areas with high homeownership rates, where it is harder to reduce their financial exposure to the housing market by renting instead of buying.

Throughout the analysis, we argue that the house price experiences of a homebuyer's far-away friends affect her mortgage leverage choice only through influencing her beliefs about future local 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 extensive 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 for each scenario 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 consistent with the risk-shifting motives that are central to 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. Finally, 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 in our sample do not buy substantially smaller houses, but instead reduce their financial exposures to the housing market by making smaller downpayments. However, the empirical relationship observed in our setting need not be universal. Indeed, our theoretical framework highlights why the relationship between beliefs and leverage choices will depend on important institutional details, such as the cost of defaulting and the ease of finding high-quality rental units. For example, we conjecture that in many European countries that feature high costs of default and a very attractive rental stock, it might be the more optimistic homebuyers that take out more leverage. We therefore hope that future empirical work will explore the important relationship between beliefs and leverage choices in other countries and institutional settings.

Our article 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 behaviour, 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. For example, 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, a pessimistic investor's ability to dispose of those assets quickly might be affected by market liquidity. 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 *et al.* \(2016\)](#). Much of this literature has focused on exploring how individuals' own experiences affect their expectations. We expand on the findings in the literature by showing 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 prices and mortgage leverage during the 2002–06 housing boom period was the result of homebuyer optimism or other forces in the economy, such as credit supply shocks ([Mian and Sufi, 2009](#); [Piazzesi and Schneider, 2009](#); [Case *et al.*, 2012](#); [Glaeser *et al.*, 2012](#); [Cheng *et al.*, 2014](#); [Glaeser and Nathanson, 2015](#); [Landvoigt *et al.*, 2015](#); [Adelino *et al.*, 2016](#); [Burnside *et al.*, 2016](#); [Di Maggio and Kermani, 2016](#); [Foote *et al.*, 2016](#); [Gao *et al.*, 2017](#); [De Stefani, 2017](#)). Our empirical focus on owner-occupiers precludes us from making strong statements about the aggregate correlation between beliefs and leverage, though it is worth noting that investment purchases only made up 15.3% of all transactions in 2005, the peak of the housing boom period ([Gao *et al.*, 2017](#)). Nevertheless, our findings suggest that, in our setting, 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 U.S. housing cycle.⁶ More broadly, our findings provide support for a literature that explores the role of beliefs as drivers of credit and business cycles (see [Gennaioli *et al.*, 2012](#); [Xiong, 2012](#); [Angeletos and Lian, 2016](#); [Gennaioli *et al.*, 2016](#), for recent contributions).

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 *et al.* \(2014\)](#), among others.

6. Note that this does not mean that shifts in homebuyers' beliefs were not important during this episode. Indeed, the results in [Bailey *et al.* \(2017\)](#) highlight that homebuyer optimism can help explain the increase in both prices and transaction volumes. Instead, our results emphasize that at least part of the story likely involves optimistic house price beliefs by lenders (which then lead to outward shifts in credit supply), plausibly in combination with optimistic house price expectations by homebuyers.

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.

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

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

where c_{0i} denotes borrowers’ date-0 consumption, and $\mathbb{E}_i[w_{1i}]$ 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 $p_0 h_{0i} \Lambda(\delta_i)$ dollars at date 0, borrowers promise to repay b_{0i} dollars at date 1. The function $\Lambda(\delta_i)$, 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

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

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 $F_i(\cdot)$:

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

where g has support in $[\underline{g}, \bar{g}]$, with $\underline{g} \geq 0$ and $\bar{g} \leq \infty$. 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

$$h_{0i} \geq \underline{h}_i, \quad (2)$$

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.⁷ 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 analyse 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 individual's housing investment to the perceived pecuniary return of that investment. In the [Online 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.

1.1.2. 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 $F_L(\cdot)$.

1.1.3. 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

7. 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 neighbourhood, but also their willingness to move to a cheaper neighbourhood in order to reduce the fraction of their portfolio allocated to housing.

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 analyse borrowers' default decisions, then characterize the loan-to-value schedules offered by lenders, and finally study the ex-ante choices made by borrowers.

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

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

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 et al., 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, 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"). Instead, our results only require that default is *more likely* when house prices decline. Put differently, the results are robust in any model in which negative equity is a necessary condition for default, even if it is not sufficient.⁸

8. 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. Under this theory, when house prices are high but households receive a negative income shock and cannot continue making their mortgage payments, they 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 centre 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. However, it is worthwhile to point out that while both the "double trigger" model and the "strategic default" model predict the same relationship between beliefs and leverage choices, the relationship between beliefs and subsequent default probabilities might vary across these two models in a modified set-up. In particular, if we expanded our model to allow pessimistic individuals to save the resources they do not use to make downpayments, these more pessimistic individuals might actually default less in the "double trigger" model, despite their higher leverage. This is because they can use the additional saved resources to smooth out negative income shocks. In the "strategic default" model, the higher leverage would make those more pessimistic individuals default more often.

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

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

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, $1+r$.

1.2.3. Borrowers' leverage choice. To determine borrowers' leverage choice in an analytically tractable way, we reformulate their problem as a function of δ_i .⁹ Formally, borrowers choose c_{0i} , h_{0i} , and δ_i to maximize

$$\max_{c_{0i}, h_{0i}, \delta_i} u_i(c_{0i}) + \beta p_0 h_{0i} \int_{\delta_i}^{\bar{g}} (g - \delta_i) dF_i(g), \quad (4)$$

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

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

Borrower i takes into account that $\Lambda(\delta_i)$ is given by equation (3), and λ_{0i} and v_{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:

$$c_{0i}: \quad \underbrace{u'_i(c_{0i})}_{\text{Marginal Benefit}} - \underbrace{\lambda_{0i}}_{\text{Marginal Cost}} = 0 \quad (5)$$

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

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

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

9. Although we let borrowers choose δ_i , the fact that $\Lambda(\cdot)$ is a monotone function of δ_i for the relevant range means that our formulation is identical to allowing borrowers to choose LTV ratios (see Appendix A.2).

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.

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 behaviour 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 (1) a scenario in which borrowers freely adjust their housing size, and (2) 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’ behaviour 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 LTV ratios, and relegate the study of consumption and housing decisions to the [Online Appendix](#).

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

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

Equation (8) follows directly from combining borrowers’ optimal housing and borrowing choices, given by equations (6) and (7). The numerator in the definition of $\mathbb{E}_i[g|g \geq \delta_i]$ 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, $\mathbb{E}_i[g|g \geq \delta_i]$. Below we characterize conditions under which changes in beliefs shift $\mathbb{E}_i[g|g \geq \delta_i]$ for any $\tilde{\delta}$ (point-wise).¹⁰

1.3.2. Fixed house size. In the fixed house size scenario, borrowers choose δ_i to solve a consumption smoothing problem.¹¹ Formally, the optimal LTV ratio is fully characterized by the following equation

$$u'_i(n_{0i} - p_0 h_{0i}(1 - \Lambda(\delta_i))) \Lambda'(\delta_i) = \beta(1 - F_i(\delta_i)). \quad (9)$$

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 $\int_{\delta_i}^{\bar{g}} dF_i(g) = 1 - F_i(\delta_i)$. 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 $F_i(\cdot)$.

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 article, 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 the [Online Appendix](#), 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 :

$$g \sim_i N(\mu_i, \sigma_i^2). \quad (10)$$

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 [Online 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

10. Throughout the article, 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.

11. 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 et al. \(2017\)](#) for recent work on how housing affects optimal asset allocation problems.

show, one desirable feature of the normal distribution is that shifts in the two moments, mean and variance, have unambiguous predictions for $\mathbb{E}_i[g|g \geq \delta_i]$ and $F_i(\delta_i)$, 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 $\mathbb{E}_i[g|g \geq \tilde{\delta}]$ is higher for any leverage choice $\tilde{\delta}$. In Figure 1, $\mathbb{E}_i[g|g \geq \tilde{\delta}]$ 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. Figure 1a shows that an increase in the average belief increases $\mathbb{E}_i[g|g \geq \tilde{\delta}]$ point-wise, inducing borrowers to choose higher leverage and invest more in housing. Figure 1b shows that an increase in σ_i also raises $\mathbb{E}_i[g|g \geq \tilde{\delta}]$, 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, $1 - F_i(\tilde{\delta})$, for a given default threshold $\tilde{\delta}$. In Figure 1, this is given by the probability-mass to the right of the default threshold. Figure 1a 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, Figure 1b 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 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

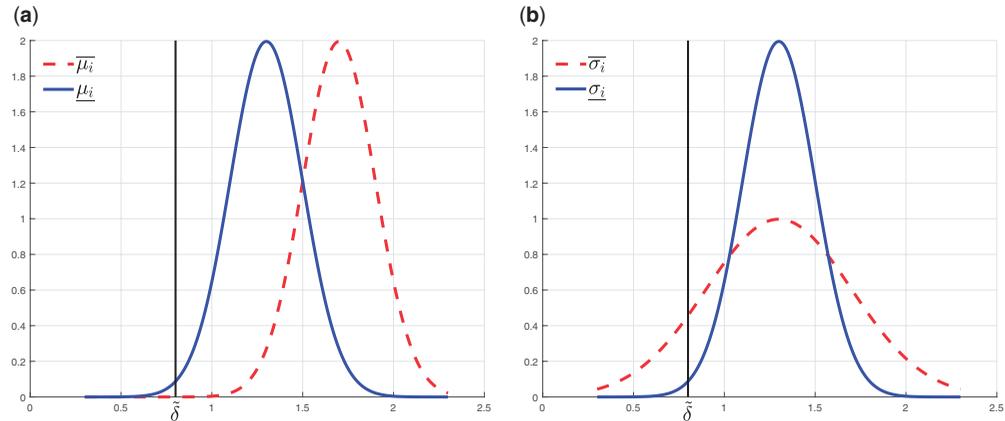


FIGURE 1

Illustration of how shifts in μ_i and σ_i affect $\mathbb{E}_i[g|g \geq \bar{\delta}]$ and $1 - F_i(\bar{\delta})$. (a) Mean shift; (b) variance shift

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

choices might be primarily determined by factors related to the consumption aspect of housing, 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' behaviour 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 the Appendix 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 (1) the magnitude of the default cost, and (2) with the average optimism of homebuyers. In the interest of brevity, we derive these additional predictions in the body of the article 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 or 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 fact, we would expect this relationship to vary across institutional settings, for example due to differences in the cost of mortgage default across countries. 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. We hope that future work will explore this important relationship in other settings.

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 measures individuals' distributions 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 neighbourhood, 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 2.2 billion monthly active users globally and 241 million monthly active users in the U.S. and Canada (Facebook, 2018). Our baseline data include a de-identified snapshot of all U.S.-based active Facebook users from 1 July 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 analyse 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 choices, we merge de-identified individuals on Facebook to information from 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. We observe no personally identifying information on these individuals. 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.¹²

Since we can only analyse 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 2 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.

12. 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.

To achieve this, we first define a set of eligible geographies as those with complete reporting of house 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 [Online Appendix](#) shows how these transactions are distributed over time.

Table 1 shows summary statistics for our sample.¹³ 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, and 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.

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 the 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 neighbourhood 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 experiences in the social networks of different homebuyers purchasing similar properties at the same point in time. We define the average house price movements across homebuyer i 's friends over 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 over the 24 months prior to time t using the Zillow house price indices.¹⁴ Figure 2c shows the distribution of the residuals when

13. 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.

14. 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.

TABLE 1
Summary statistics

	Mean	Standard deviation	P10	P50	P90
Purchase characteristics					
Transaction price (k\$)	302.3	237.8	125	225	550
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
Neighbourhood 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	1,75,000
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.

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, many 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 over the 24 months prior to time t as:

$$StDFriendHP_{i,t} = \sqrt{\sum_c (ShareFriends_{i,c} \times \Delta HP_{c,t-24m,t} - FriendHPExp_{i,t})^2} \quad (11)$$

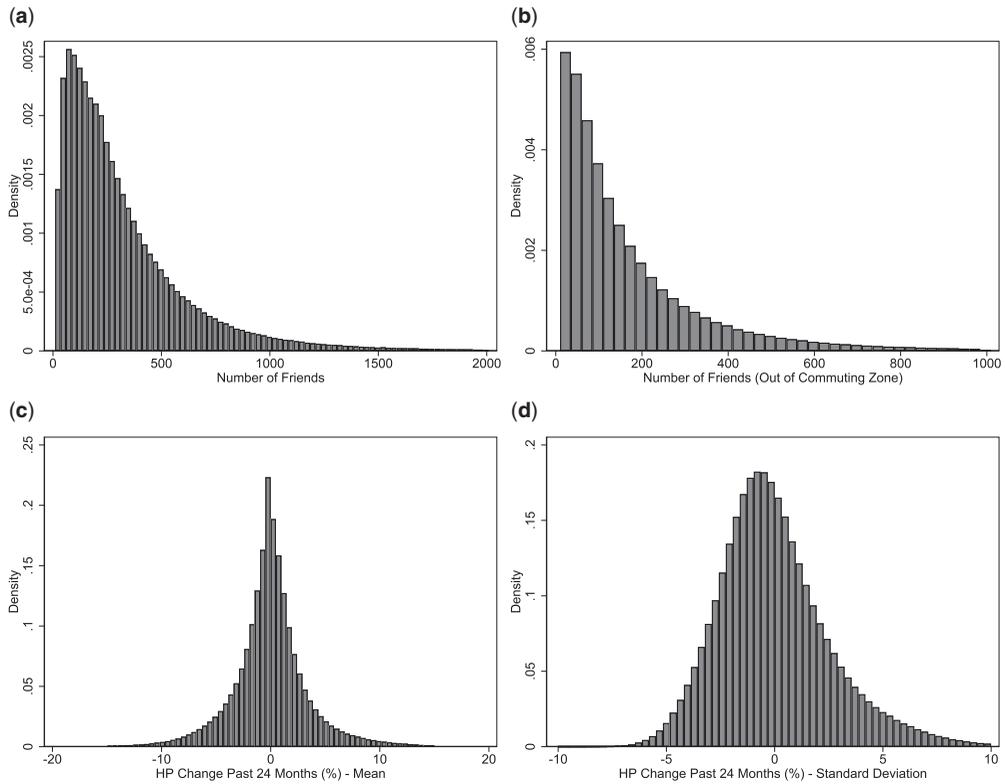


FIGURE 2
Summary statistics

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

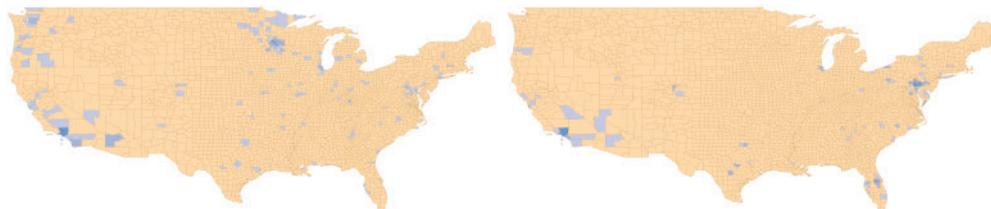


FIGURE 3
Geographic distribution of friendship links.

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.

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%. Figure 2d 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%.

Facebook is helping researchers understand what real people think about the economy. Your survey responses will be combined with the information that you publicly share on Facebook and average housing prices to help us better understand the housing economy. Help us out by answering the following questions, your responses will be kept anonymous:

How often do you talk to your friends about whether buying a house is a good investment?

Never Rarely Sometimes Often

What would you say is the percent chance that over the next 12 months the average home price in your zip code will

<input type="checkbox"/> 0%	increase by 12% or more
<input type="checkbox"/> 0%	increase by 8% to 12%
<input type="checkbox"/> 0%	increase by 4% to 8%
<input type="checkbox"/> 0%	increase by 0% to 4%
<input type="checkbox"/> 0%	decrease by 0% to 4%
<input type="checkbox"/> 0%	decrease by 4% to 8%
<input type="checkbox"/> 0%	decrease by more than 8%
<input type="checkbox"/> 0%	Total

Summing up, over the next 12 months, what do you think is most likely to happen to the average home price in your zip code?

Decrease Stay about the same Increase

FIGURE 4
Survey interface.

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

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 analyse 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 23–58 years. In all, 62% of respondents are male.

The first survey question asks 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. Figure 5a 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.¹⁵ Figure 5b and c

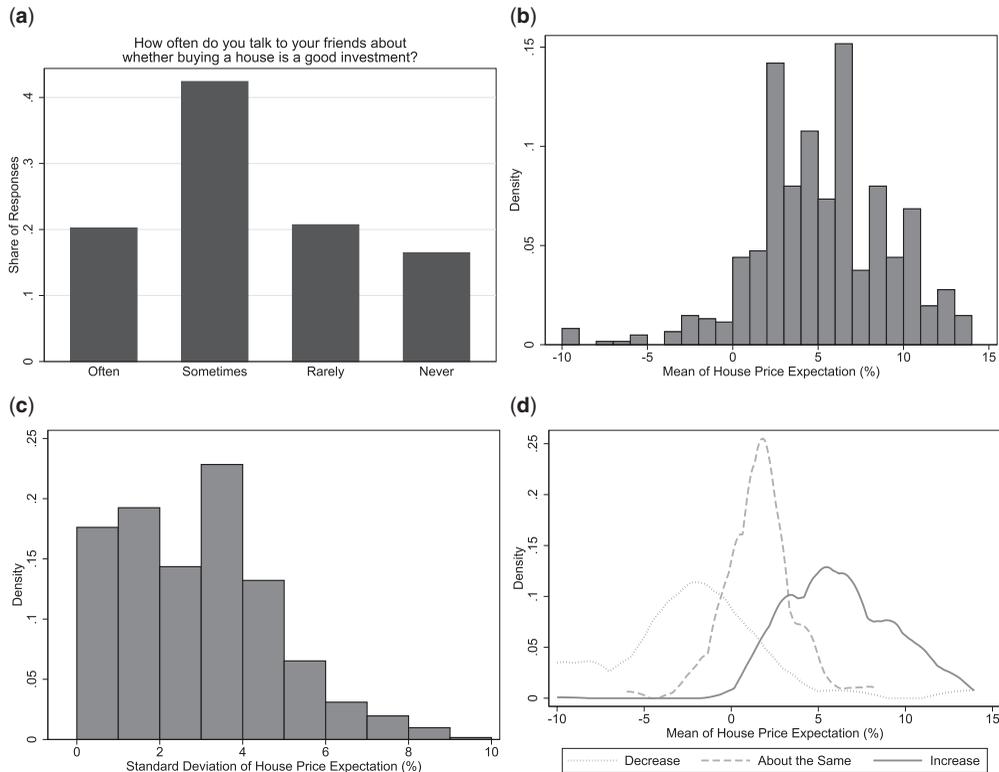


FIGURE 5

Summary statistics—survey responses.

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

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, Figure 5d 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

15. 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%.

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** (0.144)	0.322** (0.148)			-0.024 (0.055)
All Friends - St. D.			0.027 (0.145)		0.182** (0.089)	0.184** (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 analyses the determinants of individuals' expectations about house price changes in their own zip codes over the next 12 months. In columns 1–3, the dependent variable is the mean of individuals' belief distributions, based on their responses to Question 2 of the expectation survey (Figure 4); in columns 4–6, 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 IV 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 her out-of-commuting zone friends. Standard errors are in parentheses. Significance Levels: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

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 12 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 analyse how moments of the distribution of house price changes across individual i 's social network over 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 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 reported 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; we also include flexible controls for the age, gender, and the number of friends of the respondent. In columns 1–3, the dependent variable is the mean of the reported 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, $FriendHPExp_{i, Apr17}^{Out-CZ}$, is associated with a 0.19 percentage point (0.05 standard deviation) increase in the expected house price growth over the next year.¹⁶ In column 2, the main explanatory variable is the average house price experience of all friends, $FriendHPExp_{i, Apr17}$, instrumented for by the average house price experiences of the individuals' out-of-commuting zone friends, $FriendHPExp_{i, Apr17}^{Out-CZ}$. 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 2 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 does not have a statistically or economically significant effect on individuals' average house price expectations.

The dependent variable in columns 4–6 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 $StDFriendHP_{i, Apr17}^{Out-CZ}$ 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 analyse 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 the homebuyers' 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 the homebuyers' leverage choices.

16. The effect of $FriendHPExp_{i, Apr17}^{Out-CZ}$ on the R^2 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^2 of 0.362; the within-zip code R^2 is 0.074. When we include the out-of-commuting zone friends' house price experiences as an additional control variable, the R^2 increases to 0.373, and the within-zip code R^2 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 seventy-eight 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.

In our baseline regression specification **R1**, the unit of observation is a housing transaction. We regress the 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 CLTV ratio includes all mortgages originated to finance the home purchase. We also control for a rich set of homebuyer characteristics,¹⁷ and include county by purchase month by lender fixed effects, $\psi_{t,c,l}$.¹⁸ 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 LTV ratios and interest rates to choose from.

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

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 choices through their effects 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).¹⁹

3.3.1. 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.²⁰ Column 1 also

17. 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.

18. 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 a higher interest rate. 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.

19. 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}*.

20. 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. \(2017\)](#)

TABLE 3
Main results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Friends' House Prices (24m)							
Mean	-0.084*** (0.005)	-0.087*** (0.005)	-0.107*** (0.006)	-0.136*** (0.008)	-0.060*** (0.012)	-0.144*** (0.008)	-0.027** (0.012)
St. D.	0.349*** (0.013)	0.318*** (0.013)	0.319*** (0.014)	0.546*** (0.021)	0.276*** (0.015)	0.439*** (0.019)	-0.027 (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				
N	1,350,606	1,350,606	1,350,600	1,350,600	1,350,600	1,350,600	1,350,600
R ²	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 LTV 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 transaction month \times county \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 3–7, 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: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

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

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 the Appendix).

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. In column 3, we interact the buyer demographics with year fixed effects. This allows, for example, the effect of having 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 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 magnitudes of these baseline estimates? One option is to use a split-sample IV approach that combines our estimates from Table 3 with the estimates from the survey analysed in Section 3.2. This approach suggests that individuals who expect a one-percentage-point lower house price growth over the coming 12 months would choose a $\frac{0.107}{0.326} = 33$ basis points higher LTV ratio.²¹ Similarly, a one-percentage-point increase in the expected standard deviation of house price growth over the next 12 months would be associated with a $\frac{0.319}{0.182} = 175$ basis points higher LTV ratio. There are a number of reasons to treat the precise magnitudes from this split-sample IV approach with some caution. First, the numerator and denominator are estimated among different individuals and during different time periods. Second, both coefficients are estimated with non-trivial standard errors. Nevertheless, the split-sample IV approach provides useful guidance about the order of magnitude of the direct effects of house price beliefs on leverage choices.

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 distributions about the cumulative house price growth over the expected life-time of the mortgage. We therefore have to translate the responses to the expectations survey into expectations about cumulative house price changes over these long horizons. This requires some 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 the Online Appendix 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 5 years, and an almost 8 percentage point increase in the cumulative standard deviation over the next 10 years. (The median duration that buyers of single-family residences stay in their home is somewhat in excess of 10 years). With these adjustments, we find that an 8 percentage point

21. This number is obtained by dividing the point estimate on $MeanFriendHP_{i,t}$ from column 3 of Table 3 by the point estimate on the same variable from column 2 of Table 2. We are unable to run the regressions presented in Tables 2 and 3 on the same sample, since we do not observe the leverage choices of our survey respondents.

increase in the standard deviation of cumulative house price changes over the lifetime of the mortgage is associated with a 175 basis points increase in LTV ratios.²²

3.3.2. Testing additional predictions. Columns 1–3 of Table 3 documented a relationship between beliefs and leverage choices most consistent with the fixed house size scenario. Columns 4–6 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.²³ 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 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 test, and interacts the house price experiences of homebuyers' friends 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

22. An important question regarding this back-of-the-envelope calculation is whether individuals do indeed think of house prices as an AR(1) process the same way that an econometrician would. This question is particularly valid in the current setting, where we show that individuals partially base their expectations on the house price experiences of their geographically distant friends, a behaviour that likely represents a deviation from rationality. However, such partially-rational behaviour is common across a number of settings, including the “diagnostic expectation” framework of [Bordalo et al. \(2018\)](#), in which individuals are forward looking but subject to a memory limitation that reduces their ability to think about unrepresentative scenarios. In this setting, talking to friends would populate the distribution that individuals have in mind, which could then be used for forward-looking prediction based on the parameters of the fundamental process. In addition, even if households' beliefs about the process of house price changes do not correspond exactly to an AR(1) process, there is substantial survey evidence that individuals perceive there to be strong momentum in house price growth (see [Kuchler and Zafar, 2015](#), and the references therein).

23. [Ghent and Kudryak \(2011\)](#) analyse mortgage default behaviour across U.S. states, and find strong evidence that the recourse/non-recourse environment does indeed have significant effects on the default behaviour 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 \(2009\)](#).

house price changes, and to therefore perceive a lower probability of default (see [Case et al., 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.²⁴ 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 house price experiences of homebuyers' friends with the homeownership rates in the zip codes of the transactions. The homeownership rate measures how easy it is for relatively pessimistic individuals who want to live in a certain area to find a suitable rental property as a way of reducing their housing market exposure; it is therefore a proxy for the return sensitivity of the housing market investment. In particular, pessimistic individuals wanting to live in high homeownership rate zip codes (*e.g.* because of proximity to work or good schools) are less likely to find a suitable rental property. Such high-homeownership-rate zip codes should thus be a particularly good approximation of the fixed house size scenario, in which reductions in downpayments provide the primary way for households to reduce their housing market exposure. Consistent with this prediction, 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 behaviour 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.²⁵ 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 beliefs 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 choices. 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

24. Note, however, that lender beliefs may also have changed across the housing bust and housing recovery periods. Therefore, the tests in column 6 potentially test a more complex comparative static than the one we describe in Proposition 2b. An additional potential concern when interpreting these differential effects across time comes from the fact that we only observe the friendship network in 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.

25. 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 analyse 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.

TABLE 4
Robustness checks I

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Friends' House Prices (24m)							
Mean	-0.112*** (0.007)	-0.094*** (0.006)	-0.093*** (0.007)	-0.080*** (0.007)	-0.090*** (0.025)	-0.084*** (0.006)	-0.114*** (0.008)
St. D.	0.456*** (0.019)	0.283*** (0.016)	0.278*** (0.017)	0.319*** (0.014)	0.256*** (0.065)	0.273*** (0.014)	0.370*** (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.	> 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 ²	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 LTV 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 fifty out-of-commuting zone friends, in column 3 to purchases by individuals with friends in at least thirty-five 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).

across recourse/non-recourse states, 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. This is a particular concern for individuals who have many 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 fifty out-of-commuting zone friends; in column 3, we restrict the sample to transactions by individuals with friends in at least thirty-five 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 second moment of the belief distribution. The magnitude of the estimates are very similar to those in the baseline specification, suggesting that such concerns are not affecting our results.

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 IRS Tax Statistics of Income. In addition, column 5 restricts the sample to transactions 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, there are likely also more foreclosures in those counties. As a result, 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 directly affect their leverage choices. 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. This measure is based on the data provided by Zillow. While a higher foreclosure rate in friends' counties 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.²⁶ 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

26. While the house price experiences and foreclosure rates across friends' counties are naturally correlated, they are far from co-linear. 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.

TABLE 5
Robustness checks II

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Friends' House Prices (24m)						
Mean	-0.089*** (0.009)	-0.106*** (0.006)	-0.100*** (0.006)	-0.099*** (0.006)	-0.105*** (0.009)	-0.094*** (0.007)
St. D.	0.248*** (0.022)	0.326*** (0.014)	0.304*** (0.014)	0.306*** (0.013)	0.258*** (0.021)	0.324*** (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 ²	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 LTV 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 between 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 \times transaction-month level. Significance Levels: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

value of the property these optimistic individuals purchase will automatically lead to a lower LTV ratio (these optimistic individuals would 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 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.²⁷ The estimates in this sample are similar to those in the full sample, suggesting that binding DTI ratios cannot explain our findings.

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

27. 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.

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 choices 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 possible 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 value (based, *e.g.* 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 lower observed LTV ratios. 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 the [Online Appendix](#) 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 also 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, we show in the [Online Appendix](#) that in the period prior to January 2013, richer counties actually experienced *below-average* house price changes. 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.

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*** (0.014)	-0.191*** (0.030)	-0.121*** (0.012)	-0.133*** (0.018)	-0.089*** (0.017)	-0.086*** (0.033)	-0.362*** (0.027)
St. D.	0.366*** (0.035)	0.629*** (0.119)	0.254*** (0.029)	0.333*** (0.074)	0.222*** (0.039)	0.118 (0.091)	0.776*** (0.051)
Month x county x lender FE	Y	Y	Y	Y	Y	Y	Y
Demographic controls	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 ²	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 LTV 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 \times transaction-month level. Significance Levels: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

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 1–6 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.²⁸ While one might expect to inherit a house from a family 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. For those individuals, the exposure of their expected bequest to

28. 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 country as their work friends or their college friends.

out-of-state house price movements is smaller, since the properties they might inherit are likely to be located in their home state. Yet, when we use the house price experiences of their out-of-state friends to instrument for the experiences in their full social network, we obtain similar estimates as in our baseline sample. This finding provides 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 homebuyers. Bailey *et al.* (2017) show that more optimistic individuals are more likely to become homeowners, raising concerns that optimistic and pessimistic homebuyers 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.

4. BELIEFS AND LEVERAGE CHOICE: ANCILLARY EVIDENCE

The previous section documented that more pessimistic individuals make smaller downpayments, consistent with the directional predictions from the fixed house size scenario. In this section, we provide additional evidence for the importance of the downpayment protection force that is central to this fixed house size scenario. In particular, we show evidence for the risk-shifting motives of the downpayment protection force across a number of settings; however, as we discuss, these settings are not suitable to evaluate the *relative* strength of this downpayment protection force and the expected return force. Towards the end of the section, we also provide additional evidence that individuals' housing investment decisions are largely determined by consumption motives of housing, at least at the intensive margin, and are thus relatively return insensitive.

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).²⁹ 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 neighbourhood 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?"

29. Source: Survey of Consumer Expectations, 2013–2018 Federal Reserve Bank of New York (FRBNY). The SCE data are available without charge at <https://www.newyorkfed.org/microeconomics/sce> and may be used subject to license terms posted there. FRBNY disclaims any responsibility for this analysis and interpretation of Survey of Consumer Expectations data. The Survey of Consumer Expectations is a monthly online survey of a rotating panel of nationally representative household heads launched 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 12 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.

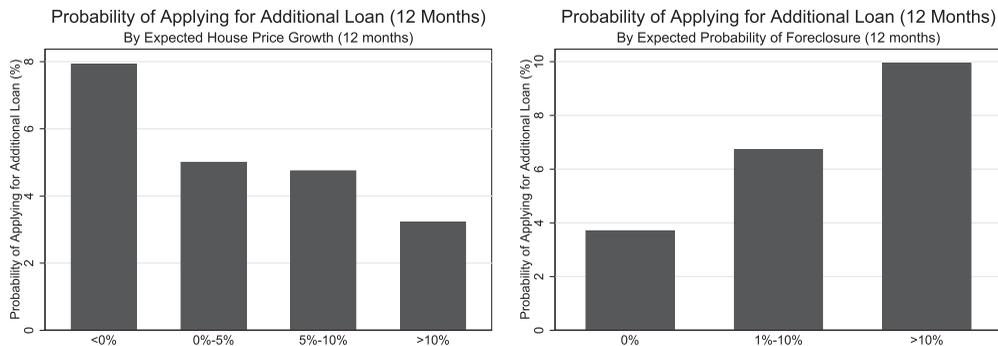


FIGURE 6

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. This evidence is consistent with an important downpayment protection force. Note, however, that by focusing on people who are already homeowners, and who have therefore already determined the size of their housing investment, the survey setting cannot elicit the relative importance of the downpayment protection force and the expected return force for new homebuyers. In addition, there are other possible explanations for the observed correlations in these survey data. For example, in regions where the economy is 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 understand 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. To emphasize this point, we designed the survey to explore the financing of a pre-determined housing investment, which shuts down the expected return force.

The DMS was administered to current homeowners via SurveyMonkey in September 2017. The demographics of the survey respondents are described in the [Online 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:³⁰

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

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 that house prices would stay 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.

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 analyses 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.³¹ The bottom row confirms this finding: across the two survey waves, there are twice as many people that recommend making

31. 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 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

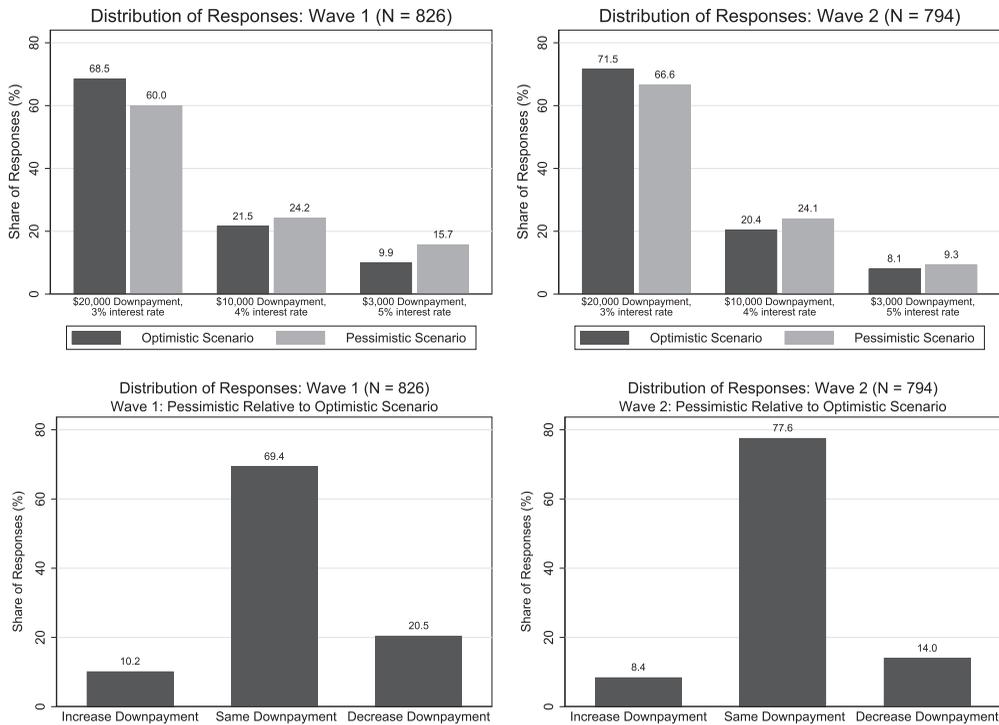


FIGURE 7

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.

a smaller downpayment in the relatively more pessimistic house price scenario than there are people that recommend making a larger downpayment. In the [Online Appendix](#), 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

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. 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 did not 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”).

TABLE 7
Stated reasons for recommending smaller downpayment under pessimistic scenario

	Wave 1	Wave 2
Optimistic first	<ul style="list-style-type: none"> • 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. 	<ul style="list-style-type: none"> • 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 would not 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	<ul style="list-style-type: none"> • 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. 	<ul style="list-style-type: none"> • Because if they think they are going to lose money, they should not 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.

likely to recommend reduced downpayments in response to the more pessimistic house price scenario.

While it is reassuring to recover the relationship between beliefs and leverage choices from the fixed house price scenario,³² 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 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.³³ Indeed, a number of

32. 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.

33. 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

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 et al., 2015](#)). Indeed, financial advice websites and blogs regularly discuss the trade-offs 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),³⁴ 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.”³⁵ 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

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.

34. <http://www.edelmanfinancial.com/education-center/articles/1/11-great-reasons-to-carry-a-big-long-mortgage>

35. <https://themortgagereports.com/18520/20-percent-downpayment-risk-mortgage-interest-rate>

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.

The [Online Appendix](#) contains 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 analyse 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?" In all 55% of respondents said that the bank could legally go after other assets, 45% responded that the bank could not.³⁶ 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.³⁷ 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 behaviour 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

36. 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 *et al.* (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.

37. 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?"

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 neighbourhood, since this would generate a substantial decline in their utility from living in the house. Instead, these pessimistic households would choose to reduce their downpayment to minimize their housing market exposure.

In this section, we analyse 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 neighbourhood, 40% required off-street parking, 39% required that the house was in their preferred neighbourhood, and 29% required that the house was in their preferred school district. Other neighbourhood requirements were proximity to shopping (29% of respondents), proximity to work (28%), proximity to family and friends (26%), and proximity to public transportation (18%). 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 article 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, *e.g.* Baker, 2018; Giglio *et al.*, 2015; Einav *et al.*, 2015; Piazzesi *et al.*, 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 effects of social interactions on social, political, and economic outcomes.

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Supplementary Data

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

APPENDIX

A. THEORETICAL DERIVATIONS

A.1. Proofs

We first provide proofs for the simplified model considered in Sections 1 and 2 of the article. 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 of the Online Appendix.

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 behaviour of $\Psi_{VHS}(\tilde{\delta}) \equiv \mathbb{E}_i [g | g \geq \tilde{\delta}]$ 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 $g \sim N(\mu_i, \sigma_i^2)$, we can express $\Psi_{VHS}(\tilde{\delta})$ as follows

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

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

$$\begin{aligned} \frac{\partial \Psi_{VHS}(\tilde{\delta})}{\partial \mu_i} &= 1 - \lambda'(\alpha_i) > 0 \\ \frac{\partial \Psi_{VHS}(\tilde{\delta})}{\partial \sigma_i} &= \lambda(\alpha_i) - \lambda'(\alpha_i) \alpha_i = \lambda(\alpha_i) (1 - (\lambda(\alpha_i) - \alpha_i) \alpha_i) > 0, \end{aligned}$$

where we have used the properties of the Normal hazard rate from Fact 2 in Section A.3 of the Online Appendix. 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 behaviour of

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

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

$$\begin{aligned} \frac{\partial \Psi_{FHS}(\tilde{\delta})}{\partial \mu_i} &= \frac{1}{\sigma_i} \phi(\alpha_i) > 0 \\ \frac{\partial \Psi_{FHS}(\tilde{\delta})}{\partial \sigma_i} &= \phi(\alpha_i) \frac{\alpha_i}{\sigma_i} = - \frac{\phi'(\alpha_i)}{\sigma_i}, \end{aligned}$$

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:

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

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 $\Psi_{FHS}(\tilde{\delta}) \equiv 1 - F_i(\tilde{\delta}) = 1 - \Phi(\alpha_i)$, we can find that

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

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

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

which is positive as long as $|\tilde{\delta} - \mu_i| > \sigma_i$. 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 article.³⁸

Borrowers' problem and default decision When borrowers face non-zero default costs, they solve the following optimization problem

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

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

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

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

38. Throughout the article, 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.

that individual default costs are larger for homeowners with larger properties. At date 1, borrowers default according to the following threshold rule,

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

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 .

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 $\Lambda_i(\delta_i)$. We also allow for potential deadweight losses associated with default, parameterized by $1 - \eta$. Therefore, the loan-to-value ratio offered to borrower i for a given promised repayment δ_i corresponds to

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

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 LTV 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

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

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

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 LTV schedule to all borrowers. A correct interpretation of our empirical findings requires that potentially unobserved characteristics used by lenders' to offer LTV 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 $n_{0i} > p_0 h_{0i}$, 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:

$$\begin{aligned} \max_{c_{0i}, \delta_i, h_{0i}} & u_i(c_{0i}) + \beta p_0 h_{0i} \left[-\chi_i \int_{\underline{g}}^{\delta_i - \chi_i} dF_i(g) + \int_{\delta_i - \chi_i}^{\bar{g}} (g - \delta_i) dF_i(g) \right] \\ & - \lambda_{0i} (c_{0i} + p_0 h_{0i} (1 - \Lambda_i(\delta_i)) - n_{0i}) + v_{0i} (h_{0i} - \underline{h}_i). \end{aligned}$$

The optimality conditions of this problem regarding consumption, promised repayment, and housing choice, are the counterparts to equations (5)–(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).

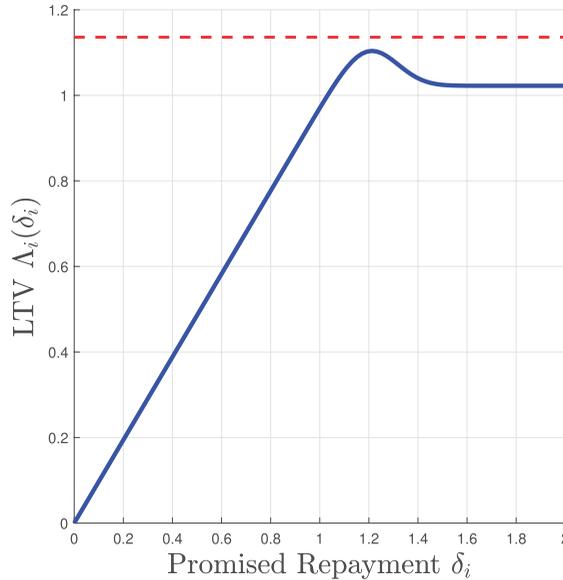


FIGURE A1
LTV schedule $\Lambda_i(\delta_i)$.

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 dashed line corresponds to the maximum LTV ratio with full recovery, which corresponds to $\frac{\mu_L}{1+r}$.

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

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

Intuitively, at an optimum in which the housing constraint is slack, a borrower is indifferent between (1) consuming a dollar, (2) using a dollar to increasing today's downpayment, and (3) leveraging the dollar to make a larger housing investment. The second and third terms in equation (A.1) 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 $\beta \int_{\delta_i - \chi_i}^{\bar{g}} dF_i(g)$, 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 $\beta \left[-\chi_i \int_{\bar{g}}^{\delta_i - \chi_i} dF_i(g) + \int_{\delta_i - \chi_i}^{\bar{g}} (g - \delta_i) dF_i(g) \right]$.

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

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

and

$$\rho_i = \max_{\delta_i} \frac{-\chi_i \int_{\bar{g}}^{\delta_i - \chi_i} dF_i(g) + \int_{\delta_i - \chi_i}^{\bar{g}} (g - \delta_i) dF_i(g)}{1 - \Lambda_i(\delta_i)}. \tag{A.2}$$

With a solution is given by

$$\frac{\Lambda'_i(\delta_i)}{1 - \Lambda_i(\delta_i)} = \frac{\int_{\delta_i - \chi_i}^{\bar{g}} dF_i(g)}{-\chi_i \int_{\bar{g}}^{\delta_i - \chi_i} dF_i(g) + \int_{\delta_i - \chi_i}^{\bar{g}} (g - \delta_i) dF_i(g)}. \tag{A.3}$$

Equation (A.3) 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 $u'_i(c_{0i}) = \beta\rho_i$, where ρ_i , defined in (A.2), 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 (A.3) 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

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

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

$$\frac{\partial J}{\partial \delta_i} = p_0 h_{0i} (u'_i(n_{0i} - p_0 h_{0i}(1 - \Lambda_i(\delta_i))) \Lambda'_i(\delta_i) - \beta(1 - F_i(\delta_i - \chi_i))) = 0. \tag{A.4}$$

Borrowers' second-order condition satisfies

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

where the second line is valid at an optimum and $M \equiv \frac{-(1-\eta)\lambda_L(\delta_i - \chi_i) + (\eta\chi_i + (1-\eta)\delta_i)\lambda'_L(\delta_i - \chi_i)}{(1-\eta\chi_i + (1-\eta)\delta_i)\lambda_L(\delta_i - \chi_i)} < 0$. Hence, sufficient conditions that guarantee that borrowers' first-order condition corresponds to an optimum are (1) a non-decreasing lenders' hazard rate, and (2) 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 (A.3) and the sustained regularity conditions, it is sufficient to establish the behaviour of

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

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 $g \sim N(\mu_i, \sigma_i^2)$, we can express $\mathbb{E}_i \left[g | g \geq \tilde{\delta} - \chi_i \right]$ and $F_i(\tilde{\delta} - \chi_i)$ as follows

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

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 $\Psi_{VHS}(\tilde{\delta})$ as

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

The relevant comparative statics in μ_i and σ_i are given by

$$\begin{aligned} \frac{\partial \Psi_{VHS}(\tilde{\delta})}{\partial \mu_i} &= \chi_i \frac{\phi(\alpha_i) \frac{1}{\sigma_i}}{(1 - \Phi(\alpha_i))^2} + 1 - \lambda'(\alpha_i) > 0 \\ \frac{\partial \Psi_{VHS}(\tilde{\delta})}{\partial \sigma_i} &= \chi_i \frac{\phi(\alpha_i) \frac{1}{\sigma_i} \alpha_i}{(1 - \Phi(\alpha_i))^2} + \lambda(\alpha_i) - \lambda'(\alpha_i) \alpha_i \\ &= \underbrace{\chi_i \frac{\lambda(\alpha_i)}{1 - \Phi(\alpha_i)} \frac{\alpha_i}{\sigma_i}}_{\geq 0} + \underbrace{\lambda(\alpha_i)(1 - (\lambda(\alpha_i) - \alpha_i) \alpha_i)}_{> 0}, \end{aligned}$$

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 $\lim_{\chi_i \rightarrow 0} \chi_i \frac{\lambda(\alpha_i)}{1 - \Phi(\alpha_i)} \frac{\alpha_i}{\sigma_i} = 0$, 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 (A.4) and the sustained regularity conditions, it is sufficient to establish the behaviour of

$$\Psi_{FHS}(\tilde{\delta}) \equiv 1 - F_i(\tilde{\delta} - \chi_i) = 1 - \Phi(\alpha_i), \tag{A.5}$$

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

$$\begin{aligned} \frac{\partial \Psi_{FHS}(\tilde{\delta})}{\partial \mu_i} &= \frac{1}{\sigma_i} \phi(\alpha_i) > 0 \\ \frac{\partial \Psi_{FHS}(\tilde{\delta})}{\partial \sigma_i} &= \phi(\alpha_i) \frac{\alpha_i}{\sigma_i} = - \frac{\phi'(\alpha_i)}{\sigma_i}, \end{aligned}$$

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^* is characterized by $F_x(x^*; \theta, \alpha) = 0$ and $F_{xx} \leq 0$, we can characterize first-order comparative statics by $\frac{dx^*}{d\theta} = \frac{F_{x\theta}}{-F_{xx}}$ and second-order comparative statics by $\frac{d(\frac{dx^*}{d\theta})}{d\alpha} = \frac{d^2 x^*}{d\theta d\alpha} = \frac{F_{xxx} \frac{dx^*}{d\alpha} \frac{d\alpha}{d\theta} + F_{xxx\alpha} \frac{dx^*}{d\theta} + F_{x\theta x} \frac{dx^*}{d\alpha} + F_{x\theta\alpha}}{-F_{xx}}$. 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 $F_{xxx\alpha}$ do.

In the fixed house size scenario, where $\Psi_{FHS}(\cdot)$ is defined in equation (A.5),

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

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.

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

which is positive as long as $|\tilde{\delta} - \mu_i - \chi_i| > \sigma_i$. 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 $\chi_i \rightarrow 0$. In that case,

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

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 (A.5),

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

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

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

which is positive as long as $|\tilde{\delta} - \chi_i - \mu_i| > \sigma_i$. 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 $\chi_i \rightarrow 0$. In that case,

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

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

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