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Accuracy of mortgage portfolio risk forecasts during financial crises☆

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ABSTRACT

This paper explores whether factor based credit portfolio risk models are able to predict losses in severe economic downturns such as the recent Global Financial Crisis (GFC) within standard confidence levels. The paper analyzes (i) the accuracy of default rate forecasts, and (ii) whether forecast downturn percentiles (Value-at-Risk, VaR) are sufficient to cover default rate outcomes over a quarterly and an annual forecast horizon. Uninformative maximum likelihood and informative Bayesian techniques are compared as they imply different degrees of uncertainty.

We find that quarterly VaR estimates are generally sufficient but annual VaR estimates may be insufficient during economic downturns. In addition, the paper develops and analyzes models based on auto-regressive adjustments of scores, which provide a higher forecast accuracy. The consideration of parameter uncertainty and auto-regressive error terms mitigates the shortfall.

1. Introduction

1.1. Motivation

The recent Global Financial Crisis (GFC) had its origin in the realization of losses in relation to sub-prime mortgage lending. Mortgage lending is traditionally one of the largest risk exposures of commercial banks. Sophisticated scoring and forecasting techniques have been developed to compute risk exposures for individual mortgages and mortgage portfolios. A key feature in modern credit portfolio management is the modeling of credit losses under severe economic downturns such as the worst outcome in 1000 years.

Given the consideration of such remote economic shock scenarios, it is astonishing that banks were surprised by the magnitude of realized losses. We analyze (i) the accuracy of default rate forecasts, and (ii) whether downturn percentiles (Value-at-Risk, VaR) for the forecast default rate reflecting parameter uncertainty are sufficient to cover default rate outcomes. Uninformative maximum likelihood and informative Bayesian techniques are compared as they imply different degrees of model risk. The accuracy of mortgage portfolio risk forecasts is analyzed prior to, and during the GFC.

An important aspect in this analysis is model risk in the form of parameter uncertainty. Measures for the co-movement of individual risks are based on time series information of limited length and the respective parameters generally attract large standard errors. Bayesian techniques with informative priors are often applied to reduce estimation risk. This is interesting as the reduction of standard errors may create a false indication of certainty if the prior information is representative with regard to the likelihood information but not representative with regard to the validation information.

The contributions of this paper are as follows. Firstly, we compare realized sub-prime mortgage losses with portfolio risk measures such as the forecast default rate and VaR. The portfolio risk measures control for observable loan-level information, macro-economic variables and unobservable systematic frailty. We find that the forecast

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default rate is lower than the realized loss rate during the GFC and that VaR models based on quarterly forecasts are sufficient under severe economic downturns. As a result, the stark increase of loss rates during the GFC were within standard confidence levels. However, annual forecasts are insufficient under severe economic downturns.

Secondly, two common approaches to measuring credit portfolio risk are compared: uninformative maximum likelihood and informative Bayesian estimation. The informative Bayesian approach is of great interest to mortgage lenders if data is available to form prior distributions of model parameters. Bayesian models lead to similar parameter estimates but lower standard errors and hence, lower VaRs after model risk is included relative to maximum likelihood estimation. The properties of informative priors given the business cycle and the origins of such priors from selected stages of the business cycle have not been explored to date. We find that model risk increases the VaR (for maximum likelihood estimation to a greater degree than for Bayesian estimation). However, the inclusion of model risk does not change our findings for the first contribution.

Thirdly, we extend our scoring model by an auto-regressive adjustment. Prior literature has included frailty effects to control for omitted time variation. We build on this literature and ‘utilize’ the auto-regressive process to improve the forecast accuracy considerably. The resulting default rate forecasts are centered around the realized default rates of the prior period and the resulting VaR forecasts are generally more likely to cover default rate realizations before and during the GFC.

The analysis is based on US sub-prime mortgage loans securitized between 2000:Q2 and 2012:Q2. The data includes over 50 million quarterly loan observations and almost one million individual loan foreclosure events. Training and validation samples are based on random draws of mutually exclusive samples.

1.2. Literature

Credit portfolio risk scoring and forecasting techniques have enjoyed great interest in the operations research and finance literature. Various authors have analyzed corporate and consumer lending portfolios. With regard to consumer credit risk, Bellotti and Crook (2013) provide an overview of consumer credit risk models. Probabilities of default are modeled by logistic regression models (compare e.g., Crook, Edelmann, & Thomas, 2007; Crook & Bellotti, 2010; Leow & Mues, 2012; Lucas, 2006) and survival analysis (compare, e.g., Bellotti & Crook, 2008; Malik & Thomas, 2009; Tong, Mues, & Thomas, 2012; Quigley & Van Order, 1991) for consumer loans. Generally speaking, the literature has focused on the scoring of individual consumer loans (e.g., credit card and other personal loans).

In addition, a variety of papers identify factors driving mortgage delinquency risk. Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010) and Goodman, Ashworth, Landy, and Yin (2010) investigate the impact of negative equity, liquidity and unemployment on mortgage default. Amromin and Paulson (2009) evaluate the relative impact of borrower, loan and macroeconomic characteristics on mortgage defaults and identify real estate prices as an important risk driver. Rajan, Seru, and Vig (2015) show that the deterioration of the accuracy of the statistical default prediction model is triggered by the change in lender behavior as the level of securitization increases. Crook and Banasik (2012) forecast time-series default rates of mortgage loans and other consumer loans based on macroeconomic variables. Our contribution relative to this literature is that we (i) compare the impact of different estimation techniques given common control variables, (ii) are able to analyze the sufficiency of economic Value-at-Risk (bank capital) models via the estimation of random frailty effects, and (iii) include a novel auto-regressive term.

The introduction of the Basel II and Basel III capital regulation has triggered the interest of banks in measuring the portfolio credit risk with measures such as VaR and Expected Shortfall. Bonollo, Mercurio, and Mosconi (2009), Duffie, Eckner, Horel, and Saita (2009), Koopman, Lucas, and Schwaab (2011), McNeil and Wendin (2007) and Rösch and Scheule (2014), Lee and Poon (2014) model the joint exposure to latent systematic risk processes in corporate credit portfolios. Default clustering in excess of observable risk factors is modeled by unobservable random factors, which are also known as ‘frailty’. Our contribution relative to this literature is the application of such econometric techniques to residential mortgage loans.

Another stream in literature that is relevant to this paper focuses on estimation risk or model risk. Model risk addresses the uncertainty with regard to estimated parameters. Examples are Jorion (1996) and Escanciano and Olmo (2010) for market risk and Hamerle and Roesch (2005), Loeffler (2003), Tarashev and Zhu (2008) and Heitfield (2009) for credit risk. These papers explicitly take into account that models are based on parameters, which are usually not observable and have to be estimated from data samples. This induces a sampling or estimation error for the parameters, as well as for model outcomes such as expected losses or Value-at-Risk metrics. These papers measure the impact of parameter estimation errors and provide evidence for the substantial impact of model risk. Our contribution relative to this literature is the application of such econometric techniques to residential mortgage loans.

The remainder of this paper is organized as follows. Section 2 develops a two-stage framework to measure mortgage portfolio risk and to estimate the model parameters. The mortgage portfolio default model is a non-linear probit regression with both observable and unobservable frailty effects. Observable co-variates, e.g., mortgage-specific and macroeconomic variables, are common in scoring models for individual retail loans. Section 3 introduces the data set on US sub-prime mortgage borrowers including loan-level and borrower-level characteristics, as well as macroeconomic information analyzed in this paper. The data is decomposed into training and validation samples, which are non-overlapping in the cross-section, i.e., relate to different mortgage loans. The training sample relates to the period prior to the GFC and is split into a prior sample for the informative Bayesian technique and a likelihood sample for both the uninformative maximum likelihood and the informative Bayesian estimation. The validation sample covers pre-crisis and crisis periods. The estimation results and empirical findings are presented. Finally, Section 4 concludes and discusses implications for mortgage portfolio risk models.

2. Methodology

2.1. Model for mortgage level default

Following the credit risk literature, we estimate a probit model for the unconditional probability of default over τ-quarters as

$$\begin{aligned} P(Y_{i,t} = 1|\boldsymbol{x}_{t-\tau}, \boldsymbol{z}_{t-\tau}) &= p_{i,t|t-\tau}|\boldsymbol{x}_{t-\tau}, \boldsymbol{z}_{t-\tau} \\ &= \Phi\left(\beta_0 + \sum_{j=1}^{q_x} x_{i,j,t-\tau}\beta_j^x + \sum_{k=1}^{q_z} z_{k,t-\tau}\beta_k^z\right) \\ &= \Phi(h_{i,t|t-\tau}), \end{aligned} \tag{1}$$

$Y_{i,\,t}$ denotes the default indicator for mortgage i at time t, taking either the value of one for default or the value of zero for non-default, i.e.,

$$Y_{i,t} = \begin{cases} 1, & \text{if mortgage } i \text{ in time } t \text{ defaults} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

$x_{i,\,j,t-\tau}$ denotes the jth co-variate for mortgage i at time $t-\tau$, $z_{k,t-\tau}$ the kth macroeconomic variable at time $t-\tau$ for $j = 1, 2, \ldots, q_x$ and $k = 1, 2, \ldots, q_z$, and $h_{i,t|t-\tau}$ is a time t default threshold predicted at time $t-\tau$. We denote a vector of mortgage-specific co-variates as $\boldsymbol{x}_{i,t-\tau} = (x_{i,1,t-\tau}, x_{i,2,t-\tau}, \ldots, x_{i,q_x,t-\tau})'$ and a vector of observable common factors as $\boldsymbol{z}_{t-\tau} = (z_{1,t-\tau}, z_{2,t-\tau}, \ldots, z_{q_z,t-\tau})'$ at time $t-\tau$.