Forecasting the Macro Determinants of Bank Credit Quality: A Non-Linear Perspective

Edoardo Otranto[§] – Mariagrazia Fallanca[§] – Antonio Forgione[§#]

Abstract

Exposure to macroeconomic shocks strongly influences the performance and profitability of the banks besides pressures bank capital and solvency. A wealth of literature has recognized significant evidence of the linkage between macro conditions and credit vulnerability, perceiving the importance of the high amount of bad loans for economic stagnation and financial vulnerability. Generally, this linkage was represented by linear relationships, but the strong dependence of bank loan default on the economic cycle, subject to changes in regime, could suggest nonlinear models as more appropriate. Indeed, macroeconomic variables affect the performance of bank's portfolio loan, but such relationship is subject to changes disturbing the stability of parameters along the time. This study is an attempt to model three different kinds of bank loan defaults and to forecast them in the case of US, detecting nonlinear and asymmetric behaviors by the adoption of a Markov Switching approach. Comparing it with the classical linear model, we identify evidence for the presence of regimes and asymmetries, changing in correspondence of the recession periods during the span 1987-2017, and a clear outperformance of the Markov Switching model concerning the linear one.

Keywords: Bank Loan Default; Markov-Switching Model; Forecasts,

[§] Department of Economics University of Messina, Italy.
[§] Department of Economics University of Messina, Italy.
[§] Department of Economics University of Messina, Italy.
[#] **Corresponding author** (fforgione@unime.it)

1. Introduction

Extensive literature shows as macroeconomic variables affect the borrowers' creditworthiness and hence loan portfolio quality. Academic studies focus on different drivers, geographic areas, countries and time frameworks.

Keeton and Morris (1987) show that depressed local economic conditions along with the insufficient performance of some sectors mainly explain loan losses. Salas and Saurina (2002) and Quagliariello (2006) find a direct, contemporaneous and lagged relationship between GDP and credit risk, stressing on the over-exuberant lending, over-optimism and herd behavior during periods of business cycle upturns, and supporting the idea that bad debts behavior is cyclical, decreasing in good macroeconomic times and increasing during downturns.

The research of Marcucci and Quagliariello (2008) on the Italian banking system, adopting a reduced VAR to prove the cyclical trend of loan quality for both the household and corporate sectors, is consistent with the previous results. However, the majority of works include many other macro variables to provide additional information on their impact on borrowers' debt servicing capacity. Louzis *et al.* (2011) link the credit quality of consumer loans to change of the real gdp growth and lending rates while finding business loans more susceptible to changes of the unemployment rate and mortgage loans less receptive to the macro conditions. Saba *et al.* (2012) regress bad debts on real GDP per capita and inflation proving a significant impact of both the macro factors and suggesting the importance of their control while issuing loans.

Stock real and financial wealth proxied by house and stock prices index are also invoked as good predictors of loans defaults. Bofondi and Ropele (2011) and Castro (2012) note the inverse relationships, indicating that positive stock and house markets reflect a positive outlook on firm's and individuals profitability, and facilitating debt improvement. Similarly, Beck *et al.* (2013) suggest that falling stock prices indices negatively affect the credit quality, especially in countries with large stock markets relative to the size of the economy. Ghosh (2015) demonstrates that changes in state housing prices along with higher state real GDP and personal income reduce credit vulnerability, while it is significantly increased by inflation, state unemployment, and public debt.

Also, interest rate affects bank loans causing more defaults Shu (2002), Ranjan and Dhal (2003), Hoggarth *et al.* (2005), Fofack (2005), and Castro (2012).

Kjosevski and Petkovski (2017) use a GMM estimation to analysis macroeconomics and bank-specific factors for a panel of 27 banks in the Baltic States with findings large consistent with the literature: GDP, inflation and domestic credit obtained as a major driver of private sector vulnerability.

Generally, all studies show similar results, adopting models, such as linear regression models, models for panel data, VAR, with stable relationships expressed by fixed parameters. Nevertheless, a simple graphical inspection of the time series of delinquency rates clearly shows that economic cycle affects credit default: during the increase-phases, credit default tends to be lesser, whereas in the recession time default rates are likely to increase. Many economic time series show a similar behavior and are modeled providing the possibility to change the parameters in correspondence of different regimes (for example, regime of growth and regime of recession); see, for example, Hamilton (1989), analyzing the US GDP, and Gallo and Otranto (2015), modeling the S&P500 financial index. Given the strong link between delinquency rates and economic cycle, the attempt of modeling the first variable with changing parameters in correspondence of different regimes seems quite natural.

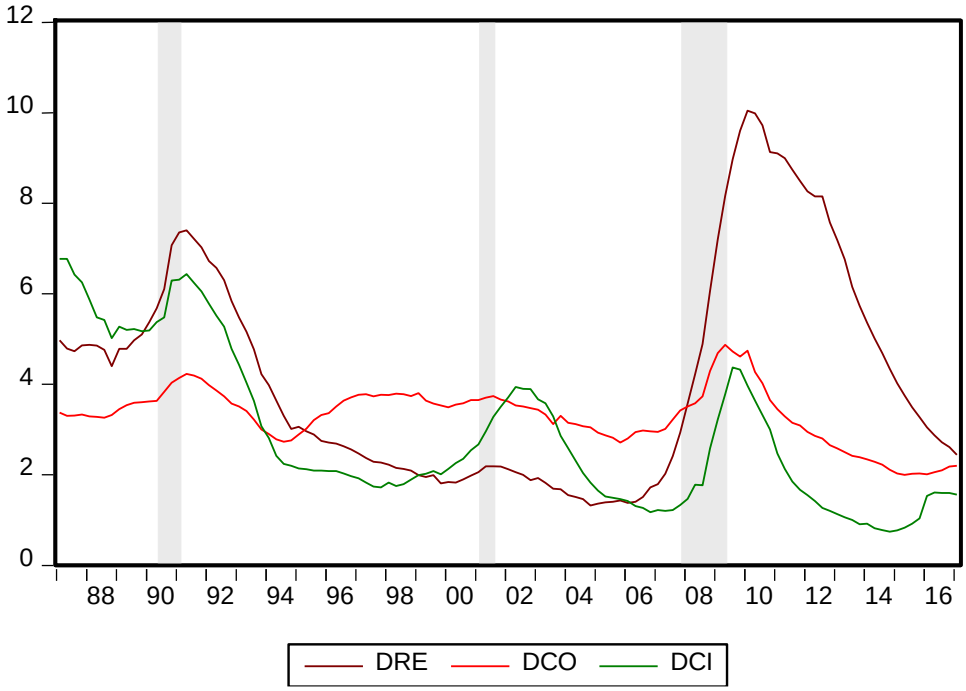
In this paper we propose to adopt a Markov Switching (MS hereafter) model (Hamilton, 1989 and 1990) in order to represent the dynamics of three kinds of US delinquency rates, using as covariates the economic variables detected in the existing (cited) literature. MS models are compared concerning the corresponding linear models, both in terms of fitting and forecasting performance.

The paper is structured in the following way: next section is an empirical illustration of the presence of regimes in delinquency rates, supported by statistical tests. Section 3 introduces the MS model for delinquency rates and Section 4 provides the empirical analysis, showing as MS models outperform the linear ones. Some final remarks will conclude the paper.

2. Nonlinearities in delinquency rates

In Figure 1 we illustrate the behavior of US delinquency quarterly rates in the period from the first quarter 1985 up to the first quarter 2017, for three different kinds of bank loans: Real Estate (*DRE*, henceforth), Consumer (*DCO*) and Commercial & Industrial (*DCI*).

Figure 1: US Delinquency rate in for loan segments. Shaded areas indicate the US recession periods detected by NBER.



Source: Federal Reserve

They show a similar dynamics with a clear increase in correspondence of the recession periods (identified by the shaded area, according to NBER dating).[1]

However, the impact of the economic cycle varies along the different bank loan segments. For instance, *DRE* shows the highest increase during the 1990 and 2007 recessions, whereas it is the lowest ratio in the 2001 downturn.

The frequent changes in level could indicate the non-stationary behavior of the three time series, without a clear trend. This intuition is confirmed by the Augmented Dickey-Fuller (ADF) test, to verify the null hypothesis of unit root against the alternative of stationarity. In the first column of Table 1, we show the values of the ADF statistic. For all the series, we do not reject the non-stationarity hypothesis. Anyway, as shown by empirical evidence, in the presence of structural breaks, the ADF is biased towards non-rejecting the null hypothesis of unit root (see, for example, Perron, 1989).

Table 1: Value of three test statistics to verify the null hypothesis of unit root without breaks (ADF) with one break (ZA) and two Breaks (CMR)

	ADF	ZA	CMR
DRE	-2.376	-4.972***	-5.548***
DCO	-2.520	-4.008	-5.645**
DCI	-2.808	-5.297***	-6.711**

***, ** indicates rejection of the null hypothesis at 1% and 5% level, respectively.

Statistical tests, such as Život-Andrews (ZA, henceforth) test, (Zivot and Andrews, 1992) and Clemente-Montañés-Reyes (CMR) test (Clemente *et al.*, 1998), which are robust against, respectively, one and two structural breaks, can be used to support the possible incorrect result of ADF. In more detail, ZA verifies the

[1] Data available at http://www.nber.org/cycles.html

null hypothesis of unit-root against the alternative of stationarity with a break identified endogenously, whereas CMR verifies the same null against the stationarity, considering two breaks (identified endogenously) in both the hypotheses. In the last two columns of Table 1, we show the ZA and CMR statistics.[2] In particular, ZA test rejects the null of unit-root in all cases except for the *DCO* series, whereas CMR test always rejects the null. Moreover, the time break detected for the same series with the two procedures are always different. In other words, this experiment seems to suggest the presence of several breaks and the stationarity of delinquency series. As a consequence, the linear model for the first difference of the delinquency series generally adopted in the literature (see, Vogiazas and Nikolaidou, 2011; Louzis, *et al.*, 2012; Baholli *et* al., 2015; Mondal, 2016; Adeola and Ikpesu, 2017; Kumarasinghe, 2017) could be based on a wrong hypothesis, not considering changes in unknown time breaks. For this reason, we propose to adopt a popular econometric model that recently has been used for several macroeconomic and financial time series, the MS model, introduced by Hamilton (1989).

3. The model proposed

The MS approach is a piecewise linear model which has recently had a large success, extending the most widespread models to a nonlinear framework. For example Hamilton (1989) inserts a MS dynamics in the autoregressive processes, Dueker (1997) in the GARCH models of Bollerslev (1986) to analyze the financial markets, Gallo and Otranto (2015) in the Multiplicative Error Models of Engle (2002) and Engle and Gallo (2006) to analyze the realized volatility, Billio and Caporin (2005) in the Dynamic Conditional Correlation models of Engle (2002) to analyze the mechanisms of contagion in financial markets.

The basic idea of MS models is that the time series analyzed follows different linear models in correspondence of different regimes (states); for example, the GDP series could be represented by two models which differ for the values of the coefficients in correspondence of the regime of growth and the regime of recession. Moreover we do not fix a priori the periods belonging to a specific regime, but we hypothesize that the regime is represented by a discrete random variable s_t and the switch from a regime to another one in contiguous periods (or the persistence in the same regime) is driven by a discrete, first order, irreducible an ergodic[3] Markov chain. Formally, the model we propose to represent the delinquency rates is:

$$y_t = \alpha_{s_t} + \beta_{s_t} y_{t-1} + \mathbf{x}_{t-1}^{'} \boldsymbol{\gamma}_{s_t} + \varepsilon_t \quad \text{with } \varepsilon_t \sim N\left(0,\ \sigma_{s_t}^2\right) \text{ and } t = 1...T$$

where y_t represents the delinquency rate at time t, $\mathbf{x}_t$ is a vector containing the explicative variables at time t, a_{s_t}, β_{s_t} and $\boldsymbol{\gamma}_{s_t}$ are unknown coefficients[4] which can change according to the state s_t and ε_t is a zero mean Normal disturbance with variance depending on the state.[5] The state s_t can assume two distinct values (let us label them 1 and 2 respectively) and its dynamics is represented in probabilistic terms by a transition probability matrix with elements:

$$p_{i,j} = Pr\left(s_{t+1} = j \mid s_t = i\right) \quad \left(i, j = 1, 2\right)$$

In practice, the transition probabilities exhibit the so-called Markov property, a "memoryless" property or statement saying that the future state of the process depends only upon the present state, not on the sequence of previous observations. The element of the matrix $p_{i,j}$ represents the probability to switch from state i to state j when $i \neq j$, or the permanence in a certain state when $i = j$.

Using the properties of the Markov Chain, we can detect the expected permanence in state i from the ratio: (see Hamilton, 1994, chapter 24, for the main properties of the MS models)

---

[2] For the CMR test, we detect the structural breaks as innovation outliers, which provides a gradual change over the time (See Perron and Vogelsang, 1992).

[3] An ergodic Markov chain is a covariance stationary process. Following Hamilton (1994), it is an irreducible Markov chain with one of the eigenvalue of the transition matrix P equal to 1 and the other eigenvalues inside the unit circle. A Markov chain is called irreducible if there is only a single communicating class in the state space. This communicating class exists if every state j is accessible from every state i within finite time. In other words, a Markov chain is irreducible if it possible (with positive probability) to go from anywhere to anywhere.

[4] $\boldsymbol{\gamma}_{s_t}$ is a vertor of unknown coefficients.

[5] Many models consider only the coefficients entering in the mean of the process as switching, whereas the variance is constant; in our experiments we will estimate models with the two alternatives of constant and switching variance.

$$\frac{1}{\left(1-p_{i,i}\right)}.$$

In order to assign each observation to a certain state, it is adopted the so-called Hamilton filter, developed by Hamilton (1990). This is a recursive procedure expliciting the likelihood function to be maximized for estimation purposes.
This procedure provides, as a sub-product, the probability:

$$\Pr\left(s_t = j \mid I_{t-1}\right)$$

which is the filtered probability that at the time t the regime is j conditional on the information set available at time *t-1* (I_{t-1}) and the probability

$$\Pr\left(s_t = j \mid I_T\right)$$

which is the smooted probability that at the time t the regime is j conditional on the full information set (I_T).
A rule of thumb assigns the observation at time *t* to regime *j* if the corresponding smoothed (filtered) probability is higher than 0.5; in general, if the model fits the data, these probabilities are near to 0 or 1, so that the assignment of each observation to a certain regime is very likely. For example, Hamilton (1989), using an MS(2)-AR(4) model with switching mean, shows that it performs better than conventional models to track the official NBER dates of US recessions for the period from the second quarter of 1952 to the last quarter of 1984.

4. Empirical analysis

There is broad literature to explain delinquency rates in terms of linear relationship with a set of covariates. We will consider the data from 1987 Q1 to 2015 Q1 for the estimation of the models, whereas we will use the rest of the data for the out-of-sample evaluation of Section 4.4.

4.1 The dataset

We conduct an empirical experiment using quarterly data on American credit quality[6] and macroeconomic time series for a period spanning from the first quarter of 1987 to the first quarter of 2017 (121 observations for each variable). Variables are drawn from the Federal Reserve Board and the International Monetary Fund, Global Financial Stability Report Tables.
Following the aforementioned literature, we have selected six covariates, which, jointly with the lagged dependent variable, allow to forecast delinquency rate.[7]
The extensive set of exogenous variables includes two indicators of economic growth (*GDP* and *Unemployment*), an indicator of price stability (the broad money supply *M2*) and two measures of changes in financial and real wealth (the house price index, *House price*, and the stock market index, *S&P*). It also comprises a measure of the burden of debt (the *interest rate*):
GDP is closely connected to the capacity to satisfy debt obligations on the immediate hypothesis that high levels of economic growth cause high levels of income for householders and firms.
Unemployment could explains delinquency rate, since, when it increases, household's level of income decreases and, as a consequence, reduces also purchasing power with cascade effects on firm turnover and profit.
Money supply is measured by the amount of money in circulation in the economy. We expect a positive relationship with our dependent variable, since expansionary monetary policy shoves banks to grant credit to low-rated borrower.

[6] We use the quarterly delinquency rates seasonally adjusted provided by the Federal Reserve Board. In US delinquent loans mainly coincide with those past due of over 30 days and still accruing interest as well as those in nonaccrual status, which also covers lease contracts.
[7] In a first attempt, we have also considered Consumer Price Index and Real Effective Exchange Rate but they were never statistically significant.

House prices explain changes in delinquency rates through the wealth effect. Falling in house prices rise curtailed borrower equity, and in addition, it makes difficult sell the collateral to extinguish the loan.[8] In contrast, increase in house prices improves the quality of loans. Furthermore, a decrease in house markets has a spillover effect on the economy, leading an increase in the probability of default.
Similarly, S&P 500 index represents a share of US households and firms wealth and it is expected to impact in the same way on the dependent variable.
Interest rate relates to default rates by reproducing the cost of borrowing. The higher the interest rate is, the higher the real value of borrower's debt and debt servicing is more expensive.
In our analysis, all the covariates are expressed in terms of quarterly percentage variations.
Following Louzis *et al.* (2012) and Ghosh (2017) we perform our analysis for the disaggregate credit quality ratio series. Through a sectorial approach, we underline the sensitivity of each loan categories to macro shock, revealing possible similarities and differences. Therefore, in this study we have three dependent variables, one for each loan type Y_i (i = 1, …, 3), namely *DRE*, *DCO* and *DCI*.[9]
Our starting model is a simple linear model with lagged covariates as regressor included the lagged dependent variable.
The first step is the estimation of a multiple linear regression model with all the covariates to select, for each dependent variable, a set of significant regressors. The model obtained will be considered as the benchmark to evaluate the MS model.

4.2 The linear model

As said, all the independent variables have been lagged. Dropping out the nonsignificant variables, we obtain parsimonious models. In detail, the lagged delinquency rate, GDP, M2 and House Price are always present, while the remaining variables are present only in some models, as shown in Table 2.
Models show a very high R^2, confirming that the regressors selected are able to explain the dependent variables.

Table 2: Linear models

	DRE	*DCO*	*DCI*
Delinquency	0.950***	0.964***	0.997***
	(0.01)	(0.02)	(0.01)
GDP	-0.041***	-0.014***	-0.038***
	(0.01)	(0.00)	(0.01)
Unemployment		-0.039***	-0.083***
		(0.01)	(0.01)
M2	0.062*	0.031**	0.060**
	(0.03)	(0.01)	(0.03)
House price	-0.173***	-0.045***	-0.058***
	(0.02)	(0.01)	(0.02)
Tbills	0.039***	0.017***	
	(0.01)	(0.01)	
S&P	-0.006*		
	(0.00)		
Constant	0.250**	0.320***	0.531***
	(0.10)	(0.10)	(0.11)
σ^2	0.057	0.010	0.034
Adj R^2	0.991	0.967	0.988

Notes: Robust standard errors in parenthesis; ***, **, * indicates statistical significant at the 1%, 5%, and 10% level, respectively.
All the variables in the first column are lagged

[8] "The net worth of borrowers changes not only in response to variations in cash flow, but also (and often, more dramatically) to changes in the valuation of the real and financial assets that they hold", Bernanke *et al.* (1999).
[9] Real estate loans include loans secured by one to four family residential properties, including home equity lines of credit; construction and land development loans, loans secured by multifamily residences, loans secured by non-farm and non-residential real estate. Consumer loans refer to secured and non-secured financing given to clients for family, personal or household scopes, or for consumable items. Differently, *C&I* loans are provided to business or corporation (not to an individual) either to finance working capital or physical assets expenditures.

Turning to the single covariates, the coefficient associated to the lagged *Delinquency* takes positive sign and is highly statistically significant; its large value indicates a strong persistence over the time that derives from a constant deterioration of banks loans portfolio and borrower's creditworthiness.
The coefficient of *GDP* takes a negative sign in all the models, confirming that a decrease in economic cycle affects the delinquency ratios in next quarter and vice versa for an increase (Salas and Saurina, 2002; Ranjan and Dhal, 2003; Fofack, 2005; Khemraj and Pasha, 2009; Espinoza and Prasad, 2010; Klein, 2013; Filip, 2014).
Surprisingly, the unemployment rate affects the *DCO* and *DCI* negatively, whereas it has not effect on *DRE*. This empirical evidence is in contrast with several empirical works (see Gambera, 2000; Nkusu, 2011; Bofondi and Ropele, 2011; Louzis *at al.*, 2012; Castro, 2012; Škarica, 2014; Gosh, 2015 and Flip, 2014). [10] Hence, such outcomes are challenging.
For consumer loans, the negative sign could mean that banks finance workers less likely to get unemployed. For the commercial and industrial model, the negative sign could be related to the short-term effect of the unemployment on firm profitability and cash flow. In detail, an increase in the unemployment rate should reduce – in the short term – the labor costs.
Regarding the estimated coefficients of *M2*, it is significant for *DRE* loans, but only at 10 percent, while at 5 percent for *DCO* and *DCI*. The positive sign can be explained by the higher disposable income in the previous quarter that may lead individuals and firms to irrationally increase their debt amount. On the supply side, an expansionary monetary policy could induce the banks to reduce their credit selections criteria, and as a consequence, give loan to less creditworthiness borrowers.
We find evidence that *House price* also affects negatively all our delinquency rates. The interpretation is trivial in the case of delinquency rate in the Real Estate loan, whereas it is less evident for the other kinds of delinquency loans. A possible explanation for *DCO* and *DCI* can be attributed to the role of collateral in the US economy[11] that raises the individuals in negative equity.
S&P stock market works similarly to change in housing market or property ownerships with the difference that stocks represents a liquid wealth. Therefore, it has been fund a similar negative relation. However, unlike the importance of the stock market in the US economy, *S&P* does not affect the US delinquency rates (except for a slight statistical significance found for the real estate loans).
Finally, *Tbills* coefficient is significant for real estate and consumer loans (at 5 percent) and *DCI* (10 percent). An increase in short-term reference rate pushes floating rate loans rising the default rate. So, also, in this case, the relationship depends on the type of mortgages products which are prevalent in the market, and the extent to which the mortgage contracts allow the mortgage interest rate to change when the interest rate changes.

4.3 The MS model

In order to verify the capability of MS model to capture the presence of regimes in delinquency rates, we consider three kinds of MS models for all loans categories: a model with only the intercept α_{s_t}as switching coefficient (see equation 3) (Markov Switching Intercept model, MS-I), a model with α_{s_t}, $\beta_{s_t}$and $\boldsymbol{\gamma}_{s_t}$as switching coefficients, but not the variance, (Markov Switching Coefficients model, MS-C) and, a model with all the coefficients that change in correspondence of the regime, as in equation 3 (Markov Switching Coefficients and variance model MS-CV).
To select the best model for each series we have performed the following procedure:

1) Apply a Likelihood ratio test to compare the MS-C model against the restricted MS-I model and select the first one if the null hypothesis of equal performance is rejected, the second one if it is not rejected;
2) Apply the likelihood ratio test to compare the MS-CV model against the *winner* of step 1); the MS model chosen is the first one if the null hypothesis of equal performance is rejected, the second one if it is not rejected.
3) Compare the selected MS model against the linear model with a loss criterion.

In step 3) it is not possible to evoke the use of the likelihood ratio test because we fall in the case of nuisance parameters present only under the alternative hypothesis and not identified under the null (see, for example, Hansen, 1992). In practice, the linear model is not nested in the MS model because the presence of the transition probabilities (the nuisance parameters); in this case, there are not the conditions to detect the asymptotic

[10] There are also study that found an insignificant relationship such as Quagliarello (2007).
[11] Consider that in US the building is the most important industry and housing the most significant component of household's wealth (13, 3% of total GDP in 2017 q1).

distribution of the likelihood ratio statistic. Psadarakis and Spagnolo (2003) have analyzed the capability of several loss functions in detecting the number of regimes in an MS framework (included the linear case), and the AIC seems to have a good performance; in step 3) we have adopted AIC, BIC, and HQ criteria.
Applying this procedure, we select the MS-CV model for *DRE* and *DCI* and the MS-C for *DCO*. Moreover, all the likelihood-based criteria favor the MS models against the linear one, confirming the presence of regimes in the delinquency rate series (see Table 3).

Table 3: Information criteria to compare linear against MS models.

DRE	Linear Regression	MS-CV
AIC	0.044	-0.859
BIC	0.214	-0.422
HQC	0.113	-0.682

DCO	Linear Regression	MS-C
AIC	-1.690	-2.113
BIC	-1.520	-1.701
HQC	-1.621	-1.946

DCI	Linear Regression	MS-CV
AIC	-0.478	-0.858
BIC	-0.332	-0.470
HQC	-0.419	-0.701

Table 4 reports the estimations of MS models. The results display as changes in macroeconomic variables affect loans delinquency rates in the two regimes since significances and sizes of the estimated coefficients depending on the regime. The estimated coefficients are quite similar in sign to the results of previous baseline regressions. The estimated intercept of each regime indicates the first regime as the "high credit vulnerability state," while the second one as the low one. The mean of a delinquency rate in each regime are shown in the lower part of the Table and, under the hypothesis of stationarity, it is obtained by:

$$\mu_{s_t} = \frac{\alpha_{s_t} + \sum \bar{\mathbf{x}}' \boldsymbol{\gamma}_{s_t}}{1 - \beta_{s_t}}$$

where $\bar{\mathbf{x}}$ denotes the vector of the means of the exogenous variables.
Turning to the transition probabilities outputs, we can see that the probabilities that the process moves from regime 1 to regime 2 and vice versa are tiny in the case we consider MS-CV. Instead, we have obtained mixed results for *DCO* parameter estimation with only parameter switching (MS-C): consumer loans tend to vary position more frequently. Expected regime durations confirm the described tendency. Moreover, periods of low delinquency rates (Regime 2) are globally longer than the other periods (Regime 1).
Focusing on the single variables, the most significant are *GDP*, *House_price* and *M2*.
The lagged dependent variables are consistent with the directional impacts. Previous quarters delinquency amounts are highly significant and positively related to both regimes confirming the dynamism and persistence of the losses. Slight differences concern the magnitude of the impact under the regimes and with the linear model results.
The *GDP* has a negative impact on all class loans, but changes in GDP are deeper for *DRE*, while it influences *DCI* only in Regime 1 and they are statistically insignificant for the *DCO* loans. Therefore, while an increase in GDP gives consumers more opportunity to repay their loans, our evidence does not let us affirm that when GDP falls, credit vulnerability increases. Unlike, business loans appear sensitive only to a deterioration of the business cycle. Regarding the magnitude of the impact of GDP on our dependent variables, consistent with previous studies, our results show that delinquency rates increase suddenly in periods of economic recession and they decline during the expansion periods.
As in the linear model, there is a negative sign associated to the coefficient of *Unemployment*. In periods of high delinquency loans, lower unemployment leads to higher delinquency rates. Similarly, in low regime, even

if mixed results are observed for consumer loans. In state 1, unemployment is positive before turning to be negative under low phase. The outcome is consistent with the existing literature. During economic crises, loss of jobs or increased unemployment reduces the purchasing power of households making it hard to pay back the loans acquired. On the contrary, in periods of low delinquency loans, higher unemployment leads to lower delinquency rate. It may happen that loans are more collateralized or that low unemployment rate does not push the consumer loans to demand. Therefore, there is not consequent increase on the supply side that conduct to grant credit also too bad creditworthiness borrower and after a quarter, the default rate does not grow.

Differently, the outcomes may reflect the fact that a lower labor participation does not allow individuals to enjoy more disposable income, to invest and increase their debt burden with the consequence that after a lag of a quarter their inability to pay does not grows too. Moreover, the fall in the demand of debt as a consequence of the fall in the level of income means a reduction in the cost of credit repayments such that individuals are less likely to miss a payment and to stay past-due. Or again, the association may be attribute to the fact that already employed borrowers, with poor probability of default, hold loans.

Regarding *DCI*, the estimated coefficient is negative and insignificant for *DCI* in the high period, whereas it is negative and significant for the lower one. This result could be related to the short-term effect of unemployment on firm cash flow, which should increase as a consequence of the reduction in labor cost.

Estimated coefficients for money supply are not homogeneous across class loans and regimes for significance and magnitude, while take the expected positive sign. Specifically, *DRE* and *DCI* loans show a significant response to restrictive monetary policies, while *DCO* loans are sensitive just to the expansionary measures. Insignificances may be linked to the protracted effects of monetary policies on the economy that can take uncertain lag and magnitude. As pointed out by Friedman (1961), monetary actions affect economic conditions only after one or more lags.

As in the linear model, *House_price* coefficients take a negative sign across all the specification and regime, even if they are not statistically significant across all loans categories and regimes. For *DRE* loans, a fall in the growth rate of house prices is significant just for the boom regime. The most significant effect of house price falling is on *DCO* and *DRE* loans, given that firms give different collateral for their debt.

In regime 1, the level of delinquency of bank loan does not depend on upward adjustments in the short-term interest rate for *DRE* and *DCO*.

DRE and *DCO* delinquency rate, but only for Regime 2, positively depend on variations of interest rates, whereas, in Regime 1 the estimated coefficients are not statistically significant.

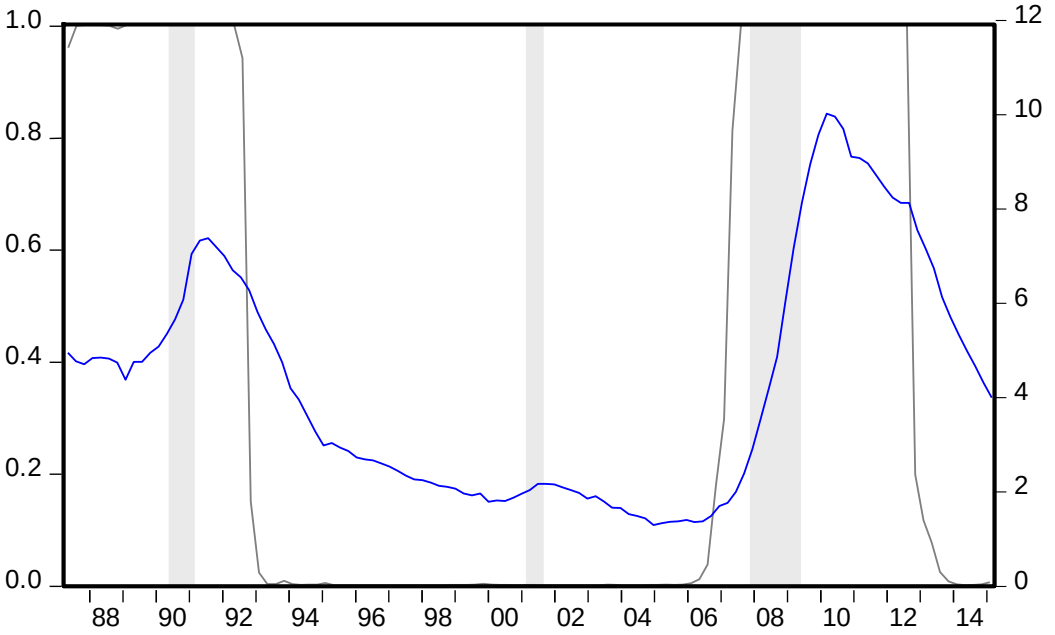
Finally, contrary to the linear case, there is an insignificant asymmetric response of *DRE* to changes of the stock market.

Table 4: Estimation of MS models

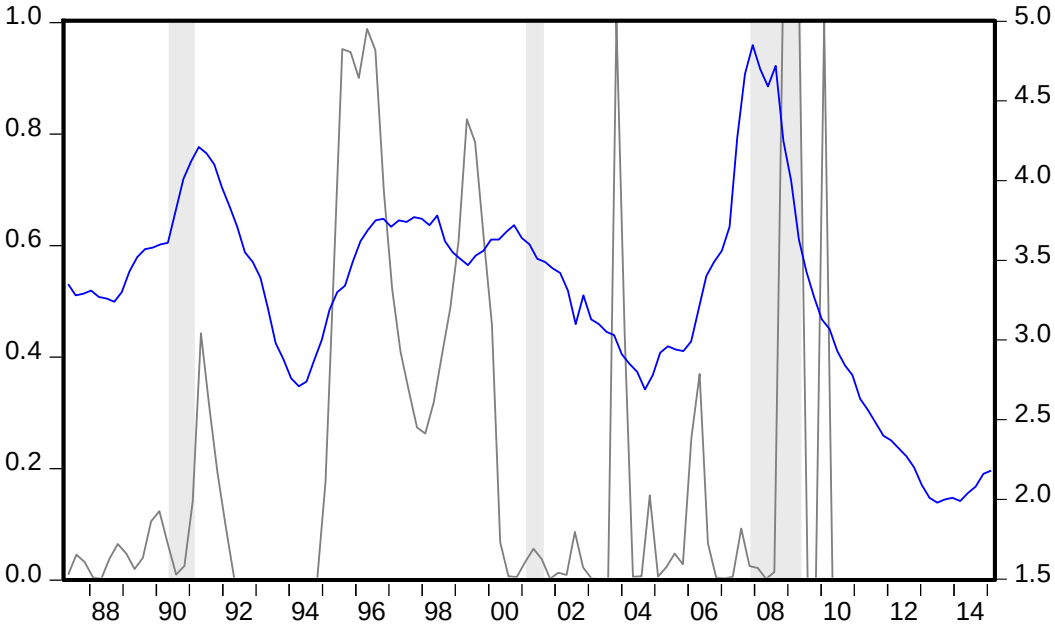
	DRE	*DCO*[#]	*DCI*
GDP	-0.059*** [1]	-0.003 [1]	-0.036* [1]
	(0.019)	(0.007)	(0.019)
	-0.009 [2]	-0.008* [2]	-0.005 [2]
	(0.006)	(0.004)	(0.007)
Unemployment		0.057*** [1]	-0.034 [1]
		(0.021)	(0.054)
		-0.039*** [2]	-0.057*** [2]
		(0.008)	(0.010)
M2	0.022 [1]	0.085*** [1]	0.031 [1]
	(0.067)	(0.030)	(0.061)
	0.035** [2]	0.016 [2]	0.031* [2]
	(0.015)	(0.010)	(0.017)
House price	-0.174*** [1]	-0.089*** [1]	-0.071 [1]
	(0.055)	(0.017)	(0.044)
	-0.022 [2]	-0.037*** [2]	-0.029*** [2]
	(0.018)	(0.008)	(0.011)
Tbills	0.035 [1]	-0.005 [1]	
	(0.030)	(0.013)	
	0.016** [2]	0.022*** [2]	
	(0.007)	(0.004)	
S&P	-0.007 [1]		
	(0.006)		
	-0.000 [2]		
	(0.002)		
Delinquency	0.934*** [1]	0.772*** [1]	0.927*** [1]
	(0.031)	(0.050)	(0.039)
	0.910*** [2]	0.933*** [2]	0.916***[2]
	(0.009)	(0.016)	(0.015)
Constant	0.547 [1]	0.567*** [1]	0.688** [1]
	(0.350)	(0.217)	(0.342)
	0.096 [2]	0.383*** [2]	0.407*** [2]
	(0.072)	(0.071)	(0.071)
σ^2	0.138*** [1]		0.040 [1]
	(0.032)	0.065***	(0.011)
	0.063*** [2]	(0.010)	0.008 [2]
	(0.013)		(0.002)
Log Likelihood	65.693	135.356	64.070
Expected duration of regimes	29.512 [1]	2.936 [1]	14.952 [1]
	40.946 [2]	13.034 [2]	25.714 [2]
Mean	4.277 [1]	3.460 [1]	3.013 [1]
	3.959 [2]	3.259 [2]	2.681 [2]
p_{11}	0.966	0.659	0.933
p_{12}	0.034	0.341	0.067
p_{21}	0.024	0.077	0.039
p_{22}	0.976	0.923	0.961

Estimates with the label [1] refer to the parameters relative to state 1, estimates with the label [2] to the parameters relative to state 2. Robust standard errors in parenthesis; ***, **, indicates statistical significant at the 1%, and 5%, level, respectively.
We estimate the transition probabilities p_{11} and p_{21}. Given the property $p_{i1}+p_{i2}=1$ ($i=1,2$), the other probabilities are obtained as $p_{12}=1-p_{11}$ and $p_{22}=1-p_{21}$ respectively.
[#] Only coefficients switching, without variance (MS-C).

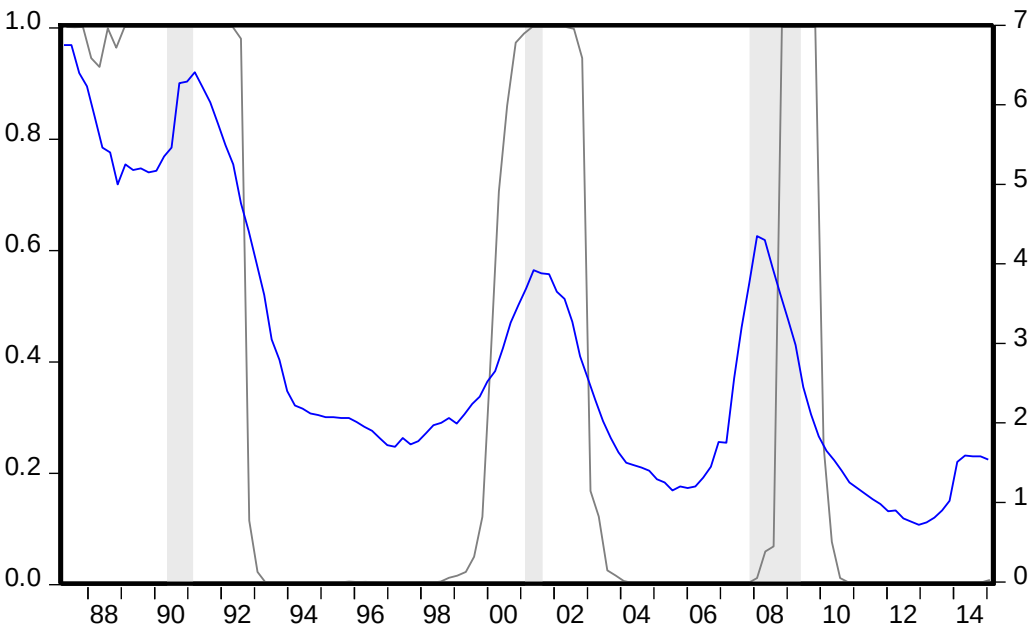
Figure 2: Smoothed probabilities of regime 1 derived from the MS models for three types of delinquency rates. The shaded area corresponds to the recession periods detected by NBER


1.0
0.8
0.6
0.4
0.2
0.0
12
10
8
6
4
2
0
88
90
92
94
96
98
00
02
04
06
08
10
12
14

DRE


1.0
0.8
0.6
0.4
0.2
0.0
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
88
90
92
94
96
98
00
02
04
06
08
10
12
14

DCO



DCI

Figure 2 shows the smoothed probabilities relative to Regime 1 of each estimated MS model. It is interesting to notice how the regime of high delinquency rates are identified in correspondence of the first and the third longer recessions, indicated by NBER, with different duration (see also the different state durations in Table 4) for *DRE* and *DCI*; the last one presents another high state in correspondence of the brief intermediate recession of 2001. On the other hand, the regimes of *DCO* seem not related to the recession dates (excluding the last one), and there are several values of the smoothed probabilities around 0.5, not identifying if the corresponding date falls in a recession or growth period. This is the series with fewer movements (see Figure 1), for which the presence of changes seems less evident from a simple linear inspection; also in Table 1, this was the most puzzling case, given the opposite indications of ZA and CMR tests. In other terms, for series *DRE* and *DCI*, there is strong empirical support for the existence of two clear regimes, whereas *DCO* does not show a clear nonlinear pattern.

Given such trends, macroeconomic factors may not be the primary determinants of *DCO* in the period previous the 2007 financial crisis. Indeed, *DCO* is more affected by personal specific economic factors and even non-economic factors then general economic factors. In addition, it is worth to note that *DCO* often diverges to *DRE* and *DCI* in term of low maturity, collateral and amount of loan.

4.4 Forecasting performance

In this section, we investigate the accuracy of MS models forecasting, comparing it with the linear model results. We address our investigation testing the two models in terms of in-sample and out-of-sample[12] forecasting performance. For the in-sample case, we use the previous estimation results on the dataset 1987 Q1-2015 Q1. For the out-of-sample case we provide two different experiments:

- Static forecasts (o.s.s.): we forecast the observations from 2015 Q2 to 2017 Q1 fixing the coefficients estimated in previous sections but updating the regressors for each forecasting step.
- Recursive forecasts (o.s.r.): we forecast the value of 1987 Q2 using the previous estimates; then we add an observation to the data set, re-estimate the models and forecast the successive observation, and so on.

Relevant differences in the results of the two alternative out-of-sample forecasts can be interpreted as instability of the estimated model.

The comparison of the forecasts with alternative models is performed by the usual loss functions Mean Squared Error (MSE) and Mean Absolute Error (MAE):

[12] In sample forecast means predictions generated for the same data set used to develop the model; the out of sample forecasts are those made for a period outside the data set used to estimate the model's parameters.

$$MSE = \frac{\sum_{t=1}^{n}\left(y_t - y_t\right)^2}{n}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|y_i - y_i\right|^2}{n}$$

where $\hat{y}_t$ denotes the forecasted value of y_t and n the size of the out-of-sample set. Models providing smaller MSE and MAE are considered better in terms of forecasting performance.
It is important to notice that a typical empirical finding in statistics and econometrics favors overparameterized models in terms of fitting (in-sample performance) whereas the simplest models (linear models) in out-of-sample terms (see, for example, Hansen, 2010).

Table 5: In-sample and out-of-sample loss functions with linear and MS models and results of the DM test. Bold values indicate the better performance

		MSE i.s.	MAE i.s.	MSE o.s.s.	MAE o.s.s.	MSE o.s.r.	MAE o.s.r.
DRE	Linear	0.0540	0.1770	0.0206	0.1265	0.0201	0.1273
	MS	**0.0347*****	**0.1247*****	**0.0016*****	**0.0339*****	**0.0013*****	**0.0290*****
DCO	Linear	**0.0095****	0.0686	0.0026	0.0420	0.0027	0.0430
	MS	0.0107	**0.0675***	**0.0025*****	**0.0415*****	**0.0026**	**0.0426**
DCI	Linear	0.0326	0.1263	**0.0250*****	**0.1190*****	**0.0250**	0.1212
	MS	**0.0294*****	**0.1158*****	0.0376	0.1471	0.0292	**0.1178**

***, **, * indicates statistical significant at the 1%, 5%, and 10% level, respectively, of the MSE and MAE difference between models estimated by the DM statistics.

In Table 5 we synthesize the results of the comparison. The in-sample evaluation always favors the MS models, excluded for the MSE of *DCO*. This is consistent with the findings described in Table 1 and Figure 2. In out-of-sample terms, the MS model again is better than the linear one, excluding the case of *DCI*. Anyway, in many cases, the differences between the loss functions of the two models are very small, so we want to verify if they are significantly different by a formal statistical test; for this purpose, we apply the well-known Diebold and Mariano (1995) test (DM). DM test compares model loss functions under the null hypothesis of equal predictive ability; to avoid problems of over-rejection of the null hypothesis in small samples, we adopt the DM version of the test proposed by Harvey *et al.* (1997). In the same Table 5, we notice that the superiority of the linear model in the in-sample case is not so clear for *DCO*, given the small value of the DM statistics; the difference is significant for the o.o.s. case, whereas in the o.o.r. case the superiority of the MS model is significant only for the *DRE* case. The last results underline as the use of more information for forecasts reduces the gap between linear and MS model, but when the switches are evident, as in *DRE* (see Figure 1), the MS model is better, in spite of the possible overparameterization.

5. Final remarks

Bad loans are a key factor of financial soundness, reflecting bank asset quality and therefore banks' liquidity and solvency. As highlights of an extensive literature, macroeconomic factors impact on bank loans performance, affecting bank borrowers default. However, to the best of our knowledge, no study has ever been conducted on forecasting the nonlinearities of such relationship.
This study aims to bridge the gap, capturing the natural asymmetries and changes along different phases of the economic cycle. It presents a macro model that reexamines the link between delinquency rate and macro factors for the US, by using the Markov switching approach to understand whether results are homogeneous across regimes. It is also conducted among different loan classes, stressing on the disaggregated specification. The study provides evidence about the validity of the non-linear approach, supporting the predictive ability of MS and showing uniformity across loans categories. It also compares the forecasting performance of MS with the linear regression.
The model allows managing the asymmetries features in the data.

Non-linear functional form performs better than benchmark linear model regarding the forecasting. We find evidence that MS globally overcomes the linear one specifically for real estate loans. Findings are consistent with literature regarding sign and statistical significance of covariates applied in empirical research. In addition, empirical results provide evidence that delinquency rates display different features regarding the impact in different phases of the business cycle (economic expansion and recession; period of high or low unemployment or interest rate and so on), the simple linear model cannot capture that.

Therefore, it can be concluded that the hypothesis of nonlinearities in the dynamics of delinquency rates is valid; the study is unique not only in making a non-linear comparative analysis of the macro determinants that affect delinquency rates of different loans types but also in that it assumes a forecasting perspective.

Results can be beneficial to financial institutions and for regulator and policymaker. Namely, as macro factors are significant predictors of an increase of delinquency loans, authorities could use results to tailor proper and responsive policies to deal with different types of loans and to diversify strategies during the different economic trends. Identifying in which periods loans became more troubled, it would be useful for the betterment of the financial health, to strengthen the banking sector against failures and prevent a rise in credit risk.

Moreover, results can help the management of the banks who can refer to the performance of macroeconomic conditions to predict the performance of their bad loans when they manage the credit risk of their loans to avoid the possibility of increasing defaults.

We acknowledge the limitations of this paper that represent opportunities for future researchers. The data for this exercise were available at a quarterly frequency, but MS may be more exhaustive with more observations and more extended research periods. Data availability will be a big challenge important to achieve different findings for comparability. Another possibility is to look at the components of each specific category.

Hence, a more extensive dataset of countries and a broader time frame can be considered to obtain substantive conclusions about the non-linear impact of macroeconomic variables on nonperforming financing.

Reference

Adeola, O. and Ikpesu, F. (2017). Macrodeterminants of Non-performing Loans in Nigeria: an empirical analysis . *Journal of Developing Areas*, 51(2), 31-43.

Baholli, F., Dika, I., and Xhabija, G. (2015). Analysis of Factors that Influence Non-Performing Loans with Econometric Model: Albanian Case. *Mediterranean Journal of Social Sciences*, 6(1), 391.

Beck, R., Jakubik, P., and Piloiu, A.. (2013). *Non-performing Loans: What Matter in Addition to the economic Cycle?* European Central Bank Working Paper, n.1515.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). The Financial Accelerator in a Quantitative Business Cycle Framework. *Handbook of macroeconomics*, 1, 1341-1393.

Billio, M., and Caporin, M. (2005). Multivariate Markov Switching Dynamic Conditional Correlation GARCH Representations for Contagion Analysis. *Statistical methods and applications*, 14(2), 145-161.

Bofondi, M. and Ropele, T. (2011). *Macroeconomic Determinants of Bad Loans: Evidence from Italian Banks.* Bank of Italy, Occasional Papers.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of econometrics*, 31(3), 307-327.

Castro, V. (2012). *Macroeconomic Determinants of the Credit Risk in the Banking System: The case of the GIPSI*. NIPE Working Papers.

Clemente, J., Montañés, A., and Reyes, M. (1998). Testing for a Unit Root in Variables with a Double Change in the Mean. *Economics Letters*, 59(2), 175-182.

Diebold, F.X., and Mariano, R.S. (2002). Comparing Predictive Accuracy. *Journal of Business & economic statistics*, 20(1), 134-144.

Diebold, F. X., and Mariano, R. S. (1995). Comparing Predictive Accuracy. *Journal of Business & economic statistics*, 13(3), 253-263.

Dueker, M.J. (1997). Markov Switching in GARCH Processes and Mean-reverting Stock-market Volatility. *Journal of Business & Economic Statistics*, 15(1), 26-34.

Engle, R. (2002). New Frontiers for ARCH models. *Journal of Applied Econometrics*, 17(5), 425-446.

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics*, 20(3), 339-350.
Engle, R., and Gallo, G.M. (2006). A Multiple Indicators Model for Volatility Using Intra-Daily Data. *Journal of Econometrics*, 131(1-2), 3-27.
Espinoza, R.A., and Prasad, A. (2010). *Nonperforming Loans in the GCC Banking System and their Macroeconomic Effects* (No. 10-224). International Monetary Fund.
Filip, B.F. (2014). Non-performing Loans-dimension of the Non-quality of Bank Lending/Loans and their Specific Connections. *Theoretical and Applied Economics*, 5(594), 127-146.
Fofack, H. (2005). *Non Performing Loams in Sub Saharan Africa: Causal Analysis and Macroeconomic Implications*. World Bank Policy Research Working Paper 3769.
Friedman, M. (1961). The Lag in Effect of Monetary Policy. Journal of Political Economy, 69(5), 447-466.
Gallo, G.M., and Otranto, E. (2015). Forecasting Realized Volatility with Changing Average Levels. *International Journal of Forecasting*, 31(3), 620-634.
Gambera, M. (2000). *Simple Forecasts of Bank Loan Quality in the Business Cycle*. Chicago, IL: Federal Reserve Bank of Chicago.
Ghosh, A. (2015). Banking-industry Specific and Regional Economic Determinants of Non-performing Loans: Evidence from US States. *Journal of Financial Stability*, 20, 93-104.
Ghosh, A. (2017). Sector-specific Analysis of Non-performing Loans in the US Banking System and their Macroeconomic Impact. *Journal of Economics and Business*, 93, 29-45.
Hamilton, J.D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica: Journal of the Econometric Society*, 357-384.
Hamilton, J.D. (1990). Analysis of Time Series Subject to Changes In Regime. *Journal of econometrics*, *45*(1-2), 39-70.
Hamilton, J.D. (1994). *Time Series Analysis* (Vol. 2). Princeton: Princeton University press.
Harvey, D., Leybourne, S., and Newbold, P. (1997). Testing the Equality of Prediction Mean Squared Errors. *International Journal of forecasting*, 13(2), 281-291.
Hoggarth, G., Sorensen, S., and Zicchino, L. (2005). *Stress Tests of UK Banks Using a VAR Approach*. Bank of England Working Paper n. 282.
Keeton, W. R., and Morris, C. S. (1987). Why Do Banks' Loan Losses Differ?. *Economic Review-Federal Reserve Bank of Kansas City*, 72(5), 3.
Khemraj, T., and Pasha, S. (2009). The Determinants of Non-performing Loans: an Econometric Case Study of Guyana.
Kjosevski, J. and Petkovski, M. (2017). Non-performing Loans in Baltic States: determinants and macroeconomic effects. *Baltic Journal of Economics*, 17(1), 25-44.
Klein, N. (2013). *Non-performing loans in CESEE: Determinants and Impact on Macroeconomic Performance* (No. 13-72). International Monetary Fund.
Kumarasinghe, P. J. (2017). Determinants of Non-performing Loans: Evidence from Sri Lanka. *International Journal of Management Excellence*, 9(2), 1113-1121.
Louzis, D. P., Vouldis, A. T., and Metaxas, V. L. (2012). Macroeconomic and Bank-Specific Determinants of Non-performing Loans in Greece: A Comparative Study of Mortgage, Business and Consumer Loan Portfolios. *Journal of Banking & Finance*, 36(4), 1012-1027.
Marcucci, J., and Quagliariello, M. (2008). Is bank portfolio riskiness procyclical?: Evidence from Italy Using a Vector Autoregression. *Journal of International Financial Markets, Institutions and Money*, 18(1), 46-63.
Nkusu, M. M. (2011). *Non-performing Loans and Macrofinancial Vulnerabilities in Advanced Economies* (No. 11-161). International Monetary Fund.
Perron, P. (1989). The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Econometrica: Journal of the Econometric Society*, 1361-1401.
Psaradakis, Z., and Spagnolo, N. (2003). On the Determination of the Number of Regimes in Markov-Switching Autegressive Models. *Journal of Time Series Analysis*, 24(2), 237-252.
Quagliariello, M. (2006). *Banks' Riskiness over the Business Cycle: A Panel Analysis on Italian Intermediaries*. Discussion Papers Banca Italia.
Quagliariello, M. (2007). Banks' Riskiness over the Business Cycle: A Panel Analysis on Italian Intermediaries. *Applied Financial Economics*, 17(2), 119-138.
Ranjan, R., and Dhal, S.C. (2003). Non-Performing Loans and Terms of Credit of Public Sector Banks in India: An Empirical Assessment. Reserve Bank of India Occasional Papers, vol.24, n.3.

Saba, I., Kouser, R. and Azeem, M. (2012). Determinants of Non-performing Loans: Case of US Banking Sector. *The Romanian Economic Journal*, 44(6), 125-136.
Salas, V., and Saurina, J. (2002). Credit risk in Two Institutional Regimes: Spanish Commercial and Savings Banks. *Journal of Financial Services Research*, 22(3), 203-224.
Shu, C. (2002). *The Impact of Macroeconomic Environment on the Asset Quality of Hong Kong's Banking Sector*. Hong Kong Monetary Authority Research Memorandums.
Škarica, B. (2014). Determinants of Non-performing Loans in Central and Eastern European Countries. *Financial theory and practice*, 38(1), 37-59.
Vogiazas, S.D., and Nikolaidou, E. (2011). Investigating the Determinants of Non-performing Loans in the Romanian Banking System: An Empirical Study with Reference to the Greek Crisis. *Economics Research International*.
Život, E., and Andrews, D. W. K. (1992). Further evidence on the Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Journal of Business and Economic Statistics*, 10(3), 251-270.