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Forecasting the macro determinants of bank credit quality: a non-linear perspective

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Received 29 October 2019
Revised 6 May 2020
Accepted 8 June 2020

Abstract

Purpose – This study aims to propose a non-linear model to describe the effect of macroeconomic shocks on delinquency rates of three kinds of bank loans. Indeed, 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.

Design/methodology/approach – 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 non-linear models as more appropriate. Indeed, macroeconomic variables affect the performance of bank's portfolio loan, but such a 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 the USA, detecting non-linear and asymmetric behaviors by the adoption of a Markov-switching (MS) approach.

Findings – Comparing it with the classical linear model, the authors identify evidence for the presence of regimes and asymmetries, changing in correspondence of the recession periods during the span of 1987–2017.

Research limitations/implications – The data are at a quarterly frequency, and more observations and more extended research periods could ameliorate the MS technique.

Practical implications – The good forecasting performance of this model could be applied by authorities to fine-tune their policies and deal with different types of loans and to diversify strategies during the different economic trends. In addition, bank management can refer to the performance of macroeconomic conditions to predict the performance of their bad loans.

Originality/value – The authors show a clear outperformance of the MS model concerning the linear one.

Keywords Forecasts, Bank loan default, Markov-switching model

Paper type Research paper

1. Introduction

Investigating the causes of bank loan portfolio soundness is a critical challenge for regulatory authorities as a result of its effects on financial stability (Louzis *et al.*, 2012; Baldini and Causi, 2020), no less than to bank management (Anastasiou, 2016). Non-performing loans (NPLs), namely, problematic loans outstanding for at least 90, are normally considered a valid proxy for the ex post bank credit risk and are believed to be a suitable early indicator of bank distress

Authors wish to thank an anonymous referee and the Editor, for their particularly useful comments and suggestions. The usual disclaimer applies. The authors contributed equally to this work.

being a common feature of many banking crises (Kaminsky and Reinhart, 1999, and recently Ari *et al.*, 2019). Actually, the financial accelerator theory provides a theoretical basis to relate the NPLs to financial stability (Bernanke and Gertler, 1989; Bernanke *et al.*, 1998). Besides, high NPLs jeopardize banks' profitability and its capacity in financing the real economy (Balgova *et al.*, 2016).

In this concern, recently, Manz (2019) carries out a systematic review article on the determinants of NPLs, pinpointing how researches address mainly three areas of bank loan performance, that is macroeconomic, bank-specific and loan-specific determinants. In essence, Manz (2019), like another recent literature review (Nikolopoulos and Tsalas, 2017), acknowledges that many studies adopt both systemic and idiosyncratic bank-level factors. Also, the authors highlight that the macroeconomic factors are still the most analysed determinant of loan performance.

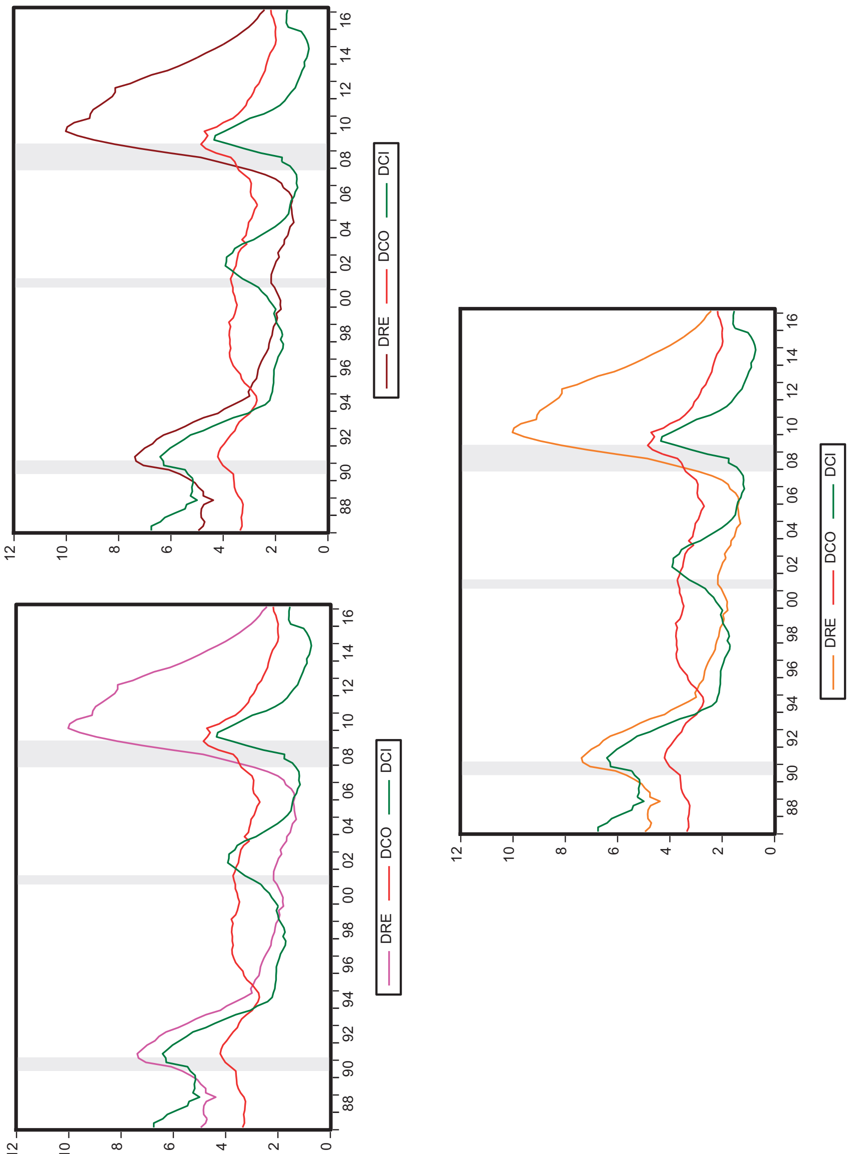
In the stream of literature relating NPLs' performance to macroeconomic variables, recently Climent-Serrano (2019) realized that factors in periods of economic growth are different compared to those in recession periods. Consequently, the author argues for considering the two stages (growth and recession) independently, investigating whether a structural break has taken place. He shows a different effect of the macroeconomic-based explanatory variables in the two situations of the economic cycle.

However, in carrying out its empirical analysis, Climent-Serrano (2019) splits the sample period 2004–2015 into two sub-periods (2004–2009 and 2010–2015), according to the business cycle phases, detecting a different reaction of NPLs to the explicative variables in periods of growth and recession, respectively. This idea is supported by empirical and theoretical evidences; for example, the seminal paper of Louzis *et al.* (2012) underlines that in growth periods the level of NPL decreases because consumers and firms have sufficient revenue to offset their debts, extending the credit to less reliable debtors and causing an increase of NPL during a recession. The importance of this effect is underlined in several papers, where generally the gross domestic product (GDP) variation represents the proxy of the business cycle (Al-Khazali and Mirzaei, 2017; Zhang *et al.*, 2016).

The idea to model the NPL in a non-linear (piecewise linear) perspective is interesting because, in theoretical terms, the different behaviour of the economic and financial actors in growth and recession periods is well documented in the literature (see, for instance, Pederzoli *et al.*, 2010; Jang *et al.*, 2016); in practical terms, the extension of this approach to model NPLs could help in understanding its dynamics and improving forecasting. However, an obvious problem of this approach is in the identification of the sub-periods in which growth and recession show their effects on NPL. Figure 1 is instructive; it shows the delinquency rates of three types of loans: real estate (DRE, henceforth), consumer (DCO) and commercial and industrial (DCI) in the USA from the first quarter of 1985 to the first quarter of 2017, with the shaded areas representing the "official" recession periods detected by the National Bureau of Economic Research (NBER) [1].

From the graphs, it is clear an increase of delinquency rates during the recession periods, but their peaks are generally reached some quarter after the end of recessions and with different lags for each time series. It means that the detection of the threshold dates to change the model cannot be fixed *a priori* and for all the series of NPLs; these dates are unknown, and each choice of the threshold is subjective.

Our idea is to adopt models with time-varying parameters depending on the state of the economy at each time, but considering this state (regime) as an unobservable variable. A widespread model including these characteristics is the Markov-switching (MS) model, developed in macroeconomics, in particular for the study of the business cycle, by Hamilton (1989, 1990) and extended to financial studies, in particular for the analysis of the volatility



Note: Shaded areas indicate the US recession periods detected by NBER
Source: Federal Reserve

Figure 1.
US delinquency rate
in for loan segments.

of financial markets, by several authors (for example, Haas *et al.*, 2004, in a generalized autoregressive conditional heteroskedasticity (GARCH) framework, and Gallo and Otranto, 2015, for the study of realized volatility). We develop this model for the study of NPLs in the USA, introducing the presence of economic regimes in classical linear models with explicative macroeconomic variables. The comparison of both in-sample and out-of-sample forecasts shows a clear improvement of this new approach with respect to the classical linear approach. The better forecasting performance, of course, could be profitably used in all financial problems concerning the evaluation of risk by both regulators and bank management, such as investors.

The paper is structured in the following way: in Section 2, we provide a review of the literature, whereas Section 3 is an empirical illustration of the presence of regimes in delinquency rates, supported by statistical tests. Section 4 introduces the MS model for delinquency rates, and Section 5 provides the empirical analysis, showing as MS models outperform the linear ones. Some final remarks will conclude the paper.

2. Literature review

There exists a wealth of literature on the determinants of NPLs, particularly after the outbreak of the global economic crisis. In this regard, several surveys provide an exhaustive sight of state of the art, and we refer to them for more details. For example, Quagliariello (2008) and, more recently, Nikolopoulos and Tsalas (2017) and Manz (2019) provided an assessment of the empirical research. Chortareas *et al.* (2020), using estimates from 56 studies, carried out a meta-analysis to explore the relationship between NPLs and the business cycle, assessing the factors underlying the variability in the empirical result of different models.

A plethora of studies examine the ability of macroeconomic variables in affecting the borrowers' creditworthiness and hence bank-loan portfolio quality, both considered standalone and jointly with bank-specific factors.

The stream of literature examining the macroeconomic or country-specific determinant of bank fragility outlines the inability of a specific variable to serve as a unique indicator, even if it reflects the general state of the economy. Indeed, research studies based on the macroeconomic contingencies usually adopt a set of covariates capturing the real economy status (growth of GDP, unemployment rate, etc.) and the condition of the financial markets (change in interest rates, stock, house market, etc.).

The pioneering study of Keeton and Morris (1987), using a vector autoregressive model, shows that depressed local economic conditions, along with the insufficient performance of some sectors, mainly explain loan losses. Similarly, Salas and Saurina (2002), Quagliariello (2007), Klein (2013), Zhang *et al.* (2016) and Dimitrios *et al.* (2016) find a direct, contemporaneous and lagged relationship between the real GDP growth and credit risk, stressing on the over-exuberant lending, over-optimism and herd behaviour during periods of business cycle upturns. This finding supports the idea that bad debts' behaviour is anti-cyclical, decreasing in good macroeconomic times and increasing during downturns. Marcucci and Quagliariello (2008) also show the cyclical trend of loan quality for both the household and corporate sectors, whereas Louzis *et al.* (2012) consider real estate, consumer and commercial and industrial loans.

Similarly to the latter variable, the unemployment rate is adopted as an explicative variable to predict the loan bank portfolio soundness as its aptitude to reveal the borrowers' ability to pay back their debts (Nkusu, 2011; Messai and Jouini, 2013; Konstantakis *et al.*, 2016).

Also, the monetary variables are considered a driver of NPLs, in the expectation that an increase in the interest rate cause more defaults. In this concern, see, for example, Shu (2002), Rajan and Dhal (2003), Hoggarth *et al.* (2005), Fofack (2005), Castro (2013) and Beck *et al.* (2015). Similarly, 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. Kjosevski and Petkovski (2017) use a generalised method of moments estimation to analyse macroeconomics and bank-specific factors for a panel of 27 banks in the Baltic States with findings broad consistent with the literature: GDP, inflation and domestic credit obtained as a significant driver of private sector vulnerability.

Other authors have also adopted house and stock prices index as predictors of loan defaults. Bofondi and Ropele (2011) and Ghosh (2017) note the inverse relationships, indicating that positive stock and house markets reflect a favourable outlook on a firm's and individual's profitability and facilitate debt improvement. Similarly, Beck *et al.* (2013) suggest that falling stock prices indices negatively affect 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, whereas it is significantly increased by inflation, state unemployment and public debt.

In the wake of the financial crisis, some studies stressed out the relationship between sovereign crisis proxy and a high level of NPLs (Reinhart and Rogoff, 2011; Louzis *et al.*, 2012; Ghosh, 2015; Konstantakis *et al.*, 2016). The downgrading in the national debt puts a lot of pressure on the bank in funding in the international markets, and in turn, it leads financial institutions to curtail credit. Moreover, the increase in taxation to finance public debt ends up to divert resources to pay back the borrows.

The literature also considers bank-level variables to predict bank loan arrears and failure; such factors are taken into account being alone or, more often, together with the macroeconomic ones. In this regard, Cole and White (2012) show that models founded on standard Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity to market risk (CAMELS) ratings well predicted the US bank default in 2009 and over the period 1985–1992 [2].

A recent literature review on the bank-specific determinants of NPLs is in Swami *et al.* (2019). In brief, previous empirical studies consider the capital adequacy, measured by the specific ratios, (e.g. recently, Ozili, 2019), on the assumption that capitalization improves bank's ability to survive in financial crisis and to reduce moral hazard issues. The empirical models often also consider a proxy for the bank liquidity founding a positive relationship between the loan-to-deposit ratio and NPLs (Karadima and Louri, 2020).

The standard bank accounting-based profitability ratios (Return on asset and return on equity) are assumed to be predictors of NPLs (Anastasiou *et al.*, 2019).

Bank size is another corporate profile widely regarded in literature since the study of Salas and Saurina (2002) or more recently, among many others, Ben Jabra *et al.* (2017) and Tan *et al.* (2020).

A particularly interesting view comes from the seminal paper of Berger (1995) that provides evidence for a causality relationship in Granger's sense among bank efficiency performance and NPLs.

Finally, the Manz (2019)'s review identifies the loan-specific determinants of NPLs in the maturity of the loan, bank-portfolio composition, disaggregated loan aspects and interaction with the real economy, namely, factors ascribed to the bank–customer relationship.

As said in the introduction section, the growth of credit vulnerability is related to macro conditions, under the additional assumption that the impact of any future path of the economic activity is subject to one or more regimes correspond to the growth of recession periods. In the next section, we consider a more general framework where the change in the regime is not fixed *a priori* in correspondence of growth or recession periods but data-driven. To reach this purpose, we first verify by statistical tests the presence of regimes, and then we will adopt a two-state MS approach where the regimes are represented by unobserved variables.

3. Non-linearities in delinquency rates

As stated previously, in Figure 1, we illustrate the behaviour of US delinquency quarterly rates in the period from the first quarter of 1985 up to the first quarter of 2017, for three different kinds of bank loans: real estate (*DRE*, henceforth), consumer (*DCO*) and commercial and industrial (*DCI*).

They show a similar dynamics with a clear increase in correspondence of the recession periods. 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 behaviour 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 the unit root (Perron and Vogelsang, 1992).

Statistical tests, such as the Zivot–Andrews (ZA, henceforth) test (Zivot and Andrews, 1992) and the 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 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 [3]. In particular, the ZA test rejects the null of unit-root in all cases except for the *DCO* series, whereas the 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 the delinquency series. As a consequence, the linear model for the first difference of the delinquency series generally adopted in the literature (Vogiazas and Nikolaidou, 2011; Louzis *et al.*, 2012; Baholli *et al.*, 2015; 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 has recently been used for several macroeconomic and financial time series, the MS model, introduced by Hamilton (1989).

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

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

Note: ***, ** indicate rejection of the null hypothesis at 1% and 5% levels, respectively

4. Model proposed

The MS approach is a piecewise linear model which has recently had a large success, extending the most widespread models to a non-linear framework. For example, Hamilton (1989) inserts MS dynamics in the autoregressive processes, Dueker (1997) in the GARCH models of Bollerslev (1986) to analyse the financial markets, Gallo and Otranto (2015) in the multiplicative error models of Engle (2002b) and Engle and Gallo (2006) to analyse the realized volatility, Billio and Caporin (2005) in the dynamic conditional correlation models of Engle (2002a) to analyse the mechanisms of contagion in financial markets.

The basic idea of MS models is that the time series analysed 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 [4] Markov chain. Formally, the model we propose to represent the delinquency rates is:

$$y_t = \alpha_{s_t} + \mathbf{x}_t\boldsymbol{\gamma}_{s_t} + \epsilon_t \text{ with } \epsilon_t \sim N\left(0,\ \sigma^2_{s_t}\right) \text{ with } t = 1 \ldots T \tag{1}$$

where y_t represents the delinquency rate at time t, $\mathbf{x}_t$ is a vector containing the explicative variables at time t, α_{s_t}, and $\boldsymbol{\gamma}_{s_t}$ are unknown coefficients [5] which can change according to the state s_t and ϵ_t is a zero-mean normal disturbance with variance depending on the state [6]. 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:

$$p_{i,j} = Pr(s_{t+1} = j | s_t = i)\ (i,j = 1,2) \tag{2}$$

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 of switching 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: (Hamilton, 1994, chap. 24, for the main properties of the MS models).

$$\frac{1}{1 - p_{i,i}} \tag{3}$$

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, explicating the likelihood function to be maximized for estimation purposes. This procedure provides, as a sub-product, the probability:

$$Pr(s_t = j | I_{t-1}) \tag{4}$$

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

$$Pr(s_t = j|I_T) \tag{5}$$

which is the smoothed probability that at 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 (1990), 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.

5. 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.

5.1 Data set

We conduct an empirical experiment using quarterly data on American credit quality [7] 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 the delinquency rate [8].

The extensive set of exogenous variables includes two indicators of economic activity (growth of GDP, *GDP* henceforth and *unemployment*), an indicator of price stability (the broad money supply *M*2) and two measures of changes in financial and real wealth (the house price index, *houseprice*, and the stock market index, *S&P*). It also comprises a measure of the burden of debt (*interestrate*).

As highlighted in Section 2, *GDP* growth is one of the most used covariates to explain the ability to satisfy debt obligations. The rationale motivating the inclusion is the hypothesis that high levels of economic growth cause high levels of income for householders and firms (Karadima and Louri, 2020).

Similarly, the unemployment rate is commonly used to explain the delinquency rate (recently, Staehr and Uusküla, 2020). Indeed, an increase in the unemployment rate decreases the households' income and, as a consequence, reduces their 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 because expansionary monetary policy shoves banks to grant credit to a low-rated borrower. Recently, Hussain *et al.* (2020) provide additional evidence of this effect.

House prices explain changes in delinquency rates through the wealth effect. Falling in house prices rise curtailed borrower equity, and in addition, it is difficult to sell the collateral to extinguish the loan [9]. In contrast, an increase in house prices improves the quality of loans. Furthermore, a decrease in house markets has a spillover effect on the economy, leading to an increase in the probability of default. Therefore, similar to Wan (2018) and many other authors, we expect a negative effect of the variable on the delinquency rate.

Similarly, the 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. This explicative is frequently included in models to predict NPLs (recently, Chavan and Gambacorta, 2019.

The 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. Therefore, as in Vouldis and Louzis (2018), our model reports this variable to predict the delinquency rate of US bank loans.

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 category to macro shock, revealing possible similarities and differences. Therefore, in this study, we have three dependent variables, one for each loan type Y_i $(i = 1, \ldots, 3)$, namely, *DRE*, *DCO* and *DCI* [10].

Our starting model is a simple linear model with lagged covariates as regressors 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.

5.2 Linear model

As said, all the independent variables have been lagged. Dropping out the non-significant variables, we obtain parsimonious models. In detail, the lagged delinquency rate, *GDP*, *M2* and *houseprice* are always present, whereas 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.

Turning to the single covariates, the coefficient associated with the lagged *Delinquency* takes the positive sign and is highly statistically significant; its large value indicates a strong persistence over the time that derives from a constant deterioration of bank's loan 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

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

Table 2. Linear models

increase (Salas and Saurina, 2002; Rajan and Dhal, 2003; Fofack, 2005; Khemraj and Pasha, 2009; Espinoza and Prasad, 2010; Klein, 2013; Filip, 2014).

Surprisingly, the unemployment rate negatively affects *DCO* and *DCI*, whereas it has no effect on *DRE*. This empirical evidence is apparently in contrast with several empirical works and the positive theoretical relationship between NPL and unemployment (Gambera *et al.*, 2000; Nkusu, 2011; Bofondi and Ropele, 2011; Louzis *et al.*, 2012; Castro, 2013; Ghosh, 2015; Filip, 2014) [11]. This result is essentially because of the specification of the model, which contains the lagged NPL proxy; in fact, the correlation is stronger when both the variables are at time t than when the variables are lagged, differently from the other covariates. For example, the correlation between DCO_t and $unemployment_t$ is 0.28, whereas between DCO_t and $unemployment_{t-1}$ is 0.17. Considering the lagged *DCO* in the model, the partial correlation between DCO_t and $unemployment_{t-1}$ (netting out the effect of DCO_{t-1}) is negative, and this explains the sign of the coefficient of this covariate [12].

Regarding the estimated coefficients of *M2*, it is significant for *DRE* loans, but only at 10%, whereas at 5% 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 loans to fewer creditworthiness borrowers.

We find evidence that *houseprice* 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 [13] that raises the individuals in negative equity.

S&P stock market works similarly to change in the housing market or property ownerships with the difference that stocks represent a liquid wealth. Therefore, a similar negative relation has been found. 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, the *Tbills* coefficient is significant for real estate and consumer loans (at 5%) and *DCI* (10%). An increase in the 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.

5.3 MS model

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 [equation (3); Markov-switching intercept model, MS-I], a model with α_{s_t}, β_{s_t} and γ_{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 3-step procedure:

(1) Applied 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) Applied 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) Compared 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 (Hansen and Gregory, 1992). In practice, the linear model is not nested in the MS model because of the presence of the transition probabilities (the nuisance parameters); in this case, there are not the conditions to detect the asymptotic distribution of the likelihood ratio statistic. Psaradakis and Spagnolo (2003) have analysed the capability of several loss functions in detecting the number of regimes in an MS framework (included the linear case), and the Akaike's information criterion (AIC) seems to have good performance; in step 3, we have adopted AIC, Bayesian information criterion (BIC), and Hannan-Quinn information criterion (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 (Table 3).

Table 4 reports the estimations of MS models. The results display as changes in macroeconomic variables affect the loan delinquency rates in the two regimes because 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," whereas 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 as follows:

$$\mu_{s_t} = \frac{\alpha_{s_t} + \sum \overline{\mathbf{x}} \gamma_{s_t}}{1 - \beta_{s_t}} \qquad (6)$$

where $\overline{\mathbf{x}}$ denotes the vector of the means of the exogenous variables, whereas β_{s_t} is the autoregressive coefficient in state s_t.

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 3. Information criteria to compare linear against MS models

Variable	*DRE*	*DCO*#	*DCI*
GDP	−0.059*** [1] (0.019)	−0.003 [1] (0.007)	−0.036* [1] (0.019)
	−0.009 [2] (0.006)	−0.008* [2] (0.004)	−0.005 [2] (0.007)
Unemployment		0.057*** [1] (0.021)	−0.034 [1] (0.054)
		−0.039*** [2] (0.008)	−0.057*** [2] (0.010)
M2	0.022 [1] (0.067)	0.085*** [1] (0.030)	0.031 [1] (0.061)
	0.035** [2] (0.015)	0.016 [2] (0.010)	0.031* [2] (0.017)
Houseprice	−0.174*** [1] (0.055)	−0.089*** [1] (0.017)	−0.071 [1] (0.044)
	−0.022 [2] (0.018)	−0.037*** [2] (0.008)	−0.029*** [2] (0.011)
Tbills	0.035 [1] (0.030)	−0.005 [1] (0.013)	
	0.016** [2] (0.007)	0.022*** [2] (0.004)	
S&P	−0.007 [1] (0.006)		
	−0.000 [2] (0.002)		
Delinquency	0.934*** [1] (0.031)	0.772*** [1] (0.050)	0.927*** [1] (0.039)
	0.910*** [2] (0.009)	0.933*** [2] (0.016)	0.916***[2] (0.015)
Constant	0.547 [1] (0.350)	0.567*** [1] (0.217)	0.688** [1] (0.342)
	0.096 [2] (0.072)	0.383*** [2] (0.071)	0.407*** [2] (0.071)
σ^2	0.138*** [1] (0.032)	0.065*** (0.010)	0.040 [1] (0.011)
	0.063*** [2] (0.013)		0.008 [2] (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

Notes: Estimates with label [1] refer to the parameters relative to State 1, and estimates with label [2] refer to the parameters relative to State 2. Robust standard errors are in parentheses. ***, **, indicate statistical significance at the 1%, and 5%, levels, 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)

Table 4.
Estimation of MS models

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*, *houseprice* and *M*2.

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*, whereas 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 with the coefficient of *Unemployment*, but interestingly only in the low NPL regime. In practice, high levels of NPL are also caused by an increase in *unemployment*, in spite of the presence of the lagged delinquency rate, and its effect on the partial correlation. In fact, we observe a significant positive coefficient of *unemployment* in state 1 with a lower coefficient of the lagged NPL (*DCO* equation) and a non-significant coefficient of *unemployment* in the *DCI* equation, in the presence of a higher coefficient of the autoregressive term of the dependent variable. 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, the presence of the autoregressive term provides a *dimming effect* on the *unemployment*, reverting the sign of its coefficient, so that the same comments made for the linear case hold.

Estimated coefficients for money supply are not homogeneous across class loans and regimes for significance and magnitude but take the expected positive sign. Specifically, *DRE* and *DCI* loans show a significant response to restrictive monetary policies, whereas *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, *houseprice* coefficients take a negative sign across all the specifications and regimes, even if they are not statistically significant across all loan 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 collaterals for their debt.

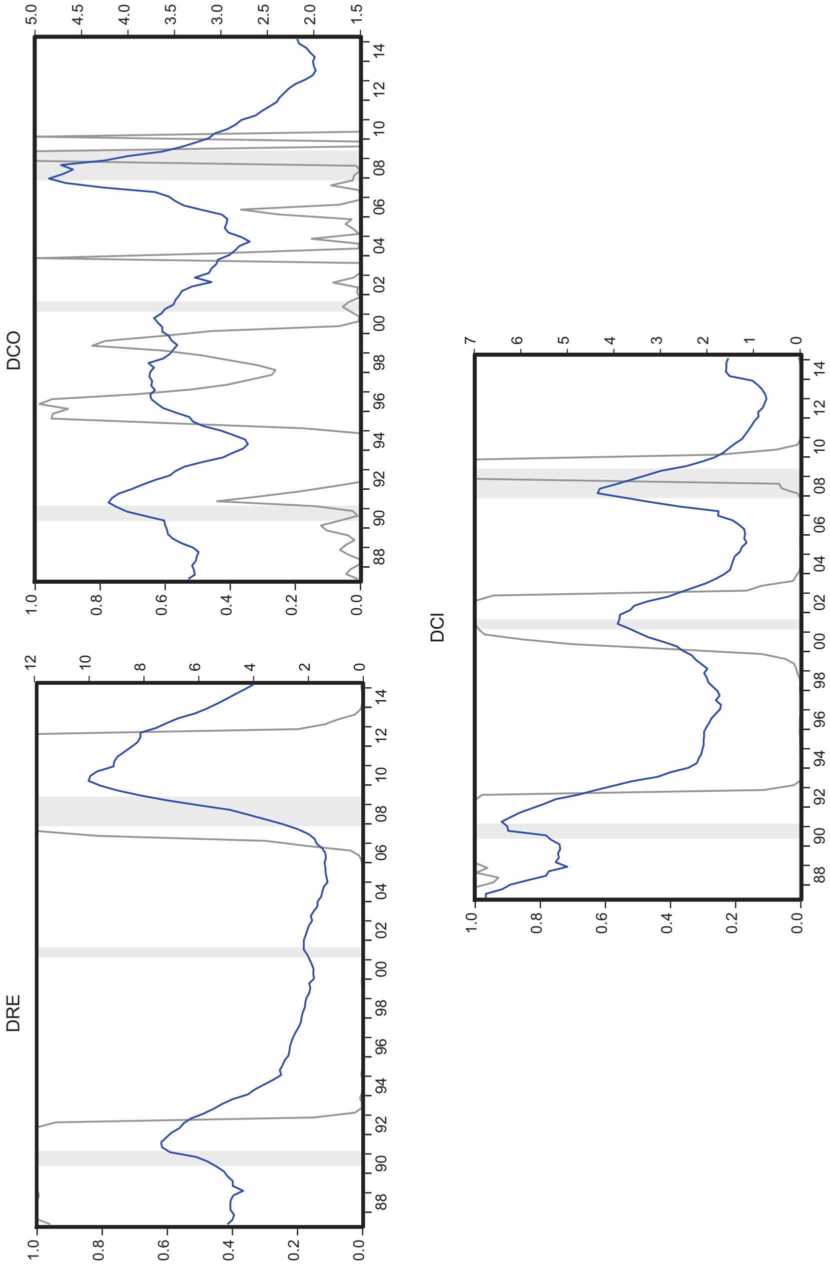
In Regime 1, the level of delinquency of bank loan does not depend on upward adjustments in the short-term interest rate for *DRE* and *DCO*.

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 in the stock market.

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 is identified in correspondence of the first and the third longer recessions, indicated by NBER, with different durations (see also the different state durations in Table 4) for *DRE* and *DCI*; the latter one presents another high state in correspondence to 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 (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 non-linear pattern.

Given such trends, macroeconomic factors may not be the primary determinants of *DCO* in the period previous to the 2007 financial crisis. Indeed, *DCO* is more affected by personal



Note: The shaded area corresponds to the recession periods detected by NBER

Figure 2.
Smoothed probabilities of regime 1 derived from the MS models for three types of delinquency rates

specific economic factors and even non-economic factors then general economic factors. In addition, it is worth noting that *DCO* often diverges to *DRE* and *DCI* in terms of low maturity, collateral and amount of loan.

5.4 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 [14] forecasting performance. For the in-sample case, we use the previous estimation results on the data set 1987 Q1–2015 Q1. For the out-of-sample case, we provide two different experiments:

(1) *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.

(2) *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*):

$$MSE = \frac{\sum_{t=1}^{n} (y_t - \hat{y}_i)^2}{n}$$
$$MAE = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_i|^2}{n} \tag{7}$$

where $\hat{y}_i$ denotes the forecasted value of y_t and n is the size of the out-of-sample set. Models providing smaller *MSE* and *MAE* are considered better in terms of forecasting performance.

Series	Specification	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*

Notes: Italic values indicate the better performance. ***, **, * indicate statistical significant at the 1%, 5%, and 10% levels, respectively, of the MSE and MAE difference between models estimated by the DM statistics

Table 5. In-Sample and out-of-sample loss functions with linear and MS models and results of the DM test

In Table 5, we synthesize the results of the comparison. The in-sample (i.s.) evaluation always favours the MS models, excluded from 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 (2002) test (DM, hereafter). The 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 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* (Figure 1), the MS model is better, in spite of the possible over-parametrization. Similarly to the latter variable, the unemployment rate is adopted as an explicative variable to predict the loan bank portfolio soundness as its aptitude to reveal the borrowers' ability to pay back their debts (Nkusu, 2011; Messai and Jouini, 2013; Konstantakis *et al.*, 2016). Similarly to the latter variable, the unemployment rate is adopted as an explicative variable to predict the loan bank portfolio soundness as its aptitude to reveal the borrowers' ability to pay back their debts (Nkusu, 2011; Messai and Jouini, 2013; Konstantakis *et al.*, 2016).

This result is not trivial; we notice that a typical empirical finding in statistics and econometrics favours over-parametrized models in terms of fitting (in-sample performance) whereas the simplest models (linear models) in out-of-sample terms (see, for example, Hansen, 2010). In other words, obtaining an out-of-sample performance of the MS model similar to the linear one, and in some case even higher, can be considered a very good result.

6. Final remarks

Bad loans are a key factor of financial soundness, reflecting bank asset quality and therefore banks' liquidity and solvency. As highlights of 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 non-linearities of such a relationship.

This study aims to bridge the gap, capturing the natural asymmetries and changes along with different regimes representing high and low NPLs levels, respectively. It presents a macro model that re-examines the link between delinquency rate and macro factors for the USA, by using the MS 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 the MS model and showing uniformity across loan categories. It also compares the forecasting performance of the MS model against the linear one.

The model allows managing the asymmetries features in the data.

The non-linear functional form performs better than the 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 several literature results, but also our empirical research provides evidence that delinquency rates display different features regarding the impact in different phases of the economy.

A model with a so good forecasting performance could help authorities to tailor proper and responsive policies to deal with different types of loans and to diversify strategies during the different economic trends. Especially given the widespread use of stress tests in the banking sector, this contribution adds to the arguments for enhancing analysis on the determinants of loan quality.

Besides, the management of the banks 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.

A further interesting contribution would be to perform this analysis at the bank-level, looking at loan delinquency rates for different types of loans of banks.

Notes

1. Data available at www.nber.org/cycles.html
2. The Uniform Financial Rating System, proposed since November 1979 by US regulators and known as CAMELS, is a framework to forecast the bank default and adopt proxies of the following corporate profile: capital adequacy, asset quality, management, earnings, liquidity and sensitivity to market risk. In the CAMELS framework, several asset quality proxies are exploited to bring back bank soundness to their lending activities (Forgione and Migliardo, 2018).
3. For the CMR test, we detect the structural breaks as innovation outliers, which provides a gradual change over the time (Perron and Vogelsang, 1992).
4. 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.
5. γ_t is a vector of unknown coefficients.
6. 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.
7. We use the quarterly delinquency rates seasonally adjusted provided by the Federal Reserve Board. In the USA, delinquent loans mainly coincide with those past due over 30 days and still accruing interest as well as those in nonaccrual status, which also covers lease contracts.
8. In a first attempt, we have also considered consumer price index and real effective exchange rate, but they were never statistically significant.
9. "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.* (1998).
10. 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, commercial and industrial loans are

provided to business or corporation (not to an individual) either to finance working capital or physical assets expenditures.

11. There are also studies that found an insignificant relationship, such as Quagliariello (2007).
12. We may think of erasing the lagged NPL proxies from the models, but we would lose in terms of forecasting performance.
13. Consider that in the USA the building is the most important industry and housing is the most significant component of household's wealth (13.3% of total GDP in 2017 Q1).
14. 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.

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