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Leading indicators of non-performing loans in Greece: the information content of macro-, micro- and bank-specific variables

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Abstract We examine the information content of a unique set of macroeconomic, bank-specific, market and credit registry variables as regards their ability to forecast non-performing loans using a panel data set of nine Greek banks. We distinguish between business, consumer and mortgage loans and investigate their differences with respect to their optimal predictors. The quasi-AIM approach (Carson et al. in Int J Forecast 27:923–941, 2010) is utilized in order to take into account heterogeneity across banks and minimize estimation uncertainty. In addition, we calculate a number of forecasting measures in order to take into account the policy makers' preferences. We find that market variables, specifically the supermarket sales, confidence indices for the services and construction sector and the business sentiment index represent good forecasting variables for most categories of NPLs. In addition, industrial production is the optimal predictor for consumer NPLs and imports for business NPLs. Finally, bank-specific variables represent top-performing leading indicators for business NPLs. Our results have significant implications for stress-testing credit risk in a top-down manner and for supervisory and macro-prudential policy design.

Keywords Credit risk · Non-performing loans forecasting · Disaggregation · Panel data · Stress testing

JEL Classification C53 · G01 · G21

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1 Introduction

According to Reinhart and Rogoff (2010), non-performing loans (NPLs) can be used to mark the onset of banking crises. NPLs represent ex ante credit risk at an aggregate level and signal future losses for the banking system. Consequently, forecasting NPLs is of primary interest for the quantitative analysis of financial stability and the design of macro-prudential policy. An investigation aiming to identify a set of leading indicators of NPLs, based on their forecasting performance, is, therefore, an important task in order to enable policy makers to have a forward-looking view of the developments in the financial stability dimension. However, according to our knowledge, no results of such an exercise have been reported before.

This paper takes a step in this direction and identifies leading indicators of NPLs in the Greek banking system. The case of Greece provides a case where the rise in NPLs can be attributed to a variety of factors; therefore, it is interesting to try to uncover the best-performing leading indicators for such a complex process. In the first place, the global financial crisis had an impact on the Greek economy which was diffused into the economy through the sovereign debt channel. In this sense, the crisis was exogenous to the banking system, and therefore, this has to be taken into account when interpreting our results. On the other hand, credit growth was extremely rapid in the years leading to the crisis;[1] therefore, there may also exist an endogenous component in the surge of NPLs caused by excessive risk taking. Overall, the determinants of the crisis and the explosion in NPLs are multi-faceted; therefore, a rich set of variables of different types could potentially represent good leading indicators of NPLs.[2]

Moreover, Greece provides a "prototypical" case of an economy experiencing a boom period to be followed by a deep recession. It can be argued that the Greek banking system represents a "clean" prototype case to examine empirically the leading indicators of NPLs. Specifically, banks in Greece operate within a liberalized institutional environment,[3] in the context of a relatively advanced economy which was growing rapidly, until the outbreak of the crisis, and whereby banks followed a traditional business model involving mainly deposit-taking and loan-granting. Therefore, the evolution of NPLs is not affected by additional factors which may be present in other jurisdictions, such as banks being highly involved in originate-to-distribute activities, or swings in international trade or exchange rates affecting the macroeconomic environment.

Our approach has four salient features. First, we employ the quasi-AIM (aggregating individual markets) forecasting methodology in order to take into account heterogeneity across banks and minimize estimation uncertainty (Carson et al. 2010). Second, we investigate the leading indicators of NPLs across three loan categories (business loans,

[1] Mitsopoulos and Pelagidis (2011) note that from 1999 (when implementation into the Greek law of the EU banking directives was completed) to 2008, the total amount of loans issued by the main financial institutions was raised to over 80% of the GDP, from a mere 24% at the beginning of this period.

[2] For an analysis of credit growth in the Greek economy for the period under examination, see Vouldis (2015).

[3] The process of liberalizing the Greek banking system ended in 2003, i.e., the first year considered in the present study (Brissimis et al. 2013).

consumer loans, mortgages) rather than the leading indicators of aggregate NPLs. The latter approach may obscure significant differences among loan categories with regard to the variables which are their most efficient predictors. Third, we employ a pseudo-out-of-sampling method for investigating the performance of leading indicators since this is consistent with a policy-making perspective where both the choice of leading indicator and the model specification have to be taken given only the currently available data (Stock and Watson 1993). Fourth, we calculate four performance measures in order to take into account different policy requirements, e.g., forecast accuracy, conservative forecast or emphasis on the direction of change. Therefore, the choice of leading indicators depends on the policy maker's preferences.

The paper is structured as follows. Section 2 places the study in context examining the development of NPLs in the banking system of Greece. Section 3 formulates testable hypotheses regarding the optimal predictors of NPLs and presents the data and the candidate leading indicators. In Sect. 4, the methodology used to assess the predictive content of the potential leading indicators is presented. In Sect. 5, the results are discussed. Finally, Sect. 6 concludes the paper and provides the policy implications of our results for the stress-testing methodologies, and the supervisory and macro-prudential policy design.

2 The Greek banking system and the evolution of non-performing loans

The liberalization of the Greek financial sector, which started in the early 1990s, has determined decisively the evolution of the NPLs. During the pre-liberalization era, decisions on extending bank credit were frequently made on the basis of non-banking criteria such as "personal contacts and social pressure" which lead to wide-spread inefficiencies as regards risk management and to problems with NPLs (Tsakalotos 1991, quoted in Gibson and Tsakalotos 1992). On the contrary, the financial liberalization around the late 1990s forced Greek banks to improve their risk management efficiency and adopt sophisticated technologies in order to achieve satisfactory levels of profitability and survive in the face of intensified competition.

During the post-liberalization era, market forces are expected to have taken over as the major drivers of NPLs and, thus, it is meaningful to investigate whether different categories of economic and financial variables can lead to improvements in NPLs forecasting. More specifically, since the 2000s the Greek banking system can certainly be characterized as a relatively mature financial sector, where market forces govern its functioning. This period encompasses a part of the booming period (which started since the mid-1990s) and the latest twin sovereign-debt and banking crisis (see Gibson et al. 2014).[4] Therefore, all phases of the business cycle are included in our empirical analysis; nonetheless, the forecasting evaluation period is restricted to the crisis period which is more challenging and poses greater interest.

During the current crisis, the evolution of Greek NPLs was primarily driven by the deteriorating macroeconomic environment leading to a NPL ratio which exceeded

[4] See Provopoulos (2014) for the origins of Greek crisis and Gibson et al. (2014) for an overview of the crisis in the Euro area.

the 25% threshold in 2103 (see Bank of Greece Annual Report 2013). This turbulent period is also characterized by the escalation of systemic risk in the Greek financial system caused by the deterioration of key financial and banking indicators (Louzis and Vouldis 2013; Louzis 2016). In addition, to the concerns raised by weakening macroeconomic and financial environment, the steep credit expansion, which occurred during the 2000s, also poses the questions regarding the quality of loans granted during this euphoric period. Generally, the high rates of credit growth during the 2000s can be attributed to rightward shifts in both the demand and the supply curves (Louzis et al. 2012; Vouldis 2015).

The ongoing crisis has also lead to a required overhauling of the Greek banking system, which reduced significantly the number of the banks and strengthened their capital base in order to absorb potential credit losses and improve their access to markets for the essential liquidity. The new structure of the Greek banking system in conjunction with the cumulative experience of 5 years of banking crisis as well as the enhanced regulatory framework via the Single Supervisory Mechanism (SSM) is expected to have positive effects on both the future NPLs evolution and NPLs management. Despite these policy interventions, credit risk still represents the main factor threatening the resilience of the banking system.

3 Data description

3.1 Non-performing loans

The target variable for the forecasting performance evaluation exercise is the NPL ratio (over the total amount of loans). NPLs are defined as the loans overdue by more than ninety (90) days. The NPLs data set is a balanced panel consisting of supervisory data for the nine (9) largest Greek banks spanning from 2003Q1 until 2009Q3. The sample banks account for almost 90% of the Greek banking system (quoted and non-quoted commercial banks) throughout the whole sampling period.

We distinguish between three types of loans: business loans, consumer loans and mortgages. It is reasonable to expect that leading indicators may differ significantly among loan categories reflecting different incentive structures (e.g., for default) depending on the collateral (or absence thereof) pledged, the typical amounts of each loan, etc. Louzis et al. (2012) document the differences among the same categories of loans with respect to their NPL ratio determinants, and it is expected that such differences may also be present with regard to the best leading indicators of NPLs.

Table 1 presents the descriptive statistics for each category of NPLs at the aggregate level. Mortgages have, on average, the lowest NPL ratio, while consumer and business loans are very close. Consumer NPLs are the most volatile exhibiting the highest positive skewness and excess kurtosis as well. This conforms to empirical evidence which shows that consumer NPLs are very sensitive to macroeconomic developments, especially lending rates (Louzis et al. 2012). Fat tails and skewness are also evident in the distribution of mortgage NPLs. The sample statistics and the Jacque–Bera test indicate the rejection of the normality hypothesis at the 1% level. On the other hand, normality is not rejected for business NPLs. Consequently, one may conclude that

Table 1 Descriptive statistics of NPL ratios, per loan category

	Consumer loans	Business loans	Mortgages
Mean value	8.38	8.01	5.29
Standard deviation	1.87	1.53	1.34
Skewness	1.84	−0.47	1.65
Kurtosis	6.54	1.84	4.99
Jacque–Bera test	29.46	2.49	16.75
(*p* value in parenthesis)	(0.00)	(0.28)	(0.00)

Table 2 List of variables

Variable name	Definition	Source
Macro		
GDP	Real GDP growth	National Statistical Service of Greece
ind_prod	Change in industrial production	National Statistical Service of Greece
export	Real change in exports	National Statistical Service of Greece
import	Real change in imports	National Statistical Service of Greece
unemp	Change in unemployment	National Statistical Service of Greece
ir_c	Interest rate on consumer loans	Bank of Greece
ir_b	Interest rate on business loans	Bank of Greece
ir_m	Interest rate on mortgages	Bank of Greece
ppi	Producer's price index	National Statistical Service of Greece
cpi	Consumer's price index	National Statistical Service of Greece
Micro		
ROE	Return on equity	Bank of Greece (supervisory data)
ROA	Return on assets	Bank of Greece (supervisory data)
solr	Solvency ratio	Bank of Greece (supervisory data)
lever	Leverage ratio	Bank of Greece (supervisory data)
inef	Inefficiency	Bank of Greece (supervisory data)
gloans_b	Growth of business loans	Bank of Greece (supervisory data)
gloans_c	Growth of consumer loans	Bank of Greece (supervisory data)
gloans_m	Growth of mortgages	Bank of Greece (supervisory data)
Market		
bus_sent	Indicator of business sentiment	Bloomberg
build_new	New buildings	Bloomberg
supmark_sales	Supermarket sales	Bloomberg
retail_conf	Index of retail confidence	Bloomberg
constr_conf	Index of construction confidence	Bloomberg
serv_conf	Index of services sector confidence	Bloomberg
car_new	Sales of new cars	Bloomberg
Credit registry data		
bounced_checks	Growth of amounts of bounced checks	Credit registry ("Teiresias")

consumer and mortgage NPLs are more likely to attain extreme values compared to business NPLs. Such differences in statistical properties provide already a justification for our approach to distinguish between types of loans and examine the leading indicators of their respective NPLs separately.

3.2 Candidate leading indicators

We classify the set of candidate leading indicators into three main categories, namely macro-, bank-specific and market indicators, and formulate corresponding hypotheses regarding the predictive power of the variables contained in each category. In addition, we use one variable that is available from the credit registry data Table 2. Our conjecture is that variables of a specific category may have a better forecasting performance for all types of NPLs or for a particular type.

Hypothesis 1 ("*systemic credit risk*" *hypothesis*) The aggregate variables characterizing the main macroeconomic developments represent the best predictor of future NPLs.

It is significant to place this assumption also into the context of the current stress-testing practices. In fact, using macroeconomic variables to forecast the future evolution of NPLs is the standard practice in stress-testing exercises which aim to estimate the resilience of banks under adverse conditions (see, for example, the stress-testing methodologies followed in exercises conducting within the Eurozone, e.g., in Greece (see Bank of Greece 2013a, b), Spain [(see Oliver Wyman 2012) and Cyprus (see PIMCO 2013)]. Losses stemming from credit risk and ensuing NPLs constitute the main factor for capital shortfalls identified by stress tests. Therefore, the "systemic credit risk" hypothesis constitutes a core assumption of stress-testing exercises and the results are heavily dependent on it. Consequently, it is critical to empirically test its validity.

The relationship between the macroeconomic environment and non-performing loans is well documented in the literature. In an important contribution, Nkusu (2013) examines a sample of 26 advanced countries that spans the period from 1998 to 2009 and finds that slower economic growth, higher unemployment and falling asset prices are associated with rising NPLs. Therefore, as regards the set of macroeconomic variables, we have included measures of economic activity (real GDP growth, industrial production, exports and imports), unemployment, interest rates for the various loan categories and inflation measures (producer's and consumer's price indices).

Louzis et al. (2012) present a detailed explanation of the linkages between macroeconomic and bank-specific variables. This study focuses on the Greek banking system and identifies GDP, unemployment and the interest rates as primary determinants of NPLs.

In this study, we extend significantly the set of potential, macroeconomic predictors with the qualification that the chosen set should only contain variables having a clear economic rationale. Therefore, we have also included as potential macroeconomic predictors both additional "economic activity" variables (specifically, industrial production, exports and imports) and price indicators (producer price index and consumer price index).

Hypothesis 2 ("*bank heterogeneity*" *hypothesis*) Bank-specific characteristics represent the best predictor of future NPLs.

This hypothesis posits bank-specific characteristics as the best predictors of NPLs. The assumption is that bank heterogeneity is a more sensitive leading indicator for the future evolution of NPLs when compared to the common and systemic effects emanating from the macroeconomic environment, i.e., that institution-specific heterogeneity dominates aggregate effects when it comes to forecasting.

There is a certain strand in the literature investigating the effect of bank-specific characteristics on NPLs. Berger and DeYoung (1997) is a seminal paper in drawing attention to the effect of bank-specific characteristics on NPLs. Berger and Young formulate possible mechanisms ("bad luck," "bad management," "skimping" and "moral hazard") and test the derived hypotheses for a sample of US commercial banks, spanning the period from 1985 to 1994. The main result is that decreases in cost efficiency lead to increased future problem loans. In the same direction, Podpiera and Weil (2008) also provide empirical evidence in favor of a negative relationship between decreased cost efficiency and future NPLs in the Czech banking industry from 1994 to 2005. Louzis et al. (2012) and Espinoza and Prasad (2010) find results which are compatible with the aforementioned research, namely that efficiency and other bank-specific attributes (performance and past loan growth, respectively) have an effect on NPLs. The former paper examines a panel of Greek banks per category of loans while the latter a panel of Gulf Cooperative Council countries. Louzis et al. (2012) provide a detailed analysis of the potential linkages among the bank-specific variables we include here and NPLs.[5]

Hypothesis 3 ("*market sensitivity*" *hypothesis*) Market variables offer the best indications for the evolution of NPLs.

The "market sensitivity" hypothesis is based on the assumption that market variables, due to their real-time or forward-looking nature, represent the best-performing leading indicators of NPLs.

Under the category of market variables, both "hard" data (new buildings, supermarket sales and sales of new cars) and forward-looking "soft" variables are included (indicator of business sentiment, indices of retail/construction/services sector confidence). The former set can be clearly linked to the idea that NPLs are related to economic activity. However, this set contains variables which proxy activity in specific sectors, because potentially these more focused variables may provide better forecasts than aggregate macroeconomic measures of economic activity. As regards the forward-looking indices, the rationale for their selection is that they may circumvent issues of information lags, which may characterize other statistical information.

Finally, a variable which comes from the Greek credit registry ("Teiresias") is included. Specifically, the growth of the average amount of bounced checks is included. This variable can be interpreted as a proxy for the ability of economic agents to fulfill their debt servicing requirements.

[5] There are also studies which focus on the impact of institutional features on NPLs. Li et al. (2007) find that incentive contracts have a positive effect on managerial efforts to reduce NPLs in the Chinese banking system while Breuer (2006) examines the influence of a very wide range of institutional variables on NPLs.

4 Forecasting NPLs

4.1 The quasi-AIM approach

We follow Carson et al. (2010), and we use a quasi-AIM (aggregating individual markets—AIM) approach in order to generate one-step-ahead NPLs forecasts. The quasi-AIM approach is in the middle of the two alternative extreme approaches, i.e., the aggregate approach and the AIM approach. In the first case, the forecaster uses the aggregate data to forecast the variable of interest (e.g., the aggregate time series of NPLs) while in the latter case the individual subcomponents (e.g., the NPLs for each bank) are forecasted separately and then are aggregated.

The main drawback of the aggregate approach is that does not exploit the heterogeneity of the individual subcomponents (i.e., the banks) while the AIM approach suffers from estimation uncertainty as the number of parameters estimated for each market–bank can be quite large. The quasi-AIM approach is a combination of the two extremes that manages to overcome, to some extent, the aforementioned weaknesses. Specifically, in the quasi-AIM approach the coefficients of the forecasting equations are estimated by panel data techniques, which in turn are used to generate forecasts for each individual bank separately. Then, the individual forecasts are aggregated in order to produce final forecasts. This technique allows the forecaster to take into account the heterogeneity across different banks while at the same time it reduces considerably the number of unknown parameters. Moreover, in cases with limited number of aggregate data, the use of panel data methods increases the total number of data used in the estimation and thus its reliability. Carson et al. (2010) found that quasi-AIM method outperformed both aggregate and AIM approaches in a study for the demand of the US commercial travel.

The equation used for forecasting the NPLs has the following general form:

$$y_{it} = \alpha_i + \phi y_{it-1} + \sum_{s=1}^{p} \beta_s X_{it-s} + \varepsilon_{it},$$
$$\text{with } |\alpha| < 1, i = 1, \ldots, N, p \geq 1, t = 1, \ldots, T \tag{1}$$

where the subscripts i and t denote the cross-sectional and time dimension of the panel sample, respectively, y_{it} is the increment in the NPLs, X_{it} denotes each of the leading indicators used for forecasting, α_i is the constant term, p is the number of lags and ε_{it} are the error terms. Equation (1) is a Dynamic Panel Data model which is consistently estimated the Generalized Method of Moments (GMMs) proposed by Arellano and Bond (1991) and generalized by Arellano and Bover (1995) and Blundell and Bond (2000). Here, the autoregressive term, i.e., the lagged dependent variable, captures the time dynamics of dependent variable while the bank-specific constant term takes into account the heterogeneity across banks.

Except from the dynamic model, we also use the following restricted versions of Eq. (1):

- $\alpha_i = \alpha$ and $\phi = 0$, which is a simple pooled OLS regression without the dynamic term, i.e., the lagged dependent variable,

- $\phi = 0$, which is a Fixed Effects (FE) regression without the AR(1) component,
- $\alpha_i = \alpha$, which is a pooled OLS regression with the AR(1) component, henceforth a Dynamic Panel Pooled (DPP) model.

The model of Eq. (1) will henceforth be abbreviated as dynamic panel with fixed effects (DPFE).

In the first case of pooled regression, all coefficients of Eq. (1) are restricted to be the same across all banks. There is an argument in favor of pooling, namely that when the parameters of the individual models are different but exhibit some similarity, pooling may lead to a reduction in the mean squared error of the estimates and forecasts if the square of the bias resulting from imposing false restrictions is outweighed by the reduction in the variance of the estimator due to restricted estimation (Hoogstrate et al. 2000; Chaudhuri and Sheen 2007). In the FE case, the constant term is allowed to be bank-specific capturing, to some extent, the bank-specific information content.

Moreover, there is no straightforward approach regarding the inclusion (or not) of a dynamic term, as in the DPP and DPFE models. Adding a lagged dependent variable as a regressor leads to the lagged variable "dominating the regression" and suppressing the explanatory power of the independent variables (Achen 2000). On the other hand, the inclusion of a dynamic term is a way to deal with the endogeneity issue. In the present paper, we take an agnostic stance regarding this question and estimate both dynamic and static specifications.

4.2 Forecasting methodology and evaluation

In order to evaluate the information content of the alternative leading indicators of NPLs, we perform an out-of-sample forecasting exercise. The data sample is divided into $t = 1, \ldots, T^{\text{in}}$ in-sample observations, spanning from 2003Q1 to 2006Q4 (i.e. $T^{\text{in}} = 16$) and in $T^{\text{out}} = T - T^{\text{in}} = 11$ out-of-sample observations.

At the end of the process, we have T^{out} out-of-sample NPL ratio forecasts for each individual bank and each category of loans. Nonetheless, as the variable of interest is the aggregate NPL ratio for each type of loan, we have to aggregate individual banks' NPL ratio forecasts. Thus, we proceed as follows: first we convert individual banks' NPL ratio forecasts into NPLs forecast by utilizing the already known level of loans for each bank, then we sum all NPLs forecasts, and we divide with the total loans of the banks used in the sample. The result is the aggregate NPL ratio forecast for each type of loans.

Our primary approach consists in using an expanding window of observations in order to forecast each bank's next quarters' NPL ratio over the T^{out} period. This means that we utilize $1, \ldots, T^{\text{in}}$ observations to estimate the model and forecast NPL ratio on $T^{\text{in}} + 1$. Next, in order to forecast NPL ratio on $T^{\text{in}} + 2$, we estimate the models utilizing $1, \ldots, T^{\text{in}}+1$ observations and so on. The number of lags used for the leading indicators in Eq. (1) is determined in each step of the process by minimizing the AIC criterion as in Stock and Watson (1993) (we use a maximum number of four lags for each leading indicator).

However, there is a continued discussion in the literature regarding the respective merits of recursive and rolling window forecasts (see, for example, Carriero et al.

2015). In our setup, the robustness which is associated with the expanding estimation sample seems to be an important consideration, given the short initial estimation sample. Therefore, we also investigate the use of a rolling window approach in which the length of the window of observations used to forecast each bank's next quarters' NPL ratio remains constant and shifts over time. This means that we utilize $1, \ldots, T^{\text{in}}$ observations to estimate the model and forecast NPL ratio on $T^{\text{in}}+1$. Next, in order to forecast NPL ratio on $T^{\text{in}}+2$, we estimate the models utilizing the set $\{2, \ldots, T^{\text{in}}+1\}$ of observations and so on. The argument in favor of the latter approach is that it may be more suitable in the presence of structural breaks.

The forecasting performance of leading indicators over the out-of-sample period is assessed using the following forecasting loss functions:

$$\text{MSE} = \left(1/T^{\text{out}}\right) \sum_{t=1}^{T^{\text{out}}} \left(\text{NPL}_t - \hat{\text{NPL}}_t^j\right)^2 \tag{2}$$

$$\text{MAE} = \left(1/T^{\text{out}}\right) \sum_{t=1}^{T^{\text{out}}} \left|\text{NPL}_t - \hat{\text{NPL}}_t^j\right| \tag{3}$$

$$\text{LINLIN} = \left(1/T^{\text{out}}\right) \sum_{t=1}^{T^{\text{out}}} \begin{cases} a\left|\text{NPL}_t - \hat{\text{NPL}}_t^j\right| & \text{if } \left(\text{NPL}_t - \hat{\text{NPL}}_t^j\right) > 0 \\ b\left|\text{NPL}_t - \hat{\text{NPL}}_t^j\right| & \text{if } \left(\text{NPL}_t - \hat{\text{NPL}}_t^j\right) \leq 0 \end{cases} \tag{4}$$

$$CR \text{ (see below for definition)} \tag{5}$$

The MSE and MAE are the standard mean squared error and mean absolute error, respectively. In the LINLIN loss function under-predictions are treated asymmetrically relative to over-predictions (Granger 1969; Ulu 2007). When the a/b ratio is greater than the unit, it implies that under-predictions are penalized more severely than over-predictions while for $a/b = 1$ Eq. (4) is identical to MAE. We set a equal to 2 and b equal to 1 as we are more interested to identify those leading indicators that tend to under-predict future NPLs. Finally, CR stands for the confusion rate (Swanson and White 1997). Confusion rate is defined as the ratio of predictions which had the wrong sign to the number of predictions which had a correct sign. Concretely, given a matrix of the following form

$$\begin{array}{llcc} & & \multicolumn{2}{c}{\text{PREDICTED}} \\ & & \text{up} & \text{down} \\ \text{ACTUAL} & \begin{array}{l}\text{up} \\ \text{down}\end{array} & \multicolumn{2}{c}{\begin{bmatrix} D_{11} & D_{12} \\ D_{21} & D_{22} \end{bmatrix}} \end{array}$$

where each element D_{ij} is the number of forecasts and where the actual and predicted values had a specific relation with respect to their upward or downward change, the confusion rate is defined as the sum of off-diagonal elements divided by the sum of the diagonal elements. This measure is particularly useful to measure the model's capability in forecasting turning points.

5 Forecasting results

Initially, we explore the performance of simple naïve forecasting models which will serve as a benchmark for our results using the AIM methodology. In particular, we use simple autoregressive models and autoregressive models augmented with the non-bank-specific variables. For both models, we use one lag. Tables 3 and 4 present the forecasting results with the simple models applying both recursive and rolling estimations. For the benchmark random walk (RW) model, the table reports the MSE, MAE, LINLIN and CR. For all other models, the table reports the relative values of the forecasting measures computed as ratios relative to the benchmark. We select the random walk results as a benchmark to express all results from now on (meaning that values lower than 1 imply better performance compared to the benchmark model). Augmenting the autoregressive models with non-bank-specific variables leads to improved forecasting performance especially when market variables are used.

Tables 5, 7 and 9 present the forecasting performance of the various potential leading indicators, under the four measures and for all difference model specifications, for consumer, business and mortgage NPLs, respectively, using a recursive window.[6] The model confidence set (MCS) variables are market with an asterisk (see "Appendix" for the description of the methodology). In general, the AIM forecasts perform better than the random walk model. The only exception pertains to the results for the confusion rate for the business and mortgage NPLs, but even in this case the top-performing variables with AIM clearly outperform the random walk model (see, for example, the results for ROE and ROA in Table 7 when dynamic panel methods are used which are equal to zero). In general, top-performing variables belong to the MCS, implying that the corresponding model's performance passes the test of statistical significance.

Furthermore, we "condense" these results by computing a metric summarizing the forecasting performance for each variable in Tables 6, 8 and 10, while also presenting the corresponding results when a rolling window is used. The aggregation is essential to enable the comparison of the different categories of predictors and the empirical assessment of the three hypotheses formulated in Sect. 4. The aggregate metric is computed by first selecting the optimal model specification for each combination of a variable and a performance criterion, defined simply as the model which gives the minimum value. Finally, the four standardized values, corresponding to the different forecasting performance measures, are added for each variable. Formally, the aggregate performance index can be written as

$$P_{i,l} = \sum_{j} \min \left\{ \text{Performance}_{k,j,m};\ k = \{\text{POOLED, FE, DPP, DPFE}\},\right.$$
$$\left. m = \{\text{Recursive, Rolling}\} \right\}$$

[6] The rolling approach outperforms (performs worse than) the recursive window approach overall, in only 12% (23%) of the cases. Specifically, this percentage is only 1% (7%) for consumer loans, 13% (30%) for business loans and 22% (33%) for mortgages. For the remaining cases (overall 64%), the two approaches differ only at the third decimal point; therefore, there is no real difference in their performance. We comment on the differences using the "condensed" information which is presented below in Tables 6, 8 and 10.

Table 3 Out-of-sample forecasting performance of time series models (using a recursive window)

NPL category	Consumer				Business				Mortgages			
	MSE	MAD	LINLIN	CR	MSE	MAD	LINLIN	CR	MSE	MAD	LINLIN	CR
RW (benchmark)	1.82	1.01	1.13	1.00	0.37	0.46	0.66	0.25	0.49	0.53	0.54	0.25
AR	0.91	1.14	1.25	0.67	1.16	1.12	0.95	1.71	1.59	1.12	1.11	1.00
AR-X												
Macroeconomic												
1. GDP	0.91	0.99	1.12	1.00	0.98	1.02	0.89	1.71	0.94	0.88	0.89	1.71
2. ind_prod	0.91	0.99	1.12	1.00	1.01	1.03	0.88	1.71	1.33	1.03	1.02	1.00
3. export	1.27	1.20	1.31	0.43	0.95	0.93	0.80	1.71	1.49	1.05	1.06	1.00
4. import	1.00	1.03	1.16	0.67	0.79	1.00	0.92	1.00	1.39	1.03	1.03	1.71
5. unemp	1.29	1.14	1.23	0.67	0.91	0.90	0.80	1.71	1.61	1.14	1.12	1.00
6. ppi	1.19	1.00	1.05	0.67	1.11	1.13	0.95	0.44	0.94	0.98	1.00	1.71
7. cpi	1.08	0.96	1.06	0.67	1.32	1.13	0.94	0.44	0.84	0.97	1.03	1.00
Market												
8. bus_sent	0.76	0.93	1.06	0.67	0.67	0.82	0.85	1.71	1.32	1.05	1.04	1.00
9. build_new	1.23	1.12	1.21	0.67	1.16	1.12	0.95	1.71	1.49	1.10	1.13	1.00
10. supmark_sales	0.64	0.78	0.94	1.00	1.00	1.03	0.97	1.71	0.76	0.85	0.92	1.00
11. retail_conf	0.80	0.94	1.02	0.67	0.59	0.79	0.85	1.71	1.40	1.07	1.09	1.00
12. constr_conf	1.19	1.08	1.15	1.00	1.10	1.09	0.95	1.71	1.55	1.09	1.08	1.00
13. serv_conf	1.40	1.20	1.27	1.00	0.65	0.77	0.76	2.67	1.56	1.13	1.13	1.00
14. car_new	1.35	1.20	1.29	1.00	0.80	0.91	0.82	1.71	1.61	1.16	1.16	1.00
Credit registry												
15. bounced_checks	1.25	1.14	1.24	1.00	1.15	1.13	0.95	1.71	1.50	1.11	1.10	1.71

The table shows the MSE, MAD, LINLIN and CR measures for the benchmark RW model in the first line and the relative values of the various forecasting measures using the random walk as a benchmark model for the rest of the models. For a description of the forecasting measures (MSE, MAD, LINLIN and CR), see Sect. 4.2. AR is an autoregressive model, and AR-X is an autoregressive model augmented with the macroeconomic, market and credit registry variables outlined in the table. For both AR and AR-X models, we use one lag

Table 4 Out-of-sample forecasting performance of time series models (using a rolling window)

NPL category	Consumer				Business				Mortgages			
	MSE	MAD	LINLIN	CR	MSE	MAD	LINLIN	CR	MSE	MAD	LINLIN	CR
RW (benchmark)	1.82	1.01	1.13	1.00	0.37	0.46	0.66	0.25	0.49	0.53	0.54	0.25
AR	1.10	1.05	1.18	0.67	1.21	1.16	0.97	1.71	1.00	0.96	1.15	1.00
AR-X												
Macroeconomic												
1. GDP	0.90	0.93	1.08	1.00	0.91	1.00	0.87	1.71	0.90	0.94	1.08	1.71
2. ind_prod	0.84	0.91	1.08	1.00	1.06	1.11	0.98	1.71	0.92	0.92	1.09	1.00
3. export	1.12	1.11	1.25	0.25	1.00	0.98	0.83	1.71	0.97	0.96	1.16	1.71
4. import	0.93	0.98	1.12	0.67	0.77	0.94	0.84	1.00	0.93	0.95	1.11	1.71
5. unemp	0.95	0.93	1.06	0.67	1.04	1.01	0.91	1.71	0.95	0.95	1.11	1.00
6. ppi	1.15	1.05	1.19	0.67	1.15	1.18	0.99	0.44	0.79	0.99	1.14	1.00
7. cpi	1.16	0.99	1.16	0.67	1.34	1.06	0.92	0.44	0.71	0.94	1.06	0.44
Market												
8. bus_sent	0.66	0.88	1.03	0.67	0.60	0.84	0.87	2.67	1.14	0.94	0.96	1.00
9. build_new	1.13	1.02	1.13	0.43	1.21	1.16	0.97	1.71	0.94	0.96	1.18	1.00
10. supmark_sales	0.57	0.76	0.96	0.67	0.96	0.99	0.94	1.71	0.84	0.91	1.03	1.00
11. retail_conf	0.86	0.97	1.05	0.67	0.53	0.74	0.79	1.00	0.93	0.96	1.15	1.00
12. constr_conf	1.27	1.09	1.17	0.67	0.96	0.98	0.87	1.00	1.13	1.00	1.22	1.00
13. serv_conf	1.17	1.10	1.18	0.43	0.72	0.82	0.82	2.67	0.88	0.93	1.10	1.00
14. car_new	0.83	0.97	1.08	0.67	0.73	0.91	0.85	2.67	0.88	0.89	0.97	1.00
Credit registry												
15. bounced_checks	1.15	1.06	1.18	0.67	1.38	1.27	1.05	1.71	0.98	0.97	1.13	1.71

The table shows the MSE, MAD, LINLIN and CR measures for the benchmark RW model in the first line and the relative values of the various forecasting measures using the random walk as a benchmark model for the rest of the models. For a description of the forecasting measures (MSE, MAD, LINLIN and CR), see Sect. 4.2. AR is an autoregressive model, and AR-X is an autoregressive model augmented with the macroeconomic, market and credit registry variables outlined in the table. For both AR and AR-X models, we use one lag

Table 5 Out-of-sample forecasting performance of leading indicators for non-performing consumer loans (using a recursive window)

	MSE				MAD				LINLIN				CR			
Method of estimation	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE
Variables																
Macroeconomic																
1. GDP	0.58	0.58	0.59	0.59	0.77	0.76	0.78	0.78	1.26	1.24	1.27	1.27	1.00	1.00	1.00	1.00
2. ind_prod	0.38*	0.38*	0.42*	0.42*	0.60*	0.59*	0.61*	0.61*	0.95	0.94	0.99	0.99	0.25	0.25	0.25	0.25
3. export	1.02	1.03	1.00	1.00	1.06	1.06	0.98	0.98	1.66	1.66	1.56	1.56	0.67	0.67	0.43	0.43
4. import	0.81	0.81	0.83	0.84	0.90	0.89	0.90	0.90	1.50	1.49	1.50	1.50	0.67	0.67	0.67	0.67
5. unemp	1.04	0.99	0.93	0.93	1.05	1.02	0.94	0.94	1.65	1.60	1.59	1.60	1.00	1.00	1.00	1.00
6. ir_c	0.97	1.01	1.12	1.13	0.97	0.98	1.03	1.03	1.65	1.64	1.72	1.73	1.00	0.67	0.67	0.67
7. ppi	0.58	0.58	0.59	0.59	0.77	0.76	0.78	0.78	1.26	1.24	1.27	1.27	1.00	1.00	1.00	1.00
8. cpi	0.38	0.38	0.42	0.42	0.60	0.59	0.61	0.61	0.95	0.94	0.99	0.99	0.25	0.25	0.25	0.25
Bank specific																
9. ROE	0.96	0.84	0.90	0.91	1.02	0.95	0.96	0.96	1.75	1.61	1.62	1.63	1.00	1.00	1.00	1.00
10. ROA	1.06	0.93	0.99	0.99	1.09	1.01	1.03	1.03	1.88	1.74	1.76	1.76	1.00	1.00	1.00	1.00
11. solr	0.99	0.97	1.03	1.03	0.96	0.96*	1.01	1.01	1.67	1.63	1.70	1.70	0.43	0.67	0.67	0.67
12. lever	0.61	0.57*	0.52*	0.52*	0.75*	0.66*	0.66*	0.66*	1.17	1.12	1.08	1.08	0.67	0.67	1.00	1.00
13. inef	1.05	0.91	0.99	0.99	1.06	0.98	1.01	1.01	1.84	1.68	1.72	1.72	1.00	1.00	1.00	1.00
14. gloans_c	0.93	0.90	0.99	0.99	0.98	0.96	0.99	0.99	1.67	1.63	1.66	1.67	0.43	0.43	0.67	0.67
Market																
15. bus_sent	0.47*	0.47	0.49*	0.49*	0.69*	0.69*	0.71*	0.71*	0.98	0.97	1.04	1.04	0.43	0.43	0.43	0.43
16. build_new	0.70	0.70	0.75	0.76	0.85	0.84	0.88	0.88	1.38	1.37	1.44	1.44	0.67	0.67	0.67	0.67
17. supmark_sales	0.48*	0.48*	0.54*	0.54*	0.60*	0.60*	0.65*	0.66*	0.85	0.85	0.96	0.96	0.43	0.43	0.25	0.25

Table 5 continued

	MSE				MAD				LINLIN				CR			
Method of estimation	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE
18. retail_conf	0.51*	0.50*	0.52*	0.52*	0.71*	0.70*	0.77*	0.77*	1.12	1.11	1.23	1.23	0.67	0.67	0.67	0.67
19. constr_conf	0.88	0.88	0.98	0.99	0.92	0.91	0.93*	0.93*	1.57	1.55	1.59	1.59	0.43	0.43	0.43	0.43
20. serv_conf	0.54	0.55	0.60	0.61	0.73	0.73	0.80	0.80	1.15	1.14	1.28	1.28	0.67	0.67	0.67	0.67
21. car_new	0.48*	0.49*	0.51*	0.51*	0.64*	0.63*	0.71*	0.71*	1.07	1.05	1.17	1.17	1.00	1.00	1.00	1.00
Credit registry																
22. bounced_checks	0.64	0.64	0.63	0.64	0.87	0.87	0.85	0.86	1.45	1.45	1.44	1.44	0.43	0.43	0.43	0.43

The table shows the relative values of the various forecasting measures using the random walk as a benchmark model. For a description of the forecasting measures (MSE, MAD, LINLIN and CR), see Sect. 4.2. Pooled stands for the pooled OLS estimation method, FE for the fixed effects method, DPP for the dynamic panel pooled and DPFE for the dynamic panel fixed effects. The asterisk denotes that the model belongs to the MCS because its p value is greater than the prespecified significance level, a, where $a = 0.10$. The MCS p values are calculate using the *range* statistic

Table 6 Aggregate forecasting performance of leading indicators for non-performing consumer loans

Rank	Variable	MSE	MAE	LINLIN	CR	Performance
(a) Using a recursive window						
1	**ind_prod**	**0.38***	**0.59***	**0.94**	**0.11**	**2.02**
2	**supmark_sales**	**0.48***	**0.60***	**0.85**	**0.11**	**2.04**
3	cpi	0.38	0.59	0.94	0.43	2.34
4	**bus_sent**	**0.47***	**0.69***	**0.97**	**0.25**	**2.38**
5	**lever**	**0.52***	**0.66***	**1.08**	**0.25**	**2.51**
6	**car_new**	**0.48***	**0.63***	**1.05**	**0.43**	**2.59**
7	**retail_conf**	**0.50***	**0.70***	**1.11**	**0.43**	**2.74**
8	serv_conf	0.54	0.73	1.14	0.43	2.84
9	GDP	0.58	0.76	1.24	0.43	3.01
10	build_new	0.70	0.84	1.37	0.43	3.34
11	ppi	0.58	0.76	1.24	1.00	3.58
12	constr_conf	0.88	0.91	1.55	0.25	3.59
13	bounced checks	0.63	0.85	1.44	0.67	3.59
14	gloans_c	0.90	0.96	1.63	0.43	3.92
15	exports	1.00	0.98	1.56	0.43	3.97
16	solr	0.97	0.96*	1.63	0.43	3.99
17	ROE	0.84	0.95	1.61	0.67	4.07
18	unemp	0.93	0.94	1.59	0.67	4.13
19	inef	0.91	0.98	1.68	0.67	4.24
20	ROA	0.93	1.01	1.74	0.67	4.35
21	ir_c	0.97	0.97	1.64	1.00	4.58
22	imports	0.81	0.89	1.49	1.50	4.69
(b) Using a rolling window						
1	**ind_prod**	**0.38***	**0.59***	**0.94**	**0.25**	**2.16**
2	**supmark_sales**	**0.48***	**0.60***	**0.85**	**0.25**	**2.18**
3	**bus_sent**	**0.47***	**0.69***	**0.97**	**0.43**	**2.56**
4	**lever**	**0.52***	**0.66***	**1.08**	**0.67**	**2.93**
5	**retail_conf**	**0.50***	**0.70***	**1.11**	**0.67**	**2.98**
6	serv_conf	0.54	0.73	1.14	0.67	3.08
7	**car_new**	**0.48***	**0.63***	**1.05**	**1.00**	**3.16**
8	bounced checks	0.63	0.85	1.44	0.43	3.35
9	GDP	0.58	0.76	1.24	1.00	3.58
10	build_new	0.70	0.84	1.37	0.67	3.58
11	constr_conf	0.88	0.91	1.55	0.43	3.77
12	imports	0.81	0.89	1.49	0.67	3.86
13	gloans_c	0.90	0.96	1.63	0.43	3.92
14	exports	1.00	0.98	1.56	0.43	3.97
15	solr	0.97	0.96	1.63	0.43	3.99
16	cpi	1.19	0.96	1.59	0.43	4.17

Table 6 continued

Rank	Variable	MSE	MAE	LINLIN	CR	Performance
17	ir_c	0.97	0.97	1.64	0.67	4.25
18	ROE	0.84	0.95	1.61	1.00	4.40
19	unemp	0.93	0.94	1.59	1.00	4.46
20	inef	0.91	0.98	1.68	1.00	4.57
21	ROA	0.93	1.01	1.74	1.00	4.68
22	ppi	1.30	1.04	1.77	0.67	4.78

The asterisk denotes that the model belongs to the MCS because its p value is greater than the prespecified significance level, a, where $a = 0.10$. The MCS p values are calculated using the *range* statistic. The rows with bold letters refer to variables which belong to the MCS at least for one of the MSE and MAE metrics

where $j = \{\text{MSE, MAE, LINLIN, C.R.}\}$, l is the index of loan type (business loans, consumer loans, mortgages) and i is the index of the leading indicator variable.

We will discuss the results across two dimensions. First, it is interesting to compare the predictive performance of each class of variables (i.e., macroeconomic and bank-specific) and assess the empirical evidence of the three respective hypotheses. In this direction, we check whether variables coming from a specific class exhibit consistently very good forecasting across loan categories. Second, we investigate also the within-class dimension of our results, i.e., which variables are the best predictors within one class of variables. A secondary aspect of the latter dimension is that we are interested whether two or more categories of NPLs have common variables as best predictors. This would testify to some kind of co-movement among the loan categories which possess common optimal predictors.

The comments and variable rankings that follow refer to the recursive window results if not specified. Explicit comparisons with respect to the rolling window results are also included. However, it can be noted upfront that the top-performing variables are the same irrespectively of the type of window used.

Regarding the inter-class comparison, it is interesting that the variables that stand out with regard to its forecasting performance and versatility (meaning that they are a good predictor for different loan categories) are market variables. More specifically, in the within-class dimension, it is noted that supermarket sales perform excellent for the two types of loans that are addressed to households, namely mortgages (best predictor) and consumer loans (second best). Moreover, retail confidence is a good versatile predictor being the third best for mortgage NPLs, the sixth best for business NPLs and seventh for consumer NPLs. The variable of car sales is the sixth optimal predictor for consumer NPLs and the fifth best for business NPLs although not performing well for mortgage NPLs. Furthermore, business sentiment ranks fourth for consumer NPLs and fifth for mortgage NPLs. Finally, it is especially intuitive that construction confidence is the second-best predictor for the mortgage category, while this variable is not performing well for the other two categories of NPLs.

Therefore, variables from the class of market variables are found to be the best overall predictors of NPLs across categories, a rather intuitive result as market variables

Table 7 Out-of-sample forecasting performance of leading indicators for non-performing business loans (using a recursive window)

	MSE				MAD				LINLIN				CR			
Method of estimation	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE
Variables																
Macroeconomic																
1. GDP	0.83*	0.79*	0.79	0.79	0.77*	0.79*	0.79	0.79	0.81	0.85	0.84	0.84	1.00	1.71	0.44	0.44
2. ind_prod	1.03	1.00	0.97	0.98	1.12	1.10	1.03	1.04	1.08	1.09	1.08	1.08	2.67	2.67	1.71	1.71
3. export	1.50	1.37	0.77	0.77	1.29	1.17	0.85	0.84	1.23	1.10	0.92	0.92	1.71	1.71	0.00	0.00
4. import	0.35*	0.32*	0.41*	0.41*	0.58*	0.55*	0.69*	0.69*	0.51	0.50	0.70	0.71	0.44	0.44	1.00	1.00
5. unemp	1.80	1.61	1.18	1.18	1.38	1.29	1.06	1.06	1.68	1.64	1.33	1.32	1.71	1.71	1.71	1.71
6. ir_b	0.68*	0.90	0.60	0.60	0.82*	0.99	0.75	0.75	0.85	1.01	0.79	0.78	0.44	1.00	0.44	1.71
7. ppi	2.99	3.00	1.31	1.30	1.93	1.90	1.29	1.29	2.42	2.41	1.63	1.63	1.71	1.71	1.00	1.00
8. cpi	2.81	3.08	1.63	1.63	1.56	1.65	1.33	1.33	2.11	2.24	1.80	1.80	1.71	1.71	0.44	0.44
Bank specific																
9. ROE	0.70*	0.50*	0.49*	0.49*	0.77*	0.67*	0.65*	0.66*	0.93	0.77	0.70	0.70	1.00	1.00	0.00	0.00
10. ROA	0.77*	0.56*	0.56*	0.56*	0.82*	0.72*	0.70*	0.70*	1.01	0.87	0.79	0.80	1.00	1.71	0.00	0.00
11. solr	0.78*	0.77	0.78	0.79	0.94	0.93	0.82	0.82	1.04	1.05	0.93	0.93	1.00	1.71	0.00	0.00
12. lever	2.82	2.68	0.68	0.68	1.27	1.25	0.81	0.81	1.04	1.07	0.88	0.88	1.00	1.00	1.00	1.00
13. inef	0.76*	0.61*	0.60	0.61	0.80*	0.71*	0.73	0.73	0.99	0.87	0.81	0.81	0.44	0.44	0.00	0.00
14. gloans_b	0.93	0.91	0.83	0.83	0.96	0.86*	0.86	0.86	1.06	1.02	0.96	0.97	1.00	1.00	0.00	0.00
Market																
15. bus_sent	1.39	1.35	0.93	0.93	1.35	1.33	1.05	1.05	1.28	1.29	0.94	0.94	1.71	2.67	1.71	1.71
16. build_new	1.02	0.91	0.90	0.91	1.06	0.98	0.95	0.95	1.09	1.02	1.02	1.03	1.71	1.71	0.00	0.44
17. supmark_sales	1.55	1.44	1.19	1.20	1.16	1.14	1.09	1.09	1.11	1.11	1.04	1.04	1.71	2.67	1.71	1.71

Table 7 continued

	MSE				MAD				LINLIN				CR			
Method of estimation	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE
18. retail_conf	0.64*	0.59*	0.28*	0.28*	0.90*	0.84*	0.58*	0.58*	0.77	0.74	0.51	0.50	1.71	1.71	1.00	1.00
19. constr_conf	0.95	0.88	0.88	0.89	0.99	0.93	0.98	0.98	1.00	0.96	1.01	1.02	1.71	1.00	0.44	0.44
20. serv_conf	1.03	1.03	0.65*	0.65*	1.12	1.12	0.84	0.84	1.17	1.20	0.93	0.93	1.00	1.00	1.71	1.71
21. car_new	0.83	0.81	0.47*	0.47*	1.00	0.99	0.68*	0.68*	1.21	1.22	0.73	0.72	1.00	1.00	0.44	0.44
Credit registry																
22. bounced_checks	0.45*	0.45*	0.35*	0.35*	0.79*	0.78*	0.70*	0.70*	0.79	0.79	0.71	0.71	2.67	2.67	1.71	1.71

The table shows the relative values of the various forecasting measures using the random walk as a benchmark model. For a description of the forecasting measures (MSE, MAD, LINLIN and CR), see Sect. 4.2. Pooled stands for the pooled OLS estimation method, FE for the fixed effects method, DPP for the dynamic panel pooled and DPFE for the dynamic panel fixed effects. The asterisk denotes that the model belongs to the MCS because its p value is greater than the prespecified significance level, a, where $a = 0.10$. The MCS p values are calculated using the *range* statistic

Table 8 Aggregate forecasting performance of leading indicators for non-performing business loans

Rank	Variable	MSE	MAE	LINLIN	CR	Performance
Using a recursive window						
1	**imports**	**0.32***	**0.55***	**0.50**	**0.44**	**1.81**
2	**ROE**	**0.49***	**0.65***	**0.70**	**0.00**	**1.84**
3	**ROA**	**0.56***	**0.70***	**0.79**	**0.00**	**2.05**
4	**inef**	**0.60***	**0.71***	**0.81**	**0.00**	**2.12**
5	**car_new**	**0.47***	**0.68***	**0.72**	**0.44**	**2.31**
6	**retail_conf**	**0.28***	**0.58***	**0.50**	**1.00**	**2.36**
7	**solr**	**0.77***	**0.82**	**0.93**	**0.00**	**2.52**
8	exports	0.77	0.84	0.92	0.00	2.53
9	**ir_b**	**0.60***	**0.75***	**0.78**	**0.44**	**2.57**
10	gloans_b	0.83	0.86	0.96	0.00	2.65
11	**GDP**	**0.79***	**0.77***	**0.81**	**0.44**	**2.81**
12	build_new	0.90	0.95	1.02	0.00	2.87
13	constr_conf	0.88	0.93	0.96	0.44	3.21
14	Lever	0.68	0.81	0.88	1.00	3.37
15	serv_conf	0.65	0.84	0.93	1.00	3.42
16	bounced checks	0.35	0.70	0.71	1.71	3.47
17	bus_sent	0.93	1.05	0.94	1.71	4.63
18	ind_prod	0.97	1.03	1.08	1.71	4.79
19	supmark_sales	1.19	1.09	1.04	1.71	5.03
20	cpi	1.63	1.33	1.80	0.44	5.20
21	ppi	1.30	1.29	1.63	1.00	5.22
22	unemp	1.18	1.06	1.32	1.71	5.27
Using a rolling window						
1	**imports**	**0.30***	**0.55***	**0.49**	**0.44**	**1.78**
2	**ROE**	**0.50***	**0.65***	**0.71**	**0.00**	**1.86**
3	**ROA**	**0.56***	**0.67***	**0.78**	**0.00**	**2.01**
4	**inef**	**0.61***	**0.71***	**0.83**	**0.00**	**2.15**
5	**retail_conf**	**0.29***	**0.60***	**0.48**	**1.00**	**2.37**
6	**gloans_b**	**0.86**	**0.86***	**0.99**	**0.00**	**2.71**
7	**GDP**	**0.73***	**0.77***	**0.81**	**0.44**	**2.75**
8	ir_b	0.67	0.83	0.89	0.44	2.83
9	build_new	0.91	0.97	1.02	0.00	2.90
10	solr	0.75	0.83	0.93	0.44	2.95
11	exports	0.81	0.86	0.86	0.44	2.97
12	car_new	0.69	0.86	1.03	0.44	3.02
13	constr_conf	0.84	0.93	0.94	0.44	3.15
14	**bounced checks**	**0.30***	**0.66***	**0.65**	**1.71**	**3.32**
15	**serv_conf**	**0.70***	**0.93**	**0.99**	**1.00**	**3.62**
16	ppi	1.40	1.34	1.70	0.44	4.88

Table 8 continued

Rank	Variable	MSE	MAE	LINLIN	CR	Performance
17	supmark_sales	1.20	1.10	1.06	1.71	5.07
18	bus_sent	1.05	1.19	1.13	1.71	5.08
19	unemp	1.18	1.06	1.32	1.71	5.27
20	ind_prod	0.87	1.06	1.04	2.67	5.64
21	lever	2.68	1.25	1.04	1.00	5.97
22	cpi	2.33	1.47	1.99	1.00	6.79

The asterisk denotes that the model belongs to the MCS because its p value is greater than the prespecified significance level, a, where $a = 0.10$. The MCS p-values are calculated using the *range* statistic. The rows with bold letters refer to variables which belong to the MCS at least for one of the MSE and MAE metrics

are expected to be leading indicators for future developments, and specifically for credit risk, in our case.

A general pattern, which pertains, for example, for the supermarket sales and the business sentiment variables, is that there are variables which perform well for both the categories of consumer and mortgage NPLs, while the set of good predictors for business NPLs is somewhat distinct, implying that the credit risk of loans related primarily to households is best forecasted by a different set of variables compared to business loans.

The above results also hold for the rolling window calculations. The only significant difference is that car sales do not score well for business NPLs in this case (twelfth position).

The state of the macroeconomy supplies the best predictor for consumer NPLs, namely the industrial production, and the best predictor for business NPLs, namely imports. On the other hand, these macroeconomic variables do not perform as well in forecasting mortgage NPLs. This is consistent with the results in Louzis et al. (2012) where it is found that mortgage NPLs are less sensitive compared to consumer and business NPLs with respect to macroeconomic developments.

The patterns observed with respect to the bank-specific variables are also very interesting pointing to a good performance of a distinct set of variables for the business NPLs category and of leverage for consumer NPLs. Specifically, the empirical evidence shows that ROE, ROA and inefficiency are in the top four predictors for business NPLs.[7] On the other hand, with respect to the other two types of NPLs, these three variables are not very good predictors. Additionally, leverage is the fifth-best predicting variable for consumer NPLs.[8]

The overall performance of market variables ranks clearly above the rest of variables, lending support to the "market sensitivity" hypothesis. The best-performing market variables are supermarket sales, car sales, retail confidence and business sen-

[7] Louzis et al. (2012) find that inefficiency is a statistically significant determinant for all NPLs ("bad management" hypothesis).

[8] The comments above apply also when the rolling window approach is used, with slight changes in the relative rankings of the mentioned variables.

Table 9 Out-of-sample forecasting performance of leading indicators for non-performing mortgage loans (using a recursive window)

	MSE				MAD				LINLIN				CR			
Method of estimation	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE
Variables																
Macroeconomic																
1. GDP	0.56	0.64	0.62	0.62	0.78*	0.83*	0.82	0.82	1.48	1.59	1.57	1.57	4.00	4.00	2.67	2.67
2. ind_prod	0.59	0.67	0.66	0.66	0.91	0.93	0.94	0.94	1.58	1.68	1.68	1.68	2.67	2.67	4.00	4.00
3. export	0.93	1.04	0.95	0.95	1.04	1.11	1.04	1.04	1.87	2.04	1.88	1.88	1.71	1.71	2.67	2.67
4. import	0.96	1.08	1.02	1.02	0.99	1.06	1.04	1.04	1.82	1.98	1.90	1.90	1.71	1.71	2.67	2.67
5. unemp	1.08	1.14	1.07	1.07	1.17	1.21	1.19	1.19	2.01	2.10	2.04	2.04	2.67	2.67	2.67	2.67
6. ir_m	1.02	1.23	1.07	1.07	1.00	1.12	1.05	1.05	1.91	2.17	2.00	2.00	1.71	1.71	2.67	2.67
7. ppi	0.73*	0.80*	0.73*	0.73*	0.70*	0.73*	0.72*	0.72*	1.28	1.38	1.33	1.33	2.67	2.67	1.71	1.71
8. cpi	0.54*	0.61	0.59	0.59	0.79*	0.84*	0.83	0.83	1.46	1.58	1.53	1.53	2.67	2.67	4.00	4.00
Bank specific																
9. ROE	0.89	0.91	0.80	0.80	0.92	0.92*	0.88	0.88	1.80	1.79	1.68	1.68	1.71	1.71	1.71	1.71
10. ROA	0.95	1.00	0.85	0.85	0.96	0.98	0.89	0.89	1.87	1.91	1.72	1.72	1.71	1.71	1.71	1.71
11. solr	0.76	0.85	0.74	0.74	0.92	0.96	0.91	0.91	1.75	1.85	1.71	1.71	1.71	1.71	1.71	1.71
12. lever	0.91	0.76	0.73	0.73	0.96	0.92	0.92	0.92	1.40	1.41	1.40	1.40	1.71	2.67	2.67	2.67
13. inef	0.94	1.02	0.88	0.88	0.96	0.99	0.91	0.91	1.88	1.94	1.76	1.76	1.71	2.67	2.67	2.67
14. gloans_m	0.81	0.84	0.67	0.67	0.93	0.97	0.82*	0.82*	1.78	1.85	1.55	1.55	2.67	2.67	2.67	2.67
Market																
15. bus_sent	0.47*	0.53*	0.51*	0.51*	0.73*	0.77*	0.77*	0.77*	1.31	1.41	1.41	1.41	1.71	2.67	2.67	2.67
16. build_new	0.67	0.76	0.68	0.68	0.84*	0.90	0.85	0.85	1.57	1.71	1.60	1.60	2.67	1.71	2.67	2.67
17. supmark_sales	0.31*	0.33*	0.34*	0.34*	0.64*	0.64*	0.65*	0.65*	0.98	1.04	1.05	1.05	2.67	2.67	1.71	1.71
18. retail_conf	0.41*	0.46*	0.44*	0.44*	0.71*	0.73*	0.71*	0.71*	1.20	1.28	1.23	1.23	1.71	1.71	1.71	1.71

Table 9 continued

	MSE				MAD				LINLIN				CR			
Method of estimation	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE	Pooled	FE	DPP	DPFE
19. constr_conf	0.67	0.76	0.69	0.69	0.77*	0.84*	0.76*	0.76*	1.50	1.65	1.48	1.48	1.00	1.00	1.00	1.00
20. serv_conf	0.47*	0.50*	0.60*	0.61*	0.69*	0.70*	0.82*	0.82*	1.25	1.28	1.53	1.54	1.71	2.67	2.67	2.67
21. car_new	0.85	0.94	0.87	0.87	1.04	1.08	1.04	1.04	1.85	1.96	1.88	1.88	4.00	4.00	4.00	4.00
Credit registry																
22. bounced_checks	0.56	0.64	0.59	0.59	0.89	0.94	0.91	0.91	1.65	1.77	1.69	1.69	4.00	4.00	2.67	2.67

The table shows the relative values of the various forecasting measures using the random walk as a benchmark model. For a description of the forecasting measures (MSE, MAD, LINLIN and CR), see Sect. 4.2. Pooled stands for the pooled OLS estimation method, FE for the fixed effects method, DPP for the dynamic panel pooled and DPFE for the dynamic panel fixed effects. The asterisk denotes that the model belongs to the MCS because its p value is greater than the prespecified significance level, a, where $a = 0.10$. The MCS p values are calculated using the *range* statistic

Table 10 Aggregate forecasting performance of leading indicators for non-performing mortgage loans

Rank	Variable	MSE	MAE	LINLIN	CR	Performance
Using a recursive window						
1	**supmark_sales**	**0.31***	**0.64***	**0.98**	**1.71**	**3.64**
2	**constr_conf**	**0.67**	**0.76***	**1.48**	**1.00**	**3.91**
3	**retail_conf**	**0.41***	**0.71***	**1.20**	**1.71**	**4.03**
4	**serv_conf**	**0.47***	**0.69***	**1.25**	**1.71**	**4.12**
5	**bus_sent**	**0.47***	**0.73***	**1.31**	**1.71**	**4.22**
6	**ppi**	**0.73***	**0.70***	**1.28**	**1.71**	**4.42**
7	lever	0.73	0.92	1.40	1.71	4.76
8	build_new	0.67	0.84	1.57	1.71	4.79
9	solr	0.74	0.91	1.71	1.71	5.07
10	ROE	0.80	0.88	1.68	1.71	5.07
11	ROA	0.85	0.89	1.72	1.71	5.17
12	inef	0.88	0.91	1.76	1.71	5.26
13	**cpi**	**0.54***	**0.79***	**1.46**	**2.67**	**5.46**
14	imports	0.96	0.99	1.82	1.71	5.48
15	GDP	0.56	0.78	1.48	2.67	5.49
16	exports	0.93	1.04	1.87	1.71	5.55
17	ir_m	1.02	1.00	1.91	1.71	5.64
18	gloans_m	0.67	0.82	1.55	2.67	5.71
19	ind_prod	0.59	0.91	1.58	2.67	5.75
20	bounced checks	0.56	0.89	1.65	2.67	5.77
21	unemp	1.07	1.17	2.01	2.67	6.92
22	car_new	0.85	1.04	1.85	4.00	7.74
Using a rolling window						
1	**supmark_sales**	**0.31***	**0.62***	**0.99**	**1.71**	**3.63**
2	**constr_conf**	**0.67***	**0.77***	**1.50**	**1.00**	**3.94**
3	**retail_conf**	**0.41***	**0.71***	**1.20**	**1.71**	**4.03**
4	**bus_sent**	**0.50***	**0.71***	**1.28**	**1.71**	**4.20**
5	**cpi**	**0.52***	**0.74***	**1.39**	**1.71**	**4.36**
6	**ppi**	**0.68***	**0.74***	**1.37**	**1.71**	**4.50**
7	**build_new**	**0.74**	**0.86***	**1.64**	**1.71**	**4.95**
8	**GDP**	**0.41***	**0.70***	**1.31**	**2.67**	**5.09**
9	**ROE**	**0.82**	**0.88***	**1.70**	**1.71**	**5.11**
10	solr	0.78	0.90	1.72	1.71	5.11
11	**lever**	**0.45***	**0.74***	**1.31**	**2.67**	**5.17**
12	ir_m	0.83	0.91	1.76	1.71	5.21
13	ROA	0.86	0.91	1.74	1.71	5.22
14	**serv_conf**	**0.52***	**0.74***	**1.37**	**2.67**	**5.30**
15	inef	0.89	0.93	1.79	1.71	5.32
16	imports	0.96	0.99	1.82	1.71	5.48

Table 10 continued

Rank	Variable	MSE	MAE	LINLIN	CR	Performance
17	exports	0.93	1.04	1.87	1.71	5.55
18	**bounced checks**	**0.58***	**0.87**	**1.63**	**2.67**	**5.75**
19	ind_prod	0.59	0.91	1.58	2.67	5.75
20	gloans_m	0.81	0.92	1.77	2.67	6.17
21	car_new	0.91	1.04	1.87	2.67	6.49
22	unemp	1.07	1.17	2.01	2.67	6.92

The asterisk denotes that the model belongs to the MCS because its p value is greater than the prespecified significance level, a, where $a = 0.10$. The MCS p values are calculated using the *range* statistic. The rows with bold letters refer to variables which belong to the MCS at least for one of the MSE and MAE metrics

Table 11 Performance among variable classes, on aggregate and per loan category

(a) Using a recursive window

Macroeconomic	Consumer	Business	Mortgages	Median
GDP	3.01	2.81	5.49	
ind_prod	2.02	4.79	5.75	
export	3.97	2.53	5.55	
import	4.69	1.81	5.48	
unemp	4.13	5.27	6.92	4.64
ir	4.58	2.57	5.64	
ppi	3.58	5.22	4.42	
cpi	2.34	5.20	5.46	
Bank-specific				
ROE	4.07	1.84	5.07	
ROA	4.35	2.05	5.17	
solr	3.99	2.52	5.07	
lever	2.51	3.37	4.76	4.03
inef	4.24	2.12	5.26	
gloans	3.92	2.65	5.71	
Market				
bus_sent	2.38	4.63	4.22	
build_new	3.34	2.87	4.79	
supmark_sales	2.04	5.03	3.64	
retail_conf	2.74	2.36	4.03	3.42
constr_conf	3.59	3.21	3.91	
serv_conf	2.84	3.42	4.12	
car_new	2.59	2.31	7.74	
Credit registry				
bounced_checks	3.59	3.47	5.77	3.59

(b) Using a rolling window

Macroeconomic	Consumer	Business	Mortgages	Median
GDP	3.58	2.75	5.09	
ind_prod	2.16	5.64	5.75	
export	3.97	2.97	5.55	
import	3.86	1.78	5.48	
unemp	4.46	5.27	6.92	4.48
ir	4.25	2.83	5.21	
ppi	4.78	4.88	4.50	
cpi	4.17	6.79	4.36	
Bank-specific				
ROE	4.40	1.86	5.11	
ROA	4.68	2.01	5.22	
solr	3.99	2.95	5.11	
lever	2.93	5.97	5.17	4.49
inef	4.57	2.15	5.32	
gloans	3.92	2.71	6.17	
Market				
bus_sent	2.56	5.08	4.20	
build_new	3.58	2.90	4.95	
supmark_sales	2.18	5.07	3.63	
retail_conf	2.98	2.37	4.03	3.62
constr_conf	3.77	3.15	3.94	
serv_conf	3.08	3.62	5.30	
car_new	3.16	3.02	6.49	
Credit registry				
bounced_checks	3.35	3.32	5.75	3.35

timent, a rather intuitive result. In addition, the construction confidence index is the second-best predictor for the mortgage category.

Turning at the credit registry variable, i.e., the growth of the amount of bounced checks, our results show that there is no evidence that this variable represents a good predictor for either type of loan irrespectively of the type of window is used.

Finally, Table 11 provides quantitative evidence to our impression that market variables represent the best leading indicators of NPLs (when the median of their performance is considered), with bank-specific variables being the second best, followed by the credit registry variable and the macroeconomic variables at the end of the ranking. Consequently, partial evidence for the "bank heterogeneity" hypothesis is provided, while the "systemic credit risk" hypothesis is not corroborated. The market variables also dominate when a rolling window is used, showing that the evidence for the “market sensitivity” hypothesis is robust to the choice of the window used. The ability of the rolling window to capture structural breaks lies probably behind the second position occupied (with a very low margin) by macroeconomic variables when the rolling window is used.

6 Discussion and conclusions

The present paper conducts a comprehensive investigation of the best leading indicators for NPLs in the Greek banking system, examining variables across a wide range of categories, namely macroeconomic, bank-specific, market and credit registry data. Hypotheses about the comparative, predictive performance of these classes of variables are formulated and tested empirically. We have adopted a policy maker’s perspective and have evaluated the forecasting performance using a pseudo-out-of-sampling method which assumes that the information set available to the policy maker at each point in time is constantly updated. In addition, we have used four different metrics to evaluate forecasting performance in order to make our results more robust and accommodate different policy makers’ preferences or priorities which may depend on the cyclical conjuncture.

We find that market variables stand out as the most versatile leading indicator for NPLs out of the 22 variables examined, across all categories of NPLs. This is a rather intuitive result pointing to the importance of the market indicators as signals for credit risk. Moreover, some bank-specific variables, related to the banks’ performance, are also good predictors of future NPLs for business NPLs, namely inefficiency, ROA and ROE. Finally, the forecasting performance of two macroeconomic variables, industrial production and imports is good for consumer and business NPLs, respectively.

Overall, empirical evidence for the “market sensitivity” hypothesis is provided, while there is also empirical support for the “bank heterogeneity” hypothesis. In contrast, the “systemic credit risk” hypothesis, which forms the basis of most current stress-testing practices, is not compatible with our results.

Consequently, our results have important implications regarding the methodology followed in stress testing, and other supervisory-related, exercises which aim to identify capital shortfalls in banks under adverse conditions. Clearly, the use only of macroeconomic variables when projecting the evolution of NPLs is not the optimal, and, therefore, modelers should also consider widening the scope of variables used. The recommendation that emerges from our study is that market- and bank-specific variables are critical in order to ensure an accurate forecast of NPLs, and, therefore, a reliable assessment of the impact of ex ante credit risk on banks’ balance sheets.

Moreover, our results reinforce the view that there are noticeable differences among the behavior of NPLs across NPLs categories, and the need to examine separately different portfolios rather than focusing on the aggregate NPLs. The value added provided by disaggregating credit (risk) developments into consumer, business and mortgage NPLs is consistent with results of previous studies of the credit market in Greece, which point to differential behavior of the various sectors of the credit market (see, e.g., Vouldis 2015; Louzis et al. 2012).

On the macro-prudential and supervisory fronts, our results point to the need for examining real-time market indicators in order to assess credit risk developments in the banking system. The informational content of these indicators is found to be highly sensitive to the realization of credit risk and thus allow for more accurate assessments of the risk exposure of financial institutions, compared to the approach of focusing on the aggregate macroeconomic variables.

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Appendix: The model confidence set (MCS)

In this appendix, we briefly describe the model confidence set (MCS) method of Hansen, Lunde and Nason (2003; 2011) used to construct a set of models, $M^*_{1-a} \subseteq M_0$, that present statistically superior predictive ability at a given confidence level.

Assuming an initial set of $M = M_0$ models, the MCS method is based on a specific loss function, $L_{m,t}$ with $m = 1, \ldots, M$, and applies an iterative process of sequential equal predictive ability (EPA) tests of the form:

$$H_{0,M_0} : E\left(d_{mk,t}\right) = 0 \quad \text{for all } m, k \in M$$

where $d_{mk,t} = L_{m,t} - L_{k,t}$ is the loss differential between models m and $k$and $L_{\bullet,t}$ is one of the RMSFE or MAFE at each point in time, t. A rejection of the null hypothesis indicates that a model has inferior predictive ability and should not be included in the MCS at an a significance level. This EPA test is repeated for the remaining M_{1-a} models, with $M_{1-a} \subset M$, and this procedure continues until the null hypothesis cannot be rejected. The final set of surviving models forms the MCS at a $1 - a$ confidence level, denoted by M^*_{1-a}. The models included in the MCS have equal predictive ability, but they outperform the eliminated models, while the MCS p-values indicate the probability of a model being a member of the MCS.[9]

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[9] For details on MCS technique and its implementation, see Hansen, Lunde and Nason (2003; 2011). The MCS is implemented using MULCOM 2.00 package for Ox, kindly provided by the authors. The MULCOM 2.00 package is available at http://mit.econ.au.dk/vip_htm/alunde/mulcom/mulcom.htm.

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