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Forecasting Credit Card Portfolio Losses in the Great Recession: A Study in Model Risk

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Abstract

Credit card portfolios represent a significant component of the balance sheets of the largest US banks. The charge-off rate in this asset class increased drastically during the Great Recession. The recent economic downturn offers a unique opportunity to analyze the performance of credit risk models applied to credit card portfolios under conditions of economic stress. Specifically, we evaluate three potential sources of model risk: model specification, sample selection, and stress scenario selection. Our analysis indicates that model specifications that incorporate interactions between policy variables and core account characteristics generate the most accurate loss projections across risk segments. Models estimated over a time frame that includes a significant economic downturn are able to project levels of credit loss consistent with those experienced during the Great Recession. Models estimated over a time frame that does not include a significant economic downturn can severely under-predict credit loss in some cases, and the level of forecast error can be significantly impacted by model specification assumptions. Higher credit-score segments of the portfolio are proportionally more severely impacted by downturn economic conditions and model specification assumptions. The selection of the stress scenario can have a dramatic impact on projected loss.

JEL classification: G20, G32, G33.

Keywords: credit cards, credit risk, stress test, regulatory capital

[1] This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in the paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. The authors thank Sharon Tang and Kaitlin DiPaola for outstanding research assistance. Contact information: José J. Canals-Cerdá, Federal Reserve Bank of Philadelphia, 10 Independence Mall, Philadelphia, PA 19106. Phone: (215) 574-4127, Fax: (215) 574-4146, e-mail: Jose.Canals-Cerda@phil.frb.org. Corresponding author: Sougata Kerr, Federal Reserve Bank of Philadelphia, 10 Independence Mall, Philadelphia, PA 19106. Phone: (215) 574-4127, Fax: (215) 574-4146, e-mail: sougata.kerr@phil.frb.org. This paper is available free of charge at www.philadelphiafed.org/research-and-data/publications/working-papers/.

I. Introduction

In this paper we analyze the relative loss-forecasting performance of credit risk models under forward-looking scenarios of economic stress applied to a representative credit card portfolio, i.e., model risk in stress tests. Our main emphasis is on the analysis of model development and implementation factors that may impact loss projection forecasting error under stressed economic conditions, while the lessons learned may also apply more generally to other aspects of risk management. Specifically, we focus our attention on three dimensions of model risk: model specification selection, sample selection, and stress scenario selection. Our analysis indicates that loss projections can be significantly impacted by model specification assumptions. This impact is heterogeneous.

Surprisingly, prime segments of the portfolio are proportionally more severely impacted by economic downturns and model specification assumptions than are the subprime segments. Models that overlook potential interactions between macroeconomic conditions and account characteristics can result in significant under-projection of prime portfolio losses under stressed economic conditions. Also, models estimated over a time frame that does not include a representative economic downturn period do not project levels of credit loss consistent with losses experienced during the Great Recession of 2007-09. Once again, the projection error is proportionally much larger for the prime segments. As the estimation sample is expanded to include a larger period of economic downturn, the models' ability to project losses under stressed economic conditions improves significantly.

Further, our analysis indicates that an economic downturn has a small impact on the account's balance exposure at default and a much larger impact on the probability of default. Thus, the primary effect of model specification and sample selection on portfolio loss under economic downturn conditions is channeled through the process of transition to default rather than the account's balance exposure at default.

Another source of model projection error, perhaps the most important, is the selection of the economic stress scenario. In this paper we emphasize the importance of stress scenario selection by analyzing the portfolio performance on a once-in-100-years economic downturn scenario: the Great Depression. We recognize the likelihood of projection error and the limitations of such an analysis. However, this kind of simulation exercise can still provide useful risk management insights by highlighting potential risks that may not be sufficiently accentuated by less severe economic scenarios.

Comparing these results with the worst two-year period of realized losses during the recent Great Recession, we observe that overall projected losses double in the Great Depression scenario. However, differences in the impact of the stress scenario on projected loss rates across risk segments are significant. While losses from the subprime segment remain higher than losses for the near-prime and prime segments, the latter two segments experience the most dramatic increase in loss rates. As the major bank card portfolios have a larger concentration of prime and non-prime borrowers, this finding highlights the risk of provisioning for loan losses arising from poorly specified credit risk models for these segments.

Reliance on models as tools for effective supervision and risk surveillance has increased significantly within regulatory agencies over the years, with the advent of the Internal Ratings Based (IRB) approach to regulatory capital postulated in the Basel II accord. More recently, in the Comprehensive Capital Analysis and Review (CCAR) exercise, now mandated by the Dodd-Frank Wall Street Reform and Consumer Protection Act, the Federal Reserve conducts its own independent assessment of capital adequacy through periodic stress testing across participant banks as a benchmark to the banks' own stress-test analysis.[2] As complex credit risk models are the foundation for these exercises, it becomes paramount to evaluate and mitigate risks associated with the development and implementation of these models. The recent regulatory guidance on model risk (OCC Bulletin 2011-12 and FED SR Letter 11-7, "Supervisory Guidance on Model Risk Management"), along with its antecedents (primarily OCC Bulletin 2000-16), stresses as much and highlights the important aspects of model risk management, including

[2] While the annual stress tests conducted by the Federal Reserve started in 2009, regulators' interest in using stress tests for capital adequacy is not new. Fed Supervisory Letter 99-18, published ten years earlier, clearly states: "Institutions should perform comprehensive and rigorous stress tests to identify possible events or changes in markets that could have serious adverse effects in the future."

model development, implementation, use, validation, governance, policies, and controls structure.

The few publicly released academic studies analyzing the performance of credit risk models before and during the Great Recession focus primarily on residential mortgage exposures, given that the real estate market was at the center of the recent financial crisis. However, other retail asset classes also performed poorly during this period of severe economic downturn. Specifically, the net charge-off rate for credit card portfolios increased more than twofold for a number of large banks during the peak of the financial crisis, and it is estimated that more than $160 billion in credit card debt has been charged off since 2008.[3] Further, recent stress tests conducted by banks and regulators showed the importance of credit card portfolios as a potential source of losses for the banks in the event of a severe economic downturn. In particular, projected losses from card portfolios of the largest banks participating in the 2012-13 DFAST stress-test exercise totaled $87 billion, or 19% of overall projected losses, over the projected stress period. Only trading and counterparty losses represented a larger share of projected losses, at $97 billion, while losses from first-mortgage portfolios were projected at $61 billion and losses for other types of mortgage exposures (junior liens, HELOC, etc.) were projected at $56 billion.[4]

Our analysis employs a panel data set of credit card accounts from the Equifax Credit Bureau over the period 2000-11. The data cover the Great Recession and afford us the opportunity to analyze the performance of credit risk models under conditions of significant economic stress. We build on the traditional framework for analyzing portfolio credit risk, which considers three components of credit risk: the risk of default or probability of default (PD); the exposure at default (EAD), representing an account balance at default; and the loss given default (LGD), representing the percentage of the exposure at default that is eventually lost after accounting for recoveries. Gross credit loss (GCL) is defined as the product of the first two components, whereas GCL times LGD defines net credit loss (NCL). Account recoveries and recovery costs are not often computed or recorded at the loan level. For this reason, loan-level information on LGD for defaulted accounts is not readily available, but recoveries from credit card defaults

[3] Data are from bank call reports and other regulatory filings (Figure 1); see also Hunt (2013). The net charge-off rate peaked at the time of the financial crisis, propelled by an increase in the net dollar charge-off rate and a decline in dollars outstanding.

[4] Board of Governors of the Federal Reserve System (2013): "Dodd-Frank Act Stress Test 2013: Supervisory Stress Test Methodology and Results, March 2013."

during economic downturns are usually low, and differences between gross and net loss have been shown to be small during these periods (Banerjee and Canals-Cerdá 2012).

For these reasons, we concentrate on the analysis of gross credit loss in this paper. In addition to the analysis of delinquency transitions, our empirical loss-projection framework also considers the analysis of account balance changes associated with accounts that transition to default. This type of analysis is also required by the Basel II rule as an intermediate step in the process of computing regulatory capital for credit risk.

Early studies on credit card portfolios over the business cycle did not find conclusive evidence of macroeconomic factors having an impact on portfolio losses. Gross and Souleles (2002) analyze credit card delinquency and personal bankruptcy in the 1990s, using panel data on credit card accounts. The authors conclude that the relation between default and economic fundamentals appears to have changed substantially over the period of study in ways not explained by their control variables; however, they did not find unemployment to have a significant impact on credit card default.

Agarwal and Liu (2003) also examine credit card delinquency and bankruptcy behavior. They note that previous empirical studies did not consistently find a significant effect of macroeconomic factors on bankruptcy, because of either inadequate data or a lack of sufficient variation in the unemployment variable during the period of analysis. Their analysis indicates that the level of unemployment appears to be a significant determinant of default, while the change in unemployment is usually insignificant. In contrast, Banerjee and Canals-Cerdá (2012), taking advantage of significant variation in policy variables, risk exposure, and performance outcomes experienced during the Great Recession, report that both the level and the change in unemployment are statistically and materially significant determinants of credit card defaults.

Qi (2009) conducts an analysis of exposure at default for a sample of credit card accounts over the period 1998–2008 using incremental accumulated dollar balances of an account at default as the analysis variable, a technique referred to as the loan equivalent exposure (LEQ), [5] and found that borrower and account risk attributes are significant drivers of LEQ. Additionally, she found LEQ to be higher in periods when overall default rates are high, which suggests EAD increases

[5] The loan equivalent exposure of an account in period t that defaults in $t+12$ can be defined as the incremental accumulated balance on the account between t and $t+12$, expressed as a percentage of undrawn balances at t.

in periods when economic conditions worsen. Interestingly, this relationship between worsening economic conditions and EAD was found to be characteristic of the 2002-03 recession. More recently, Banerjee and Canals-Cerdá (2012) report that unemployment was not a relevant factor in the account balance EAD during the Great Recession.

Existing research evaluates the performance of traditional credit risk models during the Great Recession and the effect on mortgage portfolios (Gerardi et al. 2008) and asserts that market participants should have understood that a significant decrease in house prices would result in a sharp increase in mortgage defaults. Frame et al. (2013) conduct a critical review and analyses of a regulatory stress-test model developed for Fannie Mae and Freddie Mac's first-mortgage portfolios and discuss several areas for improvement. While all the past studies concentrate on mortgages, the largest product in collateralized lending, none have yet analyzed model risk for unsecured lending. In contrast, our research focuses on the impact of model risk on credit card portfolios, the largest unsecured loan portfolios at most large banks.

In the next section, we present the data and provide descriptive statistics for some of the key variables in our sample. Section 3 contains the empirical methodology, and Section 4 presents the empirical model results. The discussion of the simulation results are in Section 5, while Section 6 concludes the paper. Tables and figures are presented in Section 7.

II. Data and Descriptive Analysis

We have access to a panel data set containing trade-line credit card information from a 5% random sample of individuals with a credit file in the consumer database from Equifax, one of the major credit bureaus in the United States. The data set includes information on credit card account characteristics, such as account age, line, and utilization, account balances, current and past delinquencies, as well as the individual's credit score. The data starts in the year 2000 and is updated biannually. It includes up to 10 active credit card accounts per individual. For the purpose of data selection, current accounts with zero balances and no activity within the last six months are excluded from the data set. Also, in the unlikely case of individuals with more than 10 active credit card accounts, we retain the 10 most recently opened accounts. For our analysis, we employ a panel with information on credit card accounts from 2000 to 2010. For each account and for each performance year in our sample, we observe account snapshot information in the months of June and December, including information on monthly account performance. Given the enormous size of the original data set, in our analysis we employ a 1% random sub-sample from the sample described above. This results in approximately 3.28 million active loans over the 11-year period.

Table 1 lists the primary risk drivers employed in our statistical analysis of credit risk. Relevant variables include account-specific characteristics like delinquency history, loan age, a proprietary Equifax risk score, account balance, account line, and account utilization (defined as the percentage of the line that is being employed at the time of observation). Other relevant variables include discrete measures of time to default and a control for seasonality. In addition, we consider the level and change in unemployment and changes in the House Price Index (HPI) as measures of economic activity. Several variables included in our model specifications are represented as dummy variables reflecting non-overlapping ranges across the overall variable range. This approach allows us to estimate the potential nonlinear impact of particular variables without having to rely on assumptions about particular functional forms.

Figure 1 provides information on the historical values of policy variables and credit card delinquencies. The policy variables considered in our study have experienced significant variation during the period of analysis. House prices increased steadily until 2006, experienced a steep decline between 2006 and 2009, and decreased moderately thereafter. Unemployment remained relatively stable between 2000 and 2007, increased significantly between 2007 and 2009, and recovered gradually thereafter. Unemployment and credit card charge-offs historically have moved together, although, in the most recent period, charge-offs decreased at a more rapid pace.

Table 2 presents descriptive statistics over time for the representative sample employed in our analysis. Looking at the proportion of new loans, we observe a significant reduction in new credit-card account originations during the years 2008 to 2010, which is associated with the economic downturn. We also observe an improvement in the risk-score distribution during the same period, partly the result of an increase in defaults of low-score loans and partly the result of fewer originations in the lowest-credit-score segments. We also observe an increase in the credit card utilization rate, followed by a reduction in the utilization rate. Consistent with Figure 1, a significant increase is seen in the highly delinquent segment proportion of the portfolio. Credit card charge-offs more than doubled between 2006 and 2010, rising from 4.8% to 10.6%, but declined quite rapidly thereafter even as unemployment remained high.

III. Empirical Methodology

We follow the traditional approach that takes into account three components of risk: PD, EAD, and LGD. It is normal industry practice to consider the analysis of each loss component separately. As mentioned earlier, we focus on projecting gross credit losses because loan-level information on LGD for defaulted accounts is not readily available and past studies have shown that LGD rates for cards, which represent a non-collateralized loan, are above 80% even under normal conditions and do not vary over the business cycle as much as the collateralized retail loans. Gross credit loss is defined as the product of PD and EAD.

Each account in our sample has an associated PD over any future time period; accounts that do not default over the period of analysis incur zero loss to the bank, while accounts that default incur a loss that is a function of the borrowed amount at the time of default, also referred to as the exposure at default. The econometric framework in this section is concerned with the estimation of these two fundamental components and the projection of potential default outcomes. Next, we describe the econometric methodology and the empirical specification considered in our analysis.

A. Transition to Default

We model the probability of default as a process of transition from the account's delinquency state at the time of observation to the default state at some point into the future. Default is defined as either 120 days past due or charge-off. We employ a simple transition to default hazard model with time-variant intensity of transition to default, or time-variant coefficients, in our most general model specification. In particular, we define the probability of default one period after the observation time, t_0, as the probability of defaulting during the time period $(t_0, t_0 + 1)$. Similarly, we define the probability of default in the second period after the observation time as the product of the probability of defaulting during the time period $(t_0 +$

$1, t_0 + 2)$ conditional on the account surviving up to that point and the probability of not defaulting prior to period $(t_0 + 1)$, or $\hat{p}(t_0 + 2) \cdot \big(1 - \hat{p}(t_0 + 1)\big)$. In general, the probability of default K periods into the future is defined as

$$\hat{p}(t_0 + K) \cdot \prod_{k=0}^{K-1} \big(1 - \hat{p}(t_0 + k)\big)$$

where $\hat{p}(t_0 + K)$ represents the probability of default at period $t_0 + K$, assuming that the account survived until that period, and $\big(1 - \hat{p}(t_0 + k)\big)$ represents the probability of survival at period $t_0 + k$ of an account that survived up to period $(t_0 + k - 1)$. This approach is motivated by the popular Kaplan-Meier estimator in the survival analysis literature.

In the empirical implementation, we define the PD at time t+k for surviving accounts at time t+k-1 as a parameterized logit specification of the form

$$\hat{p}(t + k|t) = \mathrm{P}(\mathrm{S(t)}, \mathrm{D(t + k)}; \varphi_k) = \frac{1}{1 + \exp\Big(\varphi_k\big(\mathrm{S(t)}, \mathrm{D(t + k)}\big)\Big)}, \text{ for } k = 1, \dots, K.$$

In particular, we consider the following convenient specification for the index function:

$$\varphi_k\big(\mathrm{S(t)}, \mathrm{D(t + k)}\big) = \lambda\big(t, age(t + k); \beta_k^{\lambda}\big) + \delta\big(\mathrm{S(t)}, \mathrm{D(t + k)}; \beta_k^{\delta}\big), \text{ for } k = 1, \dots, K$$

where $\lambda\big(t, age(t + k); \beta_k^{\lambda}\big)$ represents a baseline hazard of account age and time to default with a semi-parametric specification (in the spirit of Han and Hausman, 1990; Meyer, 1990; Sueyoshi, 1995; McCall, 1996; and Deng, Quigley, and Van Order, 2000).[6] The factor $\delta\big(\mathrm{S(t)}, \mathrm{D(t + k)}; \beta_k^{\delta}\big)$ captures the effect of accounts' characteristics and delinquency history, denoted as $\mathrm{S(t)}$, and dynamic macroeconomic factors, denoted as $\mathrm{D(t + k)}$, and in our empirical framework take a linear specification for simplicity and convenience of interpretation. The coefficients $\big(\beta_k^{\lambda}, \beta_k^{\delta}\big)$

[6] A similar baseline hazard specification has been employed in the economic literature on credit card default—for example, by Gross and Souleles (2002) and Agarwal and Liu (2003).

are time variant, i.e., they are allowed to vary across time intervals, in the most general model specification considered.

B. Exposure at Default

Owing to the unsecured and revolving nature of credit card lending, the credit risk analysis of a credit card portfolio must take into account the potential change in an account balance for loans that transition to default. Several EAD quantification methods have been proposed in the academic literature as well as by industry practitioners. When computing EAD, we employ the loan-over-line-equivalent concept (LLEQ), where future account draws are modeled as a function of account line as follows:

$$LLEQ = \frac{[outstanding(\$)_{tD} - outstanding(\$)_{t0}]}{Line(\$)_{t0}}$$

and where the final exposure at default estimate is computed using the following basic formula:

$$EAD(\$)_{tD} = outstanding(\$)_{t0} + \widehat{LLEQ} * Line(\$)_{t0},$$

where t_D represents the time of default. This concept incorporates information about the account's line and balance outstanding at the time of observation. The LLEQ parameter is estimated using a standard linear regression framework and is conditional on account and macroeconomic variables. Similar to the PD framework, our most general model specification incorporates time-variant coefficients to accommodate potential changes in the impact of control variables at different times to default.

Alternative approaches considered in the literature are the loan-equivalence concept (LEQ), where account draws are modeled as a function of a ratio of the available credit line at observation time, and the credit conversion factor (CCF), where account draws are modeled as a function of a ratio of the drawn amount at observation time. Both the available credit and the draw amount at observation time can take values close to zero in some cases and create outliers in measures of LEQ and CCF, as documented in earlier studies (Qi 2009). Our framework circumvents that problem.

IV. Analysis of Empirical Models' Results

In this section, we present estimation results for models of transition to default and exposure at default using the theoretical econometric framework described in the previous section. As our main research objective is the analysis of model risk, we consider four different model specifications over a variety of sampling intervals, starting with a sample period from year 2000 to year 2007 (the 2000-07 sample) and continuing with incrementally larger samples, in one-year increments, up to the 2000-10 sample, which encompasses the overall sample. We also estimate separate models for current and delinquent accounts because these two types of accounts perform very differently. In this section, we focus on a subset of representative models estimated using the sampling period 2000-10.

In Tables 3.A and 3.B we present estimation results for the sample of accounts current and delinquent, respectively, at the time of observation. The models included in the tables differ primarily in their parameterization of the macroeconomic variables, which is in line with our objective of analyzing model performance under stress economic conditions. The first model specification considered includes a baseline hazard of time to default, characterized by time dummies, account age dummies, score, utilization, and credit limit dummies for different variable ranges, as well as a control for an account's recent delinquency history. This specification does not include macroeconomic variables for consistency with the framework postulated in the early academic literature, which did not find a significant role for macroeconomic variables in credit card default.

Policy variables are added to the second model, including unemployment and change in unemployment, as well as a house price index at the state level.[7] The third model specification expands on the previous one by allowing for interactions between macroeconomic variables and credit score. Finally, the fourth and most general model specification expands on the third model by allowing for time-variant coefficients; in particular, coefficients are allowed to take on different values six months before and after the observation time. We also estimated models for different sample periods, with and without origination vintage effects, and discuss some of our

[7] We also experimented with measures of economic conditions at the county level and did not observe any major changes; the reported results using state-level variables are somewhat more significant.

findings from that exercise in the next section. In Table 3 we report parameter estimates for models one to three. Parameter estimates for model specifications not included in this paper are available from the authors.

A. Transition to Default

We focus first on models of transition to default for accounts that are current at the time of observation in Table 3.A. Parameter estimates are reported as odds ratios for ease of interpretation.[8] A coefficient above (below) one represents an increase (decrease) in the odds of default as a result of an increase in the value of the associated explanatory variable. Given the large sample size, most parameters with associated odds ratios that deviate even slightly from one will be significant.

Looking at coefficients associated with core variables shared across all models, we observe marginal changes with the introduction of policy variables. The effects of age and time dummies in our models are consistent with results reported in the existing literature and are not reported in the tables. In particular, age dummy parameters are consistent with the expectation that newly originated accounts are more likely to default in their first year from origination, and time dummy parameters indicate that current accounts are more likely to default more than six months after observation. We observe large differences in the odds of default associated with different risk-score groups. The odds ratio associated with risk-score group two, i.e., accounts with a score in the range 580-660, are about 0.34, indicating that the odds of default for an account in that group are about one-third of the odds of default associated with an account in the control group with score in the 250-580 range, assuming the same characteristics across other risk dimensions.

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[8] A convenient feature of the logit model is that the odds ratio coefficients are invariant across values of the explanatory variables, much like the coefficients in a linear regression model. The odds of default are defined by the expression

$$\frac{exp(\beta x)}{1 + exp(\beta x)} : \frac{1}{1 + exp(\beta x)} = exp(\beta_k x)$$

and can be denoted as $Odds(x)$. We can consider the odds ratio of increasing a certain characteristic x_i by a unit as equal to

$$\frac{Odds(x_{-i}, x_i + 1)}{Odds(x)} = \frac{exp(\propto + \beta_{-i} x_{-i} + \beta_i x_i + \beta_i)}{exp(\propto + \beta x)} = exp(\beta_i),$$

where $x = (x_{-i}, x_i)$, $\beta x = \beta_{-i} x_{-i} + \beta_i x_i$ and the odds ratio is independent of characteristics and equal to $exp(\beta_i)$.

The odds ratio associated with accounts in higher-risk-score groups indicates a significantly lower probability of default associated with these accounts.

The results also indicate that higher account utilization is associated with a higher probability of default. In particular, account utilization in the range of 35% to 80% is associated with a 50% increase in the odds of default when compared with account utilization below 30 %, and the odds more than double for accounts with utilization above 80%. Accounts associated with large credit lines of $7,500 or higher are also more likely to default after we control for other relevant risk characteristics. Not surprisingly, accounts that have been delinquent at some point over the past two years are significantly more likely to default in the future.

The impact of macroeconomic conditions on the transition to default is analyzed more precisely in models 2 and 3. Both a higher unemployment rate and an increase in unemployment contribute to an increase in the probability of default, while a decrease in home prices also contributes to an increase in the probability of default. Like Banerjee and Canals-Cerdá (2012), in model 3, we consider interactions between macroeconomic variables and account characteristics and find that the impact is heterogeneous, with proportionally a more significant impact of macroeconomic conditions associated with high-credit-score accounts.[9] For example, as shown in model 3, an increase of one percentage point in the unemployment rate increases the odds of default by 18% for prime borrowers, whereas the impact is considerably lower for subprime borrowers, increasing the odds of default by 1%.

Similarly, a 10% decline in house prices reduces the odds of default for prime borrowers by 20%, whereas it reduces the odds by 5% for subprime borrowers. It is also pertinent to point out the high correlation between unemployment and home prices during the period of analysis; in fact, we do not observe a significant change in the ability to fit the recent economic downturn when a house price index is not included in our models.

Models of transition to default for accounts that are delinquent at the time of observation are presented in Table 3.B. Model specifications in this case include a six-month-lag credit score variable to avoid the contemporaneous effect of the account's delinquency status on credit score.

[9] We also consider model specifications that allow for time-variant coefficients. These models are not discussed here, but will be utilized in the next section. The introduction of time-variant coefficients improves model fit in some cases, especially with respect to the impact of account payment status on PD, but it does not contribute significant new insights.

The impact of core risk variables is comparable across different model specifications. We observe that credit score is a significant driver of default, although the proportional decrease in odds ratios associated with higher-score segments is significantly smaller for delinquent accounts. In particular, the odds of default are reduced almost by half when we consider accounts with a risk-score above 660 with respect to the control group of accounts with risk-score below 580. As expected, a higher level of delinquency at the time of observation increases the odds of default significantly. In particular, the odds of default for accounts more than 90 days past due are 2.4 times higher than the odds of default for accounts that are 30 to 59 days past due.

Account utilization also has a significant impact on the probability of default. Specifically, the odds of default for delinquent accounts with utilization above 80% are 2.3 times higher than the odds of default for delinquent accounts with utilization below 30%. The effect of macro variables is significant and has the expected sign, and its impact on the odds ratio is similar in magnitude to that reported for current accounts.

In order to ascertain the ability of our model specifications to provide reasonable measures of aggregated portfolio loss, we consider the in-sample performance of the most general model specification considered in our analysis at the portfolio level and for different sub-populations in Figure 2. Looking at the survival curves for the process of transition to default, we observe that our model provides a good fit for aggregated survival curves up to three years into the future for different sub-populations by credit score, utilization, and line ranges, as well as for delinquency status. It also presents useful insights about the process of credit card default. Apart from the significant differences in the propensity of default across credit-score bands, it highlights differences in the pattern of default, where low-score accounts are more likely to default in the first 12 months after the time of observation and higher-score accounts are more likely to default more than a year after. Accounts in the highest credit score segment have a probability of default close to zero. There are also significant differences in the propensity to default across line and utilization segments. Delinquency status is the primary driver of credit card default, and the propensity of delinquent accounts to default is particularly high over a period of six months after the observation time, t_0. This is more evident in models with time-varying coefficients.

B. Exposure at Default

As we did with PD, we develop models of EAD separately for current and delinquent accounts at the time of observation. The modeling framework is as described in the previous section, and parameter estimates are presented in Table 3. Model specification takes the form of linear regressions with the dependent variable LLEQ measuring the percentage increase in line utilization from the time of observation to the time of default.

Parameter estimates for models associated with current accounts are presented in Table 3.A. The effects of age and time dummies in these models are consistent with results in the existing literature and are not reported here. Account age has the effect of decreasing the exposure at default, which, in conjunction with a similar effect on the probability of transition to default, indicates that an account's riskiness decreases as the account becomes more seasoned. On the other hand, the time to default has a positive impact on the exposure at default. This is not surprising, as an increase in the time to default also represents an increase in the time available to ramp up the account balances.

Credit score has a very small impact on the increase in account balances, except for accounts with scores above 800, which have a negative association with the LLEQ at default: a lower percentage drawdown rate in the range of 14% to 22% compared to accounts with a lower score. Prime borrowers with higher scores may be less credit constrained prior to default than subprime borrowers, which can explain the lower drawdowns of their unutilized lines. Similarly, higher credit limits are associated with a lower increase in utilization at the time of default. A higher utilization at the time of observation is also associated with a lower additional increase in utilization at the time of default. This last result is to be expected as the remaining line available decreases as utilization increases.

Further, this effect is heterogeneous across credit lines, with the strongest impact seen in lines greater than $7,500. Consistent with the existing literature (Banerjee and Canals-Cerdá 2012), policy variables play only a small or marginal role. Thus, the impact of the economic environment on the gross loss experienced by a credit card portfolio is primarily determined by its impact on the incidence of default.

Figure 3 shows the in-sample performance of the most general model specification of EAD considered in our analysis for different sub-populations. Overall, our model provides a good fit for the data by credit score, utilization, and line ranges, as well as by delinquency status. In the next section, we analyze the performance of our loss-projection framework under a variety of sample and model specification assumptions.

V. Analysis of Model Risk

After years of stable growth, short-lived recessions, and low unemployment, the 2007-09 recession, induced by a financial crisis, brought about a rapid increase in the unemployment rate and a steep decrease in house prices. The national unemployment rate topped at around 10% in October 2009, reaching levels of 14% in Michigan and Nevada and 12% in California. It remained above 8% nationwide until the third quarter of 2012.

Using the impact of this recent economic downturn on credit card default and loss rates, we analyze the performance of the standard loss-projection framework described in the previous sections under a variety of model specifications and sample estimation periods. Specifically, we consider the effect of model risk along three dimensions: 1) the impact of model specification assumptions, 2) the impact of the estimation sample, and 3) the impact of the postulated stress scenario or scenarios. The following subsections present our analysis and findings.

A. Model Uncertainty: Impact of Model Specification

In this subsection, we analyze the impact of model specification on the ability to project losses under economic stress conditions. As our review of the literature highlights, early studies of credit card default indicate that macroeconomic factors, unemployment in particular, had a limited or insignificant impact on the severity of credit card defaults. Subsequent studies using a larger sample period attribute a significant role to the unemployment level, while recent research incorporating data from the 2007-09 recession concludes that both the level and change in unemployment are significant drivers of credit card defaults.

In Table 4, we analyze the four loss projection model specifications considered in this paper. As illustrated in Table 3, the main difference across models is in the specification of macroeconomic variables. Model 1 does not allow for macroeconomic effects; this model specification is consistent with early academic studies. Model 2 allows for macroeconomic effects, while model 3 allows also for the interaction of macroeconomic effects with other account-level characteristics; thus this model specification is consistent with the most recent academic research (Banerjee and Canals-Cerdá 2012). Finally, model 4 builds on model 3 by considering a model specification that also allows for the possibility of time-to-default variant coefficients.

In Table 4 we present the model-projected cumulative loss over a two-year time interval of a credit card portfolio that includes open and active accounts in 2007 and 2008, respectively, and compare these projections with realized loss rates over the same two-year period. The models in this table are estimated over the sample period 2000 to 2010. As expected, realized losses are higher for the 2008 cohort, which over a two-year period was more directly exposed to the economic downturn. We observe significant differences in model performance for the overall sample and across credit score segments in particular.

Focusing our attention first on the two-year projected loss for the 2007 cohort, we observe that model 1, which does not include macroeconomic variables, significantly under-predicts realized cumulative two-year losses by 10%. Meanwhile, model 2 under-predicts losses by a mere 2.6%, and models 3 and 4 over-predict losses by 6%. However, these values are specific to the portfolio being considered in our analysis. An existing portfolio at a specific large bank may differ significantly from the one considered in our paper, depending on bank-specific strategy and risk appetite. Thus, we can gain a better understanding of a model’s ability to project losses by considering its performance within portfolio risk segments.

To this effect, we observe that model 1 does a good job of projecting losses for the subprime population, an under-prediction of 2.5% relative to the actuals (two-year cumulative projected loss rate of 37.6% relative to 38.6%), while the more sophisticated model 4 (two-year projected loss rate of 40.8%) over-predicts losses for this segment by about 6%. However, the performance of model 1 is significantly worse for other risk segments and achieves its worst performance for the prime segment with a 38% under-prediction rate (projected loss rate of 2.4% relative to 3.9%) over a two-year period. By comparison, the more complex model 4, with controls for macroeconomic variables, predicts losses that are almost identical to the realized losses for the prime segment.

Focusing our attention on the two-year performance of the 2008 cohort, we observe that model 1 significantly under-predicts realized cumulative two-year losses by 19% (projected loss rate of 13.9% relative to 17.1%), while model 2 under-predicts losses by a mere 1.7% and models 3 and 4 over-predict losses by about 3% overall. On the other hand, when we consider the performance of the different segments, we observe that model 1 also does a good job of projecting losses for the subprime population in this case, with a two-year loss under-prediction of 4% (projected loss rate of 39.2% relative to 40.8%). Meanwhile, the more sophisticated model 4 over-predicts losses for this segment by about 8%. As before, the performance of model 1 is significantly worse in other risk segments and achieves its worst performance for the prime segment with a 56% under-prediction rate (projected loss rate of 2.3% relative to 5.2%). By comparison, model 4 under-predicts losses by about 12% for the prime segment.

Thus, our analysis indicates that model projections are impacted significantly by model specification assumptions. However, the impact is not homogeneous across portfolio risk segments. In particular, when we consider the impact of a significant and rapid increase in unemployment during the 2007-09 recession, we observe that the near-prime and prime segments of the portfolio are proportionally the ones more significantly impacted by model specification assumptions. These results follow naturally from our finding in the previous section indicating that the subprime segment is proportionally less sensitive to changes in macroeconomic conditions than higher-credit-quality segments.

This finding has important implications for portfolio risk management, as it suggests that near-prime and prime segments of the portfolio may, at a particular point in time, be seen as less risky by risk managers and regulators, even though these segments can be impacted more severely by economic downturns.

B. Model Uncertainty: Impact of Sample Selection

Another related and potentially significant source of model risk can result from the lack of a sufficiently severe stress period in the estimation sample. This data limitation can impact the identification and estimation of model parameters and compromise a model's ability to forecast a proper level of stress when the postulated stress environment falls outside the stress levels indicated in the data. This potential data shortcoming has been recognized within the Basel II regulatory framework, which requires that banks include at least one economic downturn in the data sets employed for computing regulatory capital. As Figure 1 indicates, the recent Great Recession resulted in losses on credit card portfolios significantly larger than those experienced during the previous ten years, or at any time in the relatively short history of credit card lending. In this subsection, we analyze the impact of this potential source of model error by comparing loss-projection results for models estimated from samples that include economic downturns of varying severity. In particular we consider estimation samples incorporating data from the year 2000 to the years 2007, 2008, 2009, and 2010 respectively.

Table 5 presents results for model projections based on different samples and compares these results to realized losses. Looking first at the results for model 1 (i.e., a naïve model without controls for macroeconomic factors), we observe that the model performs very poorly when the sample does not include a period with a significant downturn. More precisely, for the 2000-07 sample, the model projects two-year losses of 11.9% while realized losses are 15.2% for the 2007 cohort. For the 2000-08 sample, the model projects two-year losses of 12.2% versus realized losses of 17.1%.

We also observe significant differences in model performance across risk segments. Specifically, for the 2007 cohort, the two-year projected loss rate for the subprime segment is equal to 35.3% while realized losses are 38.6%, reflecting a 9.5% under-prediction rate. In contrast, the two-year projected loss rate for the near-prime and prime segments is equal to 7.8% and 1.4% for the 2007 cohort, while the realized losses are 12.3% and 3.9%, respectively, representing under-prediction rates of 37% and 64%. The results are more dramatic when we look at the 2008 cohort, where the level of under-prediction is 29% for the overall sample, 11% for the subprime sample, 51% for the near-prime sample, and 73% for the prime sample. The degree of under-prediction decreases as the period of economic downturn included in the estimation sample increases. More precisely, using the 2000-10 sample and comparing it to the 2000-07 sample, the level of under-prediction for the 2008 cohort drops down to 19% from 29% for the overall sample, to 4% from 11% for the subprime sample, to 36% from 51% for the near-prime sample, and to 56% from

73% for the prime sample. In other words, the under-prediction is still extremely large for risk segments other than the subprime segment.

Looking at results for models that control for macroeconomic factors, we observe a significant improvement in loss projection, but the impact of sample selection uncertainty is still significant. We will focus our discussion on model 4, which includes controls for macroeconomic variables interacted with credit score while also allowing for time-variant coefficients. Meanwhile, model 2 is a simpler model that includes macroeconomic factors but no interactions. We observe that model 4 performs significantly better than model 1 even when the sample does not include a significant downturn period, but it is still the case that its loss-projection capabilities are seriously impacted.

As before, we observe significant differences in model performance across risk segments. More precisely, based on the 2000-07 sample and the 2008 cohort, the model projects two-year losses of 15.6% while realized losses are 17.1%. Thus, projected losses are still lower than realized losses, but they are much more accurate than in the case of model 1. Also, model 4 performs much better when the estimation sample includes a significant downturn period. In particular, using the 2008, 2009, or 2010 sample results in projected losses of 16.4%, 18.1%, and 17.7%, respectively.

Looking across risk segments, we observe that the model systematically over-estimates losses for the subprime population and under-estimates losses for the prime segment, while model performance improves significantly once a sufficiently large downturn period is included in the data. Specifically, for the 2008 cohort, using the 2000-07 data, we observe under-prediction of 9.7% for the overall sample, under-prediction of 71.2% for the prime sample, and over-prediction of 13% for the subprime sample. The level of under-prediction improves as the period of economic downturn included in the estimation sample increases. More precisely, when the 2000-10 sample is used, the level of under-prediction vanishes for the overall sample and is only 11.5% for the prime sample.

Thus, sample selection and model specification play a significant role in a model's ability to project losses consistent with the observed loss severity during the 2007-09 economic downturn. The need for a sufficiently representative downturn period in the data is particularly relevant, as we have shown, and it has a significant impact even in the most general model specification considered. Observe that our statistical analysis shows that an economic downturn has a small impact on the exposure at default and a much larger impact on the probability of default. Observe also that delinquent accounts have a high probability of default under any economic scenario and represent a small proportion of most credit card portfolios. Thus, the primary effect of model specification and sample selection on portfolio loss under downturn conditions is channeled through the process of transition to default of accounts current at observation time.

Table 6 presents parameter estimates for the coefficients associated with policy variables in model specification 4—that is, with time-variant coefficients—over different sample estimation periods from 2000-07 to 2000-10. We detect only small changes in coefficients for the subprime segment and observe the largest change in coefficients for the prime segment. This observation is consistent with our finding that model specification and sample selection uncertainty have the largest impact on the prime segment.

C. Scenario Uncertainty: The Great Recession versus the Great Depression

In the previous two subsections, we focused our attention on issues of model risk directly associated with the model specification process. Perhaps as important, or more, for risk managers conducting a stress test is to consider the uncertainty associated with the selection of the loss-projection economic scenario. While the Great Recession brought about a level of stress not experienced before in credit card portfolios, there is no reason to conclude that more significant periods of economic downturn should not be considered. Specifically, the much harsher downturn conditions experienced during the Great Depression provide an opportunity to test portfolio performance on a one-in-100-years type of scenario.

First, it is important to point out that the analysis of a Great Depression scenario falls significantly outside the level of stress observed in the data. The unsecured and revolving nature of credit card lending gives banks the opportunity to modify their lending strategies in a relatively short time frame. This suggests that changes in the economic environment that are substantially worse than the recent economic downturn are also likely to result in more restrictive bank lending policies than the ones experienced during that period. Our models are unlikely to fully internalize these dynamic changes in lending policies, which suggests that realized losses are likely to be lower than projected losses. On the other hand, a depressed economic scenario of the type experienced during the Great Depression is expected to generate complex spillover effects that may potentially affect the borrower's creditworthiness and ability to pay beyond our models' projection capabilities, thus potentially resulting in realized losses that are higher than our projected losses.

Taking these into consideration, along with our findings from the previous subsection, we need to recognize the limitations of our analysis and the likelihood of projection error in this simulation exercise. However, we believe that this kind of analysis may still provide powerful insights to portfolio managers about potential weakness in their risk management strategies.

Table 7 reports results from a synthetic economic scenario designed to mimic the unemployment experience during the Great Recession at the national level. In particular, we consider the same rate of increase in the unemployment rate as was seen during the worst two years of the Great Depression. Given the initial conditions prevailing in 2008, this brings the national unemployment rate to a high of 22% over the next two years. The decline in the HPI is left unchanged, as it was worse in the Great Recession than in the Great Depression.

Not surprisingly, the projected portfolio loses under depression conditions are staggering. Over a two-year period, projected overall portfolio losses are 33% of initial portfolio balances, while the subprime, near-prime, and prime segments of the portfolio's projected losses are 56%, 37%, and 19% of their corresponding balances, respectively. Comparing these losses to the levels experienced during the worst two-year period of realized losses during the Great Recession, we observe that overall projected losses double.

However, there are significant differences across risk segments: Projected losses in the subprime segment stand at 138% of the loss experienced during the Great Recession, which represents a relatively small increase compared with projected losses of 234% and 369% above losses experienced during the Great Recession for the near-prime and prime segments, respectively. Thus, losses from the subprime segment remain higher than losses for the near-prime and prime segment, but the differences are less significant in this severely stressed economic environment.

A detailed examination of results may help risk managers implement risk management strategies related to account monitoring and exposure reduction that contain portfolio losses.

VI. Conclusions

The focus of this paper is model risk's impact on loss projections and loan-loss provisioning specific to credit card portfolios. In particular, we concentrate our attention on the analysis of model risk as it relates to model specification, sample selection, and scenario selection. To this effect, we employ a panel data on credit card account characteristics and performance from the Equifax Credit Bureau, over the period 2000-10. We formulate a standard empirical framework for analyzing portfolio loss where projected loss of a credit card account can be represented as the product of the account's probability of default and the projected exposure at default conditional on a loan's characteristics and macro scenarios.

Our loss-projection framework fits the loss experienced in our representative portfolio well when models are estimated over the full sample. The results indicate that macroeconomic conditions have a significant and sizable impact on an account's likelihood of default. In contrast, macroeconomic conditions play a much smaller role in an account's projected exposure at default, possibly because of active line management practices at banks. We observe that the impact of macroeconomic factors is heterogeneous across portfolio segments conditional on account characteristics—credit score, in particular. The segment of accounts classified as subprime according to their low credit score has the highest loss rate in all economic environments considered, but it is proportionally less impacted by changes in macroeconomic conditions than are the near-prime and prime segments.

Our analysis indicates that loss projections are significantly impacted by model specification assumptions. Models without controls for macroeconomic variables substantially under-predict realized cumulative two-year losses under conditions of economic stress. Models that have controls for macroeconomic variables, but that do not account for interactions between these variables and measures of creditworthiness, can significantly under-predict or over-predict loss under stress for different segments of the portfolio. The impact of model specification assumptions is heterogeneous across portfolio segments. In particular, when we consider the impact of a significant and rapid increase in unemployment during the Great Recession we observe that the near-prime and prime segments are proportionally the ones more significantly impacted by model specification assumptions. These results indicate that, contrary to popular perception, model specification matters much more for prime segments than for subprime segments in unsecured lending portfolios.

The lack of a sufficiently severe stress period in the estimation sample represents another potential source of model risk and results in a significant under-prediction of portfolio losses under stressed economic conditions in our case. Model performance improves significantly once a sufficiently large downturn period is included in the data, particularly in the most flexible model specification considered.

Models without controls for macroeconomic variables perform significantly worse, even when the estimation sample includes a representative economic downturn period. Using our preferred model specification based on the 2000-07 sample, we project two-year losses of 15.6%, while realized losses are 17.1% for the 2008 portfolio cohort. Projected losses for the 2008 portfolio increases to 17.7% when the estimation sample is expanded to include the Great Recession, 2000-10. We observe significant differences in model performance across risk segments, with the near-prime and prime segments being the most significantly impacted by data limitations. If we use the 2000-07, 2000-08, 2000-09, and 2000-10 samples, projected losses for the prime segment are 1.5%, 2.0%, 3.4%, and 4.6%, respectively, while realized two-year losses are equal to 5.2%.

The economic downturn experienced during the Great Depression provides an opportunity to test the portfolio performance on a one-in-100-years type of scenario. We observe significant differences across risk segments. Projected losses in the subprime segment stand at 138% of the loss experienced during the Great Recession, which represents a relatively small increase of 38% in projected loss. In contrast, respective losses for the near-prime and prime segments are projected at 234% and 369% of the experienced loss during the Great Recession. While losses from the subprime segment remain higher than losses for the near-prime and prime segments even in the extreme economic environment of the Great Depression, the loss sensitivity of the other segments to changing economic conditions is significantly stronger than for subprime. The analysis of portfolio loss under scenarios of extreme economic stress can offer valuable lessons to risk managers. Specifically, a detailed examination of results may help them implement account management and account origination strategies that limit losses by targeting specific segments of the portfolio.

VII. References

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VIII. Tables and Figures

Table 1: Variable Definitions

t1-t5	*Baseline hazard dummies for 0-6, 7-12, 13-18, 19-24, and 25-30 months*
Loan Age 0 - 10 and 10+	*Account age dummies*
Risk Score	*Borrower's credit score*
Risk Score 1-5	*Credit score dummies for ranges 250-580, 580-660, 660-720, 720-800, and 800+*
Balance	*Current outstanding balance on the account as of the observation date*
Line 1-3	*Credit limit is less than $1500, $1500-$7500, and $7500+*
Util 1-3	*Utilization is between zero and 35%, 35%-80%, and 80%+*
Del 0-3	*Payment status dummies for current, 30-59, 60-89, and 90+ days past due*
Ever60	*Current, was 60 days past due at least once in the past 24 months*
Seasonality	*Indicator for third and fourth quarter*
HPI	*State-level House Price Index as of t.*
PCT. CHG HPIS 12M	*Percent change in HPI over the last 12 months*
UR	*State-level unemployment rate as of t (consistent with HPI)*
CHG UR 12M	*Change in unemployment rate over the last 12 months*
Variable_name & (SP, NP, PR, DQ60)	Interactions with specific subgroups: SP=Subprime, NP = Near-prime, PR = Prime, DQ60 = Seriously delinquent.

Figure 1: Credit Card Losses, Unemployment Rate, and Housing Prices

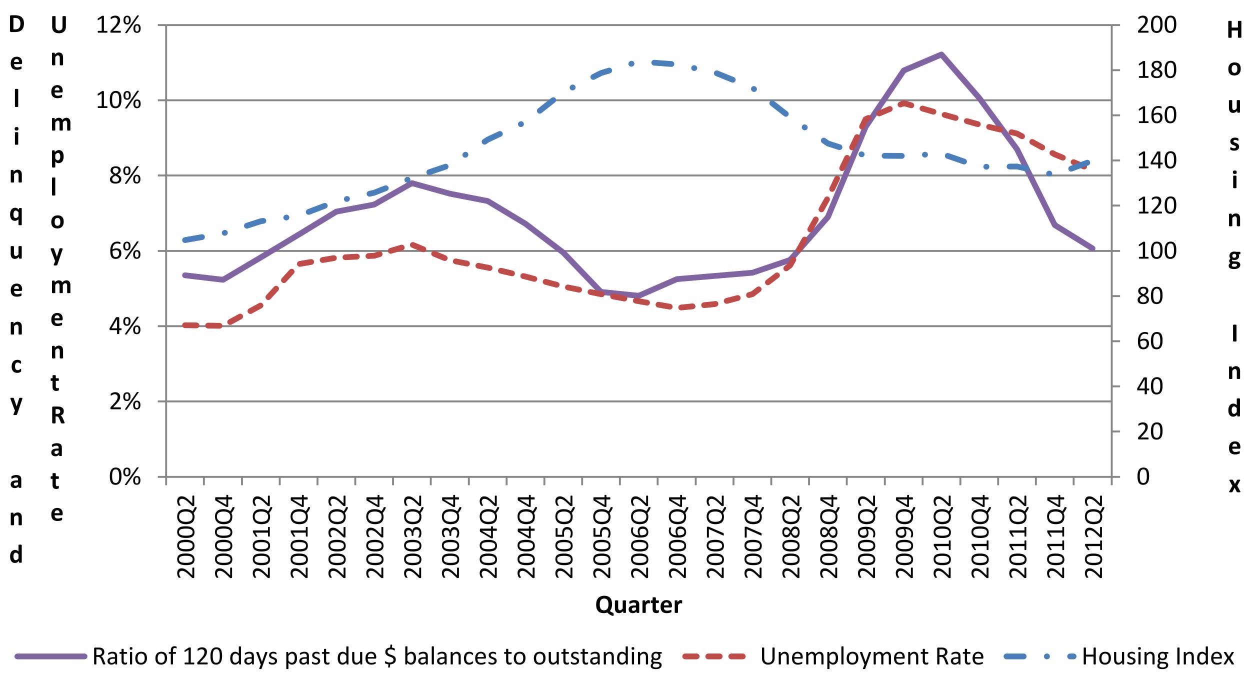

Table 2: Descriptive Statistics

Variable	2000 - 05	2006	2007	2008	2009	2010	2011	2012
Loan Age								
Loan Age 0,1	14.4	14.5	15.3	13.4	7.9	6.4	7.1	7.7
Loan Age 2	12.4	11.9	11.2	12.1	11.5	7.1	5.6	6.4
Loan Age 2+	73.2	73.6	73.5	74.5	80.6	86.5	87.3	85.9
Risk Score								
Risk Score 1	16.31	12.06	13.31	15.25	18.42	16.67	12.32	10.75
Risk Score 2	20.77	17.03	16.71	15.35	14.67	14.89	14.99	14.55
Risk Score 3	27.17	26.3	25.09	24.22	22.01	21.63	22.63	23.32
Risk Score 4	32.31	38.58	38.21	37.4	36.46	37.34	39.55	40.36
Risk Score 5	3.44	6.03	6.69	7.77	8.43	9.46	10.51	11.02
Line								
line d1	7.1	5.3	5.3	5.3	5.4	5.5	5.3	5.2
line d2	35.5	27.9	26.7	26.2	27.7	28.8	28.6	28.7
line d3	57.4	66.8	68.0	68.5	67.0	65.7	66.2	66.0
Utilization								
Utilization 1	14.3	16.9	17.1	16.1	15.1	15.4	17.8	19.2
Utilization 2	30.0	33.3	33.4	31.0	28.3	29.4	31.4	32.0
Utilization 3	55.7	49.8	49.6	53.0	56.6	55.2	50.8	48.8
Del								
Current	90.3	92.5	91.8	90.2	86.4	86.6	90.3	92.1
Del 1	3.4	2.7	3.0	3.6	3.7	2.8	2.1	2.0
Del 2,3	6.3	4.8	5.2	6.1	9.9	10.6	7.6	5.9
Balance (MM)	2115.0	2354.2	2443.2	2548.7	2515.2	2417.8	2306.0	2252.4
Ever60	10.9	8.1	8.7	10.2	14.0	14.1	10.2	8.4
Seasonality	50.7	50.7	50.6	50.9	49.8	49.1	51.3	0.0
HPI	134.5	183.2	175.6	153.4	142.1	140.1	135.3	139.9
UR	5.2	4.6	4.7	6.5	9.7	9.5	8.8	8.1

Note: The descriptive statistics in this table are balance weighted.

Table 3.A: Parameter for PD Model (Odds Ratio) and EAD Model: Current Segment

	PD Model			EAD Model		
Variable	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Risk Score 2	0.34***	0.34***	0.35***	-0.001	-0.002	0.006***
Risk Score 3	0.14***	0.14***	0.08***	0.013***	0.011***	0.011***
Risk Score 4	0.03***	0.03***	0.01***	0.013***	0.010***	-0.023***
Risk Score 5	0.01***	0.01***	0.00***	-0.145***	-0.145***	-0.223***
Util 2	1.18***	1.18***	1.17***	-0.049***	-0.050***	
Util 3	1.50***	1.50***	1.50***	-0.129***	-0.130***	
line 2	0.92***	0.92***	0.92***	-0.295***	-0.296***	-0.136***
line 3	1.11***	1.10***	1.09***	-0.352***	-0.354***	-0.134***
Line 1 * Util 2						0.053***
Line 1 * Util 3						0.018***
Line 2 * Util 2						-0.075***
Line 2 * Util 3						-0.189***
Line 3 * Util 2						-0.132***
Line 3 * Util 3						-0.284***
Ever60	1.50***	1.53***	1.52***			
Seasonality	1.06***	1.05***	1.05***			
L_UR		1.04***				
L_UR_SP			1.01***			
L_UR_NP			1.11***			
L_UR_PR			1.18***			
L_CHG_UR		1.05***			0.011***	
L_CHG_UR_SP			1.06***			0.009***
L_CHG_UR_NP			1.03***			0.011***
L_CHG_UR_PR			1.03***			0.018***
% CHG_HPI		0.93***				
% CHG_HPI_SP			0.95***			
% CHG_HPI_NP			0.84***			
% CHG_HPI_PR			0.80***			
LLR/R-Squared	609753	617458	622080	0.2335	0.2356	0.2456

Note: Model specification also includes controls for time to default (baseline hazard) and account age.

Table 3.B: Parameter for PD Model (Odds Ratio) and EAD Model: Delinquent Segment.

	PD Model			EAD Model		
Variable	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
L_score 2	0.79***	0.78***	0.74***	0.001	0.002	0.003
L_score 3	0.59***	0.58***	0.51***	-0.018***	-0.016***	-0.015***
L_score 4-5	0.40***	0.39***	0.31***	-0.001	-0.008	-0.007
Del 2	1.70***	1.70***	1.64***	0.129***	0.130***	0.130***
Del 3	2.43***	2.43***	2.33***	0.066***	0.066***	0.067***
Del2 *L_score 2			0.83***			
Del2*L_score 3			0.67***			
Del2*L_score 4-5			0.48***			
Del3*L_score 2			0.84***			
Del3*L_score 3			0.67***			
Del3*L_score 4-5			0.51***			
Util 2	1.54***	1.55***	1.53***	0.009		
Util 3	2.30***	2.29***	2.27***	0.112***		
line 2	0.93***	0.93***	0.93***	-0.269***	-0.152***	-0.147***
line 3	1.02	1.00***	1.00***	-0.334***	-0.186***	-0.182***
Line 1 × Util 2					0.071***	0.075***
Line 1 × Util 3					0.194***	0.198***
Line 2 × Util 2					-0.018	-0.020
Line 2 × Util 3					0.067***	0.066***
Line 3 × Util 2					-0.021	-0.019
Line 3 × Util 3					0.025	0.026
SEASONALITY	1.10***	1.11***	1.10***			
L_UR		1.04***				
L_UR_DQ30			1.04***			
L_UR_DQ60+			1.03***			
L_CHG_UR		1.02***	1.02***			-0.004***
% CHG_HPI		0.94***				
% CHG_HPI_DQ30			0.92***			
% CHG_HPI_DQ60+			0.95***			
LLR/R-Squared	55649	55826	55978	0.2462	0.2485	0.2493

Note: Model specification also includes controls for time to default (baseline hazard) and account age.

Figure 2: Analysis of Fit of Transition-to-Default Model 4 Estimated Over the 2000-10 Sample

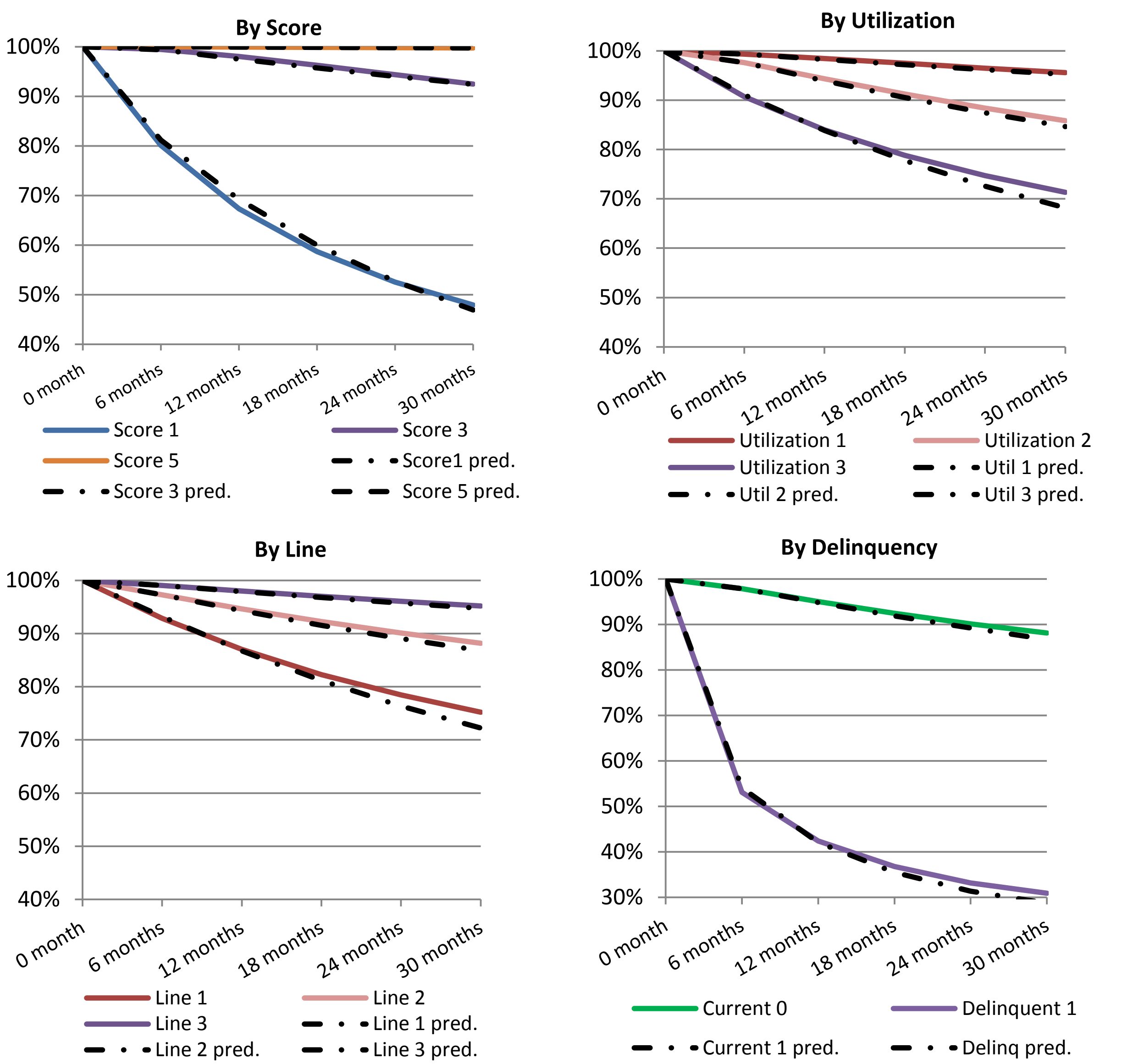

Figure 3: Analysis of Fit of Exposure at Default Model 4 Estimated Over the 2000-10 Sample

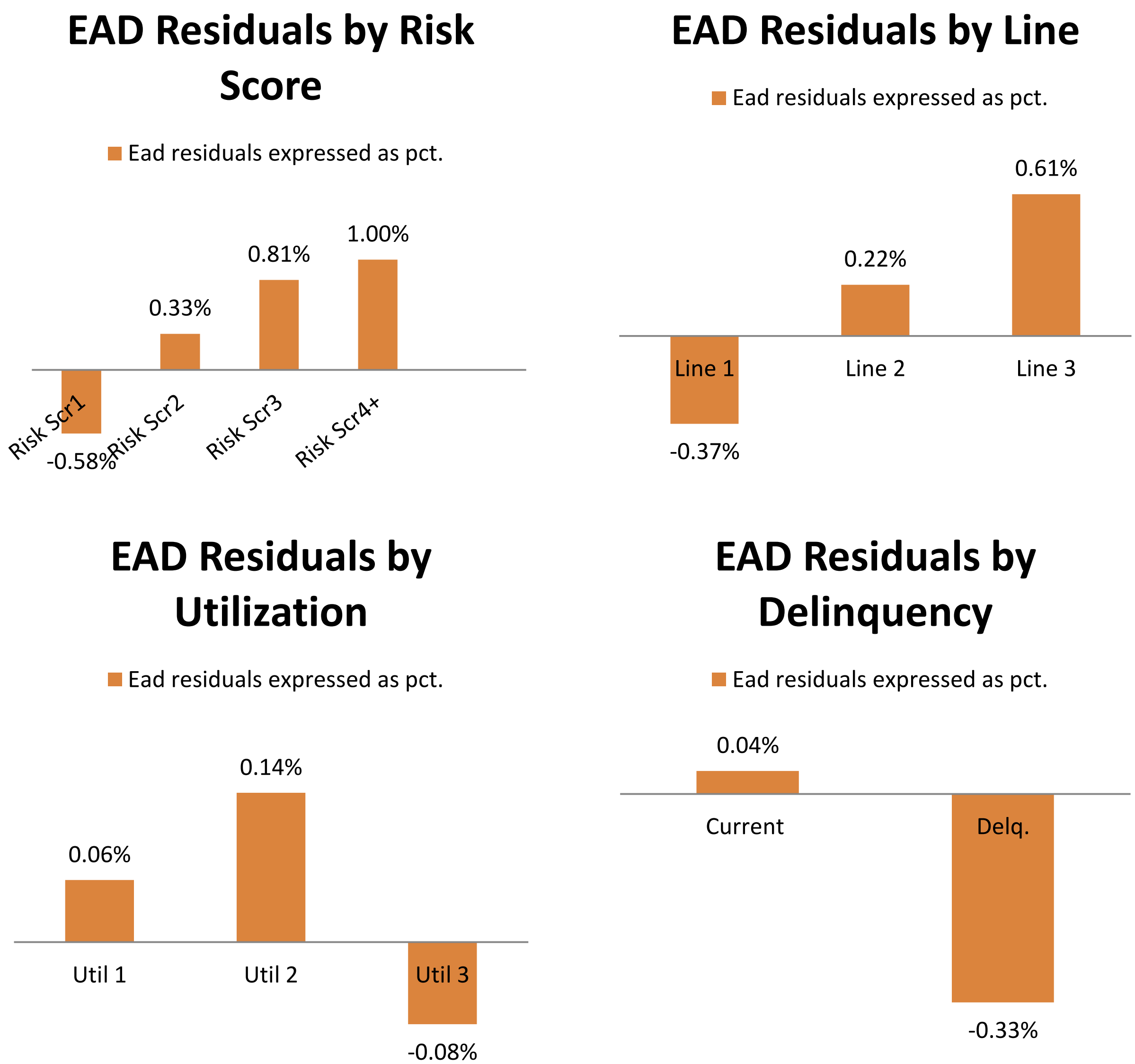

Table 4: Model Specification Uncertainty: Model Projected versus Actual Cumulative Loss Percentage

	2007 Cohort					2008 Cohort				
	(1)	**(2)**	**(3)**	**(4)**	**Actual**	**(1)**	**(2)**	**(3)**	**(4)**	**Actual**
Full Sample										
12 m	7.2	7.5	7.5	7.4	7.2	7.5	9.2	9.5	9.4	9.7
18 m	10.6	11.5	11.8	11.7	11.2	10.9	13.5	14.1	14.0	13.9
24 m	13.7	15.6	16.1	16.1	15.2	13.9	16.8	17.8	17.7	17.1
Subprime										
12 m	21.0	21.8	21.6	22.1	22.4	22.8	27.3	26.2	26.7	27.6
18 m	29.9	32.4	31.7	31.8	31.5	31.6	38.2	36.3	36.5	35.4
24 m	37.6	42.2	40.9	40.8	38.6	39.2	46.5	44.0	44.0	40.8
Near-prime										
12 m	4.5	4.7	5.0	4.5	3.6	4.4	5.8	7.0	6.3	6.7
18 m	7.4	8.3	9.1	9.0	7.7	7.2	9.6	11.7	11.4	11.5
24 m	10.2	12.0	13.7	13.9	12.3	10.0	12.9	15.9	15.6	15.6
Prime										
12 m	1.0	1.1	1.1	1.0	0.8	1.0	1.3	1.9	1.7	1.7
18 m	1.7	1.9	2.3	2.2	2.0	1.6	2.2	3.3	3.2	3.5
24 m	2.4	2.9	3.7	3.8	3.9	2.3	3.0	4.6	4.6	5.2

Table 5: Sample Selection Uncertainty: Cumulative Loss Percentage

	2007 Cohort					2008 Cohort				
Sample:	**2000-07**	**2000-08**	**2000-09**	**2000-10**	**Actual**	**2000-07**	**2000-08**	**2000-09**	**2000-10**	**Actual**
MODEL 1										
Full Sample										
12 m	6.3	6.5	6.8	7.2	7.2	6.7	6.9	7.2	7.5	9.7
24 m	11.9	12.3	12.9	13.7	15.2	12.2	12.5	13.2	13.9	17.1
Subprime										
12 m	19.7	20.0	20.6	21.0	22.4	21.4	21.7	22.3	22.8	27.6
24 m	35.3	35.7	36.8	37.6	38.6	36.9	37.3	38.4	39.2	40.8
Near-prime										
12 m	3.4	3.6	4.0	4.5	3.6	3.4	3.5	3.9	4.4	6.7
24 m	7.8	8.2	9.1	10.2	12.3	7.6	8.0	8.9	10.0	15.6
Prime										
12 m	0.6	0.7	0.8	1.0	0.8	0.6	0.6	0.8	1.0	1.7
24 m	1.4	1.6	1.9	2.4	3.9	1.4	1.5	1.8	2.3	5.2
MODEL 2										
Full Sample										
12 m	6.8	7.2	7.4	7.5	7.2	8.4	8.9	9.3	9.2	9.7
24 m	14.0	15.0	15.5	15.6	15.2	15.5	16.4	17.2	16.8	17.1
Subprime										
12 m	21.0	22.0	22.1	21.8	22.4	26.0	27.5	28.2	27.3	27.6
24 m	40.5	42.6	43.1	42.2	38.6	45.5	47.3	48.5	46.5	40.8
Near-prime										
12 m	3.8	4.2	4.5	4.7	3.6	4.7	5.2	5.7	5.8	6.7
24 m	9.7	10.7	11.6	12.0	12.3	10.7	11.6	12.8	12.9	15.6
Prime										
12 m	0.7	0.8	0.9	1.1	0.8	0.8	1.0	1.1	1.3	1.7
24 m	1.8	2.2	2.4	2.9	3.9	2.0	2.3	2.6	3.0	5.2
MODEL 4										
Full Sample										
12 m	6.7	7.2	7.4	7.4	7.2	8.1	8.7	9.5	9.4	9.7
24 m	14.0	15.2	16.2	16.1	15.2	15.6	16.4	18.1	17.7	17.1
Subprime										
12 m	21.3	22.1	22.0	22.1	22.4	26.6	27.8	27.7	26.7	27.6
24 m	41.3	42.9	41.7	40.8	38.6	46.1	47.8	46.9	44.0	40.8
Near-prime										
12 m	3.4	4.0	4.6	4.5	3.6	3.8	4.3	6.4	6.3	6.7
24 m	9.4	10.9	14.1	13.9	12.3	11.0	11.7	16.3	15.6	15.6
Prime										
12 m	0.6	0.8	1.0	1.0	0.8	0.5	0.7	1.3	1.7	1.7
24 m	1.6	2.3	3.3	3.8	3.9	1.5	2.0	3.4	4.6	5.2

Table 6: Impact of Macro Factors on Odds of Default for Current Accounts (2007 to 2010 Samples)

Sample:	**2000-07**		**2000-08**		**2000-09**		**2000-10**	
projection period:	**0-6m**	**6m+**	**0-6m**	**6m+**	**0-6m**	**6m+**	**0-6m**	**6m+**
L_UR_SP	1.02	1.05	1.02	1.06	1.02	1.05	1.02	1.02
L_UR_NP	1.08	1.12	1.08	1.10	1.13	1.13	1.14	1.10
L_UR_PR	1.04	1.10	1.04	1.09	1.08	1.13	1.12	1.17
L_CHG_UR_SP	1.03	1.06	1.02	1.06	1.03	1.05	1.02	1.06
L_CHG_UR_NP	0.89	0.94	0.90	0.95	1.00	1.03	1.00	1.05
L_CHG_UR_PR	0.81	0.85	0.81	0.86	1.01	1.00	1.06	1.04
% CHG_HPI_SP	0.97	0.95	0.95	0.93	0.96	0.95	0.96	0.95
% CHG_HPI_NP	0.93	0.92	0.99	0.87	0.85	0.84	0.85	0.85
% CHG_HPI_PR	1.00	0.96	0.95	0.83	0.86	0.77	0.88	0.80

Note: Parameter estimates are reported in odds ratios.

Table 7: Simulation of Credit Loss Under a Great Depression Scenario

	Overall	**Subprime**	**Near-Prime**	**Prime**
Great Depression Projected Loss (as % of Balance at Observation Time)				
12 m	10.9	29.1	8.2	2.6
18 m	21.1	43.7	21.1	8.9
24 m	33.3	56.3	36.5	19.2
Increase over Great Recession Projected (%)				
12 m	116.3	108.8	129.7	154.7
18 m	151.2	119.9	185.6	277.7
24 m	188.4	127.9	233.9	420.6
Increase over Great Recession Realized (%)				
12 m	111.9	105.1	121.9	150.9
18 m	152.3	123.7	183.2	253.5
24 m	194.4	138.0	234.1	369.1

IX. Appendix

Table A.1.A: Time-varying Parameters for PD Model (Odds Ratio) and EAD Model: Current Segment

Variable	PD Model (4)				EAD Model (4)			
	<= 6 mos		> 6 mos		<= 6 mos		> 6 mos	
Score 2	0.18	***	0.40	***	-0.016	***	0.008	***
Score 3	0.03	***	0.10	***	-0.045	***	0.013	***
Score 4	0.01	***	0.01	***	-0.066	***	-0.020	***
Score 5	0.00	***	0.00	***	-0.070		-0.226	***
Util 2	1.02		1.21	***				
Util 3	1.68	***	1.46	***				
line 2	0.96	***	0.91	***	-0.199	***	-0.142	***
line 3	1.39	***	1.04	***	-0.195	***	-0.141	***
Line 1 * Util 2					0.189	***	0.041	***
Line 1 * Util 3					0.246	***	-0.003	***
Line 2 * Util 2					0.065	***	-0.081	***
Line 2 * Util 3					0.089	***	-0.202	***
Line 3 * Util 2					0.047	***	-0.137	***
Line 3 * Util 3					0.049	***	-0.300	***
Ever60	1.98	***	1.36	***				
Seasonality	1.14	***	1.03	***				
L_UR								
L_UR_SP	1.02	***	1.02	***				
L_UR_NP	1.14	***	1.10	***				
L_UR_PR	1.12	***	1.17	***				
L_CHG_UR					0.00			
L_CHG_UR_SP	1.02	***	1.06	***			0.010	***
L_CHG_UR_NP	1.00		1.05				0.012	***
L_CHG_UR_PR	1.06		1.04				0.018	***
% CHG_HPI								
% CHG_HPI_SP	0.96	***	0.95	***				
% CHG_HPI_NP	0.85	***	0.85	***				
% CHG_HPI_PR	0.88		0.80	***				
LLF/R-Squared	171873		460911		0.3990		0.2380	

Note: Model specification also includes controls for time to default (baseline hazard) and account age.

Table A.1.B: Time-varying Parameters for PD Model (Odds Ratio) and EAD Model: Delinquent Segment

Variable	PD Model (4)				EAD Model (4)			
	<= 6 mos		> 6 mos		<= 6 mos		> 6 mos	
L_score 2	0.78	***	0.70	***	0.01	***	-0.01	
L_score 3	0.58	***	0.44	***	0.00		-0.04	***
L_score 4-5	0.39	***	0.23	***	0.00		-0.03	
Del 2	1.99	***	1.19	***	0.15	***	0.08	***
Del 3	3.25	***	1.34	***	0.07	***	0.04	***
Del2 *L_score 2	0.88	***	0.75	*				
Del2*L_score 3	0.81	***	0.48					
Del2*L_score 4-5	0.63	***	0.28	*				
Del3*L_score 2	0.92	***	0.72					
Del3*L_score 3	0.80	***	0.45					
Del3*L_score 4-5	0.68	***	0.25					
Util 2	1.59	***	1.42	***				
Util 3	2.76	***	1.76	***				
line 2	0.95	***	0.91	***	-0.12	***	-0.27	***
line 3	1.10	***	0.86	***	-0.10	***	-0.21	***
Line 1 × Util 2					0.11	***	0.01	
Line 1 × Util 3					0.26	***	0.12	***
Line 2 × Util 2					0.03		-0.06	***
Line 2 × Util 3					0.11	***	0.01	
Line 3 × Util 2					0.03		-0.09	***
Line 3 × Util 3					0.07	***	-0.05	
SEASONALITY	1.13	***	1.11	***				
L_UR								
L_UR_DQ30	1.06	***	1.02	***				
L_UR_DQ60	1.06		1.01					
L_CHG_UR	1.01		1.01	*				
% CHG_HPI								
% CHG_HPI_DQ30	0.89	***	0.96	***				
% CHG_HPI_DQ60	0.91		1.01	***				
LLF/R-Squared	15110		8798		0.287		0.226	

Note: Model specification also includes controls for time to default (baseline hazard).