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Analysis of macroeconomic determinants of non-performance in consumer and mortgage loans

David Cortés[a], Pilar Soriano[b,*]

[a] Universidad Carlos III de Madrid, Spain
[b] Facultat d'Economia, Universitat de València Av. Tarongers, s/n, València, 46022, Spain

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ABSTRACT

We investigate the macroeconomic determinants of non-performing loans (NPLs) in two dynamic unbalanced panels: consumer loans and mortgages, utilizing quarterly data for eight countries from 1992 to 2019. The article assesses which variables are key determinant factors, both in and out-of-sample, and whether they have the same impact in both portfolios. These variables are the lagged ratio of NPLs, credit level, real GDP, short-term real interest rates, real house price indices, and stock indices. We compare different econometric techniques applied to intermediate-sized panels and evaluate forecasting abilities. Results support pooled estimations, and mortgages exhibit higher sensitivities and better forecasting performance.

1. Introduction

Understanding non-performing loans (NPLs) and the factors that explain their evolution is an essential task at both the microeconomic and macroeconomic levels. On the one hand, risk departments of financial institutions must comply with regulators, calculate doubtful debts for all their credit portfolios, and report them regularly. On the other hand, NPLs are also crucial in the macroeconomic sphere because aggregated loan defaults serve as good indicators of the banking system's credit quality (see Berger and DeYoung, 1997; Louzis et al., 2012; or Manz, 2019, among others).

The economic literature has provided extensive evidence that business cycle and asset price shocks are among the principal systemic factors behind changes in NPLs. Manz (2019) presents a systematic literature review on the determinants of non-performance. NPL research can be divided into two groups. The first one analyses specific bank data to highlight the role of macroeconomic factors on credit quality (Salas and Saurina, 2002; Jiménez and Saurina, 2006; Louzis et al., 2012). The second group works with aggregated data produced by central banks, financial supervisors, or any other national or international office (Rinaldi and Sanchis-Arellano, 2006; Nkusu, 2011). On the other hand, if we focus on the econometric techniques used in the literature, approaches implemented are multiple, but the most used ones are panel data techniques (Jiménez and Saurina, 2006; Rinaldi and Sanchis-Arellano, 2006; Nkusu, 2011; Ghosh, 2015, 2017). This article works with aggregated data at the country level and uses panel models.

So far, most of the literature has focused either on micro or macro panels, and little attention has been paid to intermediate situations. Our paper examines the influence of several macroeconomic factors on NPLs and contributes to the empirical literature in

* Corresponding author.
E-mail address: pilar.soriano-felipe@uv.es (P. Soriano).

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several ways. First, by adding research to the scarce "large T, small N" panel literature on the economic determinants of NPLs.[1] In this case, T stands for the number of time observations and N for the number of crossections (countries in our case). Often, practitioners and regulators have to research and forecast over intermediate-sized unbalanced panels because obtaining and aggregating the data can be costly or impossible to achieve. Not every country has the same data quality and availability. Second, this study examines whether macroeconomic factors impact differently on NPLs across loan categories. Louzis et al. (2012) proved that macroeconomic and bank-specific variables influence Greek NPL categories differently. As far as we know, our study is the first one to expand this analysis to an international level for two separated loan portfolios: consumer loans and mortgages. Finally, another novelty of our study a is to add out-of-sample forecasting exercises to complement and confirm in-sample findings.

2. Data and methodology

2.1. Data

This study covers quarterly data for a sample of eight economies, namely Spain (ESP), Mexico (MXC), the United States (USA), Turkey (TUR), Colombia (COL), Peru (PER), Chile (CHL), and Argentina (ARG). We select these countries for two reasons. First, we would like to contribute to practice by providing insights into the intermediate-sized unbalanced panel literature. Often, obtaining disaggregated NPL data can be costly and not always possible. Hence, practitioners have to deal with short panels. Second, we use a real panel of countries that a Spanish commercial bank analyses under IFRS9 macroprudential policy.[2]

We select the ratio of NPLs as the endogenous variable and as a measure of credit quality. We calculate NPLs at the macroeconomic level from the consolidated balance sheets of each country's banking sector, and these are broken down into consumer and mortgage portfolios. As Louzis et al. (2012) notice, macroeconomic variables may impact each type of NPLs in different ways because the business cycle does not always affect each kind of loan and collateral in the same manner.

NPLs rates are calculated as the ratio between those loans that have been in arrears for some time and the total amount of loans in the portfolio. Appendix A describes the key variables used when defining NPLs rates and details the data sources. As explanatory variables, we consider six factors: the lagged endogenous variable (npl_{t-1}); and five macroeconomic factors that the economic literature has proven to significantly impact delinquency rates.

The first selected factor is credit level (*cred*). We include this input as a possible measure of leverage. A rapid increase in loan portfolios might be positively associated with an increase in non-performing loan ratios later on. The second factor is real GDP (*gdp*). This variable is selected as a measure of the state of the economy. GDP dynamics are closely related to households' capacity to meet their obligations, as expansionary phases of the economy tend to be associated with higher incomes to service debts and lower NPL levels (Ghosh, 2015, 2017; Manz, 2019). As a third factor, we choose short-term real rates *(rates*). Real rates measure the cost of servicing debt, and we should expect a positive relationship between delinquencies and short-term real rates. Higher real rates could translate into a higher debt burden and make it more challenging for borrowers to repair their debts. Nonetheless, there are economic situations where this positive relationship could not work well. Finally, the fourth and the fifth explanatory variables are real home prices indices (*hpr*) and equity indices (*equity*). These two variables gather wealth effects. A downturn in financial and/or real asset prices leads to more defaults via wealth effects and a decline in the collateral value.

Table 1 summarises the six explanatory variables defined above and their expected impact in line with the economic literature. Table 1 also provides information about the number of observations for each country in the panel, ranging from March 1992 to December 2019. The series extend as far back as possible in each country based on data availability, concluding in the fourth quarter of 2019 to mitigate the impact of Covid-19.[3]

Summarising, we have two unbalanced panels (consumer and mortgage loans) with a T between 37 and 113 and $N = 8$. The size of the panel is a relevant feature because, as Pesaran (2015) notes, the choice of an appropriate estimator depends on the relative size of the number of cross-sections (N) and the number of periods (T).

2.2. Methodology

The empirical analysis is based on the following expression:

$$npl^j_{n,t} = f\left(npl^j_{n,t-1}, cred^j_{n,t}, gdp_{n,t}, rates_{n,t}\ , hpr_{n,t}\ , equity_{n,t}\right) \tag{1}$$

Where $npl^j_{n,t}$ is the natural logarithm (log) of non-performing loans rate for country n, at time t and for portfolio j, and it proxies the credit risk of that portfolio (either consumer or mortgage loans). The NPLs rate is calculated as the ratio of the number of NPLs in the portfolio to the total amount of outstanding loans in that same portfolio. $cred^j_{n,t}$ is the log of the level of credit of portfolio j, for country

[1] The only relevant exception is Rinaldi and Sanchis-Arellano (2006), a European Central Bank working paper that proposes a dynamic error correction model (ECM) including seven euro-area countries over a period from 1989Q3 to 2004Q2.

[2] A non-disclosure agreement prevents the authors from mentioning the name of the bank.

[3] After the Covid-19 crisis and the support programs introduced by governments, statistical relationships between delinquencies and economic drivers were severely affected. Hence, econometric models were estimated with data before the crisis started, and none of the support economic programs was introduced. We leave this for further research.

Table 1
Explanatory variables, expected impact on NPL and observations per country.

Symbol	Explanatory variable	Expected sign
npl_lag	Previous nonperforming loan rates	(+)
cred	Previous credit levels	(+)
gdp	Real GDP	(-)
rates	Real short term rates	(+)/(indet)
hpr	Real home prices	(-)
equity	Equity index	(-)

Country	Observations	Starting date	End date
Argentina	57	Mar-06	Dec-19
Chile	45	Mar-09	Dec-19
Colombia	62	Dec-04	Dec-19
Spain	82	Dec-99	Dec-19
Mexico	57	Mar-06	Dec-19
Peru	71	Sep-02	Dec-19
Turkey	37	Mar-11	Dec-19
United States	113	Mar-92	Dec-19

n, at time t; $gdp_{n,t}$ is the log of real GDP for country n at time t; $rates_{n,t}$ is short term real rates[4] for country n at time t; *hpr* is the log of real house prices for country n at time t, and $equity_{n,t}$ is the log of equity indices for country n at time t.

Due to many temporal observations and the cross-sectional nature of datasets, time-series procedures also become relevant. Therefore, before applying any econometric model, we need to check three relevant features. First, to test for the presence of unit roots and possible cointegration relationships (Maddala and Wu, 1999; Breitung, 2000; Hadri, 2000; Choi, 2001; Levin et al., 2002; Im et al., 2003; Pedroni, 1999, 2004). Second, the presence of cross-section dependence across each country must be tested (Pesaran, 2004, 2015, and 2021). Third, the poolability of the data must be tested (Pesaran and Smith, 1995; Baltagi et al., 2008). Long panels allow estimating separate regressions for each cross-unit, and therefore it is natural to question the assumption of parameter homogeneity ($\beta_n = \beta \forall_n$) Appendix B contains these preliminary tests. Results obtained indicate that series do not show cointegration relationships, consumer loans residuals have cross-section dependence but mortgage residuals do not, and the scarce data in some countries recommend maintaining the poolability assumption.

Considering the results obtained in the preliminary tests, we estimate the following dynamic panel:

$$\Delta npl^{j}_{n,t} = \gamma \Delta npl^{j}_{n,t-1} + \beta_1 \Delta cred^{j}_{n,t-4} + \beta_2 \Delta gdp_{n,t} + \beta_3 \Delta hpr_{n,t} + \beta_4 rates_{n,t} + \beta_5 \Delta equity_{n,t} + \eta_n + \varepsilon_{n,t} \tag{2}$$

We use five estimation methods. The first two, the Poolability (Pool) and the Fixed Effects Within Group (FE-WG) models, estimate parameters with ordinary least squares. They are frequently applied when panel equations are static but show bias and inconsistencies when equations are dynamic, or errors are not independently and identically distributed (Baltagi, 1998). We also calculate two instrumental variables methods: the two-stage-least-squares (2SLS) and the three-stage-least-squares (3SLS). Both methodologies remove endogeneity problems but do not always result in efficient estimators. The 2SLS may not give efficient estimations when there exist contemporaneous cross-section correlations in the residuals. In such cases, the 3SLS proposed by Zellner and Theil (1962) would provide consistent and efficient estimators since it considers the correlation among the errors. Moreover, the 3SLS also adjusts the weighting matrix for potential heteroskedasticity problems by estimating the coefficients within a Generalized Least Square (GLS) framework. Therefore, the 3SLS technique appears as the most efficient, particularly in consumer loans, where cross-section dependence exists. Additionally, to compare results from different estimation techniques, we also calculate Dynamic Mean Group (DMG)[5] estimations. This technique was introduced by Pesaran and Smith (1995), and they showed that the average estimator of the heterogenous parameters of each cross-section could lead to consistent estimations as long as N and T tend to infinity.

[4] We preferred not to take natural logarithms for real interest rates for several reasons. First, the series oscillates around zero and does not exhibit any clear growth pattern. Second, real interest rates are negative for several periods, rendering natural logarithms undefined. Third, applying natural logarithms would need a series transformation (e.g., adding a constant) to avoid undefined results from negative real rates, which might compromise the interpretability of the results.

[5] The Dynamic Mean Group (DMG) estimation is appropriate when both T and N are sufficiently large (macro-panels). In this article, the number of cross-countries is small, and averaging countries estimates of a such a small sample could lead to inconsistent estimators, specially if the individual estimations display high variability. We included this model to also have a macropanel example, and to check how its point estimators would compare to the rest.

Table 2
Panel data estimations for consumer loans and mortgages.

Panel estimations Consumer loans						Mortgages					
	Pool	FE-WG	IV-2SLS	IV-3SLS	DMG		Pool	FE-WG	IV-2SLS	IV-3SLS	DMG
(Intercept)	−0.01				−0.06**	(Intercept)	0.00				0.00
	(0.832)				(0.015)		(0.467)				(0.961)
Δnpl_cons(t-1)	0.70***	0.67***	0.64***	0.64***	0.60***	Δnpl_mtge(t-1)	0.74***	0.72***	0.69***	0.70***	0.67***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δcred_cons(t-4)	0.27***	0.44***	0.46***	0.44***	0.66***	Δcred_mtge(t-4)	0.36***	0.39***	0.41***	0.41***	0.26
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.212)
Δgdp	−0.84***	−0.88***	−0.99***	−0.91***	−0.69**	Δgdp	−1.20***	−1.22***	−1.31***	−1.22***	−0.76
	(0.007)	(0.005)	(0.002)	(0.002)	(0.024)		(0.000)	(0.002)	(0.000)	(0.000)	(0.210)
Δhpr	−0.05	−0.11	−0.11	−0.12**	−0.29	Δhpr	−0.23***	−0.21	−0.24	−0.26***	0.08
	(0.594)	(0.398)	(0.435)	(0.047)	(0.127)		(0.007)	(0.370)	(0.326)	(0.002)	(0.875)
rates	0.34**	0.08	0.12	0.13	0.14	rates	0.19	0.45***	0.47***	0.49**	−0.81
	(0.010)	(0.679)	(0.579)	(0.313)	(0.457)		(0.190)	(0.002)	(0.001)	(0.039)	(0.220)
Δequity	−0.07***	−0.06***	−0.06***	−0.06***	−0.06*	Δequity	−0.09***	−0.09***	−0.10***	−0.09***	−0.05**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.087)		(0.000)	(0.007)	(0.003)	(0.000)	(0.018)
Num. obs.	492	492	492	492	492	Num. obs.	492	492	492	492	492

Regressors: *intercept* = constant; *Δnpl_cons(t-1)* = annual growth rate of the natural logarithm of NPL rates from the previous quarter ; *Δcred_cons(t-4)* = annual growth rate calculated over the four preceding quarters for the natural logarithm of credit volumes; Δgdp =annual growth rate of the natural logarithm of GDP.
Δhpr = annual growth rate of the natural logarithm of real house prices; rates = real interest 17 rates; Δequity = annual growth rate of the natural logarithm of equity stock index.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
Estimation: *Pool* = Poolability; *FE-WG* = Fixed Effects Within Groups; *IV-2SLS* = Two Stage Least Squares; *IV-3SLS* = Three Stage Least Squares; *DMG* = Dynamic Mean Groups. t-stats and p-values calculated with clustered standard errors in POOL, FE-WG and IV-2SLS, but not in IV-3SLS and DMG. R^2 for DMG is calculated as the multiple-R^2. Instruments used in 2SLS and 3SLS methods for Δnpl_cons (t-1) are: Δnpl_cons(t-2),Δnpl_cons(t-3) and Δnpl_cons(t-4).

Table 3
Out-of-sample forecasting results. Relative MSFE.

Relative MSFE: consumer loans

	Pool				FE-WG				IV-2SLS				IV-3SLS				DMG			
	1Y Fcast	2Y Fcast	5Y Fcast	Avge	1Y Fcast	2Y Fcast	5Y Fcast	Avge	1Y Fcast	2Y Fcast	5Y Fcast	Avge	1Y Fcast	2Y Fcast	5Y Fcast	Avge	1Y Fcast	2Y Fcast	5Y Fcast	Avge
Argentina	1.0	3.5	1.5	2.0	1.9	3.6	1.6	2.4	1.9	4.3	1.7	2.6	1.8	3.7	2.1	2.5	0.5	1.4	1.0	1.0
Chile	5.2	3.7	3.0	4.0	1.3	0.5	0.4	0.7	1.5	0.6	0.5	0.9	1.4	0.7	1.1	1.1	0.6	0.5	0.5	0.6
Colombia	0.5	2.3	1.0	1.3	1.3	4.7	1.1	2.4	1.1	4.9	1.1	2.4	1.2	6.3	1.3	2.9	2.0	10.4	0.6	4.4
Mexico	0.3	0.4	1.1	0.6	1.6	2.0	2.5	2.0	1.3	1.7	2.6	1.9	1.5	2.1	2.5	2.0	0.6	2.6	1.5	1.6
Peru	4.2	1.4	1.2	2.2	2.9	2.7	1.6	2.4	3.3	2.6	1.6	2.5	3.3	2.8	1.7	2.6	3.3	4.0	0.9	2.8
Spain	2.2	2.5	3.3	2.7	0.3	0.2	1.1	0.5	0.3	0.2	1.1	0.5	0.3	0.2	1.8	0.8	5.1	1.1	2.1	2.8
Turkey	0.6	0.5	–	0.5	0.7	0.5	–	0.6	0.6	0.4	–	0.5	0.8	0.8	–	0.8	0.7	0.9	–	0.8
United States	1.0	0.0	1.3	0.8	9.2	0.1	2.2	3.8	5.9	0.1	2.2	2.7	5.9	0.1	3.4	3.1	0.1	0.0	0.3	0.1

Relative MSFE: Mortagages

	Pool				FE-WG				IV-2SLS				IV-3SLS				DMG			
	1Y Fcast	2Y Fcast	5Y Fcast	Avge	1Y Fcast	2Y Fcast	5Y Fcast	Avge	1Y Fcast	2Y Fcast	5Y Fcast	Avge	1Y Fcast	2Y Fcast	5Y Fcast	Avge	1Y Fcast	2Y Fcast	5Y Fcast	Avge
Argentina	12.9	2.1	1.9	5.6	14.1	2.5	2.1	6.2	11.5	2.5	2.2	5.4	14.9	7.9	5.6	9.5	5.1	2.2	2.1	3.1
Chile	2.5	2.9	2.4	2.6	2.0	0.3	0.3	0.9	2.2	0.3	0.3	0.9	2.3	0.4	1.0	1.2	2.2	3.8	1.2	2.4
Colombia	0.2	6.9	1.6	2.9	0.2	11.0	1.4	4.2	0.1	11.6	1.4	4.4	0.2	12.0	2.1	4.8	0.2	13.2	1.9	5.1
Mexico	1.4	0.9	1.5	1.3	2.5	1.5	1.9	2.0	2.5	1.5	2.0	2.0	2.9	1.5	4.3	2.9	0.7	0.3	1.4	0.8
Peru	3.1	8.7	2.5	4.8	1.5	10.6	2.2	4.8	1.5	9.9	2.1	4.5	2.0	8.7	3.7	4.8	5.6	3.0	2.5	3.7
Spain	2.0	2.7	4.4	3.0	0.6	1.3	2.1	1.4	0.5	1.3	2.1	1.3	0.0	0.1	0.1	0.0	0.5	1.6	3.7	1.9
Turkey	2.3	5.6	–	3.9	1.1	2.9	–	2.0	1.0	3.1	–	2.1	1.3	7.9	–	4.6	0.4	1.1	–	0.7
United States	0.1	0.5	0.2	0.3	0.0	0.4	0.1	0.2	0.0	0.3	0.1	0.2	0.0	0.5	0.3	0.3	0.1	0.6	0.1	0.2

Estimation models: *Pool* = Poolability; *FE-WG* = Fixed Effects Within Groups; *IV-2SLS* = Two Stage Least Squares; *IV-3SLS* = Three Stage Least Squares; *DMG* = Dynamic Mean Groups. *1Y Fcast* = Relative MSFE for 1Y period; *3Y Fcast* = Relative MSFE for 3Y period; *5Y Fcast* = Relative MSFE for 5Y period; *Avge* = Average for the 3 periods. *Relative MSFE* > 1, model beats bechmark; *Relative MSFE* < 1, model underperforms bechmark. *Relative MSFE* $= \mathrm{MSFE}_{\mathrm{AR}(1)} / \mathrm{MSFE}_{\mathrm{model}}$. 5Y forecast for Turkey are not included because sample data for this country includes only 7 years.

3. Results and discussion

3.1. In-sample estimation

Table 2 displays estimated coefficients and their p-values for consumer loans and mortgages. Overall, the estimated models align with past literature. Almost all explanatory variables included in the models show the expected signs and are statistically significant. Moreover, results also confirm heterogeneity in the macro sensibilities between consumer and mortgages loans portfolios. Thus, for instance, the impact of GDP changes in delinquencies is more substantial in mortgages than in consumer loans. The same happens with real house prices and interest rates. This result should not be surprising since fundamental loan characteristics such as the cash-flow structure or the collateral behind the loans could be very different.

Results also confirm the persistent nature of delinquency rates in both portfolios. Past credit growth shows a positive effect on delinquency rates in every estimation method, confirming that rapid credit growth in previous periods leads to higher credit risk in future periods. Outcomes also demonstrate that real GDP growth and increases in equity markets are associated with decreasing NPLs.

The remaining two explanatory variables, real interest rates and growth in real house prices, show more mixed evidence. In the case of house prices, most models conclude that this variable is not significant, while in the case of real rates, it does not seem a statistically significant variable, except for mortgages. Overall, both variables exhibit expected signs, positive in the case of real interest rates, pointing to a positive impact of higher funding costs on delinquencies and negative in the case of real house prices.

Finally, another interesting outcome is related to the coefficients obtained through the different econometric techniques. It can be observed that the variability of the coefficients is low, especially between the FE-WG and Instrumental variables models. A plausible explanation could be that the number of temporal observations of the panels is high enough to remove a great deal of the bias the FE-WG estimations might show when T is not large enough. This thought is also confirmed when we look at the lagged dependent variables' coefficient estimations. At the same time, Pooled OLS exhibit higher coefficients, pointing to an upward bias of these estimators.

In summary, in-sample results obtained are in line with the literature. Macroeconomic factors are essential explanatory drivers of delinquency rates, and the heterogeneity found in the two portfolios' coefficients makes it advisable to estimate the portfolios separately. Furthermore, the unbalanced nature of the panel (where some countries have a large number of time observations to carry out individual time-series, but others do not), made us impose the poolability assumption. At the same time, T seems large enough to give very similar results between the FE-WG estimations and instrumental variables, suggesting that the FE-WG bias in dynamic estimations could be partially removed.

3.2. Robustness check

As a final robustness check, we conduct a simple out-of-sample forecasting exercise to assess whether the selected macroeconomic factors can enhance NPLs forecasts compared to a naïve benchmark model, the individual AR(1) model. We divide the sample data into two sub-samples: the first one, known as the estimation sample, is used for obtaining our panel parameter estimations, and the second one, known as the forecasting sample, is utilized for prediction. For each of the models, we forecast dynamically over three periods: a very short-term period covering four quarters (one year), a short period encompassing eight quarters (two years), and a medium-term period spanning twenty quarters (five years). Hence, the out-of-sample panel regression for each model and country is given by:

$$\widehat{\Delta npl}^{j}_{n,t+i} = \widehat{\gamma}\Delta npl^{j}_{n,t+i-1} + \widehat{\beta}_1\Delta cred^{j}_{n,t+i-4} + \widehat{\beta}_2\Delta gdp_{n,t+i} + \widehat{\beta}_3\Delta hpr_{n,t+i} + \widehat{\beta}_4 rates_{n,t+i} + \widehat{\beta}_5\Delta equity_{n,t+i} + \widehat{\eta}_n \tag{3}$$

Where $\widehat{\gamma},\ \widehat{\beta}_1,\ \widehat{\beta}_2,\ \widehat{\beta}_3,\ \widehat{\beta}_4,\ \widehat{\beta}_5$ *and* $\widehat{\eta}_n$ are estimations obtained through the different panel methods.

To evaluate forecast accuracy, we select the Mean Squared Forecast Error (MSFE) metric. We compare forecasts in terms of the relative MSFE ratio. If it is greater than 1, the panel model forecasts will outperform those obtained by the benchmark. If it is lower than 1, the opposite would be true.

Table 3 displays out-of-sample forecast results for each country and the forecasting period. In general, panel models tend to outperform the benchmark in most of the forecasting windows, and economic factors demonstrate forecasting ability. Comparing the different econometric techniques, all the models exhibit similar results, and there are no significant differences among forecasting windows, ruling out in this sample that models have greater or lesser predictive capacity depending on the time interval. Perhaps, 3SLS relative MSFE shows slightly better results at an aggregated level in both portfolios than the rest of the methodologies.

This table presents the results of an out-of-sample forecasting exercise that compares a naïve AR(1) model for each country with our selected panel regression. The exercise involves dynamically calculating forecasts for three periods: a very short-term period (four quarters), a short-term period (eight quarters), and a medium-term period (twenty quarters). To assess forecast accuracy, we utilize the Mean Squared Forecast Error (MSFE) metric. The comparison is made in terms of the relative MSFE ratio, which calculates the MSFE of the selected panel models against the MSFE of the AR(1) model for each of the three chosen forecasting periods.

At the portfolio level, forecast performance is better in mortgages than in consumer loans. In mortgage loans, panel models outperform the benchmark in all countries except the United States.

In summary, and for the sample studied, there are more cases in which models outperform the benchmark than vice versa. Hence, economic factors seem to play an essential role in forecasting NPLs, in line with the outcomes obtained in-sample.

4. Conclusions

This study explores the macroeconomic determinants of non-performing loans in two international unbalanced dynamic panels, one for consumer loans and another for mortgages. In particular, it uses quarterly data from 1992 to 2019 from the United States, Spain, Mexico, Turkey, Colombia, Peru, Argentina, and Chile. This short sample of countries is usual for practitioners because obtaining disaggregated data for NPLs is difficult and costly.

Delinquency rates show a persistent nature; past credit growth has a positive impact on NPLs, and an acceleration in real GDP, real house prices, and equity markets, along with lower funding costs, leads to lower NPLs. In-sample estimations also confirmed that the influence of GDP on delinquency rates is notably greater in mortgages compared to consumer loans, a pattern similarly observed with real estate values and interest rates. This fact invites estimating these two portfolios independently. Finally, the out-of-sample forecast confirmed that most models tend to beat the benchmark, and economic factors play an essential role in forecasting NPLs. Moreover, forecast performance is better in mortgages than in consumer loans.

This paper's results could be of relevance for academics and practitioners in several ways. First, this paper contributes to practice by focusing on intermediate-sized unbalanced panel techniques where literature is almost inexistent. Second, contrary to other research, we could not find cointegration relationships between NPLs rates and the macroeconomic factors selected. Third, the paper contributes to the debate of whether to pool or not pool in unbalanced panels, in favor of the first approach. And, finally, we propose to analyse country-level consumer and mortgage loans separately, as the influence of some macroeconomic factors are different on them.

Future research could analyse the lag structure of autoregressive panel models. Thus, estimating a PVAR structure could offer a robustness check for results. Moreover, including richer panel data disaggregated by categories would help obtain more efficient estimators and improve credit risk forecasts. In this sense, we should encourage authorities to produce more extended NPLs time series as disaggregated and broad as possible.

CRediT authorship contribution statement

David Cortés: Conceptualization, Data curation, Methodology, Writing – original draft, Writing – review & editing. **Pilar Soriano:** Funding acquisition, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declarations of competing interest

None.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2023.104939.

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