

## **Consumer Ruthlessness and Mortgage Default During the 2007-2009 Housing Bust**

Neil Bhutta<sup>\*</sup>  
Jane Dokko<sup>\*</sup>  
Hui Shan<sup>\*\*</sup>

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**Abstract:** From 2007 to 2009 U.S. house prices plunged and mortgage defaults surged. While ostensibly consistent with widespread “ruthless default,” our analysis of detailed data on home prices and mortgage performance indicates that borrowers do not walk away until they are deeply underwater – far deeper than traditional models of ruthless behavior predict. Moral aversion to default may be driving this result since sample borrowers face low default costs along other dimensions. These results suggest that the moral hazard cost of default as a form of social insurance is lower than what many may suspect.

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## **Introduction**

From 2007 to 2009 house prices in the U.S. plunged, especially in many areas of Arizona, California, Florida and Nevada (Figure 1). At roughly the same time, mortgage defaults surged, seemingly consistent with the predictions of option-theoretic models of mortgage pricing where borrowers “ruthlessly” default to maximize their wealth (Foster and Van Order 1984, 1985). Numerous media anecdotes suggest that ruthless defaults are widespread and the presumed wave of such defaults has led policy makers to propose ways to deal with ruthless or strategic defaulters. In this paper, we assess how closely borrower behavior conforms to the ruthlessness hypothesized in option-theoretic models using rich micro-data where we know the precise timing of defaults and the evolution of house prices at the ZIP code level.

We find that home equity has to turn deeply negative before most homeowners will exercise their default “option” – much more so than theoretical models predict (Kau et al 1994). Moreover, this gap cannot be easily explained by the potential financial costs of default. For example, most of the borrowers we study do not face the risk of lender recourse, or a tax liability due to canceled mortgage debt. Also, as we will discuss in more detail, borrowers who “walk away” can expect only a short-term decline in credit access and thus should not be hugely deterred by reputation effects of default.

Given recent survey evidence, we suspect that moral aversion might play an important role in deterring ruthless defaults. For example, 9 out of 10 respondents in a national survey conducted by Fannie Mae in 2010 said it is wrong for borrowers who owe more on their house

than it is worth to default on their mortgage. Similarly, Guiso, Sapienza, and Zingales (2009) find that about 80 percent of homeowners consider ruthless default morally wrong.

Despite such moral qualms, Guiso et al. believe that borrowers, at some point, will walk away and therefore ask a series of questions to gauge how deeply underwater respondents would have to be to walk away from their mortgage. They ask, for example, “If the value of your mortgage exceeded the value of your house by \$50,000 would you walk away from your house even if you could afford to pay your monthly mortgage?” If respondents say “no,” they then ask if being \$100,000 underwater would induce default, and so on. This series of questions provides the intuition behind our analysis, but we are interested in inferring the threshold level of negative equity needed to induce default using observational data rather than survey responses. Although borrowers *say* they would not default in a certain situation, they may *act* differently when the situation actually presents itself.

We observe the monthly payment status of over 130,000 home purchase loans originated in 2006 in Arizona, California, Florida, and Nevada, alongside a monthly measure of home equity based on ZIP-code-level house price indices. All of the borrowers in our sample put no money down (a combined loan-to-value of 100 percent) and many purchased homes in ZIP codes where house prices declined by more than 40 percent, on average, between 2006 and 2009. If borrowers typically refrain from walking away until they are severely underwater, it would imply that default costs in general, and perhaps moral aversion in particular, are important.

We estimate that the *median* borrower in our sample does not exercise the default option until his housing equity drops to -67 percent (the mortgage balance exceeds the house value by

67 percent), equating to a loan balance of about \$400,000 for a house with market value of just \$240,000. In contrast, the traditional option-theoretic model, which does not include monetary or emotional default costs, predicts that default is certain once equity gets to about -20 percent (Kau, Keenan, and Kim 1994).

Many papers document a strong statistical link between negative equity and default, supporting the notion that borrowers often ruthlessly exercise the default option.<sup>1</sup> Ours is similar in this respect. However, looking solely at estimates of the coefficient on equity in a default regression might not give the full story. Our main contribution is to push the data further, developing a novel strategy to estimate the distribution of threshold equity values implied by the empirical relationship between negative equity and default, which allows for a clearer assessment of whether behavior *broadly* conforms to that predicted by traditional option-theoretic models. We also exploit more detailed data on house prices than has typically been available to researchers, and take advantage of an unprecedented episode where many borrowers with low financial default costs faced huge declines in equity.<sup>2</sup> Our results reveal considerable heterogeneity in borrowers' walk-away equity threshold, but suggest that most borrowers might not be very ruthless after all – consistent with the survey evidence.<sup>3</sup>

One of the difficulties we face with observational data is that default can occur irrespective of the depth of negative equity because of income shocks that necessitate default.

<sup>1</sup> For some recent examples, see Foote et al (2008), Bajari et al (2008) and Deng et al (2000).

<sup>2</sup> Bajari et al (2008), Deng et al (2000) and Elul et al (2010) used MSA-level HPIs, while Quigley and van Order (1995) used regional HPIs. Foote et al (2008) have more disaggregated HPIs, but they face the difficulty, like others, of not having a good measure of the total loan balance at the time of default due to unobserved junior liens.

<sup>3</sup> Quigley and van Order (1995) conduct an analysis similar in spirit to ours, and conclude that there must be some factor impeding defaults, such as transaction or default costs.

For instance, if we observe that an individual defaults when their equity hits -25 percent, it is possible that a severe income shock necessitated the default, and that -25 percent does not actually represent that person's threshold equity value in the absence of the income shock. As we will discuss in more detail, our econometric strategy helps overcome this issue.

Other borrowers in the data may experience more mild income shocks that do not necessitate default, but as Elul et al. (2010) point out, these shocks may increase their marginal utility of cash and thus make them more responsive to a decline in equity. Readers should keep in mind that our threshold estimate reflects default decisions by both those not hit by shocks and those hit by mild shocks. Along similar lines, Campbell and Cocco (2010) hypothesize several sources of heterogeneity in borrowers' liquidity and the effect of liquidity on their equity threshold. As noted earlier, we only study borrowers in 2006 who put no money down to buy their homes. We chose this sample to help ensure that we measure equity as precisely as possible, but as a consequence we are likely studying a fairly homogenous group of borrowers who do not have much excess liquidity.<sup>4</sup>

These considerations actually make our results more surprising in that even highly liquidity constrained borrowers seem to require a deep drop in equity before walking away. As discussed earlier, we think moral aversion plays a role, but other emotional or behavioral factors may also be at play. For example, borrowers may not make optimal decisions because they fail to keep close track of house price changes. Alternatively, borrowers may overestimate the financial costs of default – for example believing that they will be completely shut out of credit

<sup>4</sup> Some heterogeneity remains, for example as suggested by differences in the choice of an adjustable or fixed rate mortgage. We will stratify by some of these factors to see how the results differ.

markets for life. Ultimately, we cannot evaluate the importance of these different stories with our data, but our threshold estimate seems to suggest considerable scope for such stories, and future research could endeavor to better understand their relevance.<sup>5</sup>

While purely ruthless defaults have undoubtedly occurred, our results suggest such defaults probably do not account for a large proportion of all defaults in recent years.

Widespread inability to pay *combined* with low or negative equity that makes selling one's house in the face of financial problems difficult (so called "double-trigger" defaults) might be more important than ruthless defaults. Widespread inability to pay stems from two sources. First, the severe recession beginning in 2007 generated substantial income losses across a large swath of households. Second, the sharp rise in nonprime lending during the mid-2000s, including loans without income verification or any down payment, likely means that a substantial fraction of borrowers were financially unstable even at origination.

Our finding has potentially important and broad policy implications. Mortgage default can be viewed as a social insurance program since the state enforces laws protecting borrowers (e.g. creditors must go through a lengthy process to repossess a house), thus passing on some of the costs of default to others.<sup>6</sup> As with any social insurance program, moral hazard poses potential costs, and policy makers are clearly concerned about such costs. For example,

<sup>5</sup> Two stories unlikely to be playing a large role are (1) that borrowers suffer from a sunk cost fallacy because of their down payment and (2) that borrowers have a deep emotional attachment to their home. We can largely rule out these stories since we study borrowers who put no money down and who only recently moved into their house.

<sup>6</sup> Indeed, a Pew Research Center survey (2010) indicates a substantial share of Americans view default as acceptable in certain circumstances, implying that many view default as a form of social insurance for those in financial hardship.

lawmakers passed the Bankruptcy Abuse Prevention and Consumer Protection Act in 2005 to “make bankruptcy more embarrassing and more difficult.”<sup>7</sup> As noted earlier, the recent spike in mortgage defaults along with numerous anecdotes about ruthless default reinforces the view that the stigma of default has waned, and may encourage lawmakers to make mortgage default more difficult. But if in fact consumers strongly prefer to avoid default for moral or social reasons, then the moral hazard cost of the default option as a form of social insurance is already low.

The outline for the rest of the paper is as follows. In the next section, we discuss the strategic default decision in greater depth. After that, we describe our sources of data, followed by the empirical analysis, which proceeds in two parts. In the first part, we estimate the non-linear relationship between equity and default from a discrete-time hazard model. In the second part, we back out the distribution of walk-away values for borrowers in our sample implied by the estimated default-equity relationship. Finally, we conduct robustness checks, apply the same analysis over various subsamples, and conclude.

## **I. Negative Equity and the Default Decision**

### **A. What is “ruthless default”?**

In the pure option-theoretic literature, ruthless or strategic default occurs when the value of a property falls below the cost of the mortgage and the borrower exercises an implicit put option to “sell” the house back to the lender (that is, default) in order to maximize his financial

<sup>7</sup> Senator Charles Grassley (R-Iowa) quoted in Donald Bartlett and James Steele “Soaked by Congress” in Time Magazine on May 7, 2000. Gross and Souleles (2002) provide evidence consistent with a decline in stigma over time that may have led to an increase bankruptcy filings in the 1990s.

wealth (Foster and Van Order 1984, 1985). These models abstract away from the default and transaction costs that occur in reality, but nevertheless predict that borrowers are unlikely to default when they are just slightly underwater (e.g. Kau et al. 1993). Because of the embedded put and call (prepay) options, the true cost of the mortgage generally exceeds the mortgage balance and thus ruthless default does not occur as soon as the house value sinks below the mortgage balance.

The default option insures against negative house price shocks, and the price of such protection rises in a volatile environment. For someone not too deep underwater and in a volatile environment, making the next payment and thus holding on to the option can make financial sense because there is a good chance house prices will rebound, while the default option continues to protect against losses. Kau et al. (1994) conduct simulations based on this model and find that borrowers do not necessarily walk away until equity falls to about -20 percent.<sup>8</sup>

One simplifying assumption this result depends on is that default is instantaneous and irreversible. In reality, though, as Ambrose and Buttimer (2000) point out, borrowers often have some time to reinstate a loan after they stop making payments. California for instance, where the majority of the borrowers who we study live, mandates a 90 day reinstatement period *after* the lender files a notice of default, which is usually not filed until the borrower is at least 120 days past due (Crews Cutts and Merrill 2009). Thus, borrowers in California can stop making

<sup>8</sup> Kau and co-authors also emphasize that the interest rate environment can affect the likelihood of default. A rising interest rate environment, for example, makes existing mortgages more valuable and reduces the likelihood of default (borrowers want to retain their favorable loan terms). During our observation period, however, rates were falling, making existing mortgages less valuable to borrowers. Moreover, most borrowers in our sample took out adjustable-rate mortgages, reducing the option value of their mortgages associated with interest rate changes.

payments while retaining an option to reinstate the mortgage if the housing market rebounds, and suggests the -20 percent simulation result might need to be tempered somewhat.

### **B. What are the costs of default?**

As noted above, volatility in house prices alone can push the threshold level of equity at which a borrower walks away to a value below zero. Exercising the default option may also entail certain costs that further lower the walk away threshold, including transaction, legal, and information costs. But as we discuss here, a number of factors mitigate these costs, especially for the sample and time frame we analyze.

First, as is well known, mortgage default can have a substantial effect on one's credit score and future credit access. VantageScore Solutions, a major credit scoring firm, estimates that a mortgage delinquency followed by foreclosure lowers credit scores by 21 percent (given no other simultaneous delinquencies and an initially good score). Perhaps surprisingly, however, Brevoort and Cooper (2010) note that consumers can recuperate their score in as little as nine months following foreclosure. This means that the cost of borrowing need not rise permanently after a default and, in fact, can revert to pre-default levels quite quickly, especially for non-mortgage sources of credit. And while the foreclosure record stays on credit reports for seven years and may make it difficult to get a conventional mortgage, a government (FHA) insured mortgage, which allows loan-to-value ratios of up to 97 percent, would be attainable just three years after the foreclosure based on current rules.

Second, underwater borrowers who default sometimes face recourse risk, but most borrowers in our sample purchased homes in California and Arizona, where state law prohibits recourse in the case of loans used to purchase one's principal residence.<sup>9</sup> Even in states that allow recourse (including Florida and Nevada), legal scholars point out that lenders rarely exercise their recourse option (Zywicki and Adamson 2008, White 2009).<sup>10</sup> Moreover, in 2007 Congress passed a law temporarily eliminating the tax liability on forgiven recourse debt, further reducing the costs of walking away. Overall, we conclude that recourse should not deter default in our sample of borrowers, particularly those living in California and Arizona.

Third, one must also consider the fixed costs of searching for new housing and physically moving from one place to another after default. But at the same time, defaulters generally benefit by essentially living "rent-free," only needing to pay property tax, until the lender takes possession of the house. The length of the foreclosure period varies from state-to-state, but in general borrowers will be able to stay in their house for 6-12 months after they stop making mortgage payments (Crews Cutts and Merrill 2009) – a substantial incentive to stop making payments.

In sum, the potential financial costs of default, on net, are arguably quite limited, especially for our sample and in the time frame that we analyze. As such, one less tangible cost that may help explain our results is moral aversion to default, which survey evidence suggests is significant among Americans.

<sup>9</sup> Recourse rights allow lenders to sue borrowers for losses not recovered by selling the property.

<sup>10</sup> Ghent and Kudlyak (2010) provide evidence that recourse laws affect the probability of default. Even though lenders rarely pursue the recourse option, the tax liability from forgiven recourse debt may have discouraged default.

### **C. How might a loan modification alter the cost of default?**

In theory, the possibility of a future loan modification that reduces a borrower's monthly payments through an interest rate reduction, extension of the term, principal reduction or temporary forbearance reduces the cost of the mortgage and, therefore, makes default less attractive, *ceteris paribus*.

There were few, if any, large-scale loan modification programs available to borrowers until 2008. A principal reduction loan modification program, "Hope for Homeowners," went into effect in late 2008 but modified very few mortgages as lender participation was voluntary. The Obama administration's flagship loan modification program, the Home Affordable Modification Program (HAMP), was not announced until March 2009, well into our sample period, and has modified fewer than 1 million mortgages to date. A key aspect of HAMP is that it was designed to keep strategic defaulters ineligible as borrowers must demonstrate financial hardship – an inability to pay rather than unwillingness to pay. Although possible, we think it is unlikely that many borrowers continued making payments in the hope of getting a loan modification.

## **II. Data**

### **A. Mortgage Microdata**

Our primary source of data on mortgage performance comes from CoreLogic (formerly known as LoanPerformance). CoreLogic provides detailed information on the individual

mortgages bundled into subprime and “alt-A” (collectively referred to as “nonprime”) private-label securities. Subprime loans are generally characterized as loans to borrowers with low credit scores and/or little or no down payment, while alt-A securities typically involve mortgages with reduced or no documentation of the borrower's income and assets and have a higher proportion of interest-only mortgages and option ARMs.<sup>11</sup> The CoreLogic data contain several loan characteristics at origination, including the borrower's FICO score, the ZIP code of the property, the loan amount, loan-to-value ratio, interest rate, loan type (e.g. fixed rate or adjustable rate), and loan purpose (e.g. purchase or refinance). CoreLogic also tracks the following variables at a monthly frequency: the current interest rate, current loan balance, scheduled monthly payment, and the payment status of the loan (e.g. current, 30 days delinquent, 60 days delinquent, etc.). The CoreLogic data cover the majority of securitized nonprime mortgages and thus provide information on a large number of loans originated during the peak of the most recent housing cycle (see Mayer and Pence 2008).

## **B. ZIP Code HPI Data**

To calculate housing equity for each loan in our sample in each month, we use ZIP code-level house price indexes (HPIs) – also from CoreLogic. These HPIs are monthly, repeat-sales indexes, and are available for approximately 6,000 ZIP codes from 1976 to present. The ZIP code coverage of the dataset depends on factors such as state sales price disclosure laws, the

<sup>11</sup> For the subprime securities in our data set, 60 percent of the mortgages have low or no documentation, 34 percent are interest-only mortgages, and none are option ARMs. For the alt-A securities in our data set, however, 88 percent of the mortgages have low or no documentation, 82 percent are interest-only mortgages, and 3 percent are option ARMs.

corporate history of CoreLogic, and the thickness of the ZIP code's real estate market. To the extent that homeowners form beliefs about their home's value by observing sales prices on homes in their neighborhood, these ZIP code HPIs should be a reasonable proxy for such beliefs. Alternatively, homeowners may obtain estimates of their house values using online resources, such as Zillow.com. In results not shown, we found that house price appreciation rates implied by Zillow are consistent with our ZIP code-level HPI data. The results of this comparison are available upon request.

Figure 2 shows the 1st, 50th and 99th percentile ZIP codes in terms of house price declines between January 2006 and June 2009 among the ZIP codes in our sample. The 50th percentile ZIP code experienced a price decline of over 40 percent between January 2006 and June 2009, while the 1st and 99th percentile ZIP codes experienced drops of about 20 percent and 60 percent, respectively.

### C. Estimating Equity

We estimate a borrower's equity position in percentage terms ( $\hat{E}_{itz}$ ) for borrower  $i$  at month  $t$  in ZIP code  $z$  as:

$$\hat{E}_{itz} = \left( 1 - \frac{\hat{B}_{itz}}{\hat{V}_{itz}} \right) \cdot 100 \quad (1)$$

where  $\hat{B}_{itz}$  represents our estimate of the total loan balance and  $\hat{V}_{itz}$  is an estimate of the house value. Although the CoreLogic data indicate whether a home purchase involves a junior lien, it lacks information on the payment status of the junior lien. For borrowers with a junior lien, we assume that it is paid down at the same rate as the first lien in order to estimate  $\hat{B}_{itz}$ .<sup>12</sup> In other words,  $\hat{B}_{itz}$  equals the product of the unpaid principal balance of the first lien at time  $t$  and the ratio of the CLTV to the first-lien LTV at origination. We estimate house values in the months after origination by adjusting the home value at origination ( $V_0$ ) using the monthly ZIP code-level HPI:<sup>13</sup>

$$\hat{V}_{itz} = V_{i0z} \cdot \frac{HPI_{itz}}{HPI_{0z}} \quad (2)$$

#### D. Defining Default

We define default as being 90+ days delinquent for two consecutive months, and we define the month of the default *decision* as 3 months prior to the month when the loan reaches that 90+ day delinquency mark. One might be inclined to define default as entering the foreclosure process, but the start of foreclosure depends on when the lender decides to file a notice of default, whereas halting mortgage payments reflects borrowers' decisions. Since we are interested in the borrower's equity position when he decides to default, our definition is more appropriate.

<sup>12</sup> This assumption appears to be reasonable based on our comparison of the overall pay-down rate of all first liens with those of all junior liens in the CoreLogic data.

<sup>13</sup> The sale price, calculated by dividing the first-lien loan amount at origination by the initial LTV, forms our measure of initial home value.

## **E. Sample Selection**

We selected our sample to help accurately measure equity and identify arguably exogenous variation in equity across otherwise similar borrowers. We focus on nonprime first-lien home purchase mortgages for single-family owner-occupancy originated in 2006 with a combined loan-to-value ratio (CLTV) of 100 percent in Arizona, California, Florida and Nevada. Notably, about two thirds of the non-prime purchase mortgages originated in 2006 in these states have a CLTV of 100 percent.

Our sample affords three important advantages. First, selecting borrowers with a CLTV at origination of 100 percent helps avoid measurement error due to unobserved additional mortgages – it is unlikely for borrowers to have another mortgage in addition to the reported loans financing 100 percent of the purchase price. Second, the decline in prices soon after these borrowers purchased their home in 2006 makes the refinance option largely irrelevant. As such, with our sample, we avoid the problem of many borrowers exiting the sample via a refinance before defaulting.<sup>14</sup> The price decline and lack of home equity also make it unlikely that borrowers took out an unobservable junior mortgage after the initial home purchase. Third, we exclude refinance mortgages because CLTV is potentially mismeasured for these loans. More precisely, outstanding junior liens, which may not be simultaneously refinanced, are not reported at the time the refinance occurs.

<sup>14</sup> Less than 7 percent of the mortgages in our data refinanced during the sample period. Almost all of these refinances occurred in late 2006 and early 2007, likely because house prices in some areas did not start to fall until then.

## **F. Summary Statistics**

Table I provides summary statistics for the loans in our sample and selected statistics for their counties or ZIP codes. Seventy-eight percent of the loans in our sample default by the end of the observation period (September 2009) by our definition of default.<sup>15</sup> The median percent equity at “termination” – either the month of default or the end of the observation period for loans that survive – is just under -27 percent, and the median loan age at termination is just 18 months. Figure 3 shows that the distribution of negative equity at the time of default is skewed in the direction of deeper levels of negative equity. About half of default decisions occur when negative equity is less than 30 percent, but many decisions occur when negative equity is greater than 70 percent. The interest rate at termination is nearly identical on average to that at origination, suggesting that interest rate changes are probably not a major factor inducing defaults in our sample. The median FICO score of 676 is in prime territory, but recall that these loans have 100 percent CLTVs and, potentially, other risk factors such as incomplete income and employment documentation.

We merged county-level unemployment rates from the Bureau of Labor Statistics (BLS) and county level credit card 60+ day delinquency rates from TransUnion's TrenData to the

<sup>15</sup> One may be concerned that our default definition leads to an overstatement of the default rate in the sample. Some borrowers who are 90+ days delinquent may self-cure and avoid foreclosure. Adelino, Gerardi, and Willen (2009) argue that such “self-cure risk” may partially explain why servicers have been reluctant and slow to renegotiate loans that are seriously delinquent. Unlike in their data, we find that only about 2 percent of loans that are 90+ days delinquent for two consecutive months in our sample cure during the observation period. In a robustness check not shown, we drop the 2 percent self-cured loans from our sample and our results remain the same.

CoreLogic data. Table I shows that the unemployment rate increased by 1.8 percentage points over the four quarters leading to the termination month, while the credit card delinquency rate rose by 0.35 percentage points. In addition, we merge in select ZIP code characteristics from the 2000 Census. For the average ZIP code in our sample, the median home value is \$172,000 and the median household income is just over \$46,000. The substantially higher median home values at origination reported for loans in our sample largely reflects that between 2000 and 2006, house values more than doubled in Arizona, California, Florida and Nevada (recall Figure 1). About a quarter of the residents in the average ZIP code has at least a Bachelor's degree, 27 percent are Hispanic and 9 percent African-American. These averages are very similar to those of California overall, which is the state where the majority (63 percent) of sample loans were originated.

### **III. Empirical Analysis**

#### **A. Overview**

As noted earlier, the intuition behind our analysis derives from a series of survey questions asked by Guiso et al. (2009) in December 2008 and March 2009 about how far underwater they would have to be in order to walk away from their mortgage. We are interested in inferring the threshold level of negative equity needed to induce default using observational data rather than survey responses. However, borrowers default for many reasons and not just because of negative equity, which our estimation strategy will have to address. Consider the following three types of borrowers. Borrower A is exposed only to declining house prices. If she were to make a payment when equity was -30 percent, but not at -40 percent, we would infer that

her walk-away value is between -30 and -40 percent. Borrower B, on the other hand, is exposed to a random and severe income shock, such as a job loss, necessitating default. In his case, there is a binding cash-flow constraint and [the *depth* of negative equity does not predict the timing of his default]. Finally, consider Borrower C who is exposed to a mild income shock that does not necessitate default. But his marginal utility of cash-on-hand might increase as a result of this shock and make him more responsive to a drop in equity than Borrower A.

The first part of our analysis non-parametrically estimates the relationship between equity and default in a discrete-time hazard model. Our main motivation here is to generate estimates of the probability that borrowers had to default because of a severe shock (like Borrower B) as opposed to making more of a ruthless decision in response to a decline in equity (like Borrowers A and C). These estimates feed into the second part of our analysis where we estimate the threshold level of negative equity at which the median borrower walks away. A simple model underlies the estimation strategy where borrowers have heterogeneous default costs drawn from a distribution, and they default when negative equity exceeds that cost. We use the results from the first part to identify defaults likely to have been liquidity-induced, rather than equity-driven. Thus our estimated distribution will be one that is consistent with the relationship between equity and default estimated in the first part.

## **B. A “Naïve” Estimate**

Table I provides a simple, but incorrect, estimate of the median walk-away threshold, showing the median percent equity at termination in the sample is -27 percent. One reason this

estimate is biased (towards zero) is that it ignores the possibility that many defaults arise from borrowers like Borrower B, who have no choice but to default because of a severe cash flow problem (in combination with negative equity). The equity level at termination for these double-trigger defaults underestimates such borrowers' walk-away equity thresholds in the absence of cash-flow insolvency.

A second reason it is biased is that it ignores the fact that some borrowers in the sample did not default during the observation period and that their walk-away equity level is therefore lower (more negative) than the lowest equity level they experienced during the observation period. Our two-part empirical analysis addresses these identification and censoring issues.

### **C. The Unconditional Relationship between Equity and Default**

Figure 4 displays the fraction of monthly payment decisions that were to default within equity bins one percentage point in width, similar to a typical raw hazard plot but in default-equity space rather than default-loan-age space. The raw data demonstrate a strong positive relationship between negative equity and default decisions, as one would expect if borrowers are more likely to walk away as equity falls further below zero. The default rate at negative equity of 50 percent is about four times than at 0. However, in light of Kau et al.'s (1994) finding that default should occur with near certainty once negative equity reaches about 20 percent, we were surprised to find that the default rate does not rise sharply towards 100 percent even at deeper levels of negative equity. Moreover, this unconditional relationship may *overstate* the true equity-default relationship since the delinquency rate of loan pools tend to rise in the first few

years after origination, even in a stable house price environment, as the weakest borrowers quickly fall behind.<sup>16</sup> Figure 5 shows that equity and loan age, not surprisingly, are correlated in our sample. As such, we need to control for loan age or, in other words, for the baseline hazard function. In addition, local job market conditions might covary with both equity and default. These conditions therefore should be controlled for as well.

It is important to keep in mind that equity does *not* vary in our sample because of initial, borrower-specific choices about their down payment since all of the borrowers in our sample bought their homes with no money down. Rather, the variation in equity in our dataset arises over time and through geographic differences in house price appreciation. Also, although we focus just on four states, as noted earlier there is considerable heterogeneity in house price appreciation rates across ZIP codes within these states (Figure 2).

#### **D. Step 1: Estimating the Relationship Between Equity and Default**

To address the identification concerns associated with the unconditional relationship, we estimate a discrete-time hazard model (see Allison 1982):

$$P_{it} = \Lambda(A_{it} \cdot \text{countygroup}_j + \mathbf{X}\boldsymbol{\beta} + E_{it}) \quad (3)$$

where  $P_{it} = \Pr(T_i = t | T_i \geq t, A_{it}, \mathbf{X}_{it}, E_{it})$ .  $T_i$  is the month of borrower  $i$ 's default decision.  $\Lambda$  is the logistic function.  $E_{it}$  represents a set of equity dummy variables. The baseline hazard specification is flexible, with loan age dummy variables ( $A_{it}$ ) interacted with county group

<sup>16</sup> The Public Securities Association publishes a “standard default assumption” used widely in the mortgage industry where the probability of default, conditional on not having defaulted already, climbs during the first 30 months (Sherlund 2008).

dummy variables ( $\text{countygroup}_j, j = 1, 2, 3$ ), where the groups are based on changes in the county unemployment rate between June 2006 and June 2009.  $\mathbf{X}_{it}$  is a vector of other variables that are related to the probability of default for liquidity reasons and may also be correlated with equity. These variables include: (1) quarterly time fixed effects, (2) the change in the individual mortgage's contract interest rate, (3) the four-quarter change in the county unemployment rate, and (4) the four-quarter change in the county credit card delinquency rate. The quarterly time indicators account for national-level shocks, such as gasoline price changes and tax rebates. Interest rate changes capture the potential impact of interest rate resets on default. And changes in county-level unemployment and credit card delinquency rates account for local, time-varying economic conditions. Finally, recognizing that defaults due to income shocks also require low or negative equity (otherwise a borrower in need of cash could sell his home), we exclude observations with positive equity when estimating the hazard model (equivalent to interacting the full set of covariates with an indicator variable for equity less than or equal to 0).

Table II displays the coefficient estimates and standard errors from estimating (3) along with odds ratios. Clearly, deeper levels of negative equity have stronger and highly significant effects on default. Changes in the interest rate and in county credit card delinquency rates also appear to be related to default.

Figure 6 summarizes the results by plotting predicted default probabilities (averaged within each equity bin) from our hazard model as a function of negative equity, as well as the predicted probabilities with the relevant equity dummy variables turned off (as if equity had not fallen from zero). We interpret the latter as the probability of default due to “liquidity shocks” or

an inability to pay, whereas the difference between the two functions, also shown, yields our estimate of the probability of walking away as a function of negative equity.

Figure 6 suggests that almost all of the increase in the probability of default between zero and -20 percent equity can be explained by liquidity problems. This result makes intuitive sense; at negative equity levels near zero, transaction costs and the still-realistic possibility that home equity could rebound should minimize purely ruthless defaults. After that, however, the two functions diverge implying that negative equity largely drives the *rising* default rate beyond -20 percent equity.

### **E. Step 2: Estimating the Distribution of Default Costs**

The second step of our estimation strategy aims to measure the level of negative equity that exceeds the costs of default and therefore triggers strategic default. We apply a maximum likelihood strategy that estimates the parameters of the walk-away equity distribution based on borrowers who default and those who do not. We infer from a borrower continuing to make loan payments that he has not yet experienced a level of negative equity sufficient to induce default. A borrower who does not default by the end of the observation period ( $T$ ) must have a default cost ( $C_i$ ) that exceeds negative equity in this final period ( $C_i > -E_{iT}$ ).<sup>17</sup>

On the other hand, we infer from a borrower defaulting in a given month (which by definition will be the terminal month for that loan) that she either experienced a severe liquidity

<sup>17</sup> Since prices basically fell monotonically during the observation period, equity generally hit its lowest value in the final period, implying that a loan that is still alive at the end of the observation period must have  $C_i > -E_{iT}$ .

shock ( $s_{iT} = 1$ ; think of Borrower B from our earlier discussion) or met the condition that the benefit of default exceeds their cost of default ( $C_i < -E_{iT}$ ). If the default is triggered by illiquidity ( $s_{iT} = 1$ ), then we do not know what would have happened in the absence of illiquidity but we can at least infer that  $C_i > -E_{iT-1}$ , otherwise the borrower would have defaulted in a prior period.

Finally, conditional on not experiencing a severe liquidity shock, if the borrower did not default in the previous period when his equity was  $E_{iT-1}$  but defaults in this period when he faces an equity of  $E_{iT}$ , we can bound his cost of default to be between  $-E_{iT-1}$  and  $-E_{iT}$  :

$$\Pr(D_{iT} = 1 | E_{iT}, E_{iT-1}, s_{iT} = 0) = \Pr(-E_{iT-1} < C_i < -E_{iT} | E_{iT}, E_{iT-1}, s_{iT} = 0) \quad (4)$$

With all of these pieces in hand, we construct the likelihood function:

$$\prod_{i=1}^N [1 - F(-E_{iT} | \boldsymbol{\theta})]^{1-D_{iT}} \cdot \left\{ [1 - F(-E_{iT-1} | \boldsymbol{\theta})]^{s_{iT}} \cdot [F(-E_{iT} | \boldsymbol{\theta}) - F(-E_{iT-1} | \boldsymbol{\theta})]^{1-s_{iT}} \right\}^{D_{iT}} \quad (5)$$

where  $F(\cdot)$  is the cumulative gamma density function and  $\boldsymbol{\theta} = (\mu, \kappa)$ . For estimation purposes, we assume  $C_i$  is gamma-distributed with shape parameter  $\mu$  and scale parameter  $\kappa$ . Gamma is a flexible distribution and has non-negative support, corresponding to our assumption that  $C_i$  be non-negative. Non-defaulters contribute  $[1 - F(-E_{iT} | \boldsymbol{\theta})]$  to the likelihood, while defaulters contribute  $[1 - F(-E_{iT} | \boldsymbol{\theta})]^{s_{iT}} \cdot [F(-E_{iT} | \boldsymbol{\theta}) - F(-E_{iT-1} | \boldsymbol{\theta})]^{1-s_{iT}}$ .

Note that we only use the terminal or final month of each loan for this second step.

Therefore we collapse the loan-month level dataset described earlier into a dataset with just one observation per loan, specifically the month of default or, for loans not observed to default, the final month of the observation period.

Our approach here is quite similar to estimating an average failure time from duration data, but with “failure” (i.e. default) occurring at a particular level of equity rather than at a particular time.<sup>18</sup> As with duration data, censoring is a problem. In our case, censoring occurs when  $D_{it} = 0$  or  $s_{it} = 1$ . Thus the first two bracketed expressions in equation (5) represent censored observations, while the last bracketed expression represents uncensored observations.

One final issue is that  $s_{it}$  is not observed directly. Instead, we use the results from the first step of our analysis to estimate  $\Pr(s_{it} = 1 | E_{it}, D_{it} = 1)$ . Thus, for each borrower who defaults, there is some probability that the observation is censored. To estimate this probability, first, note that:

$$\Pr(s = 1 | E, D = 1) = \frac{\Pr(s = 1, D = 1 | E)}{\Pr(D = 1 | E)} \quad (6)$$

Moreover,  $\Pr(s = 1, D = 1 | E) = \Pr(s = 1 | E)$  since a severe cash flow shock always induces default. Therefore, at each level of equity  $E$ , we estimate  $\Pr(s = 1 | E, D = 1)$  as

$$\frac{\sum_{E_{it}=E} \hat{s}_{it}}{\sum_{E_{it}=E} D_{it}}, \quad (7)$$

where  $\hat{s}_{it}$  is the predicted value from the hazard model estimated earlier with the equity dummy variables turned off (recall Figure 6).<sup>19</sup> For instance, because the red and blue lines in Figure 6 basically overlap when negative equity is less than 10 percent, defaults that occur in this equity range will be almost entirely classified as censored ( $s_{it} = 1$ ).

<sup>18</sup> See Greene’s (2003) discussion of analyzing duration data.

<sup>19</sup> To compute (7) we round equity to the nearest integer and then sum within each integer value.

Column (1) of Table III shows that in the full sample, the estimated shape parameter ( $\mu$ ) is 2.88 and scale parameter ( $\kappa$ ) is 26.6. These estimates imply that the median borrower walks away from his home when he is 67 percent underwater. Figure 7 presents the cumulative distribution function (CDF) for the  $\Gamma(\mu, \kappa)$  distribution. Less than 10 percent of borrowers will have walked away by the time negative equity reaches 15 to 20 percent, which contrasts with theoretical results from Kau et al (1994) who estimate that the default rate spikes towards unity around -20 percent equity. Furthermore, the shape of the estimated CDF is not particularly steep at any value of negative equity, suggesting that the probability of default does not increase sharply at any particular level of negative equity..

To assess the importance of liquidity shocks in influencing the median walk-away level of equity, we also estimated the parameters assuming all defaults were ruthless (i.e.  $s_{iT} = 0$  for all borrowers that default). In this case, we find that the median borrower walks away when equity hits just -29 percent (column 2). Comparing columns 1 and 2 illustrates that our strategy to account for liquidity shocks among borrowers in the sample is quantitatively very important; failing to account for liquidity shocks makes borrowers appear far more ruthless.

## **F. Summarizing**

Our main result that borrowers do not walk away until they are deep underwater can be intuitively understood by looking back at Figures 3 and 6. Figure 3 simply shows the distribution of negative equity values at termination, and one can see that about 40 percent of defaults in our sample occur when negative equity is no more than twenty percent. At the same

time, Figure 6 indicates that very few defaults at these low levels of negative equity are statistically related to the depth of negative equity, suggesting that defaults in this range are largely induced by liquidity shocks. (This result makes sense theoretically; at negative equity levels closer to zero, transaction costs plus the possibility of a rebound in prices should minimize purely ruthless defaults.) Thus our estimated distribution of walk-away values or default costs simply reflects the long tail of the distribution shown in Figure 3, and this is why we end up finding such a large median walk-away value.

#### **IV. Caveats and Robustness Checks**

##### **A. Measurement Error in Equity**

In order to reliably identify the relationship between negative equity and default, and therefore our estimate of the distribution of default costs, we need to be confident in our measure of borrower equity. Measuring borrower equity is often difficult. For one, information on second liens is not available in many datasets leading to upward biased measures of equity. Our data, on the other hand, provide information on second mortgages taken out at the time of the house purchase. Moreover, we focus on borrowers that have zero equity at origination, making it unlikely that they would have gotten another mortgage post-origination (which we would not observe).

Another difficulty facing past research has been the lack of disaggregated house price data. Previous studies typically use state- or MSA-level HPIs, which mask considerable variation in house price changes at more granular geographic levels, as noted recently by Mian

and Sufi (2009) and Dorsey et al. (2010), leading to relatively noisy equity measures. In contrast, we take advantage of far more detailed ZIP code level HPIs. These indexes are constructed using the same repeat-sales methodology underlying other HPIs such as the S&P Case-Shiller indexes and the Federal Housing Finance Agency (FHFA) indexes that are widely employed.<sup>20</sup> As a rough quality check, we compared the CoreLogic HPIs to those from Zillow.com, a popular online source of home price information available to consumers, and found that appreciation rates from CoreLogic were highly correlated with what homeowners might reasonably be expected to believe about their house values based on Zillow.com. All that said, there will still be some within-ZIP variation in house prices and thus readers should keep in mind that inexact equity measures will dampen the effect of equity on default to some extent.

One last issue with respect to equity is that for the baseline estimates we use an “all-in” HPI that includes distressed sales (e.g. short sales). If homes involved in distressed sales tend to be in poor condition and sell at deep discounts, yet do not accurately represent the value of other homes in the same ZIP code, the all-in HPIs may not be appropriate to use. We obtained CoreLogic’s HPIs that exclude distressed sales and re-estimated the parameters using only loans in ZIP codes where the house price appreciation rate between 2006 and 2009 for the two indexes are within 10 percentage points of each other. Approximately one quarter of sample ZIP codes are excluded as a result, but the results remain little changed (Table IV).

<sup>20</sup> Repeat-sales indexes have been criticized on theoretical grounds. Najaraja, Brown, and Wachter (2010) discuss and empirically compare the repeat-sales method to a “hybrid” method that uses both repeat sales and single sales data. Although the hybrid method has the “best predictive performance”, the two index types are extremely highly correlated.

## **B. Omitted Variables**

Another potential identification concern might be omitted variables bias because we have very little borrower-specific information regarding liquidity shocks.<sup>21</sup> However, we believe the scope for such bias is fairly narrow. For one, individual heterogeneity in our sample is limited because all borrowers put no money down and bought in similar areas of the country at roughly the same time. Moreover, only those liquidity shocks uncorrelated with loan age, calendar time and county-time-level economic conditions but correlated with the timing of ZIP code-level house price changes would confound our estimates of negative equity's effect on default decisions. When we control for ZIP code-level foreclosure rates in the first half of 2006 using data from RealtyTrac in the first-step hazard regression to help capture ex-ante underlying economic conditions across ZIP codes, the estimated median threshold hardly rises (Table IV). Finally, to reiterate a point made earlier, our controls for liquidity shocks turn out to be quantitatively very important and unobserved confounding liquidity shocks simply suggest that the median walk-away threshold is even further below zero than we have estimated.

## **C. House Price Expectations and Volatility**

Perhaps house price expectations and volatility can help explain our finding that borrowers do not walk away until they are quite deeply underwater. Maybe borrowers hold

<sup>21</sup> To be clear, we are referring to omitted variables that are correlated with equity, as opposed to the issue of independent unobserved heterogeneity in the estimation of hazard models. Unobserved heterogeneity, which we do not attempt to account for, can bias estimates of duration dependence (e.g. Lancaster 1990). But we are not interested in duration dependence. Moreover, Monte Carlo results from Nicoletti and Rondinelli (2010) suggest that one can ignore unobserved heterogeneity in discrete duration models and still obtain unbiased estimates of expected survival probabilities, especially in large samples, which is the key thing for this paper.

optimistic subjective beliefs as in Brunnermeier and Parker (2005), whereby they believe there is a *good* chance that house prices will rebound strongly *and* quickly, that lead them to justify making mortgage payments even when they are 40 or 50 percent underwater (recall that our estimate of the *median* threshold is 67 percent).

There are some problems with this type of explanation. First, such beliefs would have to be particular to our sample of borrowers and, at the same time, not widespread across the population. Presumably if such optimistic beliefs were widely held, prices would have begun to reflect such optimism, but, in fact, house prices continued to fall well after our sample period.

Second, empirical evidence suggests that expectations for asset prices are often informed by recent price changes (Case and Shiller 1989, Shiller 2007). If borrowers tend to extrapolate, then the house price declines in 2007 and 2008 would lead to subjective beliefs of further declines rather than extremely optimistic expectations about house prices. Moreover, it is simply difficult to imagine such extreme optimism amid a deep recession, a sharp contraction in the availability of credit, high vacancy rates, and weak inflation expectations.<sup>22</sup>

Further making the case that optimistic house price expectations are an unlikely explanation, we identify areas where house prices are least likely to rebound and estimate that the median walk-away value among borrowers in these areas is still quite high. First, we note that the likelihood of a strong positive shock to house prices is smallest in the least volatile ZIP codes. So focusing solely on borrowers in ZIP codes in the lowest quartile of historical volatility,

<sup>22</sup> For example, TIPS spreads fell throughout 2008 to around zero by the end of the year.

we find a median walk-away threshold of -67 percent (Table IV).<sup>23</sup> Second, we estimate the walk-away threshold for the sub-sample of Arizona borrowers, where housing supply is quite elastic (Glaeser et al. 2008) and the homeowner vacancy rate had more than tripled to 3.8 percent from 2005 to 2008.<sup>24</sup> It is also worth noting that Arizona borrowers did not face the risk of recourse by lenders. The estimated median walk-away value for Arizona borrowers is still quite high at -51 percent (Table IV).<sup>25</sup>

#### **D. Estimates by State**

Table IV also shows separate estimates of the distribution of walk-away values for borrowers in each of the four states we study. Our baseline estimate of -67 percent does not appear to be driven by borrowers in one particular state.

Despite being a non-recourse state, California borrowers exhibit the largest median walk-away threshold of -78 percent. As noted earlier, Arizona is the other non-recourse state among the four states we study and its borrowers have a relatively low (though still high in absolute terms) median threshold at -51. Other distinctions between the two states, including greater historical house price volatility in California, might be driving this difference.

#### **E. Potential Sources of Borrower Heterogeneity**

<sup>23</sup> Following Banks et al. (2007), we calculate a local house price volatility measure using our ZIP code level HPIs.

<sup>24</sup> The homeowner vacancy rate is proportion of owner-occupied and vacant-for-sale units that are vacant for sale. See <http://www.census.gov/hhes/www/housing/hvs/hvs.html> for definitions and to get data.

<sup>25</sup> Note that for all subsample estimates, we run both steps of the estimation using the subsample.

The estimated distribution of default costs, as illustrated in Figure 7, implies significant heterogeneity across borrowers: some borrowers walk away from their homes when equity falls just below -20 percent, whereas some other borrowers continue to pay their mortgages when they owe twice as much as their home value. We explore two potential sources of heterogeneity in walk-away values by stratifying our sample by two loan characteristics.

First, we estimate the default-cost distribution separately for borrowers fully documenting their income and assets and those that did not (for example, the borrower may not have provided the lender with enough information to verify his stated income). As indicated in Table I, 70 percent of our sample loans have reduced or no documentation, but it is important to note that in the broader population, low or no documentation loans are not very common. Previous research suggests that so-called “liar’s loans” were concentrated among those with reduced or no documentation loans (Jiang et al. 2011). Our estimates suggest that those who fully document their income and assets – and who may better represent borrowers more generally – tend to walk away at deeper levels of negative equity, which would be consistent with greater moral aversion to default among this group.

We also stratify the sample by mortgage type – fixed rate mortgages versus adjustable rate mortgages, usually hybrid loans such as “2/28’s” and “3/27’s.” When house prices were rising quickly, these hybrid loans reduced the initial mortgage payments and may have been popular among those speculating that house prices would continue to rise. They may also have been popular among the most liquidity-constrained borrowers. Table IV shows that borrowers who chose such mortgages have only slightly lower walk-away levels of equity.

## **F. Has Moral Aversion to Default Decayed Over Time?**

Using data from Google Insights, Figure 8 shows that few people searched for “strategic default” online during our observation period. The search index increased significantly during 2010, however. Interestingly, Google Insights also indicates that the highest volume of searches for this term were in Nevada, Arizona and Florida (not shown). With more learning about other borrowers strategically defaulting on their mortgages or about the available legal and counseling resources to “walk away” in the most cost-minimizing manner, the cultural environment may have shifted to make strategic default less stigmatizing and more acceptable.<sup>26</sup> Thus, the distribution of default costs among borrowers may be different today than in our sample. In addition, as the number of defaults and foreclosures reach record high levels, lenders may find it increasingly worthwhile to pursue deficiency judgments among borrowers, which would change the potential legal liabilities of default. Suitable data are not yet available to test whether the implied costs of default have changed over time, but this would be an important direction for future research.

## **V. Conclusions and Policy Implications**

<sup>26</sup> Shiller (2010) has argued that over time, strategic defaults are likely to have grown “substantially...The sense that ‘everyone is doing it’ is already growing and will continue to grow...because of a building backlash against the financial sector, growing populist rhetoric, and a declining sense of community with the business world. Some people will take another look at their mortgage contract, and note that nowhere did they swear on the bible that they would repay.”

This paper takes advantage of the precipitous decline in house prices in Arizona, California, Florida, and Nevada from 2007 through 2009 and better measures of housing equity than have typically been available to researchers to estimate the level of negative equity that triggers ruthless mortgage default. Our empirical analysis has two parts. In the first part, we estimate the relationship between equity and default based on a flexible hazard model and show that negative equity does not drive mortgage defaults until equity falls below about -20 percent. These results feed into the into the second part, where we assume a simple theoretical framework where borrowers walk away from their houses when the financial benefits of doing so exceed the costs, and estimate the distribution of default costs among our sample borrowers. The results suggest that the median sample borrower does not walk away until their negative equity exceeds 67 percent. To the our best knowledge, this is the first paper to quantify the walk-away values of mortgage borrowers using actual loan-level data.

We find it difficult to reconcile the depth of negative equity when borrowers decide to walk away with the seemingly low financial costs of default. Most borrowers in our sample who would walk away will not face lender recourse or a tax liability due to forgiven mortgage debt, and will not be shut out of credit markets for a very long time. Furthermore, they will be able to live rent-free for many months until being evicted, which provides a substantial benefit to help offset other costs of default (e.g. moving and search costs). Finally, as discussed, optimism about house prices is not a likely explanation for the results.

We think non-financial costs might help explain the results. Moral aversion to default is a good candidate explanation given the empirical support in its favor in several recent national

surveys. Moreover, we can rule out (at least to some extent) other possibilities such as emotional attachment to the house or a sunk cost fallacy because our sample borrowers have not lived in their houses very long, and none made any down payment. Finally, the presence of such non-financial costs might better explain the skewness in behavior we observe. The highly skewed distribution of walk-away values we estimate may reflect that some people will try to repay the debt no matter how far the house price falls.

Our results pose a challenge to models in which rational and “ruthless” agents facing low financial default costs walk away when they are moderately underwater (e.g. Kau et al. 1994). A direction for future research might be to investigate whether such a model, perhaps under some different assumptions or parameter choices, can explain the result that borrowers, who seemingly have little to lose by strategically defaulting on their mortgages, do not walk away until they are deeply underwater. Another direction for future research might be to explore the role of procrastination or other behavioral issues play in borrowers’ decisions to default.

Strong moral aversion and the associated low moral hazard cost of the default option have important implications for the administration and design of policies providing social insurance against severe negative life events. Opponents of the generosity of these policies, which include bankruptcy laws, unemployment insurance, and, most obviously, the Obama administration’s Home Affordable Modification Program (HAMP; a program offering reductions in mortgage payments to eligible borrowers demonstrating financial hardship), frequently contend that these programs induce additional defaults (or job losses) by lowering the costs of default (or job losses). However, high moral aversion relative to the financial generosity of social

insurance programs, combined with a stringent requirement for applicants to demonstrate true hardship, can mitigate the extent of the moral hazard problem. Indeed, that the number of defaults does not increase noticeably around March 2009, when HAMP went into effect, provides *prima facie* evidence consistent with low moral hazard costs for lenders. This paper provides an explanation why lenders might face low moral hazard costs. Further research estimating the *causal* behavioral response to HAMP would be worthwhile.

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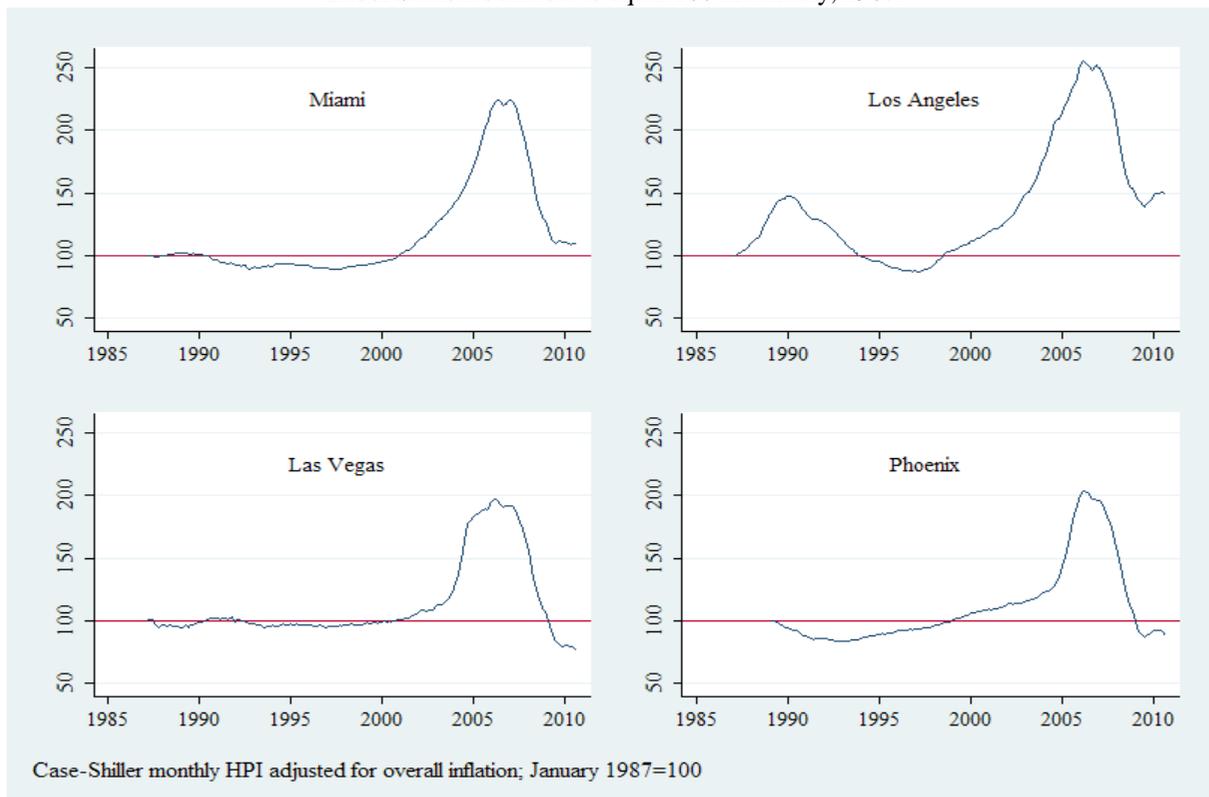
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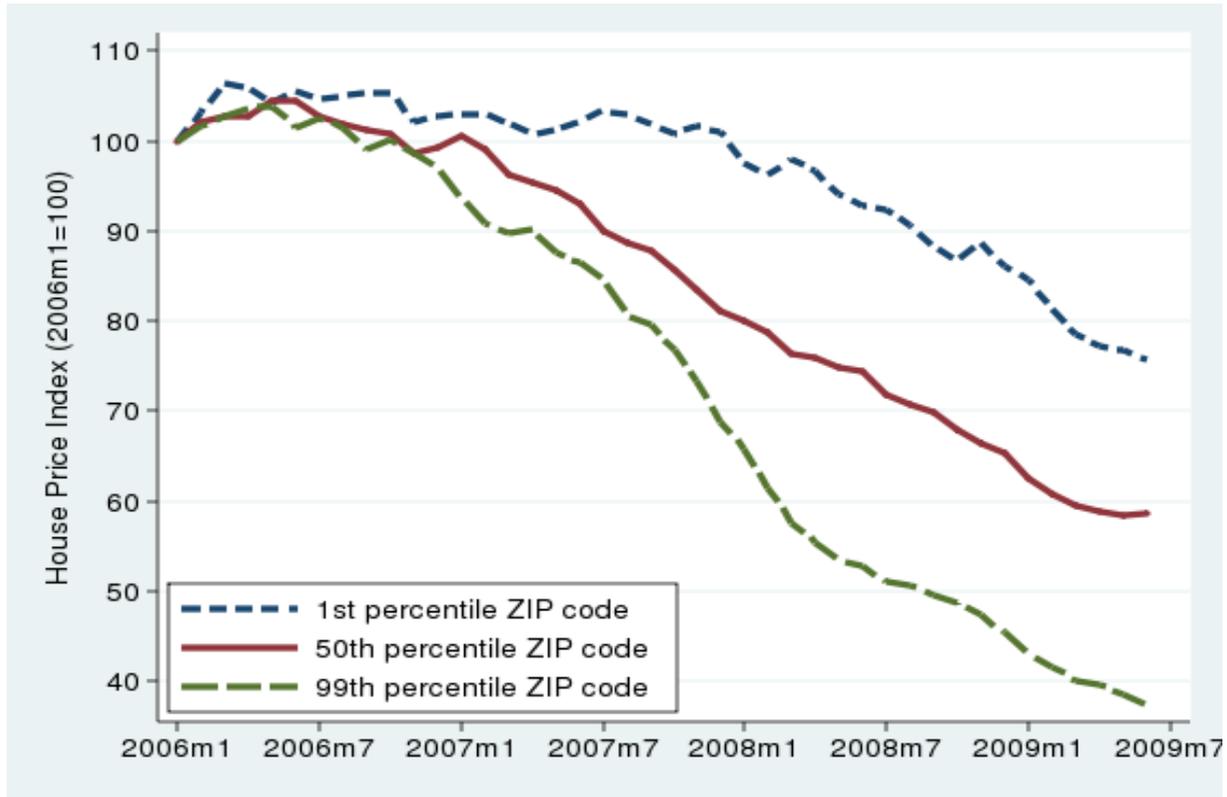
### 1. Home prices in selected metropolitan areas, January, 1987 to August, 2010

Figure 1 shows home price indices for four major metropolitan areas in the four states that we study. The price indexes were adjusted for overall inflation using the all-urban Consumer Price Index (CPI) from the Bureau of Labor Statistics and set to equal 100 in January, 1987.



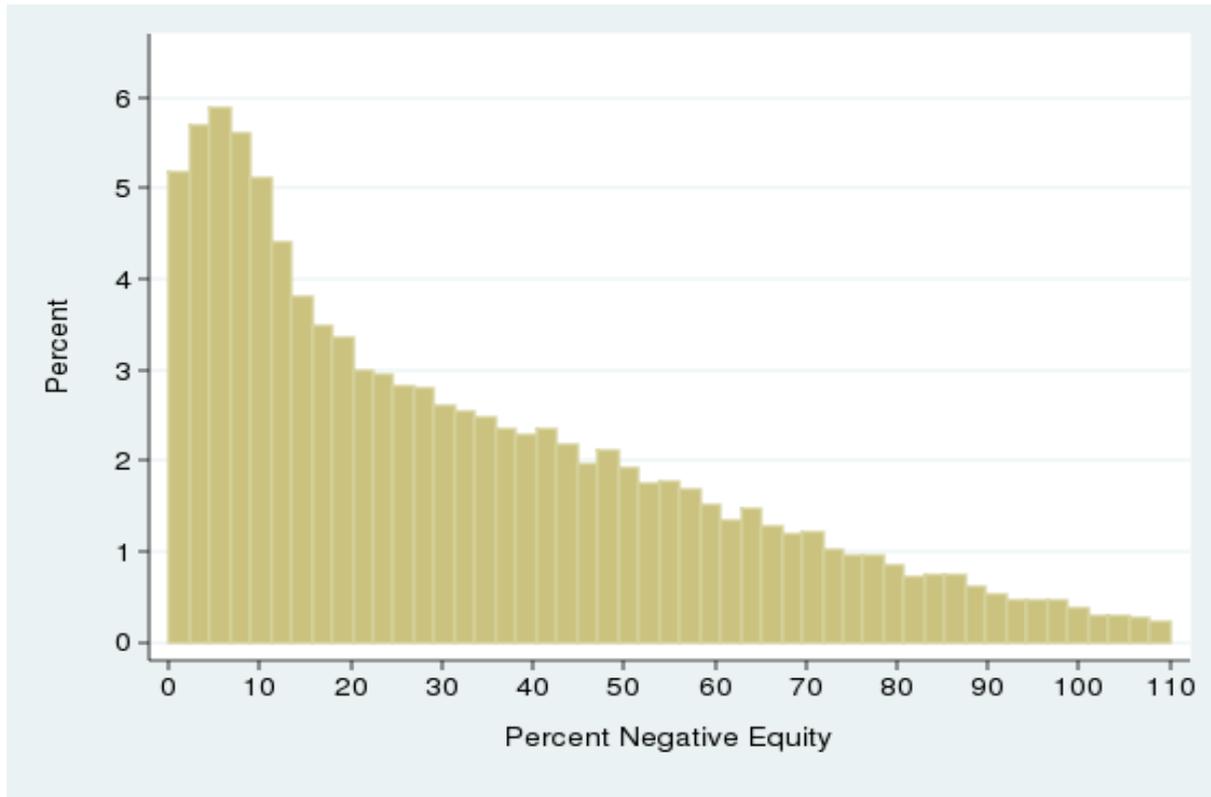
## 2. ZIP code house price declines from January, 2006 to June, 2009

Figure 2 shows house price changes at the ZIP code level based on the CoreLogic HPIs for the 1st, 50th and 99th percentile ZIP codes in terms of overall HPI declines between January, 2006 and June, 2009.



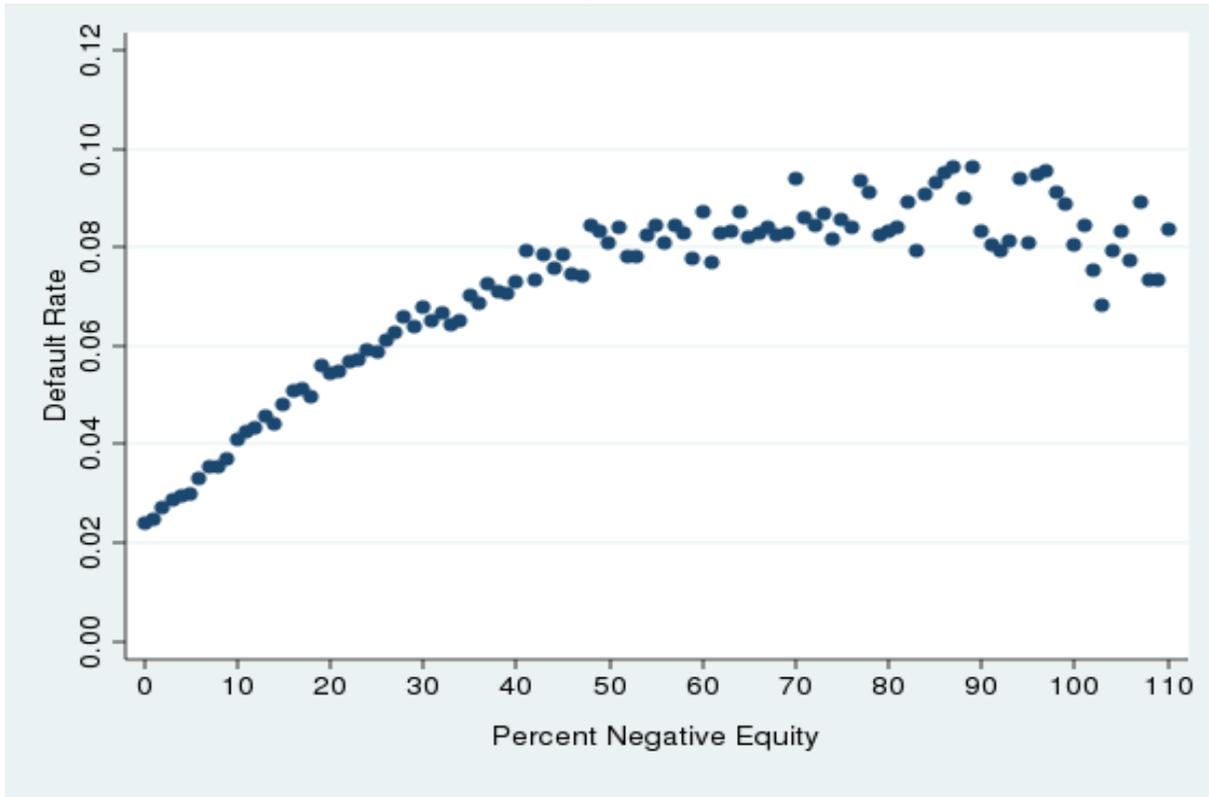
### 3. Distribution of negative equity at time of default decision

Figure 3 shows the distribution of terminal negative equity values for borrowers who defaulted with zero or negative equity. See text for our definition of default, and how equity was calculated.



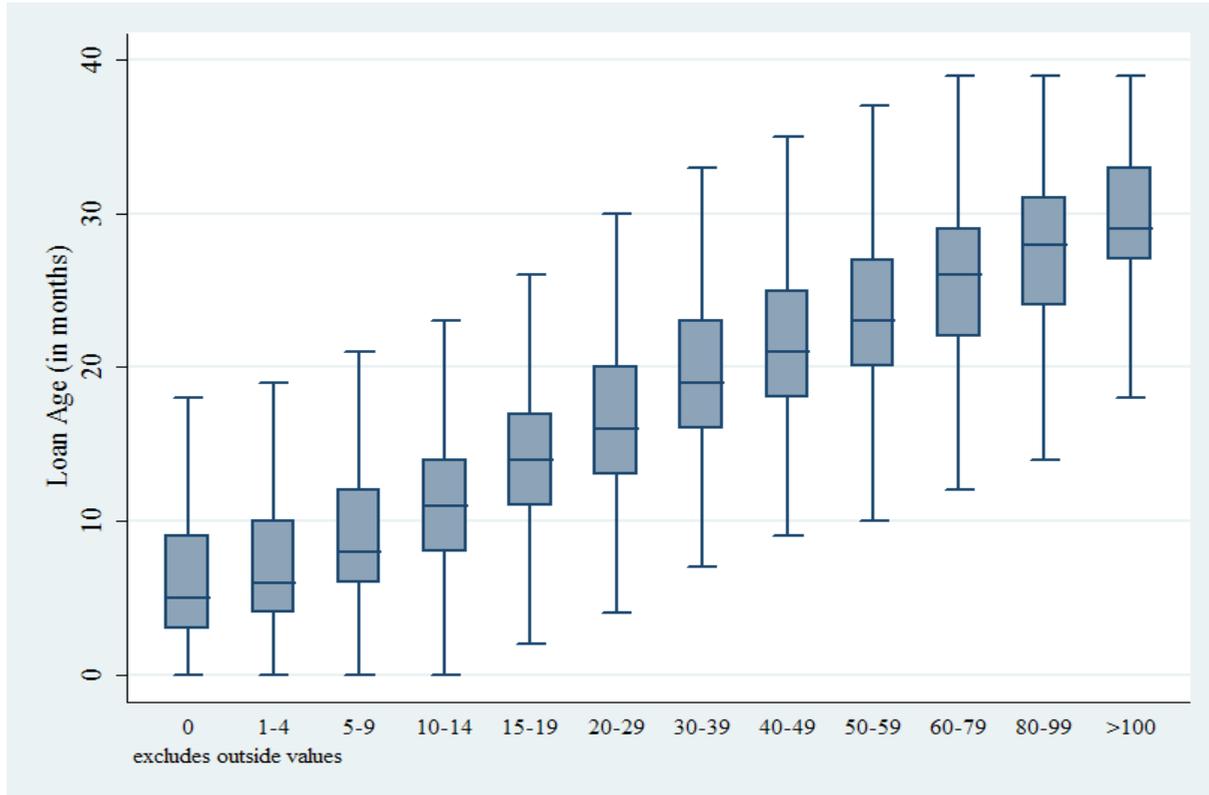
#### 4. Unconditional relationship between negative equity and default

Figure 4 shows the fraction of monthly decisions made at each equity level that were to default. Equity values were rounded to the nearest integer and each data point reflects decisions made within a bin of one percentage point.



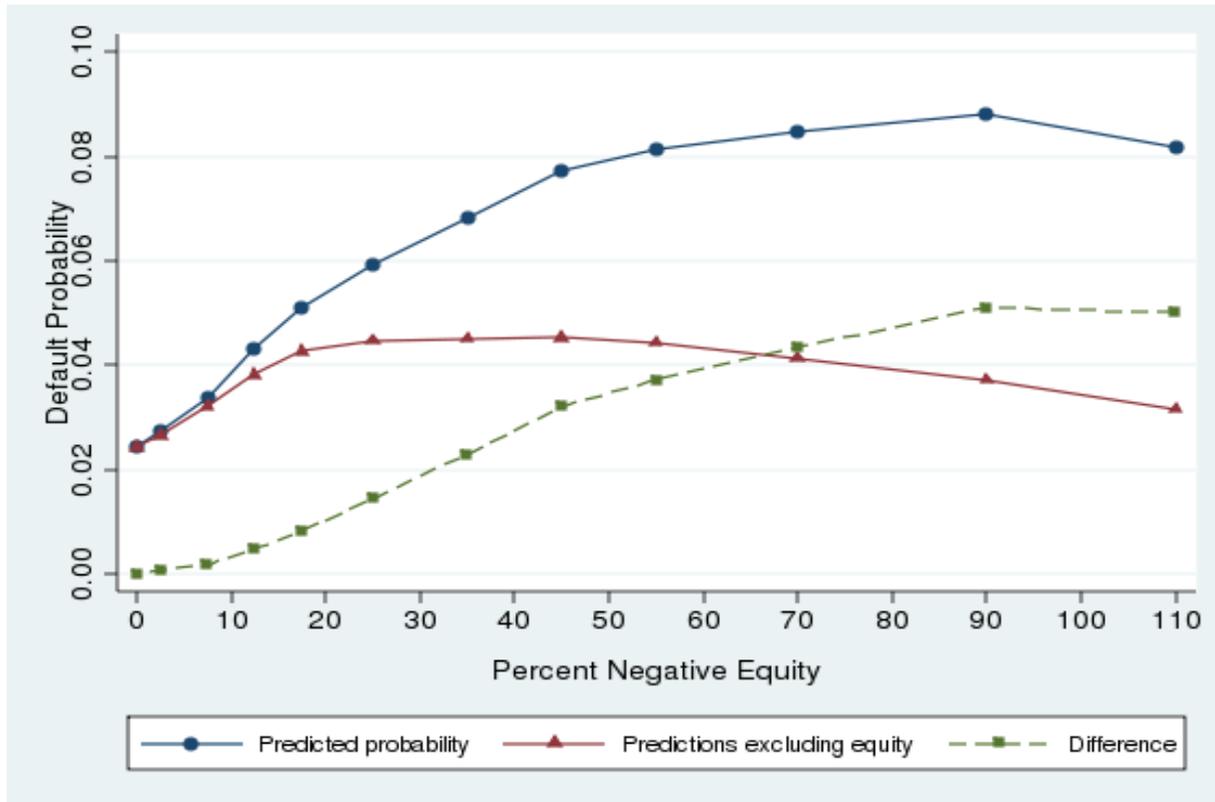
### 5. Distribution of loan age by negative equity groups

Figure 5 shows box plots of loan age within each equity group corresponding to the equity dummy variables we use in our default hazard regression. The box covers the 25th to 75th percentiles of loan age, and the line in the box corresponds to the median value; lines extend from the box the upper and lower adjacent values, and outside values are not shown.



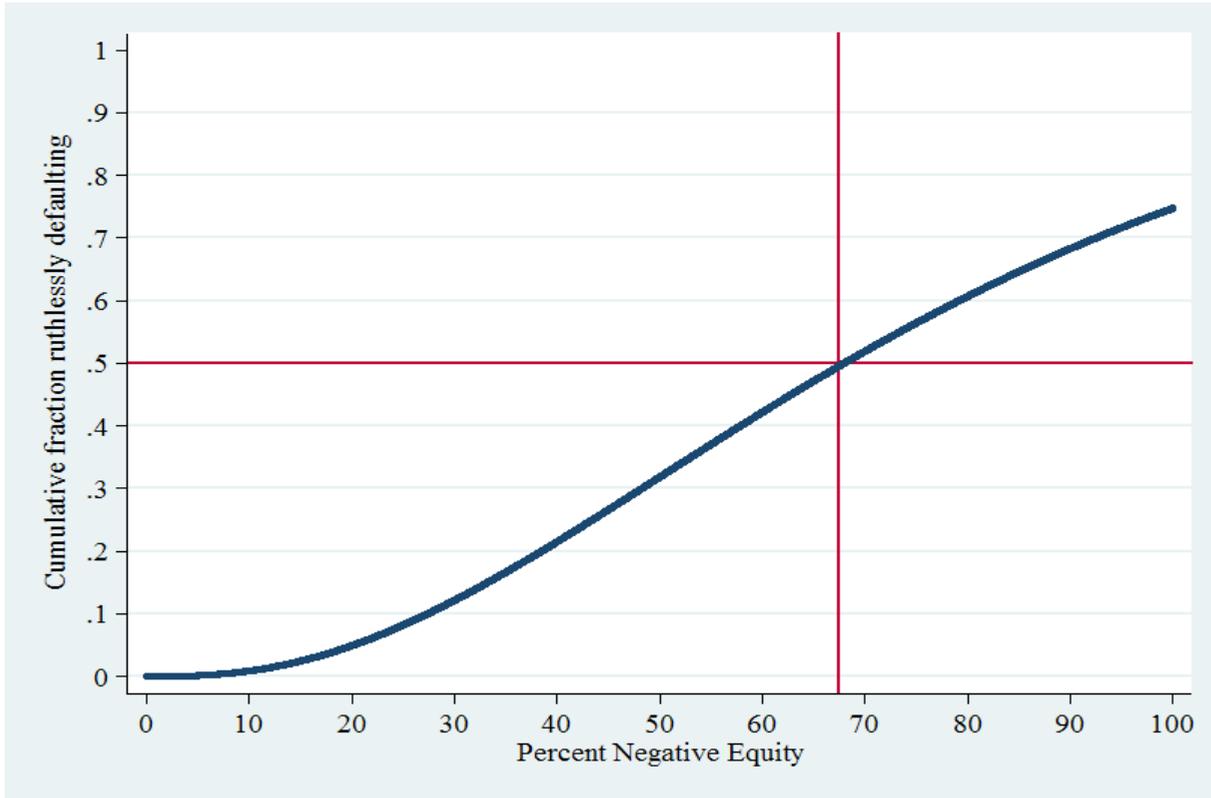
## 6. Decomposition of default probability by negative equity

Figure 6 shows predicted default probabilities based on estimates of equation 3 in the text. The blue markers show average predicted probabilities across observations within each equity bin and trace out a pattern that closely corresponds to the raw data plot shown in figure 4. The red markers show predicted probabilities holding equity constant at zero, while the green markers show the difference or the independent contribution of equity to the overall default probability.



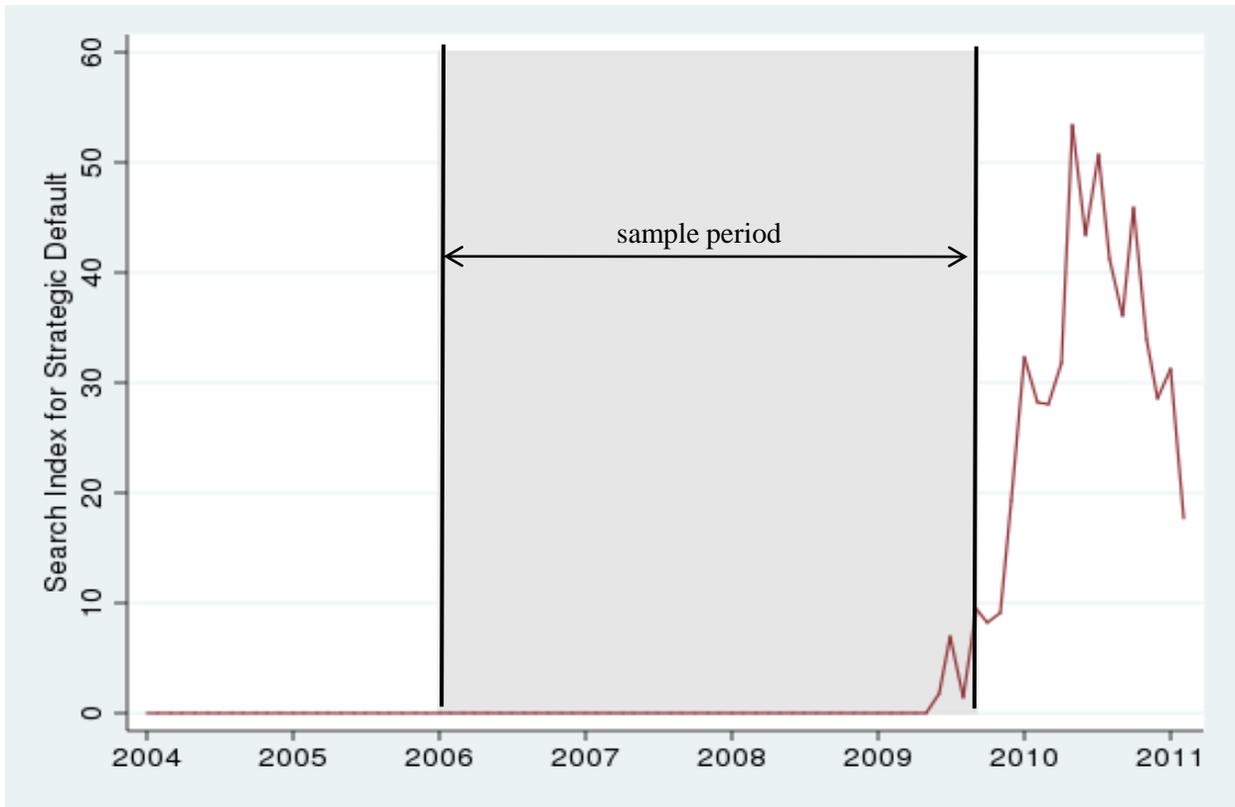
### 7. Estimated cumulative gamma distribution of default costs for sample borrowers

Figure 7 shows the cumulative gamma distribution derived from our baseline estimate of the distribution of default costs or walk-away thresholds among sample borrowers'; as shown in table 3 our estimate of the gamma shape parameter ( $\mu$ ) is 2.88 and our estimate of the scale parameter ( $\kappa$ ) is 26.6. The red lines indicate the median value of the distribution of 67 percent.



### 8. "Strategic default" internet search volume

Figure 8 shows data from Google Insights on the volume of web searches for the term "Strategic default."



## I: Summary Statistics

The top panel shows characteristics at the loan level; the bottom panel shows some characteristics of the ZIP codes where sample borrowers' properties were located based on Census 2000 data and weighted by ZIP code population.

Notes: 1. "Termination" refers to the last month of the sample period for loans that have not defaulted, and the month of default for loans that have defaulted. 2. Unemployment rate data come from the Bureau of Labor Statistics and are measured quarterly. 3. Delinquency data from TransUnion's Trend Data and are measured quarterly.

	(1)	(2)	(3)
	<b>Mean</b>	<b>Median</b>	<b>SD</b>
<b>Loan Characteristics (N=133,281)</b>			
Defaulted During Observation Period	0.78	1	0.42
Home Value at Origination (\$ 000's)	393	360	183
Percent Equity at Termination <sup>1</sup>	-36.9	-27.2	35.7
Equity at Termination (\$ 000's)	-84.9	-66.2	79.2
Scheduled Monthly Payments at Termination (\$)	2011	1828	927
Loan Age at Termination (months)	18.4	18.0	9.8
Interest Rate at Origination (%)	7.4	7.5	1.2
Interest Rate at Termination (%)	7.6	7.5	1.1
FICO Score at Origination	676	671	50.7
Low or No Documentation	0.70	1	0.46
Originated in Arizona	0.09	0	0.28
Originated in California	0.63	1	0.48
Originated in Florida	0.24	0	0.43
Originated in Nevada	0.05	0	0.21
4-Quarter Change in County Unemployment Rate at Termination <sup>2</sup>	1.80	1.30	1.70
4-Quarter Change in County Credit Card 60+ Day			
Delinquency Rate at Termination <sup>3</sup>	0.35	0.30	0.44
<b>ZIP Code Characteristics in 2000<sup>4</sup> (N=1,551)</b>			
Median Home Value (\$ 000's)	172	146	100
Median Household Income (\$ 000's)	46.7	43.2	15.5
Fraction Residents Over Age 25 w/ Bachelor's Degree	0.24	0.21	0.13
Fraction Residents Hispanic	0.27	0.20	0.23
Fraction Residents Black	0.09	0.04	0.13

## II: Logit Estimation of the Probability of Default

Table II shows selected coefficients, standard errors and odds ratios from estimating equation 3 in the text, based on 1.9 million loan-month observations. Other variables controlled for but not shown include quarterly time fixed effects and monthly loan age fixed effects interacted with three county group dummies that indicate the extent to which the county unemployment rate increased between June 2006 and June 2009. Standard errors in parentheses are clustered at the county level.

	(1)	(2)	(3)
	<b>Coefficient</b>	<b>Std Error</b>	<b>Odds Ratio</b>
<b>Housing Equity Fixed Effects</b>			
Equity between -1% and -4%	0.03	(0.03)	1.03
Equity between -5% and -9%	0.05	(0.05)	1.06
Equity between -10% and -14%	0.12	(0.06)	1.13
Equity between -15% and -19%	0.19	(0.07)	1.20
Equity between -20% and -29%	0.30	(0.08)	1.34
Equity between -30% and -39%	0.44	(0.09)	1.55
Equity between -40% and -49%	0.57	(0.10)	1.77
Equity between -50% and -59%	0.65	(0.10)	1.92
Equity between -60% and -79%	0.77	(0.11)	2.16
Equity between -80% and -99%	0.93	(0.11)	2.52
Equity -100% or below	1.01	(0.11)	2.74
Change in Interest Rate	0.41	(0.01)	1.50
Change in Interest Rate Lag 1	0.38	(0.03)	1.46
Change in Interest Rate Lag 2	0.23	(0.01)	1.26
Change in Unemployment Rate	0.16	(0.08)	1.17
Change in Unemployment Rate Squared	-0.01	(0.01)	0.99
Change in Credit Card Delinquency Rate	0.52	(0.08)	1.68
Change in Credit Card Delinquency Rate Squared	-0.20	(0.06)	0.82

### III: Maximum likelihood parameter estimates of the distribution of default costs

Column 1 of the top panel presents our baseline gamma distribution parameter estimates based on the likelihood function shown in equation 5 of the text. Column 2 shows parameter estimates assuming that all defaults are ruthless or, in other words, that the only source of censoring stems from borrowers that do not default during the observation period. The bottom panel describes the estimated distributions of default costs or negative equity threshold values. Standard errors in parentheses are clustered at the ZIP code level.

	(1)	(2)
	<b>Baseline estimates</b>	<b>Estimates assuming <math>s_{iT} = 0</math> for all <math>i</math></b>
Gamma Shape Parameter ( $\mu$ )	2.88 (0.03)	1.31 (0.01)
Gamma Scale Parameter ( $\kappa$ )	26.6 (0.40)	28.1 (0.39)
Percentiles of the Estimated Distribution of Default Costs as Percent of Home Value		
25th percentile	43	14
Median	67	29
75th percentile	101	52
N	94,216	94,216

#### IV. Robustness Checks on the Estimated Distribution of Default Costs

Table IV shows descriptive statistics for various estimated default cost distributions from different specifications or sub-samples of borrowers. In each case, both steps of the estimation are re-run.

	(1)	(2)	(3)
	<b>25th</b>	<b>Median</b>	<b>75th</b>
Baseline Result	43	67	101
Excluding ZIP codes with very different all-in versus non-distressed HPI	44	71	107
Controlling for ZIP code level foreclosure rate in 2006:H1	43	70	107
Including only ZIP codes in the bottom quartile of historical volatility	41	67	105
Including only ZIP codes in the top quartile of historical volatility	49	77	113
Borrowers in Arizona	29	51	83
Borrowers in California	48	78	120
Borrowers in Florida	46	75	115
Borrowers in Nevada	36	66	109
Loans with Full Documentation	59	88	124
Loans with Low or No Documentation	41	67	101
Fixed Rate Mortgages	56	82	116
Adjustable Rate Mortgages	45	72	109