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The role of the economic environment on mortgage defaults during the Great Recession†

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This article shows that the rise in unemployment played a very significant factor in the rise of mortgage delinquencies during the Great Recession. Estimation results, moreover, show that changes in the Unemployment Rate (UR; from loan origination) as opposed to the level of the UR explain mortgage default. Mortgage default is found to be significantly less responsive to declines than to increases in the UR.

Keywords: mortgage; default; unemployment; competing risk models

JEL Classification: C25; C33; G21; D14

I. Introduction

The 2-year period that followed the US subprime market meltdown in August 2007 was marked by a severe deterioration of economic indicators. In that period, House Prices (HPs) (Case–Shiller Index) declined by 35% and the Unemployment Rate (UR) increased from 4.7% to 9.4%. During this stress period, financial institutions needed to markedly increase loss allowance (busting reserves) in anticipation to write-offs and charge-offs. While deterioration of economic indicators during the Great Recession yielded worsening forecasts on default rates and loss allowances, it is also expected that some reversal on the credit exposure at bank portfolios will occur once the economy recovers. Past research by Bangia *et al.* (2002) and others have examined the differential in the loss distribution of credit portfolios in periods of expansion and contraction.

This article shows the effect of the rise in unemployment on mortgage delinquencies during the Great Recession. This article tests whether the trigger of mortgage defaults during this period stems from the change in the UR (from the time the loan is originated to the termination event) or from the level of the UR (at the termination event). This article also examines whether default is significantly less responsive to declines than to increases in the UR.

Results have important implications for financial institutions. For example, *ceteris paribus*, if the change in the UR is the representation (for unemployment) driving default, then lower credit risk valuations (for new originations) may occur under high URs. This would be the case, for example, if the UR is expected to decrease onward from the point of the loan origination. This is relevant since a mortgage application requires proof of employment.

Overall, this article findings reveal important insights on the role of environmental triggers on mortgage defaults.

†This article solely represents the authors' own perspectives and opinions.

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II. Definition of Default

In a mortgage contract, the borrower needs to make monthly scheduled payments. When the borrower is 90-days delinquent in the mortgage payments, the lender usually sends a notice of default. The process of foreclosure is generally started when an attorney is contacted, and the process of foreclosure to property disposition may take 6–24 months depending on the jurisdiction.

For estimation, as in Foote *et al.* (2009) and Bhutta *et al.* (2010), we define default at the time the loan first becomes 90-days delinquent. This event corresponds to the time a notice of default is sent to borrowers. Modelling this early delinquency event allows the model to capture the role of environmental factors on default without the distortions that affect the later stages of default. These distortions are caused by policy variables that relate to foreclosure moratoriums and loan modification programmes intended to reduce the probability of default (Adelino *et al.*, 2009).[1]

III. The Underpinning of Mortgage Defaults

To end a mortgage contract, the borrower has two options. The first option is voluntary prepayment – under this event, the borrower decides to pay off the loan due to either relocation or refinance incentives. The second option is involuntary prepayment – under this event, the borrower exercises the default option at the expense of losing the house that is posted as collateral for the loan. The property is thus taken by the Bank.

The borrower decision to default on the mortgage is generally rational since the borrower always has the choice to voluntarily prepay on the loan. In simple terms, if the value of the collateral surpasses the loan outstanding, then involuntary prepayment (default) is not a rational option.[2]

Strategic default occurs if the borrower has the ability to pay, but still decides to exercise the option to default due to the negative equity associated with the loan. Yet, research has shown that the decision to default is not just a simple strategic calculation. For example, recent work at the Kellogg School of Management has recently surveyed that one-fourth of mortgage defaults are strategic.[3] Also, the number of borrowers under water (~25%) widely exceeds the combined per cent of both defaulted and currently seriously delinquent loans. Therefore, other factors in addition to the equity position explain loan defaults (Ronel *et al.*, 2010).

Overall, borrowers default if they foresee being 'better off' (generate more utility) with the decision to default relative to the alternative options. And the decision to default is not solely driven by the equity position that the borrower has on the loan. Ability to pay and willingness to pay are likely factors, in addition to loan equity, in explaining the choice of mortgage default.

For modelling borrower choice, we observe the default event and are, therefore, able to model the probability event of default in terms of its main drivers as follows:

$$\begin{aligned}&\text{Prob(Default at time } t)\\&\quad = F(\text{Ability to pay, willingness to pay,}\\&\qquad \text{equity position})\end{aligned} \tag{1}$$

A difficulty in modelling Equation 1 is that we only observe proxies for ability to pay, willingness to pay and equity position. For example, to proxy equity position, the literature uses regional housing price indexes to update property values needed to calculate equity position at default.[4] For willingness to pay, we have the creditworthiness of the borrower. To proxy creditworthiness, the industry uses credit (FICO) score (Fabozzi, 2006), a credit quality index based on credit repayment history.[5] Ability to pay is captured by a curtailment on income that the borrower may experience during the life of the loan – the most significant source of curtailment of income is the loss of employment. This information, however, is not readily available at the borrower level.[6] Therefore, as an observable proxy for ability to pay, we use the regional change in the UR index, which captures borrowers' likelihood of entering the pool of the unemployed.

In modelling ability to pay, a question is whether the change in the UR (from the time the loan is

[1] Capozza and Thomson (2006) model the factors that explain the transition of the loan from early default (90-days delinquent) to foreclosure and Real Estate Owned (REO) statuses.
[2] Modelling mortgage default has a different response behaviour than that observed in bankruptcies (Hillegeist *et al.*, 2004).
[3] See Guiso *et al.* (2010).
[4] Changes in HPs are the main drivers of mortgage defaults (Archer *et al.*, 1996; Deng *et al.*, 2000).
[5] We use the FICO at the point of loan origination.
[6] For example, the Lender Processing Services (LPS) data do not include information on the employment status of the borrower.

Table 1. Variable definitions

Variable	Definition
FICO	Original FICO scores as reported in the LPS data set
MTMLTV	Outstanding balance at time t/estimated property value at time t
Outstanding balance at time t	Outstanding loan balance (at time t) as reported by LPS
Estimated property value at time t	(Property value at origination) × (HP at time t)/(HP at origination) HP refers to the Federal Housing Finance Agency (FHFA) HP Index (evaluated at the state level)
Change on UR from loan origination	$\ln(UR_t/UR_0)$ UR_t is the state employment rate at time t UR_0 is the state unemployment rate at origination UR refers to the unemployment rate as reported (at the state level) by the Bureau of Labor Statistics
Change on HP from loan origination	$\ln(HP_t/HP_0)$ HP_t is the state House Price Index at time t HP_0 is the state House Price Index at loan origination HP refers to the Federal Housing Finance Agency (FHFA) House Price Index (evaluated at the state level)

originated to the termination event) is a better predictor of defaults than the level of the UR (at the termination event). Intuitively, the change in the variable better captures the probability of the borrower entering the pool of the unemployed and, therefore, it is likely to be a more adequate proxy for ability to pay than the level of the UR.

Table 1 details the variable definitions that are used in the model to capture equity position, willingness to pay and ability to pay. [7] Using the proxies and definitions in Table 1, Equation 1 can be more concretely represented as

$$\begin{aligned}&\text{Prob(Default at time } t)\\&\quad = F(\text{MTMLTV}_t,\ \ln(\text{HP}_t/\text{HP}_0),\\&\qquad \text{FICO},\ \ln(\text{UR}_t/\text{UR}_0))\end{aligned} \tag{2}$$

IV. Estimator of Mortgage Default

There are different alternative estimators of Equation 2. The model can be estimated, for example, in terms of the unconditional probability of default. Rigour is, however, an important component in estimation of a survival function. In modelling Equation 2, a method that is widely adopted in industry and academics is to estimate the probability of default with a panel data (see, e.g. Foote *et al.*, 2009; Bhutta *et al.*, 2010). The panel data framework tracks each payment of the borrower until a termination event (due to either prepayment or default). The theoretical foundations of the panel structure in modelling default stems from the competing hazard risk framework (Hosmer *et al.*, 2008).

The competing risk framework has two main attributes: (1) it successfully addresses the censoring component of modelling defaults and prepayments and (2) it encompasses an econometric structure that is flexible and simple to estimate. Importantly, it allows default to be modelled independently from attrition (Hosmer *et al.*, 2008). Different variants of the competing risk framework (e.g. panel logistic versus continuous time framework) have been shown to yield similar projections.

To properly implement estimation of Equation 2, the data are set up so the loan permanently falls from the panel after the termination event. This event occurs when either the borrower either prepays on the loan or the borrower incurs a 90-days delinquency. The competing hazard framework thus requires a censoring of the data. The censored data capture the probability of default at each payment cycle for loans that are active up to that payment cycle.

After properly censoring the data, estimation can proceed using a simple logistic regression. Estimation of the default equation thus uses the familiar structure

$$\begin{aligned}&\text{Prob(Default at month } t \mid \text{Survive up to time } t)\\&\quad = \exp(I_{\text{Dt}})/[1+\exp(I_{\text{Dt}})]\end{aligned} \tag{3}$$

where, from Equation 2, $I_{\text{Dt}} = F(\text{MTMLTV}, \ln(\text{HP}_t/\text{HP}_0), \text{FICO}, \ln(\text{UR}_t/\text{UR}_0))$.

To estimate the response of default in Equation 3 to each covariate, we use the LPS data set.[8]

V. Estimation

The LPS is a public data source that collects monthly activity data on mortgages from servicers. The data report late payments, outstanding balance and indicators of whether the borrower prepaid or defaulted

[7] It is important to recognize that there are alternative proxies (such as interest rates) that may explain default.
[8] This data set is increasingly used to examine recent periods of mortgage default (e.g. Elul, 2009; Foote *et al.*, 2009).

on the loan. The data include the credit score and equity position of the loan at origination. Researchers at top originating, issuing, investing and rating organizations depend on LPS database-driven modelling and analytics to evaluate portfolio collateral performance.

The LPS data provide monthly information on the delinquency status of the loan and whether the loan is active. The data thus allow estimation of Equation 3 using a panel framework. The default event is defined at the first reported 90-days delinquency event on the loan.

The LPS data contains the Loan to Value (LTV) ratio of the loan at origination. The data, however, do not report the current equity of the loan. To calculate the current equity (Market-to-Market LTV, MTMLTV) at account time t, we use the ratio of the loan outstanding balance and the value of the property at account time t. The property value is updated each month using state-level price indexes from the FHFA. Data on state-level changes in the rate of unemployment are extracted from Bureau of Labor Statistics. We use both the UR at origination and the UR at each account period t.

It is expected that the probability of default is larger when a loss on the value of the loan collateral is observed. It is also expected that the probability of default is larger when the UR spikes since more borrowers are unable to meet their obligations. In the model specification, the economic environment is modelled in terms of the effect of HPs on loan equity as well as the change in the UR from loan origination up to the account date.

For the functional structure in Equation 3, we allow for an asymmetric response of default to changes in unemployment. Specifically, the change in the UR from loan origination – $\ln(UR_t/UR_0)$ – is allowed to have a nonlinear impact on default. To better identify the effect of unemployment on default, we also incorporate in the model the change in HP from loan origination to the account date – $\ln(HP_t/HP_0)$. This HP effects enters in addition to its effect on MTMLTV.

FICO and MTMLTV also enter nonlinearly in the estimation of Equation 3. Nonlinearity is important because an increase in LTV from 80 to 90 will have a different impact (on absolute values) that an increase in LTV from 90 to 100. We use splines to capture the nonlinear responses in Equation 3.

The estimation sample consists of a panel of default events for Fixed-Rate Mortgage (FRM) products reported in the period January 2007 to June 2009. This period captures the dynamics of the Great Recession and its impact on mortgage defaults. During this period, the per cent of loans that were 90-days (or more) delinquent jumped from 0.82% to 4.13%; the average MTMLTV increased from 63% to 78%; the per cent of loans with negative equity jumped from 1.9% to 17%; and the UR increased from 4.6% to 9.3%.

Estimation of Equation 3 uses a logistic regression and it is implemented using a standard procedure in SAS. Table 2 shows the coefficient estimates. The table yields the expected relationship between default and the proxies for loan equity, willingness to pay and ability to pay.

In assessing the coefficients in Table 2, an important diagnostic test is whether coefficients of variables in the model are identified. For example, severe multicollinearity across covariates may preclude separation (identification) of the impact of economic factors on default. Table 3 examines the validity of the model specification in Table 2 for inference analysis.

Table 3 shows that tolerance and Variance Inflation Factor (VIF) of time-varying covariates in Table 2 ranges from 0.5 to 0.9 and from 1 to 2.5, respectively. Since a tolerance of less than 0.20 and/or a VIF of 5 (and above) indicates a multicollinearity problem (O'Brien, 2007), then the model specification has acceptable levels of collinearity among covariates. Checking for such diagnostic is necessary for reliable inference analysis.[9]

Importantly, from Table 3, the test indicates that multicollinearity should not preclude inclusion of both the UR and HP index in the model. The two series are sufficiently uncorrelated to generate reliable inferences.

VI. The Effect of Unemployment on Mortgage Default

Table 2 shows the effect of the rise in unemployment on mortgage defaults during the period that captures the dynamics of the Great Recession. From the coefficients in Table 2, Fig. 1 shows the hazard (odds) ratios of unemployment growth on conditional default rates. The baseline for the hazard ratios is the case of no change in the UR.

From the figure, an increase in the UR of 80% (e.g. from 5% to 9% UR) explains an increase in the monthly default rate of 230%. It also shows that an increase in UR of 50% (e.g. from 5% to 7.25% UR) explains an increase of conditional default by 80%.

[9] To implement the multicollinearity test, we use PROC REG command with options VIF TOL in SAS.

Table 2. The impact of loan attributes on conditional defaults

Variable	Estimate	SE coefficient	χ^2	p-value
Constant	1.63	0.04	1430	< 0.0001
FICO[a] $\leq$660	−0.01	0.0001	24 054	< 0.0001
660 < FICO $\leq$ 720	−0.02	0.0002	13 114	< 0.0001
FICO > 720	−0.02	0.0002	7756	< 0.0001
MTMLTV[b] < 75	0.17	0.02	94	< 0.0001
0.75 $\leq$ MTMLTV < 0.95	2.41	0.05	2390	< 0.0001
0.95 $\leq$ MTMLTV < 1.05	3.10	0.16	366	< 0.0001
MTMLTV $\geq$ 1.05	0.77	0.12	40	< 0.0001
$\ln(HP_t/HP_0) > 0$	−1.59	0.06	81.75	< 0.0001
$\ln(HP_t/HP_0) < 0$	−0.85	0.04	357	< 0.0001
$\ln(UR_t/UR_0) > 0$	1.43	0.01	16 126	< 0.0001
$\ln(UR_t/UR_0) < 0$	0.30	0.03	66	< 0.0001
Dummy variable for 80LTV	0.09	0.01	88	< 0.0001

Notes: [a]FICO is modelled as a spline functional:
$-0.01 \times \text{FICO}$
$-0.02 \times (\text{FICO} - 660) - 6.6$
$-0.02 \times (\text{FICO} - 720) - 7.8.$
[b]MTMLTV is also modelled as a spline functional:
$2.41 \times (\text{MTMLTV} - 0.75) + 0.13$, if $\text{MTMLTV} \in [0.75, 0.95)$
$3.10 \times (\text{MTMLTV} - 0.95) + 0.61$, if $\text{MTMLTV} \in [0.95, 1.05)$
$0.77 \times (\text{MTMLTV} - 1.05) + 0.92$, if $\text{MTMLTV} > 1.05$.

Table 3. Tolerance and variance and inflation factor tests

Variable	Tolerance	VIF
FICO $\leq$ 660	0.65	1.53
660 < FICO $\leq$ 720	0.41	2.40
FICO > 720	0.57	1.72
MTMLTV < 75	0.68	1.46
0.75 $\leq$ MTMLTV < 0.95	0.50	1.99
0.95 $\leq$ MTMLTV < 1.05	0.49	2.00
MTMLTV $\geq$ 1.05	0.72	1.37
$\ln(HP_t/HP_0) > 0$	0.65	1.53
$\ln(HP_t/HP_0) < 0$	0.74	1.35
$\ln(UR_t/UR_0) > 0$	0.70	1.42
$\ln(UR_t/UR_0) < 0$	0.63	1.58
Dummy variable for 80LTV	0.95	1.04

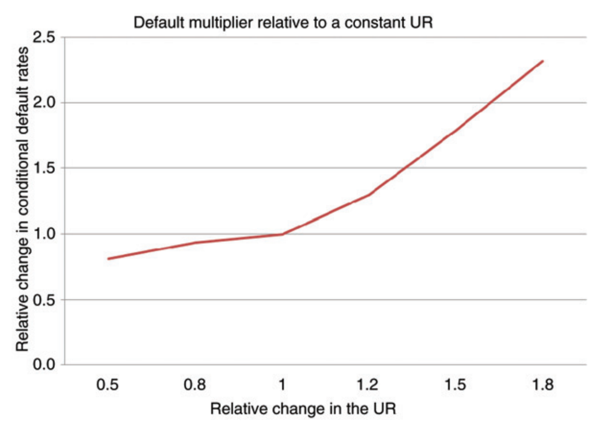

Fig. 1. Default multiplier to changes in the unemployment rate

Figure 1 also underscores the smaller sensitivity of default to decreases in the UR. An increase in the UR of 10% yields an increase in the probability of loan default of 15%, while a decrease in the unemployment of 10% yields a decrease in the probability of loan default of 3%.

The impact of unemployment on mortgage default can be further exemplified by mapping changes in unemployment onto a FICO-like metric.

Figure 2 shows a representation of changing unemployment (Fig. 1) under a FICO metric. From the table, a FICO score of 660 with no change in unemployment has a similar performance than a FICO score of 723 originated in a period where UR increased by 80%. More generally, 7 FICO points penalty is equivalent to a 10% increase in the UR.

The derived mapping to the FICO score underscores the correlation of underwriting conditions with the economy.[10] That is, after a loan is originated, a FICO score has very different inferences on default depending on whether economy is expanding or contracting. The large downgrades of FICO under a

[10] Sarmiento (2009) uses iso-risk curves to map FICO scores to different underwriting cycles.

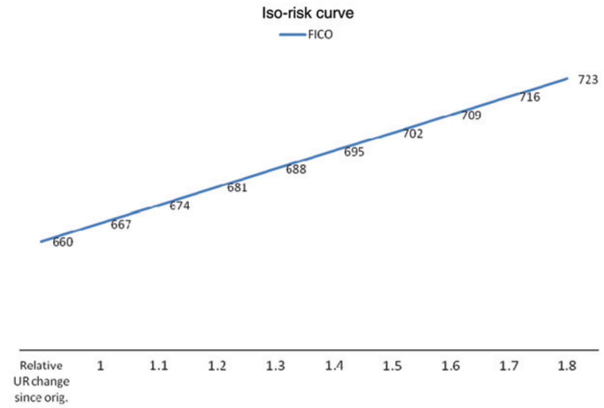

Fig. 2. Level curve between FICO and changes in the unemployment rate

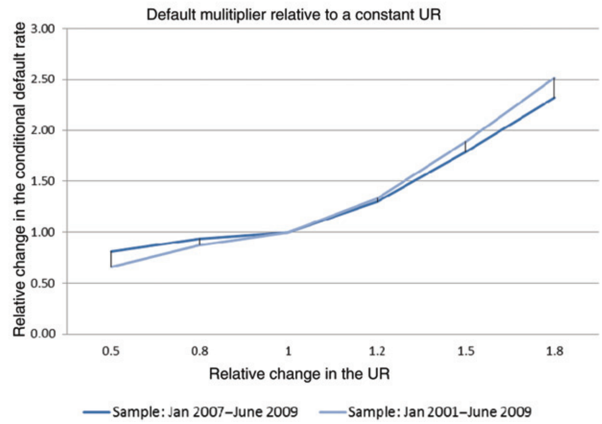

Fig. 3. Default multiplier under different sample sizes

period of increasing URs (such as the Great Recession) underscore the importance for financial institution to build reserves under stress scenarios.[11]

VII. Comparing Change Versus Levels

Two alternative structures to model the effect of unemployment on loan default are (1) to model the change in the UR (from the time the loan is originated to the termination event) and (2) to model the level of the UR (at the termination event). The implications of the selected structure for the UR are important. For example, if the change in the UR is the representation (for unemployment) driving default, then lower credit risk valuations (for new originations) may occur under high URs. This would be the case, for example, if the UR is expected to decrease onward from the point of the loan origination. This is relevant since a mortgage application requires proof of employment.

Using the structure of the estimated model in Table 2, but allowing for different treatments of the unemployment covariate in the model, we test whether the change in the UR (from loan origination) better captures mortgage defaults than the level of the variable. The structure of the test for use of levels versus change in the UR is

$$\text{Prob(Default)} = \exp(\gamma Y_1 + (1-\gamma)Y_2)/(1+\exp(\gamma Y_1 + (1-\gamma)Y_2)) \quad (4)$$

where Y_1 is the prediction of the default model (Equation 3) associated with using the level of the UR and Y_2 is the prediction of the default model (Equation 3) associated with using the change in the level of the UR (from loan origination).

The structure of the test in Equation 4 is an adaptation of the forecasting encompassing test structure introduced by Fair and Shiller (1990). The test allows us to weigh the importance of competing model structures in explaining the decision to default on the mortgage. In our application, estimation of Equation 4 yields $\gamma = 0.04$ with a $\Pr > \text{chi} = 0.16$. Therefore, we cannot reject the null hypothesis that the level of the UR does not explain mortgage default beyond the power provided by the change in the UR (from loan origination). The change in the UR is a better proxy of ability to pay than using the UR.

Consistent with the nonnested test, estimation results in Table 2 show large differences in the sensitivities of default to a change in the UR. Default is significantly less responsive to declines than to increases in the UR. This result is found to be robust to alternative model specifications.[12]

To further examine the robustness of the result that default is significantly less responsive to declines than to increases in the UR, we examine different time periods of the data. Specifically, we re-estimate Equation 3 including periods that extend the Great Recession period. For the estimation period January 2001 to June 2009, Fig. 3 shows that default is significantly less responsive to declines than to increases in the UR. The result indicates that this

[11] An interesting area of research is how updates to the model underlying FICO affect the predicted power of FICO and how changes to the FICO model are affected by the economic environment.

[12] The variable change in HPs from loan origination to the account date in Table 1 helps to better identify the effect of unemployment on default. An alternative model formulation that uses dummy variables for vintage (rather than HP changes from origination) yields similar estimates of the effect of unemployment on mortgage default.

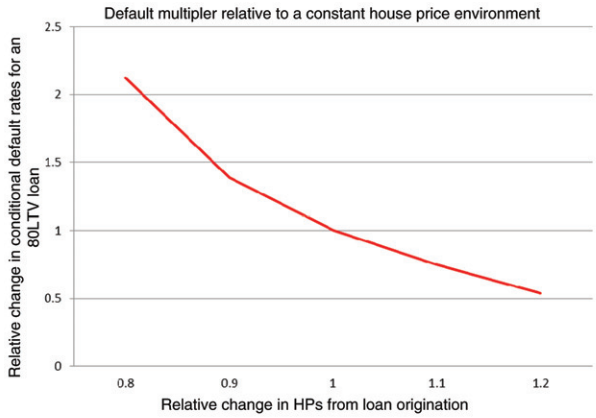

Fig. 4. Default multiplier to house price environments

premise of this article holds for an extended period of time. And, yet, the multiple of the change in the UR on default does change (as expected) with the estimation period. This implies that the interpretation of the point estimates depends on the period under consideration.

VIII. Modelling HPs

Only borrowers with negative equity have the incentive to default. While ideally to estimate default, we would have information on changes in the appraised values of the property across the life cycle of the loan, such information is not readily available and it is beyond the scope of this article. In the absence of appraisals, the literature uses price indexes to update LTV ratios at each account period. Estimation of Equation 3 uses information (available for this study) that is provided by (state level) HP indexes.[13]

From the coefficients in Table 2, Fig. 4 shows default multiples under different HP environments. HPs impact default through changing the MTMLTV as well as directly through the HP change variable. Figure 4 shows, as expected, that default is more responsive to HP inclines than to HP declines for a typical 80LTV loan.

In the interpretation of Fig. 4, it is important to emphasize that HP indexes are only proxies of the actual economic circumstance of each borrower. As a result, Fig. 4 may not fully reveal the importance of 'actual' equity changes on default. This limitation is present in most studies of mortgage default currently in the literature (Ronel *et al.*, 2010).

IX. Conclusions

The most defining feature of the Great Recession was the increase in the UR. While mortgage defaults are practical only when the borrower faces no equity, we estimated increases in the likelihood of default that stems from an increase on the UR.

Nonnested test indicated that the change in the UR (from origination) is a better predictor of default than the level of the variable. Consistent with the nonnested test, estimation results show large differences in the sensitivities of default to a change in the UR. Default is significantly less responsive to declines than to increases in the UR.

A promising area of future work is examining more refined data sets to test the hypotheses tested in this article. For example, research that is able to match LPS data to a borrower's actual loss of employment event is likely to generate important breath of information.

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[13] Future work should examine the gains in precision from using ZIP-level indexes (and other aggregation levels) relative to state-level indexes. Data on ZIP level indexes were not available in this study.

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