Mortgage Default Risk and Local Unemployment

Working Paper: March 2011

By
Roberto G. Quercia
Anthony Pennington-Cross
Chao Yue Tian

Center for Community Capital
The University of North Carolina at Chapel Hill

Prepared with financial support from The Ford Foundation

Center *for* Community Capital
Research and analysis on the transformative power of capital

UNC
COLLEGE OF
ARTS & SCIENCES

Mortgage Default Risk and Local Unemployment

Roberto G. Quercia

University of North Carolina at Chapel Hill

Chapel Hill, NC, 27599

Phone: (919) 843-2493 Fax: (919) 843-2080

quercia@email.unc.edu

Anthony Pennington-Cross

Marquette University

Phone: (414) 288-1452 Fax: (414) 288-5756

anthony.pennington-cross@marquette.edu

Chao Yue Tian

University of North Carolina at Chapel Hill

Chapel Hill, NC, 27599

Phone: (919) 843-0544 Fax: (919) 843-2080

tianc@email.unc.edu

March 2011

Abstract

In response to the recent housing market downfall and economic crisis, a federal program, Hardest Hit Fund (HHF), was created to help troubled families stay in their homes. Eighteen states and the District of Columbia were selected due to high unemployment rates in 2009 and/or sharp house price declines. Using a sample of community reinvestment loans originated between 1997 and 2009, we examine empirically the potential effectiveness of the program. Consistent with the program intentions, we find that default rates have been more sensitive to changes in local unemployment in the participating states than in the rest of the nation. However, at the county level, we find that changes in default rates are most sensitive to changes in the structural component rather than the level of local unemployment rate. As a result, the HHF could be more effective in reducing default risks if it targeted counties where the long run unemployment situation is worsening.

I. Introduction

The Great Recession changed in the first quarter of 2009. The crisis changed from one driven by the boom and bust of the subprime market to one driven by worsening employment conditions. Today, because employment is a precondition for most households to meet their financial obligation, reducing local unemployment rates is seen an important step toward lowering mortgage defaults and foreclosures. As a result, the US Department of Treasury developed the "Hardest Hit Fund"[1] (HHF), which was authorized under the Emergency Economic Stabilization Act of 2008. HHF attempts to stabilize local housing markets by providing funds to 18 states and the District of Columbia that have experienced high unemployment level or a steep decline in property values in 2009.

The role of local and national unemployment rates on mortgage performance has been examined in the literature. Often used as a proxy for adverse (trigger) events (Quercia and Stegman 1992), the unemployment rate has been found to be positively associated with mortgage delinquency (Campbell and Dietrich 1983), mortgage default (Capozza, Kazarian, and Thomson 1997, Deng, Quigley, and Van Order 2000, and Pennington-Cross and Ho 2010), mortgage foreclosure (Elmer and Seelig 1999), and negatively associated with mortgage prepayment (Campbell and Dietrich 1983, Deng, Quigley, and Van Order 2000, and Pennington-Cross and Ho 2010). On the other hand, the pattern of mortgage default in response to the level of local unemployment rate has not been established.

[1] http://www.financialstability.gov/roadtostability/hardesthitfund.html accessed November 2010.

Unemployment rates reflect the different stages of the business cycle. The rates can be viewed as a combination of a permanent (or trend, structural) component, a cyclical component, and a seasonal component. Unemployment caused by long term mismatches between labor supply and demand is often referred to as structural unemployment while cyclical unemployment is associated with temporary labor market conditions. These two components may have distinct patterns of movement and statistical properties (Mocan 1999).

Theoretical or empirical links between the business cycle theory and the mortgage market have yet been established in the literature. If structural unemployment is the underlying determinant of mortgage performance, using the level of unemployment rate may not be the most effective mechanisms to target HHF resources aimed at reducing mortgage risks by dealing with the unemployment problem. In this paper, we examine the relationship between the business cycle and the mortgage market by decomposing the local unemployment rate into its permanent and cyclical components and examining their respective relationship to default risks. We examine such patterns using a sample of Community Reinvestment Act loans originated between 1997 to 2009. We use both the Beveridge-Nelson (BN) decomposition (Beveridge and Nelson 1981) and the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997) as decomposition alternatives.

The findings show that decomposition matters. When decomposition is not used, we find that mortgage default risks in areas that have experienced sustained high monthly unemployment or the largest increase in monthly unemployment between 1997 and 2009 are not the most responsive to changes in local unemployment rates. In contrast, when decomposition is used, we find that default rates are most sensitive to changes in local unemployment in areas where the structural component of local unemployment rate is increasing (or the long run unemployment is worsening). These findings have important policy implications dealing with the ongoing foreclosures and defaults.

The remainder of the study is divided into four sections. The next section discusses the business cycle and unemployment decomposition followed by a description of the empirical strategy and the data. The empirical findings are presented in Section IV. In the last section, we use the findings to derive implications for the HHF and similar efforts aimed at reducing default risks by addressing the unemployment problem.

II. Local Unemployment within the Business Cycle Context

A seasonally adjusted time series y is viewed as the combination of a permanent component and a cyclical component as follows

$$y_t = c_t + \tau_t \qquad (1)$$

where c is the cyclical component and τ is the trend component. Numerous approaches have been proposed to separate the cyclical component and the trend component in equation (1) (for a review, see Ozyildirim and Zarnowitz 2006) including the unobserved component approach (Harvey 1985), the BN decomposition, the HP filter, and the Band-pass filter (Baxter and King 1999). These different approaches are based on assumptions about features of the permanent component and the cyclical components that can lead to different decomposition results. For example, the estimated trend component using the BN decomposition is often much closer to the actual series than that estimated using the HP filter. This is because the BN decomposition assumes correlated trend and cyclical components while the HP filter imposes a smooth shape on the trend. The difference between the BN decomposition and the unobserved component approach is also due to the fact that the latter imposes a zero correlation between trend and cycle innovations. Morley, Nelson, and Zivot (2003) and Sinclair (2009) introduce correlation in the structural models of the latter.

Perhaps the most intuitive (and the empirically least complicated) decomposition technique is the linear deterministic trend approach. However, this approach is not theoretically (or empirically) sound when the series is not stationary (Stock and Watson 1988). Many tests have been designed to detect unit roots in time series including Dickey and Fuller (1981), Perron and Phillips (1988), and Perron (1989). The existence of a unit root process indicates that a series is not stationary. The augmented Dickey-Fuller tests are performed on the unemployment rates between 1990 and 2009 for different counties and the US.[2] The results show that among the 540 counties examined, test statistics reject a unit root process at 10 percent level for only 12 counties. The same tests reject a unit root process of the first difference of unemployment rates for 534 counties. Table 1 is

[2] The results will be available from the authors upon request.

the Augmented Dickey-Fuller test results for the US unemployment rate (seasonally adjusted) and its first difference. It shows the US unemployment rate is an I(1) process (unit root in the level but not in the first difference).[3] These results, combined with the fact that empirical results are often sensitive to de-trending techniques, indicate it is necessary to examine decomposition techniques that do not require a series to be stationary. This paper uses the BN decomposition and the HP filter as alternative de-trending techniques. The BN decomposition requires a series to be difference stationary. This is indicated by the augmented Dickey-Fuller tests in our case and the HP filter does not require the series to be stationary.

Insert table 1 here:

BN Decomposition

Denote the first difference of the non-stationary series y in equation (1) by w. w is stationary and it can be expressed as follows

$$w_t = \mu + \varepsilon_t + \lambda_1 \varepsilon_{t-1} + \dots \qquad (2)$$

where μ is the expectation of w. Beveridge and Nelson (1981) show that the trend component can be expressed as

3 It has been argued that the US unemployment rate is stationary (see Mocan 1999 for a review), especially given that it is bounded by definition. This study simply relies on the particular unit root test as the basis for examining different de-trending techniques rather than joining the discussion of whether the (US) unemployment rate is stationary.

$$\tau_t = y + \left(\sum_{1}^{\infty} \lambda_i\right)\varepsilon_t + \left(\sum_{2}^{\infty} \lambda_i\right)\varepsilon_{t-1} + \ldots \quad (3)$$

and the cyclical component is $\left(\sum_{1}^{\infty} \lambda_i\right)\varepsilon_t + \left(\sum_{2}^{\infty} \lambda_i\right)\varepsilon_{t-1} + \ldots$.

HP Filter

The idea of the HP filter is to assume the trend component τ in equation (1) to be smooth over time and the series $\{\tau_t\}$ is estimated by solving the following problem.

$$\min_{\{\tau_t\}} \left\{ \sum_t c_t^2 + \lambda \sum_t \left[(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})\right]^2 \right\} \quad (4)$$

where λ (a different parameter than the one in equation 2) determines how smooth the series $\{\tau_t\}$ is and larger values correspond to more smoothed series.

III. Empirical Strategy and Data

Following Deng, Quigley, and Van Order (2000) McCall (1996), and Pennington-Cross and Ho (2010), a competing risk, proportional hazard model and data from a national sample of community reinvestment loans are used to examine the relationship between unemployment and loan performance.

Survival and Hazard Specification

Under the competing risk, proportional hazard framework, the loan default and prepay are jointly modeled while addressing the data censoring issue. The estimation relies on the construction of the hazard and the survival functions, which are introduced as follows.

Let λ_i^r be the hazard rate of default ($r = D$) or prepay ($r = P$) for loan i. The hazard is specified as

$$\lambda_i^r\left(t \mid X_i(t), \theta_D, \theta_P\right) = \exp\left(\lambda_0^r(t) + X_i(t) * \beta_r + \theta_r\right) \tag{5}$$

where λ_0^r is the baseline hazard, $X_i(t)$ are the risk determinants at time t and β_r are coefficients to be estimated and θ_r is the heterogeneity which is independent of observed characteristics. The prepayment and default events are assumed to be independent and the corresponding survival function S_i is defined as:

$$\begin{aligned} & S_i\left(t \mid X_i(t), \theta_D, \theta_P\right) \\ & = \exp\left(-\int_0^t \left[\lambda_i^D\left(s \mid X_i(t), \theta_D, \theta_P\right) + \lambda_i^P\left(s \mid X_i(t), \theta_D, \theta_P\right)\right] ds\right) \end{aligned} \tag{6}$$

The log likelihood, LL, is expressed in discreet time assuming risk determinants are constant within each time interval.

$$LL = \sum_{uncensored} \log \lambda_i^r\left(t \mid X_i(t), \theta_D, \theta_P\right) + \sum_{all} \log S_i\left(t \mid X_i(t), \theta_D, \theta_P\right) \tag{7}$$

The baseline hazard is estimated using local regression to smooth the Kaplan-Meier hazards of prepay and default. The smoothing parameters are set to maximize the Akaike information criteria (AIC), 0.32 for default and 0.27 for prepay. The same set of risk determinants are chosen for both default and prepayment. Default is defined as the first month with an observed 90-day delinquency on a mortgage and prepayment as the month in which the loan is paid off prematurely. The specification of heterogeneity mass point p_m for group m, following Pennington-Cross and Ho (2010), is defined in a logistic transformation which bounds the probabilities between zero and one.

$$p_m = \frac{e^{q_m}}{\sum_m e^{q_m}} \tag{8}$$

where $q_m \in (-\infty, +\infty)$ and q_1 is normalized to 0.

Decomposition Implementation and County Grouping

This study examines unemployment rates between 1997 and 2009 in 540 counties. Local Area Unemployment Statistics data from the Bureau of Labor Statistics provide unemployment information for each county with no seasonal adjustment. Therefore, each series is seasonally adjusted using the Census X11 method.[4]

The implementation of BN decomposition follows Newbold (1990). Assume that w_t in

4 The most current version of seasonal adjustment at Census is X12 and the authors do not find significant difference in adjusting the US unemployment rate for the sample period using X11 and X12.

equation (2) follows an ARMA(p, q) process and let ϕ_1 through ϕ_p be the AR parameters. Let $\hat{w}_t(j)$ be the forecast of w_j (w at time j) at time t , $\overline{w}$ be the mean of the forecast and the cyclical component follows

$$c_t = \sum_{j=1}^{q}\left(\hat{w}_t(j) - \overline{w}\right) + \left(1 - \sum_{1}^{p}\phi_i\right)^{-1}\sum_{j=1}^{p}\sum_{i=j}^{p}\left[\phi_i\left(\hat{w}_t(q-j+1) - \overline{w}\right)\right] \tag{9}$$

The determination of the ARMA process can be computationally demanding. Since we are trying to find patters for about 500 series, we rely on the Bayesian Information Criteria (BIC) or Schwarz criteria to determine the ARMA process. Each series allows for up to ARMA(4,4) with the default being AR(1).[5] The Schwarz criteria tend to select lower order ARMA processes. For example, 129 counties are determined to be ARMA(1,0) during the sample period. A summary of counties by ARMA process selected is presented in table 2.

Insert table 2 here:

The BN decomposition is sensitive to the potentially less accurate forecasting mentioned above as well as the $\left(1 - \sum_{1}^{p}\phi_i\right)^{-1}$ in equation (9). As a result, extreme values of cyclical components are set to zero when the absolute value of estimated trend difference between January 1997 and January 2009 is greater than 0.15 or when the absolute value of the

[5] The results for all counties and all cases will be available from the authors upon request.

cyclical component in any single period is greater 0.1. This affects 59 out of the 540 counties. In these counties, the trend component is treated as missing while the trend difference of BN decomposition is set to be the difference in level of local unemployment rate.

The smoothing parameter for the HP filter is set to be 129,600 following Ravn and Uhlig (2002) given the analysis is done at monthly level. Figure 1 illustrates the seasonally unadjusted, adjusted, and the BN, the HP trend components of the US unemployment rate as an example.

Insert figure 1 here:

The relationship between the business cycle, local unemployment, and loan performance is examined in a series of experiments. In each experiment, the loan sample is divided into groups and survival analysis is performed on each individual group. We start with the examination of loan performance on Hardest Hit Fund areas and other states. Then, we examine the impact of local unemployment rate on mortgage default by the number of months that local unemployment is higher or lower than the national average, the long run change in local unemployment rate, and the long run change in local structural unemployment. Counties are grouped into three similarly sized categories, reflecting the level of local unemployment (high, medium, and low unemployment areas)[6] and long

[6] The high unemployment areas include 180 counties or a third of the total counties. Of the 180 high unemployment counties, 14 counties (8%) are identified as worsening HP structural unemployment

run changes in the level and structural components of local unemployment (worsening, stable, and improving unemployment areas) between January 1997 and January 2009. Using the survival analysis estimates, default hazards for individual groups are simulated to investigate the hazard response to changes in the level of local unemployment rate.

Community Reinvestment Loans

The Community Advantage Program (CAP) was established by Self-Help Venture Fund, Fannie Mae, and the Ford Foundation in 1999. CAP provides a secondary market outlet for community reinvestment loans that otherwise would remain in the portfolio of primary lenders. About 46,000 CAP loans were originated to low- or moderate-income families that reside in low-income areas, minority areas, or are minorities.

Community Advantage Program (CAP) participants compare favorably to a national sample of homeowners who would have met Self-Help's program eligibility guidelines for race and household income. Quercia, Riley, and Ru (2009) compared CAP demographic characteristics with those of the low-income and minority homeowners who participated in the 2003 Current Population Survey. Their results suggest that CAP participants are similar to low-income and minority Current Population Survey respondents with respect to household income, minority representation, and household size distributions. However, the CAP sample over-represents the South, and CAP

---

counties, 11 counties (6%) are identified as worsening BN structural unemployment counties, and 51 counties (28%) as worsening both in HP and BN structural unemployment counties.

participants are somewhat more educated and more attached to the labor force than are comparable Current Population Survey respondents.

The analysis sample is limited to loans originated in 1997 or later; 30 year, fixed rate loans; home purchase loans, excluding manufactured homes (most home purchase loans made to purchase single family homes). A summary of the loans by year of by year of origination is presented in Table 3.

Insert table 3 here:

About 20,358 loans have complete loan and borrower information. The hazard analysis is performed on a monthly basis for loan history (loan age) up to 120 months. Three risks factors are included in the analysis: debt-to-income ratio (*dti*), borrower credit score at origination (*credit score*), current loan-to-value ratio (*cltv*). The version of the debt-to-income ratio used in this paper is commonly called the front-end ratio and is the ratio of mortgage payments to household income. Households with larger debt burdens should be more susceptible to any income or other debt payment shocks, thus triggering delinquency and potentially default. The impact of high debt burdens on prepayments is more ambiguous. Prepayments may be more likely if they are used to refinance in the presence of a negative shock but high debt burdens may also make it harder to qualify to refinance. Because credit history is negatively associated with mortgage default and positively associated with mortgage prepayment (Pennington-Cross 2003), we include credit score at origination (*credit score*). High loan-to-value ratio is associated with higher probabilities of default (Kau, Keenan, and Kim 1994) and *cltv* is estimated using the outstanding balance on the loan and an estimate of current house value generated through Federal Housing Finance Agency's metropolitan area House Price Index (HPI).

A measure of the net present value gain from refinancing a fixed rate mortgage ($refi$) is constructed as follows. At time t, the gain from refinancing is the percentage reduction in discounted value of all future mortgage payments if refinance, PV_r versus holding current mortgage, PV_c:

$$refi_t = \left[\frac{PV_{ct} - PV_{rt}}{PV_{ct}} \right] \tag{10}$$

where

$$PV_{jt} = \sum_{m=0}^{RMT} \frac{P_{jt}}{(1+d_t)^m} \tag{11}$$

where $j = c, r$, RMT is remaining mortgage term in months that varies with t, discount rate d_t is the ten-year T-Bill rate, and

$$P_{jt} = i_{jt} Q \left[\frac{(1+i_{jt})^{RMT}}{(1+i_{jt})^{RMT} - 1} \right] \tag{12}$$

where i_{ct} is the mortgage interest rate on current mortgage and i_{rt} is the 30-year fixed conventional mortgage rate from the federal reserve (reported by Freddie Mac). We expect prepayment hazards to rise with $refi$.

Finally, county unemployment rate, mortgage rate volatility, and house price volatility are included as risk determinants. The county level unemployment rate is used to proxy for labor market conditions. Higher unemployment rates should indicate a higher probability that the borrower has lost their job or has a lower income stream making it more difficult to make mortgage payments. Unemployment may also increase the use of "distressed" prepayments but it also makes it harder to meet underwriting requirements to refinance. Interest rate volatility is the 24-month forward looking moving variance of 30-year fixed rate conventional mortgage rate and house price volatility is the 24-month forward looking moving variance of metropolitan area HPI. We expect that more volatility in interest rates will reduce refinance probabilities since borrowers may wait for interest rates to lower even further. Similarly, house price volatility increases the value of delaying the default (Kau and Kim 1994 and Kau and Keenan 1995). If borrowers believe that prices will increase in the future and reduce the financial gain associated with default, they will do so sooner. In contrast, if they believe prices may drop even further, thus increasing the size of the potential gain, they may delay default.

Variable definitions are presented in table 4. Summary statistics by different groupings are presented in table 5, 6, 7, and 8. We discuss them in turn. Table 5 summarizes loans originated in areas currently in the HHF program versus non-HHF program areas. Loans originated in HHF states experience higher local unemployment rates and more volatile house price movements. The borrowers with loans in HHF states have slightly higher income, lower credit score, and they borrow more. The option to refinance is more 'in the money' to those borrowers as well.[7]

Insert table 4 here:

Insert table 5 here:

Table 6 summarizes loans originated in high, medium, and low unemployment areas by the level of local unemployment rate from January 1997 to January 2009. We find no consistent pattern. Loans originated in areas with more instances of high monthly unemployment than the national average experience higher average local unemployment rates and intermediate volatility house price fluctuations. These fluctuations are more volatile in medium unemployment areas. Fluctuations are least volatile in low unemployment areas. The borrowers with loans in high unemployment states have lower income, lower credit score, and they borrow significantly less. They also are more likely to have the option to refinance 'in the money'.

Insert table 6 here:

Table 7 summarizes loans originated in worsening, stable, and improving unemployment areas by the difference in the level of local unemployment rate between January 1997 and January 2009. Loans originated in worsening unemployment areas experience higher

[7] Over 80 percent of the analysis sample are loans in HHF states.

average local unemployment and intermediate volatility in house price movements. The volatility for house prices is highest in unemployment stable areas. Borrowers in unemployment stable areas have more income, borrow more, and their option to refinance is more ‘in the money’. With the exception of one variable, the findings are similar when the analysis is replicated with areas defined using the structural trend unemployment estimated through the HP filter (Table 8) and the BN decomposition (Table 9). In both tables 8 and 9, borrower income is higher in worsening unemployment areas.

Insert table 7 here:

Insert table 8 here:

Insert table 9 here:

IV. Estimation Results

We complement the descriptive analyses above with an in depth multivariate examination of the relationship between unemployment and default risks. Two sets of results are presented: competing risks, proportional hazard survival analysis and a simulation of the impact of changes in local unemployment on risks hazard. Although both the default and prepay results are presented, we focus our discussion on default issues primarily.

Survival Analysis Results

The results of the competing risk, proportional hazard, with heterogeneity survival analyses are organized in tables 10 to 19. Tables 10 and 11 present the results for samples grouped by whether or not states are in the Hardest Hit Fund program. Tables 12 and 13 present the results for samples grouped by the level of local unemployment rate. Tables 14 and 15 present the results for samples grouped by the long run level difference in local unemployment rate. Tables 16 and 17 present the results for samples grouped by the long run HP structural rate difference of local unemployment. Finally, tables 18 and 19 present the results for samples grouped by the long run BN structural rate difference of local unemployment. For each set of tables, the first table presents the results for the default outcome and the second the results for the prepayment outcome.

Insert table 10 here

Insert table 11 here

Insert table 12 here

Insert table 13 here

Insert table 14 here

Insert table 15 here

Insert table 16 here

Insert table 17 here

Insert table 18 here

Insert table 19 here

The significance of risk determinants varies on the basis of the sample under consideration. In HHF states, higher credit scores are associated with lower default risks, while higher debt-to-income ratio increases, current loan-to-value ratio, "*refi*" value, and unemployment rate are associated with higher default risks. Contrary to expectations, higher volatility in future mortgage interest rate and future house price movement are found to increase default risks. In non-HHF states, debt-to-income ratio, local unemployment rate, and future interest rate volatility show no significant effect.

For samples grouped by the level of local unemployment rates, most risk determinants have the expected sign. Lower credit scores and higher debt-to-income ratio, current loan-to-value ratio, "*refi*" value, and local unemployment rate increase default risks in all high, medium, and low unemployment areas. The variance in future mortgage interest rate increases default risk only in high unemployment areas and variance in future house price volatility increases default risk only in medium unemployment areas.

For samples grouped by the long run difference in the level of local unemployment rates, the significance of risks factors depends on the area under consideration. Lower credit scores and higher debt-to-income ratio, current loan-to-value ratio, "*refi*" value, local unemployment rate, and future mortgage interest rate volatility have consistent positive impacts on default risk only in worsening unemployment areas and stable unemployment areas. The variance in future house price volatility increases default risk only in worsening unemployment areas. In improving unemployment areas, defaults are not very responsive to changes in debt-to-income ratio, unemployment rate, and future house price volatility. The results are similar when the samples are grouped by the long run difference in the HP and BN trend component of local unemployment rate, except that future mortgage interest rate volatility is not significant in unemployment improving areas classified by the HP trend difference.

Simulation Results

Next, we focus our attention on the impact of changes in the local unemployment rate on mortgage default hazard for the same five groups discussed above. For each group, the default hazard with respect to changes in local unemployment rate is simulated using its own survival model estimates and its own mean characteristics. All hazards are simulated for mortgages that are 24 months old. The results are illustrated in figures 2 to 6.

Insert figure 2 here:

Insert figure 3 here:

Insert figure 4 here:

Insert figure 5 here:

Insert figure 6 here:

Figure 2 depicts the default hazard patterns for loans in HHF and non-HHF states. In HHF states, default risks appear to be very responsive to changes in local unemployment rate. This is not the case in non-HHF states. Thus, from this broad perspective, HHF can be expected to have a positive impact if future mortgage default behaviors and risk patterns in the future are similar to those in our study period.

However, a closer examination raises some questions about HHF's expected effectiveness. Figure 3 depicts the default hazard patterns for loans grouped by the level of local unemployment from January 1997 to January 2009. Defaults in high unemployment counties are clearly the least responsive to changes in the local unemployment rate. Similarly, when the sample is grouped on the basis of long run differences in local unemployment (Figure 4), defaults in counties with worsening unemployment are not as responsive to changes in local unemployment rate as defaults in stable unemployment areas. These results suggest that if an initiative such as HHF is designed to reduce mortgage default risks by lowering local unemployment rates, identifying areas for assistance on the basis of the level of unemployment, or long run differences in such level, may not lead to the most efficient results

Figures 5 and 6 suggest that program efficiency may be improve if structural unemployment patterns are taken into account. When structural unemployment is estimated with the HP filter (Figure 5), default risks in worsening unemployment areas is most responsive to changes in local unemployment rate. Default risks pattern change when unemployment rates are below 12 percent. In such a case, changes in default risks in worsening and stable unemployment areas appear to be similar. When structural unemployment is estimated with the BN decomposition (Figure 6), default risks in both worsening and stable unemployment areas are responsive to changes in local unemployment rate. Thus, an initiative designed to lower default risks by lowering local unemployment rates could be made more efficient if it targeted areas on the basis of structural unemployment trends rather than the level of unemployment.

V. Conclusions

In this study, we examined the relationship between unemployment and mortgage performance from 1997 to 2009 taking into account business cycle considerations. More narrowly, we simulated default hazards with respect to changes in local unemployment using survival analyses estimates and on the basis of the simulation results we derived implications for a federal initiative (HHF) aimed at reducing default risks by lowering unemployment rates.

Overall, we find that default risks are very responsive to changes in local unemployment rate for loans in HHF states compared to loans in the rest of the country. This indicates the *potential* efficiency of the program. However, this potential efficiency is based on the assumption that future mortgage default behaviors will be similar to those in our study period.

However, the simulation results raise some concerns about the full efficiency of the program. When classified by the level of local unemployment rate (as HHF does in part), mortgage defaults risks in high unemployment areas and worsening unemployment areas are not the most responsive to changes in local unemployment rate. In contrast, , when classified on the basis of the long run structural component of unemployment, mortgage defaults in areas with worsening unemployment are found to be consistently the most responsive to changes in local unemployment rate. Thus, government programs such as HHF designed to deal with the foreclosure problem by lowering local unemployment rate may not achieve full efficiency if they target assistance on the basis of the level of local unemployment. The findings suggest that program efficiency could be improved if areas for intervention are targeted on the basis of structural unemployment trends.

We believe that the study findings are suggestive enough to warrant further examination. Future work needs to examine the relationship between unemployment and lending risks with alternative methodologies, measures, and datasets. A better understanding of this relationship is imperative with foreclosures still on the rise, unemployment rates hovering around 9 percent for the foreseeable future, and the lingering impacts of the Great Recession likely to be felt for years to come.

Acknowledgements

The authors would like to Sarah Riley for help with the data.

References

Baxter, M., and R. G. King. 1999. Measuring Business Cycles: Approximate Band-Pass Filters For Economic Time Series. *The Review of Economics and Statistics* 81(4): 575-593.

Beveridge, S., and C. R. Nelson. 1981. A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the `Business Cycle'. *Journal of Monetary Economics* 7(2): 151-174.

Campbell, T. S., and J. K. Dietrich. 1983. The Determinants of Default on Insured Conventional Residential Mortgage Loans. *The Journal of Finance* 38(5): 1569-1581.

Capozza, D. R., D. Kazarian, and T. A. Thomson. 1997. Mortgage Default in Local Markets. *Real Estate Economics* 25(4): 631-655.

Deng, Y., J. M. Quigley, and R. Van Order. 2000. Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options. *Econometrica* 68(2): 275-307.

Dickey, D. A., and W. A. Fuller. 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica* 49(4): 1057-72.

Elmer, P. J., and S. A. Seelig. 1999. Insolvency, Trigger Events, and Consumer Risk Posture in the Theory of Single-Family Mortgage Default. *Journal of Housing Research* 10(1): 1-25.

Harvey, A. C. 1985. Trends and Cycles in Macroeconomic Time Series. *Journal of Business & Economic Statistics* 3(3): 216-27.

Hodrick, R. J., and E. C. Prescott. 1997. Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking* 29(1): 1-16.

McCall, B. P. 1996. Unemployment Insurance Rules, Joblessness, and Part-Time Work. Econometrica 64(3): 647-682.

Mocan, H. N. 1999. Structural Unemployment, Cyclical Unemployment, and Income Inequality. *The Review of Economics and Statistics* 81(1): 122-134.

Morley, J. C., C. R. Nelson, and E. Zivot. 2003. Why Are the Beveridge-Nelson and Unobserved-Components Decompositions of GDP So Different? *The Review of Economics and Statistics* 85(2): 235-243.

Newbold, P. 1990. Precise and Efficient Computation of the Beveridge-Nelson Decomposition of Economic Time Series. *Journal of Monetary Economics* 26(3): 453-457.

Pennington-Cross, A. and G. Ho. 2010. The Termination of Subprime Hybrid and Fixed Rate Mortgages. *Real Estate Economics* 38(3): 399-426.

Perron, P. 1989. The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Econometrica* 57(6): 1361-1401.

Perron, P., and P. C. B. Phillips. 1988. Testing for a Unit Root in Time Series Regression. *Biometrika* 75(2): 335-346.

Ravn, M. O., and H. Uhlig. 2002. On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. *The Review of Economics and Statistics* 84(2): 371-375.

Quercia, R. G., S. F. Riley, and H. Ru. 2009. Community Advantage Program Database: Overview and Generalization. *Cityscape*, 11(3).

Sinclair, T. M. 2009. The Relationships between Permanent and Transitory Movements in U.S. Output and the Unemployment Rate. *Journal of Money, Credit and Banking* 41(2-3): 529-542.

Stock, J. H., and M. W. Watson. 1988. Variable Trends in Economic Time Series. *Journal of Economic Perspectives* 2(3): 147-174.

Ozyildirim, A. and V. Zarnowitz. 2006. Time Series Decomposition and Measurement of Business Cycles, Trends and Growth Cycles. *Journal of Monetary Economics*, 53(7), 1717-1739.

Table 1: Augmented Dickey-Fuller Test for US Unemployment Rate and Its First Difference (1990-2009)

Null Hypothesis: US unemployment rate has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.528229	0.8820
Test critical values:	1% level	-3.457984	
	5% level	-2.873596	
	10% level	-2.573270	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: First difference of US unemployment rate has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.989747	0.0000
Test critical values:	1% level	-3.457984	
	5% level	-2.873596	
	10% level	-2.573270	

*MacKinnon (1996) one-sided p-values.

Table 2: Summary of Counties by ARMA Processes Selected Using BIC Information Criteria

ARMA process	Number of cases (counties) selected by BIC
ARMA(1,0)	129
ARMA(1,1)	58
ARMA(1,2)	70
ARMA(1,3)	11
ARMA(1,4)	5
ARMA(2,0)	23
ARMA(2,1)	26
ARMA(2,2)	37
ARMA(2,3)	31
ARMA(2,4)	14
ARMA(3,0)	9
ARMA(3,1)	4
ARMA(3,2)	24
ARMA(3,3)	25
ARMA(3,4)	17
ARMA(4,0)	0
ARMA(4,1)	0
ARMA(4,2)	9
ARMA(4,3)	18
ARMA(4,4)	31

Table 3: Number of Loans by Year Originated

Year	Number of Loans
1997	1,349
1998	1,798
1999	1,682
2000	3,070
2001	3,469
2002	2,557
2003	1,651
2004	1,658
2005	1,609
2006	1,153
2007	362
Total	20,358

Table 4: Variable Definitions

Variable	Definition
dti	Debt-to-income ratio or front-end ratio. The fraction of combined income that goes toward mortgage payments
credit score	Borrower's credit score at origination
cltv	Current loan-to-value ratio
refi	Percentage reduction in present value of future payments if refinance into the market rate
unemp_rate	County level unemployment rate
varmrate	Variance of future national mortgage rate
varhpi	Variance of MSA level house price index reported by Federal Housing Finance Agency

Table 5: Descriptive Statistics of Samples Grouped by Hardest Hit Fund Program (HHF)

		Hardest Hit Fund (HHF) states		Non HHF states	
		Mean	Std Dev	Mean	Std Dev
Constant within each loan	*original balance*	$85,366	$33,255	$81,421	$31,221
	annual income	$31,846	$10,938	$30,780	$10,247
	credit score	678	64	684	58
	dti or front-end ratio	0.28	0.08	0.27	0.07
	Loans	16,389		3,969	
Varies within each loan	*refi*	0.089	0.083	0.066	0.065
	loan age	42.4	26.5	41.2	23.3
	cltv	0.797	0.151	0.810	0.133
	unemp_rate	5.570	1.813	4.635	1.128
	varmrate	1.55E-05	1.08E-05	1.34E-05	1.03E-05
	varhpi	2.59E-05	4.66E-05	1.03E-05	1.24E-05
	Observations	687,673		186,168	

Table 6: Descriptive Statistics of Samples Grouped by Level of Unemployment Rate

		High unemployment areas		Medium unemployment areas		Low unemployment areas	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Constant within each loan	*original balance*	$76,663	$33,128	$89,099	$32,637	$89,922	$31,075
	annual income	$29,973	$11,291	$32,665	$10,862	$32,692	$9,970
	credit score	670	64	684	61	685	61
	dti or front-end ratio	0.27	0.08	0.28	0.07	0.28	0.07
	Loans	7,834		5,516		7,008	
Varies within each loan	*refi*	0.100	0.083	0.079	0.080	0.070	0.073
	loan age	42.4	27.3	42.7	26.1	41.4	24.1
	cltv	0.804	0.152	0.789	0.158	0.802	0.133
	unemp_rate	6.354	1.805	5.197	1.521	4.408	1.100
	varmrate	1.53E-05	1.07E-05	1.56E-05	1.10E-05	1.45E-05	1.06E-05
	varhpi	2.57E-05	4.06E-05	3.02E-05	5.91E-05	1.34E-05	2.29E-05
	Observations	340,503		227,281		306,057	

Table 7: Descriptive Statistics of Samples Grouped by Level Difference of Unemployment Rate

		Worsening unemployment areas		Stable unemployment areas		Improving unemployment areas	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Constant within each loan	*original balance*	$85,698	$32,290	$86,567	$32,827	$79,889	$33,888
	annual income	$31,814	$10,814	$32,222	$11,129	$30,578	$10,371
	credit score	679	63	678	64	681	59
	dti or front-end ratio	0.28	0.07	0.28	0.08	0.27	0.08
	Loans	10,323		5,373		4,662	
Varies within each loan	*refi*	0.085	0.083	0.088	0.081	0.077	0.071
	loan age	44.1	27.0	38.4	24.9	41.8	24.0
	cltv	0.795	0.143	0.806	0.153	0.802	0.150
	unemp_rate	5.490	1.836	5.292	1.438	5.197	1.767
	varmrate	1.57E-05	1.08E-05	1.53E-05	1.08E-05	1.36E-05	1.05E-05
	varhpi	2.35E-05	4.81E-05	2.51E-05	3.42E-05	1.79E-05	3.52E-05
	Observations	448,832		217,528		207,481	

Table 8: Descriptive Statistics of Samples Grouped by HP Trend Difference

		Worsening unemployment areas		Stable unemployment areas		Improving unemployment areas	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Constant within each loan	*original balance*	$86,148	$32,247	$84,196	$33,868	$81,800	$32,873
	annual income	$32,072	$10,947	$31,828	$11,053	$30,481	$10,131
	credit score	680	63	672	64	686	59
	dti or front-end ratio	0.27	0.07	0.28	0.08	0.28	0.08
	Loans	9,889		5,819		4,650	
Varies within each loan	*refi*	0.085	0.082	0.093	0.082	0.073	0.071
	loan age	43.0	26.8	40.3	26.1	42.5	23.6
	cltv	0.808	0.140	0.795	0.150	0.786	0.158
	unemp_rate	5.545	1.822	5.380	1.675	4.993	1.537
	varmrate	1.57E-05	1.08E-05	1.51E-05	1.07E-05	1.37E-05	1.05E-05
	varhpi	2.32E-05	4.70E-05	2.47E-05	3.72E-05	1.86E-05	3.66E-05
	Observations	430,189		240,203		203,449	

Table 9: Descriptive Statistics of Samples Grouped by BN Trend Difference

		Worsening unemployment areas		Stable unemployment areas		Improving unemployment areas	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Constant within each loan	*original balance*	$86,848	$32,517	$84,006	$34,071	$79,982	$32,218
	annual income	$32,174	$10,950	$31,400	$10,878	$30,627	$10,361
	credit score	680	63	675	64	680	60
	dti or front-end ratio	0.28	0.07	0.28	0.08	0.27	0.08
	Loans	11,127		4,361		4,870	
Varies within each loan	*refi*	0.083	0.082	0.093	0.085	0.079	0.071
	loan age	43.4	26.8	39.6	25.3	41.2	24.0
	cltv	0.796	0.145	0.793	0.155	0.811	0.147
	unemp_rate	5.417	1.779	5.365	1.526	5.273	1.778
	varmrate	1.57E-05	1.08E-05	1.50E-05	1.08E-05	1.37E-05	1.05E-05
	varhpi	2.37E-05	4.71E-05	2.40E-05	3.47E-05	1.88E-05	3.53E-05
	Observations	486,863		171,844		215,134	

Table 10: Completing Risk Results for Samples Grouped by Hardest Hit Fund Program -- Default

	Hardest Hit Fund (HHF) states		Non HHF states	
	Coef	Std Err	Coef	Std Err
dti	0.132*	0.020	0.050	0.051
credit score	-0.660*	0.023	-0.696*	0.060
cltv	0.470*	0.025	0.332*	0.069
refi	0.325*	0.029	0.276*	0.061
unemp_rate	0.151*	0.021	-0.006	0.055
varmrate	0.106*	0.024	0.084	0.058
varhpi	0.044*	0.020	0.119*	0.036
loc1	-0.287*	0.137	-1.002	0.584
loc2	0.015	0.081	-0.115	0.225
q1	0		0	
q2	-0.331*	0.106	-0.426	0.277
Loans	16,389		3,969	
Obs	687,673		186,168	
Loglike	-56,864		-13,729	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 11: Completing Risk Results for Samples Grouped by Hardest Hit Fund Program -- Prepay

	Hardest Hit Fund (HHF) states		Non HHF states	
	Coef	Std Err	Coef	Std Err
dti	0.054*	0.015	0.056	0.030
credit score	0.315*	0.016	0.137*	0.035
cltv	-0.288*	0.017	-0.314*	0.034
refi	0.660*	0.017	0.497*	0.031
unemp_rate	-0.206*	0.015	-0.140	0.029
varmrate	-0.120*	0.015	-0.047	0.028
varhpi	0.034*	0.014	0.034	0.029
loc1	0.560*	0.043	0.470*	0.107
loc2	-1.408*	0.090	-1.720*	0.316
q1	0		0	
q2	-0.331*	0.106	-0.426	0.277
Loans	16,389		3,969	
Obs	687,673		186,168	
Loglike	-56,864		-13,729	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 12: Completing Risk Results for Samples Grouped by Level of Unemployment Rate -- Default

	High unemployment areas		Medium unemployment areas		Low unemployment areas	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
dti	0.124*	0.028	0.133*	0.040	0.116*	0.040
credit score	-0.620*	0.027	-0.718*	0.054	-0.765*	0.047
cltv	0.438*	0.032	0.534*	0.057	0.364*	0.048
refi	0.395*	0.035	0.251*	0.048	0.252*	0.048
unemp_rate	0.071*	0.029	0.242*	0.036	0.124*	0.041
varmrate	0.171*	0.031	0.071	0.046	0.035	0.046
varhpi	-0.001	0.032	0.104*	0.039	0.065	0.040
loc1	0.301*	0.083	-1.727	1.007	-1.235*	0.393
loc2	-0.052	0.095	0.237*	0.091	-0.129	0.132
q1	0		0		0	
q2	-0.374*	0.116	-0.200	0.336	-0.418*	0.199
Loans	7,834		5,516		7,008	
Obs	340,503		227,281		306,057	
Loglike	-27,690		-18,601		-24,218	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 13: Completing Risk Results for Samples Grouped by Level of Unemployment Rate -- Prepay

	High unemployment areas		Medium unemployment areas		Low unemployment areas	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
dti	0.051*	0.023	0.026	0.025	0.048*	0.022
credit score	0.344*	0.024	0.255*	0.025	0.223*	0.023
cltv	-0.380*	0.025	-0.156*	0.029	-0.260*	0.027
refi	0.626*	0.025	0.649*	0.028	0.591*	0.024
unemp_rate	-0.152*	0.022	-0.212*	0.024	-0.149*	0.020
varmrate	-0.126*	0.023	-0.160*	0.025	-0.046*	0.020
varhpi	0.042*	0.021	0.021	0.025	0.075*	0.016
loc1	0.537*	0.055	0.496*	0.110	0.529*	0.070
loc2	-1.745*	0.126	-1.139*	0.211	-1.334*	0.177
q1	0		0		0	
q2	-0.374*	0.116	-0.200	0.336	-0.418*	0.199
Loans	7,834		5,516		7,008	
Obs	340,503		227,281		306,057	
Loglike	-27,690		-18,601		-24,218	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 14: Completing Risk Results for Samples Grouped by Level Difference of Unemployment Rate -- Default

	Worsening unemployment areas		Stable unemployment areas		Improving unemployment areas	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
dti	0.140*	0.026	0.132*	0.035	0.024	0.049
credit score	-0.714*	0.046	-0.680*	0.037	-0.700*	0.048
cltv	0.464*	0.038	0.449*	0.065	0.314*	0.065
refi	0.248*	0.036	0.473*	0.049	0.278*	0.053
unemp_rate	0.196*	0.028	0.181*	0.039	0.019	0.050
varmrate	0.078*	0.031	0.170*	0.044	0.153*	0.048
varhpi	0.099*	0.025	-0.034	0.054	-0.011	0.058
loc1	-1.363*	0.676	-0.077	0.141	-0.230	0.153
loc2	0.197*	0.063	-0.351*	0.174	-0.476*	0.218
q1	0		0		0	
q2	0.080	0.174	-0.505*	0.191	-0.669*	0.160
Loans	10,323		5,373		4,662	
Obs	448,832		217,528		207,481	
Loglike	-36,549		-18,340		-15,619	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 15: Completing Risk Results for Samples Grouped by Level Difference of Unemployment Rate -- Prepay

	Worsening unemployment areas		Stable unemployment areas		Improving unemployment areas	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
dti	0.028	0.018	0.027	0.026	0.112*	0.028
credit score	0.375*	0.021	0.224*	0.029	0.123*	0.029
cltv	-0.210*	0.021	-0.361*	0.035	-0.337*	0.030
refi	0.695*	0.022	0.577*	0.028	0.536*	0.028
unemp_rate	-0.214*	0.019	-0.252*	0.025	-0.143*	0.028
varmrate	-0.133*	0.019	-0.131*	0.025	-0.022	0.026
varhpi	-0.013	0.019	0.061*	0.021	0.083*	0.025
loc1	0.639*	0.072	0.572*	0.076	0.418*	0.064
loc2	-1.154*	0.105	-1.411*	0.170	-2.037*	0.236
q1	0		0		0	
q2	0.080	0.174	-0.505*	0.191	-0.669*	0.160
Loans	10,323		5,373		4,662	
Obs	448,832		217,528		207,481	
Loglike	-36,549		-18,340		-15,619	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 16: Completing Risk Results for Samples Grouped by HP Trend Difference -- Default

	Worsening unemployment areas		Stable unemployment areas		Improving unemployment areas	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
dti	0.163*	0.026	0.123*	0.033	-0.049	0.057
credit score	-0.730*	0.042	-0.689*	0.036	-0.695*	0.057
cltv	0.468*	0.035	0.402*	0.056	0.404*	0.062
refi	0.275*	0.035	0.375*	0.043	0.218*	0.058
unemp_rate	0.193*	0.028	0.142*	0.036	0.008	0.059
varmrate	0.077*	0.031	0.146*	0.038	0.073	0.056
varhpi	0.105*	0.025	-0.091	0.050	0.028	0.049
loc1	-1.870*	0.772	0.152	0.115	-1.011*	0.315
loc2	0.223*	0.055	-0.240	0.126	-0.015	0.206
q1	0		0		0	
q2	0.174	0.170	-0.338*	0.161	-0.967*	0.222
Loans	9,889		5,819		4,650	
Obs	430,189		240,203		203,449	
Loglike	-34,146		-20,515		-15,815	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 17: Completing Risk Results for Samples Grouped by HP Trend Difference -- Prepay

	Worsening unemployment areas		Stable Unemployment areas		Improving unemployment areas	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
dti	0.006	0.019	0.017	0.025	0.139*	0.025
credit score	0.373*	0.021	0.262*	0.028	0.130*	0.027
cltv	-0.205*	0.021	-0.354*	0.032	-0.271*	0.036
refi	0.689*	0.023	0.559*	0.027	0.542*	0.027
unemp_rate	-0.233*	0.019	-0.304*	0.028	-0.036	0.024
varmrate	-0.122*	0.019	-0.144*	0.025	-0.022	0.025
varhpi	-0.033	0.020	0.079*	0.021	0.081*	0.026
loc1	0.621*	0.074	0.666*	0.072	0.326*	0.066
loc2	-1.140*	0.105	-1.368*	0.145	-2.039*	0.310
q1	0		0		0	
q2	0.174	0.170	-0.338*	0.161	-0.967*	0.222
Loans	9,889		5,819		4,650	
Obs	430,189		240,203		203,449	
Loglike	-34,146		-20,515		-15,815	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 18: Completing Risk Results for Samples Grouped by BN Trend Difference -- Default

	Worsening unemployment areas		Stable unemployment areas		Improving unemployment areas	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
dti	0.155*	0.026	0.125*	0.041	0.037	0.044
credit score	-0.728*	0.044	-0.721*	0.046	-0.662*	0.042
cltv	0.470*	0.034	0.330*	0.065	0.387*	0.059
refi	0.243*	0.035	0.464*	0.056	0.311*	0.047
unemp_rate	0.212*	0.027	0.160*	0.042	0.034	0.047
varmrate	0.077*	0.030	0.207*	0.047	0.160*	0.044
varhpi	0.094*	0.024	-0.120	0.071	0.017	0.048
loc1	-1.340*	0.498	0.079	0.131	0.003	0.126
loc2	0.203*	0.065	-0.294*	0.128	-0.523*	0.207
q1	0		0		0	
q2	-0.181	0.169	-0.251	0.169	-0.516*	0.159
Loans	11,127		4,361		4,870	
Obs	486,863		171,844		215,134	
Loglike	-39,145		-15,167		-16,217	

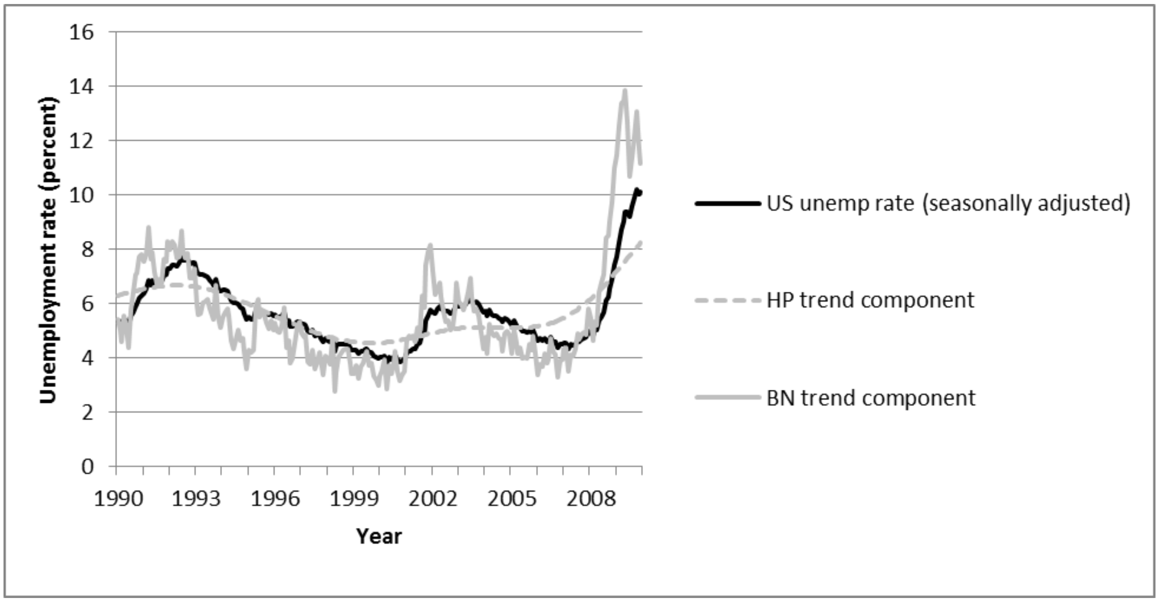
Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Table 19: Completing Risk Results for Samples Grouped by BN Trend Difference -- Prepay

	Worsening unemployment areas		Stable unemployment areas		Improving unemployment areas	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
dti	0.020	0.018	0.054	0.028	0.085*	0.029
credit score	0.364*	0.019	0.213*	0.032	0.118*	0.029
cltv	-0.219*	0.021	-0.335*	0.033	-0.389*	0.032
refi	0.684*	0.021	0.557*	0.031	0.548*	0.028
unemp_rate	-0.228*	0.018	-0.210*	0.029	-0.166*	0.029
varmrate	-0.128*	0.018	-0.147*	0.028	-0.023	0.026
varhpi	0.025	0.017	0.033	0.026	0.045	0.027
loc1	0.524*	0.062	0.785*	0.078	0.451*	0.068
loc2	-1.280*	0.119	-1.233*	0.151	-1.879*	0.200
q1	0		0		0	
q2	-0.181	0.169	-0.251	0.169	-0.516*	0.159
Loans	11,127		4,361		4,870	
Obs	486,863		171,844		215,134	
Loglike	-39,145		-15,167		-16,217	

Notes: * indicates significance at 95 percent.
unemp_rate is the level of unemployment rate in all regressions.
loc1 and *loc2* are shift parameters of the two heterogeneity groups.
q1 and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero.

Figure 1: US Unemployment Rate (Unadjusted and Seasonally Adjusted) and Its Permanent (Trend) Components



Notes: The sereis is seasonally adjusted using Census X11.

BN decomposition is based on ARMA(1,2) forecasting selected by BIC information.

HP filter smoothing parameter is 129,600.

Figure 2: Default Pattern for Samples Grouped by Hardest Fund Program

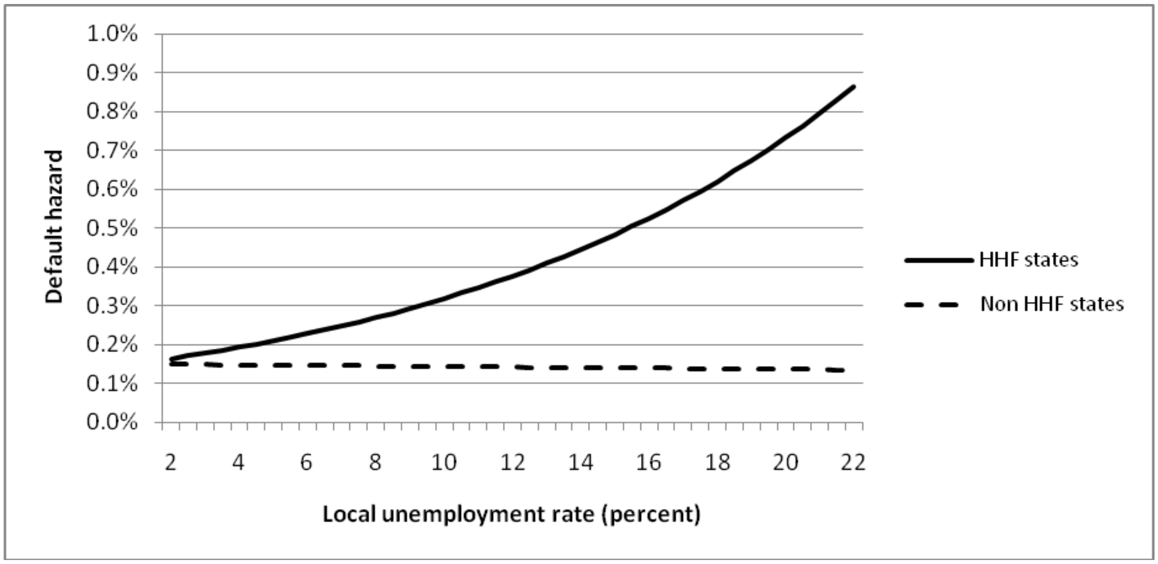


Figure 3: Default Pattern for Samples Grouped by Level of Unemployment Rate

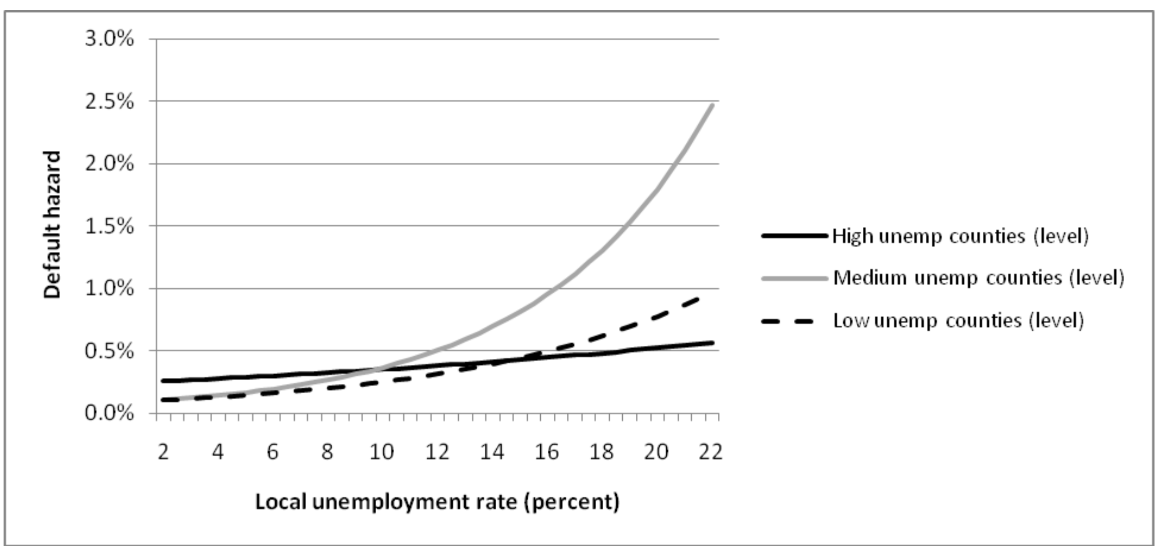


Figure 4: Default Pattern for Samples Grouped by Level Difference of Unemployment Rate

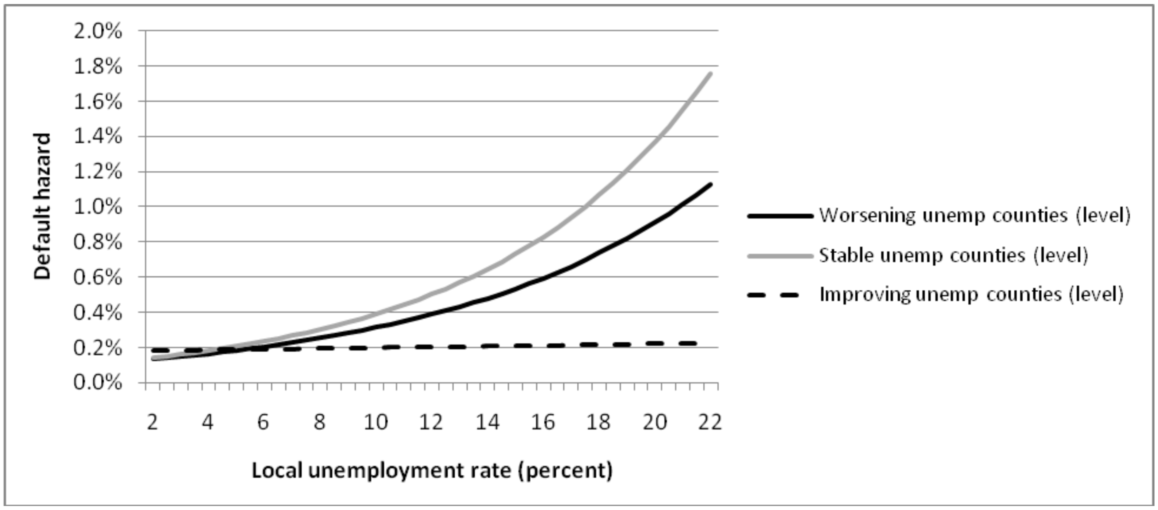


Figure 5: Default Pattern for Samples Grouped by HP Trend Difference

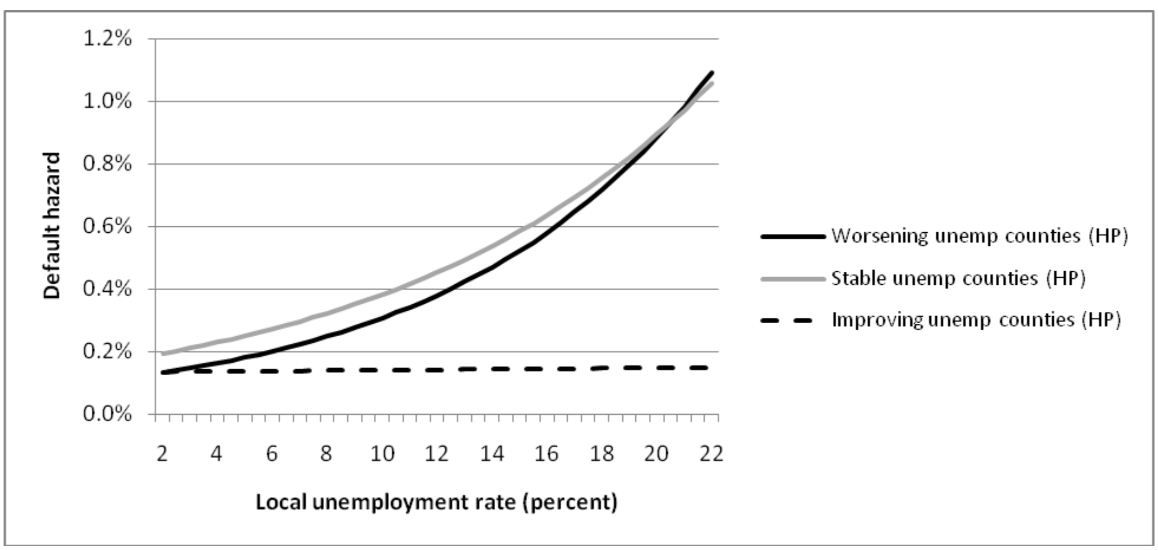


Figure 6: Default Pattern for Samples Grouped by BN Trend Difference