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# A COMBINED STATISTICAL FRAMEWORK FOR FORECASTING DEFAULT RATES OF GREEK FINANCIAL INSTITUTIONS' CREDIT PORTFOLIOS

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**Abstract**

Credit risk modeling remains an important research topic both for financial institutions and the academic community due to its significant contribution to the issue of a bank's capital adequacy. In this paper we build macro models for the default rates of Greek bank's loan portfolios. Modeling is performed at two levels: First we use common techniques: regime switching regression, Bayesian regression averaging and linear regression; subsequently we combine the forecasts of the three statistical techniques. This results in increasing performance accuracy and minimizing model risk. Our main goal is twofold: First we attempt to investigate the determinants and the sensitivities of default rates in the Greek banking system where Non Performing Loans (NPLs) have risen sharply due to the sovereign debt crisis which led to a decrease in GDP from 2007 to 2016 of 25%. Secondly, the suggested statistical models can serve as the basis of projecting Greek portfolio dynamics under various macro scenarios. We find that dynamic forecasting combinations exhibit higher predictive accuracy than individual methods. This may provide practitioners with significant insight and policy tools for the banking supervision division in order to enhance monitoring efficiency and support informed decision making.

*Keywords*: Forecasting Default Rates, Forecast Combination, Stress Testing

*JEL-classifications*: G01, G21, C53

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## 1. Introduction

Proactively monitoring and assessing the credit riskiness of financial institutions has always been the cornerstone for supervisory authorities in supporting informed and timely decision making. As a response to the global financial crisis of 2007-2008, which led to numerous defaults of credit institutions, the Basel Committee on Banking Supervision (BCBS) introduced an updated set of regulations, known as the Basel III[1] accord and its revisions to further improve the quality and effectiveness of banking supervision. Furthermore, since the recent financial turbulence, micro and macro prudential supervision has been enhanced through rigorous system wide stress testing exercises with increased scrutiny of portfolio credit risk losses.

One of the basic components of stress testing exercises is the use of satellite models for propagating the macroeconomic shock through to financial institutions' balance sheets, so as to project their future P&L by forecasting future loan loss provisioning due to newly defaulted/non performing loans[2]. Our motivation for this study stems from the increasing need to perform rigorous stress testing exercises for financial institutions and particularly to develop a satellite model for forecasting default rates in the Greek banks loan portfolios. Default rates are defined as the percentage of performing loans migrating to a non-performing status (i.e. on becoming Non Performing Loan (henceforth NPL)). Default rates can be examined either on gross basis in which case one does not take into account the respective curing (i.e. the migration of a non performing loan to performing status) or on a net basis where the respective cure rates are included. In the present study we focus on the second approach so we model net default rates. It is evident from the above that default rates are a crucial component when approaching the issue of NPL formation.

To realize our aim, we make use of three well-established econometric techniques, a regime switching regression, Bayesian regression averaging and linear

[1] http://www.bis.org/publ/bcbs189.pdf

[2] In particular, the stress test methodologies currently available publicly are: the European Banking Authority exercise (2014-2018), the FED's Comprehensive Capital Analysis and Review (2017), the Bank of England PRA exercise (2013), the European Central Bank's top down exercise (2013), Bank of Canada (2014), Austrian Central bank (2011) and the International Monetary Fund (2013).

regression, in order to triangulate our forecasts and increase performance accuracy so as to fully account for any regime-dependent specificity.

The capacity to effectively explore the determinants of default rates and adequately project credit risk parameters in the near future can facilitate banking supervisors and macro-prudential authorities in formulating a forward looking view of banking sector vulnerabilities under different scenarios. Essentially, the output from a satellite credit forecasting model using macro variables can be a core input into an integrated balance sheet stress testing exercise. In a top-down stress test, a default rate forecasting model could be used so as to project their evolution for the whole banking sector. While, in a bottom-up stress test, it could serve as a benchmarking tool for supervisory authorities to challenge the banks' underlying assumptions. Therefore, it is really important for supervisors and policy makers to have forecasting model for the default rate in order to monitor the resilience of a financial system under possible macroeconomic shocks and assess the impact of shocks on NPL formation.

Additionally, our model could be used as an integrated part of the Supervisory Review and Evaluation Process (SREP) in assessing the resilience of financial institutions. This enhanced framework would steer decision making, via triggering the imposition of any necessary targeted corrective actions, leading vulnerable institutions back to sustainable and viable business performance.

## 2. Literature review

In the last decade, a plethora of alternative approaches have been published in academic articles to address the problem of modeling the path of either non-performing loans, or default rates using macro variables to measure the underlying credit risk. We limit our references to studies in the recent decade as we deem more relevant to our proposed models.

To this end, Banachewicz et al. (2008) using U.S. default data implements a Hidden Markov model with exogenous macro covariates to forecast portfolio default rates. According to this approach the hidden states of the postulated HMMs reflect the state of the economy, which can switch between expansion and recession periods (normal risk, high risk) while the time varying transition probabilities are impacted by interest rates, GDP and stock market returns. Ali and Daly (2010) investigate the impact of macroeconomic variables under adverse economic conditions on default rates comparing two economies (US and Australia) which were asymmetrically impacted by the recent economic crisis. Castrén, Dées and Zaher (2010) employ a global vector autoregressive model to analyze the behavior of corporate default rates in the euro area against global macro financial scenarios with respect to GDP, the exchange rate, the price of oil and equity prices. Castro (2013) utilized dynamic panel data to analyze the relationship between macroeconomic variables and credit risk (measured by NPL at the country level) for Greece, Ireland, Portugal, Spain and Italy (GIPSI). According to the empirical results NPL formation is significantly affected by GDP, the stock market index, the unemployment rate, interest rate and credit growth. In a similar framework Siakoulis (2017) utilized dynamic panel data, employing a global data set for 31 countries covering a fifteen year period, so as to measure the effects of fiscal policy on NPLs leading to a forecasting in nature model.

Bellotti and Crook (2013) implemented a discrete time survival model on borrower defaults for credit card portfolio data and according to their empirical findings, macroeconomic variables significantly improve the forecasting of defaults. Rösch and Scheule (2014) introduce a stochastic model for measuring and forecasting jointly portfolio probabilities of default and loss rates given default using bond ratings, borrower characteristics and macroeconomic information, such as GDP, as important explanatory variables. Finally, Dendramis, Tzavalis and Adraktas (2017) implement a discrete-time survival model on mortgage loan data for the Greek economy. The model developed allows for a structural break in its hazard function to better capture the Greek sovereign shock, utilizes inflation mortgage rate and unemployment rates as macroeconomic explanatory variables.

There is a vast amount of information on default rate satellite model build up, on studies and publications of banking regulators regarding the implemented stress testing frameworks. Since the international financial crisis of 2008, stress testing methodologies have become critical tools for monitoring the resilience of the banking sector to various internal and external shocks. The satellite macro models outlined are employed to translate the impact of a predefined macroeconomic path of core variables like GDP, unemployment into the evolution of key items of the financial statements of banks. In particular, statistical models usually play a key role in translating the macro scenarios into scenarios for the credit risk parameters such as Probability of Default (for which historical default rates are usually used as proxy) and Loss Given Default. These satellite models are broadly used nowadays and appear in almost all advanced and mature stress testing methodologies. These have led to a significant number of papers from both academics and financial market participants containing enhanced statistical frameworks attempting to simulate banks' balance sheets under various adverse macro scenarios with a view to quantify the impact in their profitability and capital absorbing capacity. Furthermore, after the introduction of Basel II/Basel III accord, banks and regulators have been actively engaged in developing more accurate and robust systems to model the future evolution of credit quality in bank portfolios.

In particular since the outbreak of the sovereign crises in Greece, Bank of Greece has performed a series of system wide stress testing exercises either standalone (Bank of Greece 2012 and 2014) or in cooperation with the EBA (European Banking Authority 2014 and 2016) and the ECB. In two diagnostic exercises for assessing the credit risk portfolio, the Bank of Greece commissioned Black Rock Solutions (2011 and 2014) to model projected losses for credit portfolios. Based on the methodology employed and published in the Bank of Greece (2014), Black Rock followed a stochastic modeling approach to model the transition probabilities of Greek loans in various states of delinquency using important macro variables like GDP and the unemployment rate.

Furthermore the use of satellite models in credit risk stress testing modules is encouraged either by individual banks or National Competent Authorities. The ECB supports this process by offering top down adjustments (benchmarks) in the credit risks parameters translating the macro variables into yearly percentage changes of default rates across a three year horizon. At the same time other competent authorities have developed robust frameworks for performing stress testing (European Central Bank 2012, 2013 and 2017). A robust stress testing framework is presented by the Central Bank of Austria (Oesterreichische Nationalbank 2002, 2011, 2012 and 2013) called ARNIE. It is composed of a series of satellite models that connect macro variables to the default rates. Hasan, Schmieder and Puhr (2011) present a stress testing framework primary focusing on enhancing current methodologies by injecting flexibility and risk sensitivity on calculation of profitability and risk weight assets. A critical component in the architecture of the framework is the use of satellite models to establish macro-financial linkages over the stress horizon. The European Central Bank (2013 and 2017) has published the background of stress test analytics it employs for macro prudential purposes. This includes a group of statistical tools developed to support stress testing exercises across financial institutions in the euro area. Specifically, for credit risk it implements Autoregressive Distributed Lag (ADL) models with a Bayesian averaging layer to decrease model uncertainty; in this setup, default rates are regressed on lagged history as well as contemporaneous and lagged real economy and financial market indicators.

In this study we integrate the most widely used statistical techniques in the literature to develop a group of robust models to simulate the evolution of default rates in Greek banks' retail, mortgages, and corporate credit portfolios. We simultaneously implement three widely used and popular econometric models i.e. linear regression, regime switching, and Bayesian average regression to adequately model the underlying macro dynamics for default rates under almost a full business cycle period, is characterized both by rapid credit expansion and a prolonged period of sharp recessionary credit contraction in the general framework of European Sovereign Debt Crisis (Gibson et al., 2013). In a second level analysis, combination methods are explored in order to increase forecasting efficiency by aggregating the performance of each individual model and minimize the model risk. Our modeling aims both to capture the determinants that strongly affect portfolio default rates and to create a statistical tool for forecasting their future evolution. The proposed framework could prove to be an important tool for assessing the credit risks on a system-wide level from a macro prudential perspective supporting policy decision making.

## 3. Data sample description

Our dataset comprises actual yearly default rates by institution and by portfolio (mortgages, corporate, retail) on a quarterly frequency from 2007 until 2016. Default migration is estimated using quarterly regulatory data submitted by commercial Greek banks to Bank of Greece. The estimation of default rates is based on the yearly flows by delinquency type. By definition the default rates estimated are net of cured loans (net default rates). It is evident that this is a challenging dataset with a structural break associated with the recent economic crisis. The time series are characterized by a period of low default rates followed by an exponential growth in default rates from 2009 leading to different sensitivities to the explanatory macro variables. In addition the relevant policies introduced by the banks and the active management of their credit portfolios by the offer of significant restructuring products to delinquent obligors render the estimation of actual default rates during the recession a challenging task. Thus in order to estimate the actual default rates by portfolio, significant data cleansing and adjustments to the restructuring population were performed to account for noise in the performing status of creditors. In addition another significant structural break during the time period of our analysis was the consolidation of the banking system to four significant banks through the resolution of a series of smaller banks. In order to address this issue, we performed backward adjustment to the balance sheet of the 4 largest banks consolidating the data submitted by the resolved bank to the corresponding buyer. As a final note our dataset starts from 2007 due to the fact that this date is a milestone for data quality since banks' data capabilities improved with preparations for the implementation of Basel II and III accord.

Furthermore our dataset includes a series of candidate independent variables identified in the current literature as strong predictors of credit portfolio quality. The main data source is Bloomberg. The variables include the change in the unemployment rate (D_UNR), real Gross Domestic Product (GDP) growth, inflation (CPI growth), House Price Index (HPI) growth, Gross Capital Formation[3] (CAPITAL)

3 Tt measures the value of acquisitions of new or existing fixed assets by the business sector, governments and households.

growth, export (EXPORT) growth and consumption (CONSUMP) growth. We employ current values (useful for scenario analysis purposes) along with 1, 2 and 4 quarters lagged values.

## 4. Methodological framework

In tackling the problem of forecasting default rates we enrich the group of traditional linear time series statistical techniques already employed with non linear and Bayesian methods, since in times of high systematic uncertainty in a country, the level of non-performing loans may not smoothly evolve in line with macroeconomic fundamentals, but could undergo abrupt structural breaks. This is particularly evident in the case of Greece in which the sovereign debt crisis along with the subsequent recession restricted household and business income causing a substantial rise in non-performing loans.

Therefore we employ a suite of popular approaches for modelling financial time series which allow for temporal dynamics and structural breaks. They are widely used in academia and the finance industry for forecasting macro and market financial variables and we investigate the potential for switching regimes. More precisely, we investigate two well-established econometric techniques, Markov regime switching models and Bayesian regression averaging, in order to boost the forecasting accuracy of the default rate.

### 4.1. Markov regime switching models

In our effort to model non linear behavior in default rates we first employ a Markov Regime switching model (MRS). Its structure comprises two processes: one hidden process (St) which is used to simulate the state of the economy (expansion, recession) that satisfies the Markov property. The second process (Yt), which is the observable one, follows an autoregressive process whose parameters depend on the state of the hidden process. Due to its structure it is also known as a Hidden Markov Model (HMM). Under this setup, MRS offers a flexible and general purpose modelling framework for univariate and multivariate analysis, especially for discrete time series and classification data. Figure 1 shows the general architecture of a Markov regime switching model. The value of (Yt) is observed (measured) and depends on the value of the hidden process (St) which is inferred from its interaction with (Yt). In our study, the fundamental state of the Greek economy is represented by a Markov process and the default rates of the credit portfolios are the observed stochastic process.

[Insert Figure 1]

The two stochastic processes assumed under a regime switching autoregressive model (MS-AR) have the following properties:

a. The hidden underlying stochastic process ($S_t$) follows a Markov chain and characterizes the state of the economy at time t. Thus, the hidden process satisfies the Markov property:

$$P(S_{t+1} = s_{t+1}|S_t = s_t) = P(S_{t+1} = s_{t+1}|S_t = s_t,\ S_{t-1} = s_{t-1}, \dots, S_0 = s_0) \quad (1)$$

b. The observed stochastic process ($Y_t$) depends on the current state of the hidden stochastic process and the autoregressive terms (AR). This property is described by the following mathematical relationship:

$$\mathrm{P}(Y_t = y_t|Y_{t-k}^{t-1} = y_{t-k}^{t-1}, S_t = s_t, \dots, S_0^t = s_0^t\ ) = \mathrm{P}(Y_t = y_t|Y_{t-k}^{t-1} = y_{t-k}^{t-1}, S_t = s_t) \quad (2)$$

where: $Y_{t-k}^{t-1}$ = ($Y_{t-1}$ ,..., $Y_{t-k}$) the k lag values of Y process

According to this structure, the value $Y_t$ is an autoregressive process of order k whose coefficients evolve in time according to the regime $S_t$.

In this empirical study we consider the probability of default as endogenous and employ a regime switching heteroscedastic autoregressive model for each credit portfolio (mortgages, corporate, consumer loans) to explore the transmission channels of various macroeconomic and market related variables in determining the evolution of NPL formation. Under the proposed setup default rates are assumed to follow an MS-AR model that is specified as follows:

$$Y_t = C_{S_t} + \sum_{p=1}^{k} \Phi_{S_t} * \ Y_{t-p} + \sum_{l=1}^{L} B_{S_t} * \ \Delta_l + \sum_{s=1}^{S} \Gamma_S * \ A_S \ + \ \varepsilon_t$$

$$\text{where: } \varepsilon_t \sim \text{i.i.d. } \mathrm{N}\left(0, \sigma_{S_t}^2\right). \quad (3)$$

In the above equation,

- $C_{s_t}$ is the constant term that is subject to the regime process;
- $Y_{t-p}$ is the lagged dependent variables, the coefficients ($\Phi_{s_t}$) of which depend on the regime process;
- $\Delta_l$ are cross sectional variables, the coefficients ($B_{s_t}$) of which depend on the regime process;
- $A_S$ are cross sectional variables, the coefficients ($\Gamma_s$) of which are invariant to the state of the system, that is, they have the same impact in all regimes;
- $\Phi_{s_t}$, $B_{s_t}$, $\Gamma_s$ denote the respective vectors of coefficients.

The transition probabilities of the current (t) state from the previous (t-1) state ($P_{t-1,t}$) can be expressed in the case of a two state model by the probability matrix:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \tag{4}$$

where: $p_{i1} + p_{i2} = 1, \quad p_{ij} = P(S_t = j | S_{t-1} = i)$

Forecasting of default rates ($Y_{t+1}$) under this approach is performed following the steps: First, we perform inference of the state of the economy at time t and, in the second step, we assume one transition based on the estimated Markov chain to t+1 and estimate the weighted average between the related smoothed transition probabilities (5) and the respective values of the corresponding autoregressive models.

Model training and coefficient estimation is performed by employing the expectation maximization (EM) algorithm, i.e. parameters are estimated via an iterative method that maximizes the log likelihood of the observations and overcomes the existence of latent variables by substituting them in each step by their posterior expected value. This method for estimation of the MS-AR was first introduced in Hamilton (1989).

Model estimation is performed using the Markov regime switching functionality available in Eviews. In the specific implementation, switching (regime variant) and not switching (regime invariant) lagged cross sectional explanatory variables are employed along with autoregressive terms in order to boost the forecasting capacity of the model. Regime driven heteroskedasticity is also tested in the modelling process to account for differing volatility behavioral patterns in the default rates evolution and enhanced robustness in capturing shocks to the dependent variable. This approach offers increased flexibility in order to capture effectively the structural dynamics and temporal dependencies of a time series of default rates.

### 4.2. Bayesian model averaging

In order to account for the uncertainty surounding the main determinants of credit risk dynamics especially in a period of recession a Bayesian Model Averaging (BMA) econometric technique is also employed. This approach is able to handle a short time series of defaults rates which is usually the case for credit risk due to the relatively recent introduction of the Basel II framework which obliged Greek Banks to systematically collect and report defaulted loan data to the regulatory authorities.. Thus BMA offers the possibility to perform multivariate modeling including all potential predictors with different weight.

Using BMA, a pool of equations is generated using a random selection subgroup of determinants. Subsequently a weight is assigned to each model that reflects their relative forecasting performance. Aggregating all equations using the corresponding weights produces a posterior model probability. The number of equations estimated in the first step is large enough to capture all possible combinations of a predetermined number of independent variables. Thus Bayesian model averaging addresses model uncertainty and misspecification in selected explanatory variables in a simple linear regression problem.

To further illustrate BMA, suppose a linear model structure, with $Y_t$ being the dependent variable, $X$ the explanatory variables, α constant, β the coefficients and $\varepsilon_t$ a normal error term with variance σ.

$$Y_t = \alpha_\gamma + \beta_\gamma X_{\gamma,t} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \sigma^2 I) \qquad (5)$$

A problem arises when there are many potential explanatory variables in a matrix $X_t$ which transforms the task of selecting the correct combination quite burdensome. The direct approach to inference in a single linear model that includes all variables is inefficient or even infeasible with a limited number of observations. It can lead to overfitting, multicollinearity and increased manual re-estimations to account for non significant determinants. BMA tackles the problem by estimating models for all possible combinations of $\{X\}$ and constructing a weighted average over all of them.

Under the assumption that $\mathrm{X}$ contains K potential explanatory variables, BMA estimates $2^{\mathrm{K}}$ combinations and thus $2^{\mathrm{K}}$ models. Applying Bayes' theorem (6), model averaging is based on the posterior model probabilities.

$$p(M_\gamma|Y,X) = \frac{p(Y|M_\gamma,X)p(M_\gamma)}{p(Y|X)} = \frac{p(Y|M_\gamma,X)p(M_\gamma)}{\sum_{s=1}^{2^K} p(Y|M_s,X)p(M_s)} \qquad (6)$$

In equation (6), $p(Y,X)$ denotes the integrated likelihood which is constant over all models and is thus simply a multiplicative term. Therefore, the posterior model probability (PMP) is proportional to the integrated likelihood $p(Y|M,X)$ which reflects the probability of the data given model $M$. Thus the corresponding weight assigned to each model is measured using $p(M_\gamma|Y,X)$ in equation (6).

In equation (6), $p(M)$ denotes the prior belief of how probable model $M$ is before analyzing the data. Furthermore, to estimate $p(Y,X)$ integration is performed across all models in the model space and to estimate the probability $p(Y|M,X)$ integration is performed given model M across all parameter space. By performing renormalization of the product in equation (6), PMPs can be inferred and subsequently the model's weighted posterior distribution for estimator β is given by

$$p(\beta|Y,X) = \sum_{\gamma=1}^{2^K} p(\beta|M_\gamma,Y,X)p(M_\gamma|X,Y) \qquad (7)$$

The priors, posteriors and the marginal likelihood employed in the estimation are described analytically in Appendix B.

## 5. Empirical application

### 5.1 Model development and specification

For model development, the dataset is split into two parts: An in-sample dataset, comprising data in the period 2007-2014; and an out of sample dataset, 2015-2016. The latter out of sample data is used to test the forecasting efficiency of the models produced during a two year stress period, 2015-2016, while data up to 2014 are used for development and parameter estimation. Regime switching models perform well when the underlying training data are driven by regime shifts. In order to capture this adequately, the data used for training should refer to all the possible regimes we aim to model. Thus under the current setup, training data include both expansion and recession years of the Greek economy.

We refrain from applying traditional stationarity tests such as KPSS, due to their size and power distortion in strongly auto correlated and relatively short time series (Muller, 2004).

### 5.2 Bayesian Model Average model (BMA)

Before applying the Bayesian Averaging algorithm [4] we remove and linearly interpolate the outliers utilizing Friedman's 'super smoother' algorithm[5]. In Bayesian Model Averaging estimation we employ unit information prior (UIP)[6], which sets $g = N$ commonly for all models. We use also a birth/death MCMC algorithm (20000 draws) due to the large number of covariates included since using the entire model space would lead to a large number of iterations. We fix the number of burn-in draws for the MCMC sampler to 10000. Finally the models prior employed is the 'random theta' prior by Ley and Steel (2008), who suggest a binomial-beta hyperprior on the a priori inclusion probability. This has the advantage that is less

[4] We employ the utilities of BMS R package

5 The algorithm is encompassed in the tsclean function in R.

[6] For robustness purposes we varied the used prior employing the Fernandez et al (2001) propositions but the results were not substantially different.

tight around prior expected model size (i.e. the average number of included regressors) so it reflects prior uncertainty about model size more efficiently.

[Insert Tables 1, 2, 3]

Tables 1 to 3 present the results by portfolio. The Bayesian Model Averaging output matrix shows the variable names and corresponding statistics for the 12 most important variables by portfolio. The second column Post Mean displays the coefficients averaged over all models, including the models wherein the variable was not contained (implying that the coefficient is zero in this case). The autoregressive term has a comparatively large coefficient and seems to be most important. The importance of the variables in explaining the data is given in the column PIP which represents posterior inclusion probabilities - i.e. the sum of posterior model probabilities for all models wherein a covariate was included. In other words it shows the probability of each variable occurrence in the "true" model. We see that with probability over 70%, virtually all of posterior model mass rests on models that include an autoregressive term. This could partly attributed to re-default rates of past forborne defaulted loans, where the borrowers cannot fulfill the terms of restructuring so past defaulted volumes affect future volumes. The coefficient sign also can be inferred from the column "Conditional Positive Sign". In all encountered models containing those variables, the (expected values of) coefficients for the autoregressive parameter and the unemployment rate are positive whereas the signs for GDP growth, house price index growth, inflation, gross capital formation and consumption growth are mostly negative. Those findings are in line with theory showing that increase in unemployment, low GDP growth, a fall in real estate prices and falling gross capital growth lead to higher default rates.

We deduce from the results that for different portfolios different variables affect the evolution of default rates. In the business portfolio low GDP growth, increase in unemployment rate and falling inflation tend to increase default rates while the other covariates do not seem to matter much. In the mortgage portfolio with the exception of the autoregressive term, results indicate that the yearly lagged terms of house price index growth are key determinants for the default rates since falling house prices are directly linked to increasing default rates in mortgage portfolio. We expect this to stem from a wealth effect and not so much from a "strategic default" effect, due to the high percentage of house ownership for residential purposes in Greece. Furthermore the lags of gross capital formation growth exhibit also negative correlation with the dependent variable. Finally, based on the estimation output for consumer portfolio the most important drivers for the respective default rates are consumption, gross capital formation and export growth which are negatively correlated with the dependent variable as anticipated. Increasing unemployment rate leads also to higher default rates in the consumer portfolio whereas it seems that the importance of GDP growth as a predictor reduces, as consumption growth is a more effective metric in this particular category of loans.

### 5.3 Regime Switching Model (RSW)

For the development of the RSW, model selection was performed utilizing the log likelihood metric along with the BIC criterion on the in-sample estimation, in order to avoid over-fitting and end up with a parsimonious setup. Furthermore, during the finalization process of the candidate models, additional criteria were assessed like the sum of square residuals of each combination, while variables that were highly statistically insignificant were excluded. Moreover, autocorrelation in residuals was tested using the Durbin-Watson criterion and regime specification was investigated through the transition probabilities allocated to the estimated Markov process. Finally, we investigated a time varying probabilities setup across all portfolios, but candidate models resulted in poorer estimates and higher sum of squared residuals. Tables 4 to 6 present the final RSW models equations selected by portfolio type:

[Insert Tables 4, 5, 6]

One of the key findings regarding the RSW models developed is that the lagged dependent variable displays significantly different behavior across the high and low uncertainty regimes. Specifically default rates in corporate and consumer portfolio become more persistent in high uncertainty periods whereas this is not true for mortgage portfolio. This could be partly due to the fact that re-default rates are higher in crisis periods especially in business and consumer portfolios whereas in mortgages people tend to fulfill the restructuring terms. The unemployment rate is a key indicator of the health of the economy therefore rising unemployment changes increase delinquency rates in all credit portfolios. As anticipated, house price index growth, being a proxy for the value of the collateral, negatively affects mortgage default rates. We expect this to stem from a wealth effect and not so much from a "strategic default" effect, due to the high percentage of house ownership for residential purposes in Greece. Another key finding based on the finalized RSW models is that a key determinant of consumer default rates is consumption growth which is also supported from the BMA estimation where consumption growth is more probable to be found in the "true" consumer default rate model than GDP growth. This leads to the conclusion that under recession significant losses of wealth in retail customers lead to decreased consumption and a tendency to mitigate it through the default in their loan obligations.

To further explore the economic intuition of the RSW developed and assess their robustness we analyze the regimes identified during the in sample period. The posterior forward probabilities between the two states are exhibited in Figures 2 to 4. Our empirical findings indicate that that recessions (high uncertainty) are expected to last longer than the expansionary part (low uncertainty) of the economic cycle. This finding is anticipated due to the fundamental structural deficiencies related to the current account deficit and the high debt to GDP ratio in the current state of the Greek economy. Not surprisingly, the probabilities of being in the high uncertainty regime in the corporate model (P(S(t) = 2): regime 2) are high during the recession phase (after 2009), while the probabilities of being in the low uncertainty regime (P(S(t) = 1): regime 1) are high during the expansion phase (before 2009), in line with the GDP growth evolution of Greece for the period under assessment. This is valid also for the mortgage and consumer portfolio where regime 1 matches the economic recession of the Greek economy.

[Insert Figure 2, 3, 4]

### 5.4 Linear Least Squares Regression Model (LS)

To assess the superiority of our RSW and BMA models, an AR linear regression model is also estimated for providing comparative results relative to a benchmark. In addition due to its parsimonious nature AR models are also included in the final combined forecasting phase. To determine the number of AR terms, we explore the autocorrelation and partial autocorrelation functions of the dependent variable for up to 20 lags. We also limit our AR model to the variables provided more frequently in the stress test scenarios from regulatory authorities (namely GDP, CPI, HPI growth and UNR) so to obtain a more parsimonious and easy to apply in stress testing exercises model. The parameters are estimated by using the same in sample dataset. Tables 7 to 9 summarize the estimation of the coefficients of the models along with statistical tests for fitting and significance across all credit portfolios. For illustrative purposes we show the results for the 2007-2016 sample so as to provide insight also on the capital control year effect (2015) by employing a relative dummy variable.

[Insert Tables 7, 8, 9]

Due to its linear nature the final specification of the AR include a limited number of determinants whereas we employ also one lagged value of the dependent variable. Regarding the key macro variables GDP and HPI growth and along with changes in UNR display significant predictive power in forecasting default rates. Higher inflation (CPI growth) seems to weaken borrower’s ability to service debt in retail portfolios by reducing real income. Finally the capital control year seems to have affected mostly the business and the consumer portfolio.

### 5.5 Horizontal view of models and forecast combinations

From the horizontal qualitative assessment of the models we deduce that that unemployment rate is a key determinant factor of the level of default rates across all portfolios and techniques with minor exceptions. HPI is a key determinant for mortgage default rates but we expect this to be a wealth effect rather than a “strategic default” effect, due to the high percentage of house ownership for residential purposes in Greece. GDP growth plays significant role in business default rate evolution but in the residential and consumer portfolio its predictive performance is rather limited across all models probably due to the high correlation with other key macro variables like UNR and HPI growth.

Additionally in order to gain insight and validate further the dependencies between default rates and macro variables we extend our sample on a bank level and we employ panel data regressions on default rates and Distance to Default measures (DtD[7]) on an extended number of Greek banking institutions (14 banks) for the period 31/12/2006 – 31/12/2016 (Tables 13-15 in Appendix A). We verify that GDP growth plays significant role when forecasting business default rates, HPI is a key determinant in residential portfolio and UNR is a basic factor in forecasting consumer portfolios.

Due to inherent non-linearities in our time series which may not be completely captured by the employed methodologies, we exploit forecast combinations that allow us to assign different weights to each of the obtained predictions (Stock & Watson, 2004). It should be expected to yield improved predictive performance. This approach can lead to a decrease in dynamic forecast errors by aggregating across all statistical techniques and minimizing model risk misspecification.

We perform first simple forecast averaging where each forecast has equal weight (SIM). An OLS forecast combination is based on linear regression between the in sample observed and fitted values for each of the methodologies and applies the coefficients as weights in the out-of-sample. Robust regression performs the same but minimizes a different loss function, which is less sensitive to outliers (ROB). Constrained least squares (CLS) minimize the sum of squared errors under the restriction that the weights sum up to 1, and that the forecasts themselves are unbiased. Finally the variance-based method (VAR) computes the mean squared error and weights the forecasts according to their accuracy. Accurate forecasts

[7] Distance to Default is defined as $DtD = -N^{-1}(Default\ Rate)$

(based on MSE metric) receive relatively more weight[8].

### 5.6 Forecast evaluation

We evaluate the models based on the variance of the residuals along with the usual forecast metrics of Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the Exponential Error Measure (EXP). In this way we create a forecasting in nature model very useful for regulatory purposes, such as benchmarking own bank projections based on stress testing scenarios. Due to the small time span of the forecasted period (8 obs) we cannot employ the Diebold and Mariano (1995) the for comparing across forecasts since it can be subject to large size distortions in small samples, which can be spuriously interpreted as superior predictive ability for one forecast. This is due to the fact that, in the test, the long run variance is replaced by a consistent estimate and standard limit normality is then employed, but this may be unsatisfactory in relatively small samples.

We can though gain insight into the relative efficiency of our forecasts by using a Mincer-Zarnowitz (1969) regression for testing forecast efficiency. This method consists of regressing forecast errors on a constant by using autocorrelation-corrected standard errors and testing whether the latter is equal to zero. In that regression what is being tested is whether the forecast errors have a zero mean, that is, whether there is no systematic bias in the forecasts. Efficient forecasts should not systematically over or under-predict because simply adding the constant to the forecasts improves them. We notice that beside some standalone cases, as a general rule, our specifications provide efficient forecasts as we cannot reject the null of mean zero for the forecast errors (MZ p-value). By combining intuitively the error and efficiency metrics we select the following models by category and forecast type.

### 5.7 Out-of-sample forecasting performance

In order to assess the performance of the three statistical techniques both on a standalone basis against the joint models generated, we estimate the

[8] ForecastCombinations R package (Ravin, 2015) was employed for combining different forecasts into a single forecast series.

aforementioned metrics for both a static and dynamic forecasting setup. The out of sample dataset, includes data pertaining to the period 2015-2016 (8 quarters). In stress testing exercises usually a three year (12 quarters) horizon is used but in our case we need an adequate development sample (2007-2014). We compute both static and dynamic forecasts for the aforementioned period. In the first case the forecast is performed sequentially for each quarter where the actual current value of the lagged dependent variable enters in each step on the calculation of the fitted value. In the dynamic case the previous forecasted value of the dependent variable enters lagged in each step of the forecast calculation. Also the out-of-sample forecasting was performed on lagged values of the independent variables so as to avoid contemporaneous variable issues.

Under the static forecast approach during the out of sample period, based on a majority voting of the error metrics in Table 10, the best performing proposed model for each portfolio is:

1. Business Portfolio : Variance-based forecast combination
2. Residential Portfolio: Regime Switching
3. Consumer Portfolio: Regime Switching

The Mincer Zarnowitz regression cannot reject the null of zero forecast errors indicating efficacy of our projections. Regime switching models exhibit higher forecasting efficacy than the other 2 models in the static forecast case due to their ability to recognize the exact regime in which the banks credit portfolio is found.

The performance of dynamic forecasting is considered crucial under a stress testing exercise which usually is defined on a three year horizon. As anticipated, error metrics increase across all models due to the inheritance of the forecast error of every quarter in the whole forecasting period. Nevertheless performance of the best candidate models is considered remarkable whereas the Mincer Zarnowitz regression cannot reject the null of zero forecast errors at 5% level of confidence.

Under the dynamic forecasting approach during the out sample period (2015-2016), the proposed candidate model for each portfolio is:

- Business Portfolio: Simple Average Forecast Combination
- Residential Portfolio: Robust regression Forecast Combination

- Consumer Portfolio: Ordinary Least Squares Forecast Combination

[Insert Table 10]

[Insert Table 11]

It is evident that when dynamic forecasting is applied combination of all models increases the predicting efficacy of our analysis minimizing the error of its individual statistical technique. This may provide practitioners with significant insight and policy tools for the banking supervision division in order to enhance monitoring efficiency.

To further investigate the modeling efficacy of the proposed framework we extend our forecasting evaluation in the gross default rates i.e. the default rates estimated for the period 2015-2016 without adjusting for the cure rates of non-performing loans. By examining the Gross Default rates, as implied from bank regulatory submissions, we notice that the Root Mean Square Errors are comparable to that of the Net Default rates. This fact increases the confidence of the proposed framework and guarantees its robustness when employed under a stress testing exercise.

[Insert Table 12]

## 6. Conclusions

In this study we tackle the problem of forecasting default rates for Greek financial institutions' credit portfolios. We envisaged providing a stress testing toolkit for modelling credit risk of Greek financial institutions for both the ongoing monitoring supervisory processes and ad hoc stress testing exercises. To ameliorate model risk we proposed ensemble combination framework for averaging out model uncertainty of individual statistical techniques. We performed an extensive experimental evaluation of our approach, using a two year out of sample dataset (2015-2016).

Our approach exploited well-established statistical techniques used in forecasting financial time series. To validate the efficiency of the models developed we estimate a series of well known statistical metrics on out of time dataset using both a static and a dynamic setup. Looking at the models individually, regime switching models exhibit superior performance against AR linear regressions and BMA since they capture better non linear behavior and temporal patterns across the state of the economy. The regimes identified recognize successfully the periods of expansion and recession of the Greek economy and succeed in assigning different sensitivities to the independent variables. Out-of-sample results suggest that combining the statistical techniques employed increases the overall forecasting performance significantly.

From a qualitative point of view, it is evident that default rates are persistent across all models and portfolios playing an important role in determining its future evolution. From a macro perspective, the unemployment rate, CPI and capital investment explain a significant part of the variability in default rates. Furthermore HPI is a key determinant in forecasting default rates in the mortgage loans portfolio. Finally GDP growth plays significant role in business default rate evolution but in the residential and consumer portfolio its predictive performance is rather limited.

For forecasting purposes, we find that where we use dynamic forecasting combination methods, higher predictive accuracy is evident compared to individual methods. This may provide practitioners with significant insight and policy tools for the banking supervision division in order to enhance monitoring efficiency and support informed decision making regarding future NPL formation. It can also enhance the toolbox of macroeconomic satellite credit forecasting models that are a core input into an integrated balance sheet stress testing exercise.

## Appendix A

**Table 1: Business Portfolio Bayesian Model Average estimation Output -12 most important variables (2007-2014 sample).**

| | PIP | Post Mean | Post SD | Cond. Pos. Sign. |
|---|---|---|---|---|
| **CORP(-1)** | 0.984 | 0.848 | 0.155 | 1.000 |
| **D_UNR(-2)** | 0.117 | 0.091 | 0.289 | 1.000 |
| **CPI growth (-4)** | 0.111 | -0.023 | 0.079 | 0.000 |
| **GDP growth(-2)** | 0.087 | -0.012 | 0.046 | 0.000 |
| **D_UNR(-4)** | 0.083 | -0.013 | 0.052 | 0.000 |
| **GDP growth** | 0.079 | -0.002 | 0.010 | 0.000 |
| **GDP growth(-1)** | 0.073 | -0.008 | 0.042 | 0.010 |
| **GDP growth(-4)** | 0.071 | 0.037 | 0.186 | 0.982 |
| **D_UNR** | 0.064 | -0.006 | 0.030 | 0.009 |
| **HPI growth** | 0.056 | -0.011 | 0.059 | 0.011 |
| **CAPITAL growth(-2)** | 0.050 | -0.001 | 0.030 | 0.464 |
| **CAPITAL growth(-1)** | 0.049 | -0.001 | 0.007 | 0.016 |

**PIP column shows importance of the variables in explaining the data, Post Mean column displays the coefficients averaged over all models, Post SD column is the relevant standard deviation and Conditional Positive Sign column is the probability that the coefficient has a positive sign.**

**Table 2: Residential Portfolio Bayesian Model Average estimation Output -12 most important variables (2007-2014 sample).**

| | PIP | Post Mean | Post SD | Cond. Pos. Sign. |
|---|---|---|---|---|
| **RRE(-1)** | 0.700 | 0.475 | 0.357 | 0.999 |
| **HPI growth(-4)** | 0.342 | -0.061 | 0.094 | 0.000 |
| **HPI growth(-1)** | 0.339 | -0.084 | 0.135 | 0.000 |
| **CAPITAL growth (-1)** | 0.286 | -0.010 | 0.018 | 0.000 |
| **HPI growth** | 0.279 | -0.058 | 0.107 | 0.002 |
| **CAPITAL growth** | 0.142 | -0.003 | 0.009 | 0.004 |
| **CAPITAL growth (-4)** | 0.124 | 0.003 | 0.010 | 0.932 |
| **GDP growth(-4)** | 0.122 | -0.008 | 0.040 | 0.187 |
| **CPI growth(-4)** | 0.076 | -0.006 | 0.057 | 0.277 |
| **EXPORT growth (-1)** | 0.072 | 0.001 | 0.008 | 0.804 |
| **D_UNR(-2)** | 0.071 | 0.014 | 0.106 | 0.871 |
| **GDP growth** | 0.069 | 0.000 | 0.024 | 0.484 |

**PIP column shows importance of the variables in explaining the data, Post Mean column displays the coefficients averaged over all models, Post SD column is the relevant standard deviation and Conditional Positive Sign column is the probability that the coefficient has a positive sign.**

**Table 3: Consumer Portfolio Bayesian Model Average estimation Output -12 most important variables (2007-2014 sample).**

| | PIP | Post Mean | Post SD | Cond. Pos. Sign. |
|---|---|---|---|---|
| **CONS(-1)** | 0.716 | 0.461 | 0.346 | 1.000 |
| **CONSUMP growth** | 0.456 | -0.144 | 0.186 | 0.000 |
| **CAPITAL growth (-1)** | 0.319 | -0.017 | 0.029 | 0.009 |
| **D_UNR(-2)** | 0.242 | 0.371 | 0.758 | 1.000 |
| **EXPORT growth (-2)** | 0.226 | -0.020 | 0.043 | 0.003 |
| **GDP growth(-2)** | 0.216 | -0.056 | 0.137 | 0.023 |
| **CPI growth(-4)** | 0.203 | 0.108 | 0.287 | 0.974 |
| **D_UNR(-1)** | 0.184 | 0.240 | 0.600 | 1.000 |
| **CPI growth(-2)** | 0.156 | -0.055 | 0.387 | 0.522 |
| **CAPITAL growth (-4)** | 0.149 | -0.006 | 0.017 | 0.020 |
| **CPI growth (-1)** | 0.146 | 0.070 | 0.255 | 0.968 |
| **CPI growth** | 0.141 | 0.039 | 0.135 | 0.955 |

**PIP column shows importance of the variables in explaining the data, Post Mean column displays the coefficients averaged over all models, Post SD column is the relevant standard deviation and Conditional Positive Sign column is the probability that the coefficient has a positive sign.**

## Table 4: Business Portfolio Regime Switching estimation Output (2007-2014 sample)

**Regime 1– Low Uncertainty**

| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **Constant** | 1.608749 | 0.191590 | 8.396841 | 0.0000 |
| **CORP(-1)** | 0.225374 | 0.048710 | 4.626874 | 0.0000 |
| **HPI growth** | -0.137704 | 0.040469 | -3.402689 | 0.0007 |
| **Log(SIGMA)** | -1.235693 | 0.276394 | -4.470769 | 0.0000 |

**Regime 2– High Uncertainty**

| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **Constant** | 0.513805 | 0.974770 | 0.527104 | 0.5981 |
| **CORP(-1)** | 0.810585 | 0.155768 | 5.203804 | 0.0000 |
| **HPI growth** | -0.123614 | 0.205775 | -0.600727 | 0.5480 |
| **Log(SIGMA)** | 0.285527 | 0.196464 | 1.453333 | 0.1461 |

**Common Variable**

| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **D_UNR(-2)** | 0.850340 | 0.238360 | 3.567461 | 0.0004 |

**Transition Matrix Parameters**

| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **P11-C** | 2.666659 | 1.536128 | 1.735961 | 0.0826 |
| **P21-C** | -2.566938 | 1.016483 | -2.525314 | 0.0116 |

**Model Statistics**

| | | | |
|---|---|---|---|
| **Mean dependent var** | 7.393742 | **S.D. dependent var** | 5.141386 |
| **S.E. of regression** | 1.796815 | **Sum squared resid** | 71.02795 |
| **Durbin-Watson stat** | 1.935811 | **Log likelihood** | -43.98685 |
| **Akaike info criterion** | 3.547539 | **Schwarz criterion** | 4.056373 |
| **Hannan-Quinn criter.** | 3.713406 | | |

### Table 5: Residential Portfolio Regime Switching estimation Output (2007-2014 sample)

| | | | | |
|---|---|---|---|---|
| **Regime 1– Low Uncertainty** | | | | |
| | Coefficient | Std. Error | z-Statistic | Prob. |
| **RRE(-1)** | 1.483404 | 0.114635 | 12.94022 | 0.0000 |
| **Regime 2– High Uncertainty** | | | | |
| | Coefficient | Std. Error | z-Statistic | Prob. |
| **RRE(-1)** | 0.732871 | 0.052321 | 14.00726 | 0.0000 |
| **Common Variables** | | | | |
| | **Coefficient** | **Std. Error** | **z-Statistic** | **Prob.** |
| **HPI growth (-4)** | -0.105830 | 0.035157 | -3.010193 | 0.0026 |
| **CAPITAL growth(-1)** | -0.038318 | 0.010726 | -3.572322 | 0.0004 |
| **D_UNR(-2)** | 0.402201 | 0.202559 | 1.985602 | 0.0471 |
| **Log(SIGMA)** | -0.533606 | 0.153965 | -3.465754 | 0.0005 |
| **Transition Matrix Parameters** | | | | |
| | Coefficient | Std. Error | z-Statistic | Prob. |
| **P11-C** | 2.453720 | 0.883572 | 2.777045 | 0.0055 |
| **P21-C** | -1.400031 | 1.115341 | -1.255250 | 0.2094 |
| **Model Statistics** | | | | |
| **Mean dependent var** | 5.208774 | **S.D. dependent var** | | 2.606353 |
| **S.E. of regression** | 1.393750 | **Sum squared resid** | | 48.56350 |
| **Durbin-Watson stat** | 2.292810 | **Log likelihood** | | -36.62551 |
| **Akaike info criterion** | 2.879065 | **Schwarz criterion** | | 3.249126 |
| **Hannan-Quinn criter.** | 2.999696 | | | |

## Table 6: Consumer Portfolio Regime Switching estimation Output (2007-2014 sample)

**Regime 1– Low Uncertainty**

| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **Constant** | 2.823551 | 0.509636 | 5.540334 | 0.0000 |
| **CONS(-1)** | 0.338768 | 0.069634 | 4.864974 | 0.0000 |

**Regime 2– High Uncertainty**

| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **Constant** | 3.782673 | 0.657761 | 5.750833 | 0.0000 |
| **CONS(-1)** | 0.624877 | 0.080547 | 7.757950 | 0.0000 |

**Common Variables**

| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **CONSUMP growth** | -0.071679 | 0.044346 | -1.616370 | 0.1060 |
| **D_UNR(-2)** | 0.936938 | 0.348556 | 2.688057 | 0.0072 |
| **Log(SIGMA)** | -0.574987 | 0.154328 | -3.725747 | 0.0002 |

**Transition Matrix Parameters**

| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| **P11-C** | 1.600423 | 0.666837 | 2.400023 | 0.0164 |
| **P21-C** | -0.925948 | 0.883440 | -1.048117 | 0.2946 |

**Model Statistics**

| | | | |
|---|---|---|---|
| **Mean dependent var** | 9.758258 | **S.D. dependent var** | 4.646635 |
| **S.E. of regression** | 1.737719 | **Sum squared resid** | 72.47200 |
| **Durbin-Watson stat** | 2.070783 | **Log likelihood** | -41.43674 |
| **Akaike info criterion** | 3.253983 | **Schwarz criterion** | 3.670302 |
| **Hannan-Quinn criter.** | 3.389693 | | |

**Table 7: Business Portfolio Least Squares estimation Output (2007-2016 sample)**

| | Coeff | SE | t-stat | p-value |
|---|---|---|---|---|
| **CORP(-1)** | 0.878 | 0.048 | 18.297 | 0.000 |
| **Dummy-2015** | 1.698 | 0.991 | 1.714 | 0.095 |
| **CPI growth** | 0.118 | 0.127 | 0.930 | 0.359 |
| **GDP growth(-1)** | -0.219 | 0.086 | -2.533 | 0.016 |
| **$R^2$/RMSE** | 0.952 | 1.950 | | |
| **F** | 172.829 | | | |

**Table 8: Residential Portfolio Least Squares estimation Output (2007-2016 sample)**

| | Coeff | SE | t-stat | p-value |
|---|---|---|---|---|
| **RRE(-1)** | 0.793 | 0.081 | 9.749 | 0.000 |
| **Dummy -2015** | 0.969 | 0.677 | 1.431 | 0.161 |
| **CPI growth** | 0.176 | 0.081 | 2.164 | 0.037 |
| **HPI growth** | -0.136 | 0.063 | -2.179 | 0.036 |
| **$R^2$/RMSE** | 0.958 | 1.218 | | |
| **F** | 202.949 | | | |

**Table 9: Consumer Portfolio Least Squares estimation Output (2007-2016 sample)**

| | Coeff | SE | t-stat | p-value |
|---|---|---|---|---|
| **CONS(-1)** | 0.787 | 0.081 | 9.713 | 0.000 |
| **Dummy -2015** | 2.855 | 0.866 | 3.299 | 0.002 |
| **CPI growth** | 0.421 | 0.169 | 2.491 | 0.018 |
| **HPI growth** | -0.149 | 0.106 | -1.407 | 0.169 |
| **D_UNR** | 0.702 | 0.419 | 1.674 | 0.103 |
| **$R^2$/RMSE** | 0.980 | 1.535 | | |
| **F** | 335.222 | | | |

**Table 10: Static Forecast Out-of-sample performance metrics. Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Exponential Error Measure (EXP).**

**Business portfolio**

| | LS | RSW | BMA | SIM | OLS | ROB | CLS | VAR |
|---|---|---|---|---|---|---|---|---|
| MSE | 7.108 | 8.074 | 8.118 | 6.794 | 7.157 | 6.940 | 6.744 | **6.675** |
| RMSE | 2.666 | 2.841 | 2.849 | 2.607 | 2.675 | 2.634 | 2.597 | **2.584** |
| MAE | 2.178 | 1.637 | 2.215 | 1.874 | 1.696 | 1.923 | 1.694 | **1.834** |
| EXP | 0.122 | 0.262 | 0.161 | 0.134 | 0.163 | 0.134 | 0.144 | **0.132** |
| MZ p-value | 18% | 42% | 51% | 69% | 96% | 60% | 100% | **74%** |

**Residential portfolio**

| | LS | RSW | BMA | SIM | OLS | ROB | CLS | VAR |
|---|---|---|---|---|---|---|---|---|
| MSE | 2.096 | **1.185** | 2.934 | 1.761 | 1.984 | 2.026 | 1.741 | 1.793 |
| RMSE | 1.448 | **1.088** | 1.713 | 1.327 | 1.409 | 1.423 | 1.319 | 1.339 |
| MAE | 1.168 | **0.900** | 1.119 | 1.027 | 1.149 | 1.260 | 1.007 | 1.036 |
| EXP | 0.542 | **0.611** | 0.757 | 0.663 | 0.703 | 0.641 | 0.678 | 0.661 |
| MZ p-value | 88% | **100%** | 64% | 73% | 88% | 92% | 71% | 73% |

**Consumer portfolio**

| | LS | RSW | BMA | SIM | OLS | ROB | CLS | VAR |
|---|---|---|---|---|---|---|---|---|
| MSE | 6.753 | **5.157** | 6.796 | 5.773 | 5.919 | 6.080 | 6.052 | 5.774 |
| RMSE | 2.599 | **2.271** | 2.607 | 2.403 | 2.433 | 2.466 | 2.460 | 2.403 |
| MAE | 2.261 | **1.846** | 2.315 | 2.069 | 2.114 | 2.155 | 2.145 | 2.077 |
| EXP | 0.180 | **0.171** | 0.193 | 0.173 | 0.172 | 0.172 | 0.173 | 0.172 |
| MZ p-value | 60% | **79%** | 87% | 85% | 80% | 73% | 75% | 83% |

**Models shown are Least Squares (LS), Regime Switching (RSW), Bayesian Model Average (BMA) and the forecast combination techniques: Simple Average (SIM), Ordinary Least Squares (OLS), Robust regression (ROB), Constraint Least Squares (CLS) and Variance Based (VAR).**

**Table 11: Dynamic Forecast Out-of-sample performance metrics. Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Exponential Error Measure (EXP).**

**Business portfolio**

| | LS | RSW | BMA | SIM | OLS | ROB | CLS | VAR |
|---|---|---|---|---|---|---|---|---|
| MSE | 10.225 | 14.829 | 8.167 | **6.217** | 7.916 | 6.814 | 7.302 | 6.356 |
| RMSE | 3.198 | 3.851 | 2.858 | **2.493** | 2.814 | 2.610 | 2.702 | 2.521 |
| MAE | 2.782 | 2.962 | 2.677 | **2.006** | 2.227 | 2.091 | 2.169 | 1.986 |
| EXP | 0.148 | 0.538 | 0.136 | **0.109** | 0.150 | 0.121 | 0.134 | 0.111 |
| MZ p-value | 14% | 6% | 16% | **90%** | 34% | 70% | 46% | 93% |

**Residential portfolio**

| | LS | RSW | BMA | SIM | OLS | ROB | CLS | VAR |
|---|---|---|---|---|---|---|---|---|
| MSE | 4.380 | 4.306 | 6.005 | 4.358 | 4.788 | **3.904** | 4.539 | 4.350 |
| RMSE | 2.093 | 2.075 | 2.450 | 2.088 | 2.188 | **1.976** | 2.130 | 2.086 |
| MAE | 1.694 | 1.751 | 1.574 | 1.521 | 1.748 | **1.562** | 1.563 | 1.516 |
| EXP | 0.789 | 0.800 | 0.855 | 0.813 | 0.821 | **0.791** | 0.818 | 0.812 |
| MZ p-value | 39% | 99% | 96% | 92% | 97% | **90%** | 100% | 89% |

**Consumer portfolio**

| | LS | RSW | BMA | SIM | OLS | ROB | CLS | VAR |
|---|---|---|---|---|---|---|---|---|
| MSE | 9.955 | 11.478 | 15.950 | 9.228 | **7.981** | 8.204 | 8.079 | 8.739 |
| RMSE | 3.155 | 3.388 | 3.994 | 3.038 | **2.825** | 2.864 | 2.842 | 2.956 |
| MAE | 2.570 | 3.139 | 3.744 | 2.798 | **2.385** | 2.448 | 2.433 | 2.664 |
| EXP | 0.317 | 0.266 | 0.365 | 0.253 | **0.254** | 0.269 | 0.260 | 0.251 |
| MZ p-value | 76% | 97% | 99% | 95% | **97%** | 92% | 92% | 93% |

**Models shown are Least Squares (LS), Regime Switching (RSW), Bayesian Model Average (BMA) and the forecast combination techniques: Simple Average (SIM), Ordinary Least Squares (OLS), Robust regression (ROB), Constraint Least Squares (CLS) and Variance Based (VAR).**

**Table 12: Root Mean Square Errors of Gross Default rates**

| RMSE Gross Default Rates | | |
|---|---|---|
| **Portfolio** | **Static Forecast** | **Dynamic Forecast** |
| Business | 2,5 | 1,8 |
| Residential | 1,3 | 1,3 |
| Consumer | 2,2 | 2,2 |

**Table 13: Business Portfolio Panel data regression on Default rates (1), OLS and Panel data regression on Distance to Default (2) and (3).**

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | DR | DtD OLS | DtD Panel |
| CORP(-1), | 0.449*** | | |
| | (0.0510) | | |
| DtD CORP(-1), | | 0.712*** | 0.602*** |
| | | (0.136) | (0.0405) |
| CPI growth | -0.0245 | -0.00473 | 0.0193 |
| | (0.0186) | (0.0123) | (0.0264) |
| GDP growth(-1), | -0.00355** | -0.0151*** | -0.0223 |
| | (0.00122) | (0.00508) | (0.0131) |
| Constant | 0.119** | -0.524** | -0.969*** |
| | (0.0435) | (0.246) | (0.114) |
| Observations | 672 | 40 | 655 |
| R-squared | 0.225 | 0.921 | 0.465 |
| Number of bank | 17 | | 17 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 14: Residential Portfolio Panel data regression on Default rates (1), OLS and Panel data regression on Distance to Default (2) and (3).**

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | DR | DtD OLS | DtD Panel |
| RRE(-1) | 0.704*** | | |
| | (0.0143) | | |
| DtD RRE(-1), | | 1.796*** | 0.568*** |
| | | (0.302) | (0.0602) |
| CPI growth | 4.20e-05 | 0.0434*** | 0.0488* |
| | (0.000930) | (0.0139) | (0.0240) |
| HPI growth | -0.00138*** | 0.0329* | -0.0354*** |
| | (0.000411) | (0.0163) | (0.00798) |
| Constant | 0.0191*** | 1.436** | -1.051*** |
| | (0.00207) | (0.570) | (0.156) |
| Observations | 514 | 40 | 510 |
| R-squared | 0.710 | 0.876 | 0.391 |
| Number of bank | 14 | | 14 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 15: Consumer Portfolio Panel data regression on Default rates (1), OLS and Panel data regression on Distance to Default (2) and (3).**

| VARIABLES | (1)<br>DR | (2)<br>DtD OLS | (3)<br>DtD Panel |
|---|---|---|---|
| CONS(-1), | 0.254** | | |
| | (0.112) | | |
| DtD CONS(-1), | | 1.376* | 0.634*** |
| | | (0.705) | (0.0554) |
| CPI growth | -0.0167 | 0.0411 | 0.00852 |
| | (0.0108) | (0.0277) | (0.0247) |
| HPI growth | -0.0201 | -0.00475 | -0.0122 |
| | (0.0138) | (0.0127) | (0.0102) |
| D_UNR, | 0.0727 | -0.0946 | 0.127* |
| | (0.0733) | (0.146) | (0.0636) |
| Constant | 0.0866 | 0.428 | -0.795*** |
| | (0.0535) | (1.009) | (0.132) |
| Observations | 620 | 40 | 598 |
| R-squared | 0.090 | 0.473 | 0.455 |
| Number of bank | 16 | | 16 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Figure 1: Architecture of a Markov regime switching model**

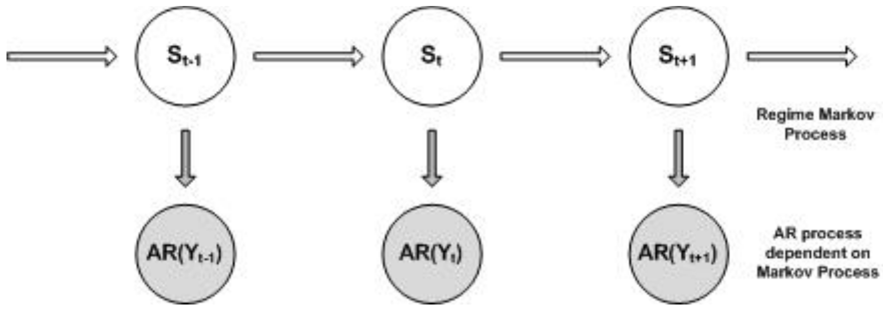


**Figure 2: Business Portfolio - Transition matrix probabilities across stages**

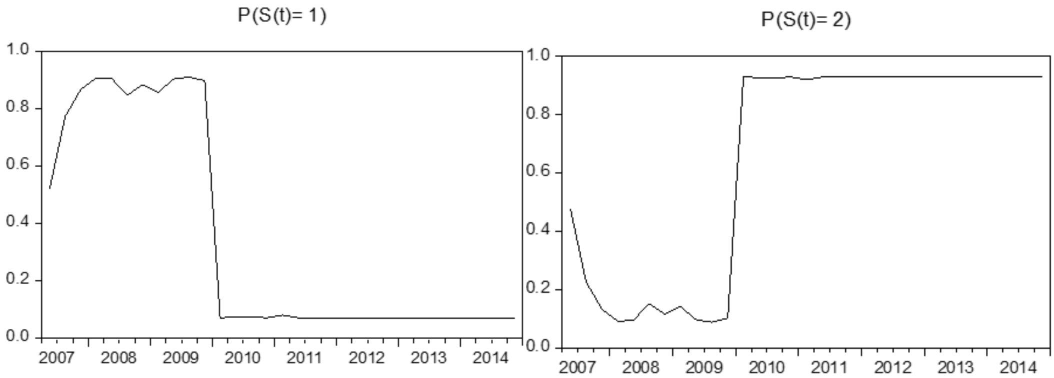



**Figure 3: Residential Portfolio - Transition matrix probabilities across stages**

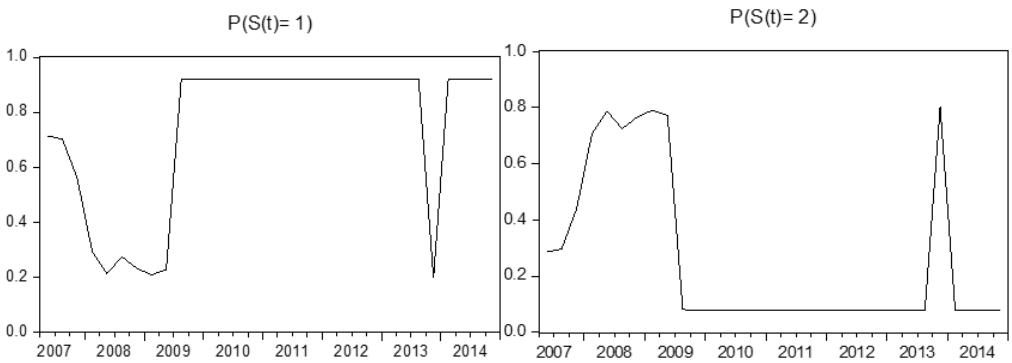



**Figure 4: Consumer Portfolio - Transition matrix probabilities across stages**

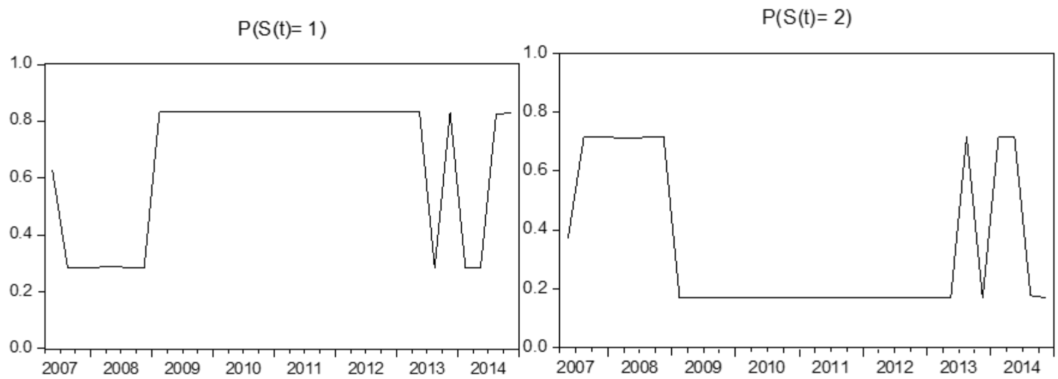


**Figure 5: Business Portfolio – Historical evolution of default rates (Real) and the respective in sample fit for the period 2007-2014. Models shown are Least Squares (LS), Regime Switching (RSW), Bayesian Model Average (BMA).**

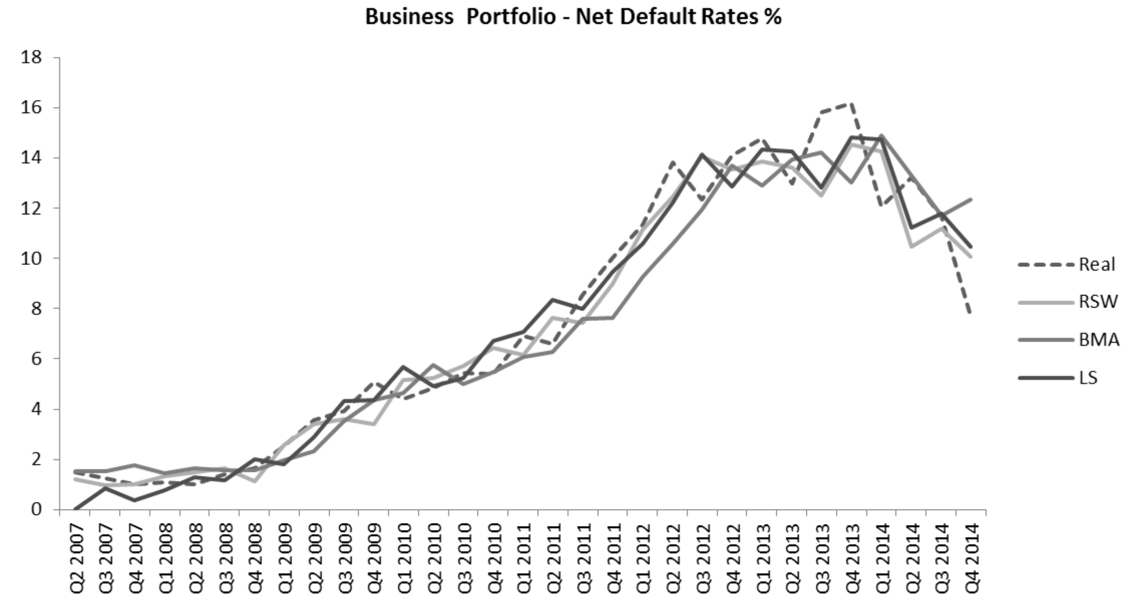



**Figure 6: Residential Portfolio Historical evolution of default rates (Real) and the respective in sample fit for the period 2007-2014. Models shown are Least Squares (LS), Regime Switching (RSW), Bayesian Model Average (BMA).**

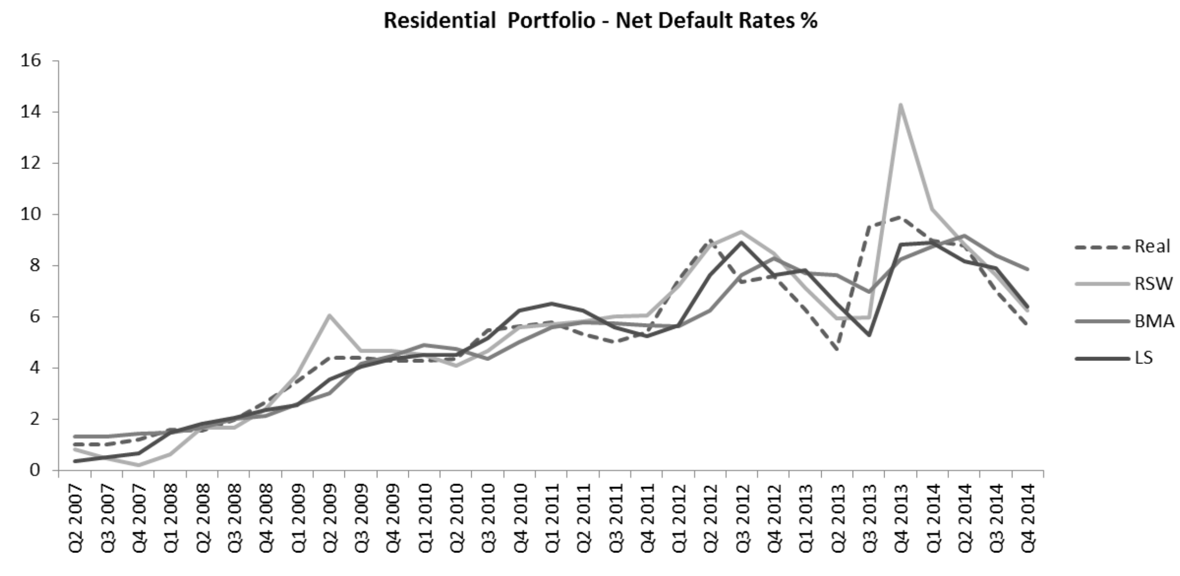
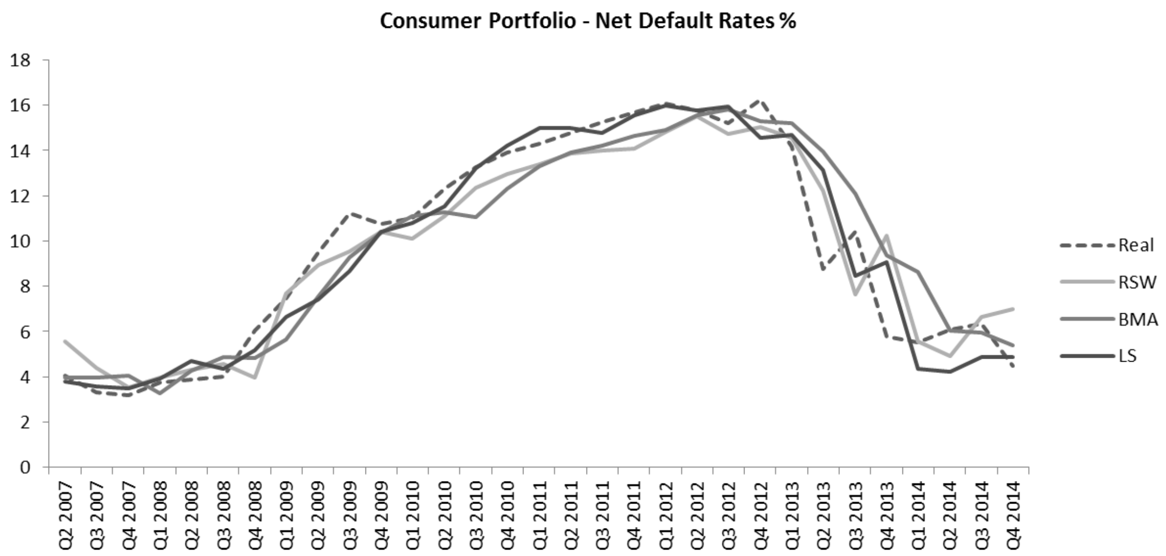


**Figure 7: Consumer Portfolio Historical evolution of default rates (Real) and the respective in sample fit for the period 2007-2014. Models shown are Least Squares (LS), Regime Switching (RSW), Bayesian Model Average (BMA).**



## Appendix B

It is a popular choice to set a uniform prior probability for each model to represent the lack of prior knowledge. It is often the case in BMA to assume no prior knowledge for each model and assign a uniform prior probability i.e. $p(M_\gamma) \propto 1$. Regarding the marginal likelihoods $p(M_\gamma|Y,X)$ and the posterior distributions $p(\beta|M_\gamma,Y,X)$ the literature standard is to use a specific prior structure called Zellner's g prior in order to estimate posterior distributions in an efficient mathematical way. In this setup the prior knowledge for the coefficients is assumed to be a normal distribution with pre-specified mean and variance. Specifically the parametric formulation is given by (8).

$$\beta_\gamma|g \sim N\left(0, \sigma^2 \left(\frac{1}{g} X_\gamma{}' X_\gamma\right)^{-1}\right) \qquad (8)$$

According to (8) coefficients are assumed to have zero mean and a variance-covariance structure which is broadly in line with that of the data $X_\gamma$ . The hyper-parameter g denotes the prior level of confidence that the coefficients are zero. The posterior distribution of the coefficients follows a t-distribution with expected value $\frac{g}{1+g}\widehat{\beta_\gamma}$ where $\widehat{\beta_\gamma}$ is the standard OLS estimator for model γ. Thus as $g \to \infty$ the coefficient estimator approaches the OLS estimator. Similarly, the posterior variance of $\beta_\gamma$ is affected by the value of g (9).

$$Cov(b_\gamma|Y,X,g,M_\gamma) = \frac{(Y-\bar{Y})'(Y-Y)}{N-3} \frac{g}{1+g}\left(1-\frac{g}{1+g}R_\gamma^2\right)\left(X_\gamma{}' X_\gamma\right)^{-1} \qquad (9)$$

The posterior covariance is similar to that of the OLS estimator, times a factor that includes $g$ and $R_\gamma^2$ .(OLS R squared for model γ). For BMA, this prior framework results in α marginal likelihood which includes a size penalty factor adjusting for model size $k_\gamma$ given by

$$p(Y|M_\gamma,X,g) \propto (Y-\overline{yY})'(Y-\overline{Yy})^{-\frac{N-1}{2}}(1+g)^{--\frac{k_\gamma}{2}}\left(1-\frac{g}{1+g}\right)^{-\frac{N-1}{2}} \qquad (10)$$

The "default" approach for hyper-parameter g is the "unit information prior" (UIP), which sets g = N for all models.

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