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Household's Financial Behavior during the Crisis

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Abstract. *This paper presents a framework for credit risk modeling of the household sector that follows a top-down approach using panel techniques. The results indicate that the determinants of default on bank loans are unemployment, exchange rate, industrial production, indebtedness and interest rate spreads. It is remarked that default events for the household sector occur with delay in case of adverse macroeconomic developments. There are two possible explanations: i) there is no personal bankruptcy law for individuals, and ii) public administration appears to adjusts slower during recessions, an important part of the work force being part of this system.*

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REL Code: 11B.

1. Introduction

In recent years, one area that has emerged as an objective on which public authorities pay more attention is financial stability. An important lesson from this crisis is that price stability alone is not enough to achieve sustainable, non-inflationary growth and a high level of employment, as it is stated in the objectives of the most important central banks. Governments have spent huge amounts of money to bail out banks that were in a bad shape. The costs were important and that has also contributed considerably to the increased budget deficits in some of these countries that are troubling now governments. That is why public authorities are taking now a more proactive stance in building a new supervisory and regulatory framework in which the forward looking component is much more important.

The goal of this paper is to provide a framework for credit risk modeling for the household sector in Romania. The methodology is the one proposed by Wilson (1997) and integrated in Credit Portfolio View. This involves the development of a multifactor model for systematic default risk that captures the relationship between default on bank loans and economic cycle. Monthly aggregated data at county level is employed using panel estimation. The non-linear relationship between credit risk and macroeconomic conditions is modeled through the logistic transformation of the default rates. This is the most frequently used transformation to account for the fact that credit risk increases substantially more in times of high stress. The definition of default used in this paper follows the Basel II framework, and counts any credit obligation that is past due more than 90 days.

2. Literature review

A substantial amount of literature devoted to credit risk macro models follows the methodology proposed by Wilson (1998). In his paper he describes a new approach that tabulates the loss distribution arising from correlated credit events for arbitrary portfolios of nonfinancial corporations, both at a regional and at industry sector level. The importance of having a loss distribution rather than a single potential loss is highlighted by the fact that counterparty defaults can be predicted with a degree of uncertainty and are not perfectly correlated. Another important improvement consists in relating the loss distribution to the actual state of the economy, rather than based on the unconditional or historic averages of losses from default events, that do not reflect portfolio’s true credit risk in resonance with present macroeconomic conditions.

Pesola (2001) proposed a dynamic panel model to study the period with banking crisis that affected the Nordic countries during the 1990's. Results indicate that indebtedness is the most important explanatory variable, being a proxy for the financial fragility. Kalirai and Scheicher (2002) estimate time series regressions of total loan loss provisions for the Austrian banking sector with respect to a wide range of macroeconomic variables divided in six categories: cyclical indicators, price stability indicators, household indicators, corporate indicators, financial market indicators and external variables. Baboucek and Jancar (2005) use an unrestricted VAR model to empirically investigate the transmission mechanism between a set of macroeconomic variables describing the development of the Czech economy and the credit channel. Willem, Hoeberichts and Tabbae (2006) study credit risk for the Dutch banking sector by means of panel regression estimations with fixed effects that account for bank specific characteristics.

3. Methodology

The methodology developed in this section follows the work of Wilson (1998) and Virolainen (2004) and tries to develop a framework to assess vulnerabilities stemming from the banking sector by building a credit risk model for the household sector. This is a distinctive feature of the paper, as most of the work that has been done before regarding credit risk analysis is confined to the corporate sector only.

First, average historic default rates are modeled with the logistic functional form that is extensively used in the literature to model bankruptcies. This logit transformation has the advantageous property that confines the default rates to the interval between 0 and 1. It is now widely accepted the idea that the relationship between default events and macro factors is non-linear, as the experience has shown that in high stress times extreme outcomes are more the rule than the exception (credit risk is by its nature not randomly distributed). That is represented as:

$$dr_{j,t} = \frac{1}{1+\exp(y_{j,t})}$$

where $dr_{j,t}$ is the default rate for the count yj at time t and $y_{j,t}$ is a county idiosyncratic macroeconomic index that stands as an indicator for the general state of the economy and whose parameters will be estimated. There is an inverse relationship between default rate and the state of the economy, represented explicitly through the macroeconomic index, in the sense that a better shape of the economy implies a higher $y_{j,t}$ and a smaller default rate $dr_{j,t}$.

Having the observed historic default rates available, but not the macroeconomic index we apply the inverse of the logistic function to the previous relationship and obtain:

$$y_{j,t} = \ln\left(\frac{1 - dr_{j,t}}{dr_{j,t}}\right) \tag{1}$$

Next, $y_{j,t}$ is assumed to be a function of various exogenous macroeconomic variables that determine the state of the economy. For the *household sector*, the model will be estimated by means of panel regressions techniques, in the form of:

$$y_{j,t} = \beta_0 + \beta_1 \times x_{1j,t} + \beta_2 \times x_{2j,t} + ... + \beta_n \times x_{nj,t} + u_j + v_{j,t} \tag{2}$$

where β_k is the set of coefficients to be estimated, $x_{kj,t}$ are the explanatory macroeconomic factors at time t that can be either specific to each county (eg unemployment, wages, degree of indebtedness) or common at the country level (exchange rate, interest rates, industrial production). There is a composite error structure, that consists of two parts: i) $v_{j,t}$, that is the traditional random error term being independent and identically normally distributed by assumption, associated with county j at time t, and ii) u_j that stands for the individual effects (random effects for this model, according to the Hauseman test performed to establish the correct estimation method) that allow for different intercepts among the 42 counties. This implies the existence of a structural default rate that varies across regions and that could be explained by a multitude of factors that generally are of a qualitative nature or can't be easily quantified (the omitted variables problem). Among these factors one could mention the degree of education (schooling), financial culture or credit standards that banks apply according to their internal lending policy that is very different from county to county (in the sense that is much harder to be granted a loan in a less developed county than in Bucharest). This is an important advantage of panel methods compared to other estimation techniques and serves reasonably well the goals of this paper. On the other hand, a somehow restrictive assumption of the model is that the sensitivity of the default rates to common explanatory variables (like industrial production) is the same in different regions of the country, which is at least debatable.

4. Data

The definition for default that will be used for the empirical work in next part of the paper will be the one suggested by Basel Committee - 90 days past due. Monthly data is used in order to model credit risk in territorial profile for households, starting from January 2006 till April 2010, which sum up to around 2000 observations (42 counties and 52 months).

The explanatory variables of the model fall into two sub-groups: a) specific to each county (indebtedness, unemployment, average wages), and b) common to all debtors in the country (industrial production, inflation, nominal exchange rate, interest rates and interest rate margins for lei and Euro denominated loans). Unit root tests indicate that the dependent variable, industrial production and the degree of indebtedness are stationary.

5. Estimation and results

Main determinants that are used in the literature to explain the dynamics of default rates are: i) interest rates, ii) exchange rates, iii) the state of the economy measured by various variables, iv) level of indebtedness or v) inflation.

When building the model, a criteria followed was to try to include at least one variable from the five categories mentioned previously and to consider time lags that have a meaningful sense in explaining the attitude towards defaulting on bank debt.

The econometric tools used to estimate the credit risk model for the household sector involve panel techniques. The steps that must be followed begin by testing the null that the intercepts are equal. This would imply that there are no structural differences from county to county with respect to systematic default risk. If the null is accepted, the data are pooled and the estimation is done by means of simple OLS. If the null is rejected, a Hausman test is performed to see if the random effects estimator is insignificantly different from the unbiased fixed effects estimator. If the null is rejected, the fixed effects estimator is used instead, otherwise if the null is not rejected the random effects estimator is used.

The outcome of these tests indicates the presence of heterogeneity among counties and that the better method of estimation is by using random effects. Error testing also indicates the presence of contemporaneous correlation and cross-section heteroskedasticity. This means that the default rates are reacting together to shocks, but this reaction has different magnitude amongst counties. In order to compute robust standard errors, a White cross-section method for the coefficient covariance estimator will be employed. Serial correlation is not present at a 10% significance level, according to a Wooldridge test for autocorrelation in panel data.

Table 1

Credit risk model for the household sector

Variables	Lag	Coefficient	Standard error	t-statistic
Constant		2.24 ***	0.50	4.41
D (Unemployment)	3	-0.22***	0.06	-3.67
Indebtedness	4	-0.60 ***	0.15	-4.05
D (Exchange rate)	6	-1.66 ***	0.42	-3.95
Industrial production	1	0.04 ***	0.004	8.90
D(Spread Euro)	12	-0.55 ***	0.13	-4.15
D (Spread Leu)	9	-0.03 **	0.01	-2.58
Adj. R-squared =0.71 DW 1.81				

Significance level: * Significant at 10% level, ** Significant at 5% level, *** Significant at 1% level.

The final model comprises unemployment, the degree of indebtedness, exchange rate, industrial production, and spreads charged by the banks over short-term markets interest rates both for the local and foreign currencies (mostly euro). Table 1 summarizes the parameter estimates, their significance and also the reported adjusted R-squared and Durbin-Watson statistics. Non-stationary variables are introduced in first differences in the model. All variables are significant at a 1% level, except interest rate spread on local currency (at 5% significance level) and show the expected sign. The explanatory power of the model is satisfactory, as measured by R-squared (just above 70%).

The lag structure of the model has some interesting features. Having in mind the definition of default (90 days past due), the model suggests that unemployment has an immediate impact, in the sense that when an individual becomes unemployed, the next day will stop repaying the debt. In case of the degree of indebtedness and movements in the exchange rate, default events are prolonged with one and three months. A possible explanation is that for a few months, debtors might consider the situation to be temporarily and maybe reversible, and when that isn't the case the default occurs. Spreads exert longer lags because variable interest rates are commonly reseted every three to six months, depending on banks. Considering another couple of months to account for reasons related to expectations described previously, it makes the whole effect on defaults to take up to almost a year, also depending on the currency. Unlike the other variables, industrial production has a more contemporaneous effect, mainly due to the fact that it has the specific characteristic of being forward looking.

One way to see the performance of the model is to compare aggregate default rates (at country level) with what the model would predict. The aggreated default rate is just the weighted average of counties' default rates. In order to eliminate some of the volatility in the data quarterly default rates were computed. Figure 1 indicates that when observing defaults on longer time periods (ie. at least quarters) the model performs reasonably well. For example, for the twelve months from may 2009 to april 2010, the default rate was 7.59% and the model prediction was 7.38%, approach that is in line with the scope of this paper (estimating the one year probability of default).

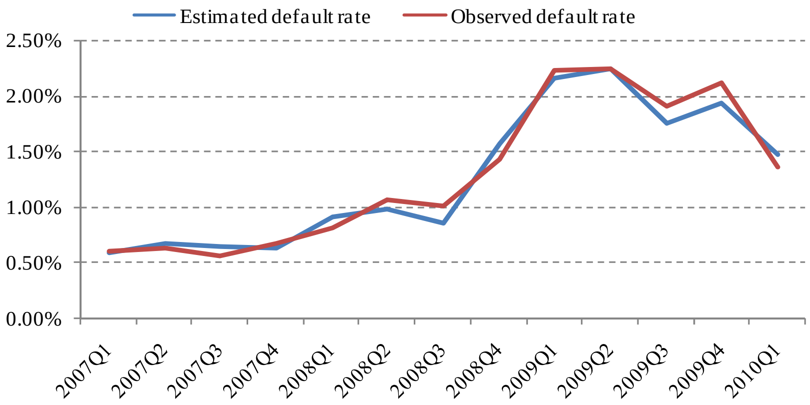

Figure 1. *Performance of the model on aggregated quarterly default rates, household sector*

6. Conclusions

The aim of this paper was to provide a framework for assessing credit risk for the household sector in Romania following a top-down approach. It was found that determinants of defaults on bank loans are: unemployment, exchange rate, the degree of indebtedness, industrial production, and interest rate spreads charged by banks over the market interest rate. The lag structure of the model indicates that the household sector appears to react with a delay to adverse macroeconomic developments. One possible explanation is the absence of a personal insolvency law in Romania to protect natural persons from creditors. Due to this individuals try to postpone the default event, hoping that shocks are temporary. This could be the case for exchange rate shocks. Another reason is that an important part of the population works in public administration. Regarding the macro index as the overall state of the economy, and not only the variables that stayed in the final specification, it can then be said that the public administration adjusts slower during downturns in terms of restructuring than the real economy. This adjustment usually means layoffs and wage cuts, and therefore takes more time to affect defaults. The advantage of a longer lag in the model is that it is easier to perform a forecast.

The relatively simple approach to modeling credit risk that was employed in this study presents both pros and cons. Advantages refer to the fact that having a small number of explanatory variables it is less costly in terms of the assumptions needed to perform forecasts for the probability of default. Embarking on a top-down approach is also less costly in terms of data constraints and even time. On the other hand, the disadvantage is that a macro perspective can't capture important details that are at a micro level only. The shortness of the series is another limitation of the model.

Another drawback of the estimated parsimonious model is that second round effects of financial distress to the economy are not captured. Bridge models that connect credit risk models with DSGE models could accommodate such an issue.

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References

Baboucek, I., Jancar, M., „A VAR Analysis of the Effects of Macroeconomic Shocks to the quality of the Aggregate Loan Portfolio of the Czech Banking Sector", *Czech National Bank, Working paper 1,* 2005

Cihak, M., „Introduction to Applied Stress Testing", *IMF Working Paper 59*, 2007

Jakubik, P., Schiemeder, C., „Stress Testing Credit Risk: Comparison of the Czech Republic and Germany", *Financial Stability Institute, Award Paper*, 2008

Kalirai, H., Scheicher, M., „Macroeconomic Stress Testing: Preliminary Evidence for Austria", *Oesterreichische Nationalbank, Financial Stability Report 3,* 2002

Pesola, J., „The Role of Macroeconomic Shocks in Banking Crisis", *Bank of Finland, Discussion Paper 6,* 2001

Virolainen, K., „Macro Stress Testing with a Macroeconomic Credit Risk model for Finland", *Bank of Finland, Discussion Paper 18,* 2004

Willem, J., Hoeberichts, M., Tabbae, M., „Modelling Scenario Analysis and Macro Stress-Testing", *DNB Working Paper 119*, 2006

Wilson, T.C., „Portfolio Credit Risk", *Federal Reserve Bank of New York, Economic Policy Review* 3, 1998