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Vasilis Siakoulis

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FISCAL POLICY EFFECTS ON NON-PERFORMING LOAN FORMATION

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ABSTRACT

The fiscal situation in an economy may have a significant impact on the evolution of Non-Performing loans (NPLs). Austerity measures limit the loan servicing capacity of households and businesses (Perotti, 1996) whereas public borrowing accelerates markedly ahead of sovereign debt and banking crisis (Reinhart and Rogof, 2010). We empirically approach the effects of fiscal policy on NPLs employing a global data set for 31 countries covering a fifteen year period. We control also for other macroeconomic factors so as to quantify effects stemming from fiscal policy measures. We employ panel data methodologies since they provide us the means to deal with unobserved country heterogeneity when examining the determinants of asset quality. We also examine the one period ahead forecasting performance of our models in line with the cross sample panel data validating suggestions of Granger and Huang (1997). Our findings imply that, on a global level, when accounting for variables linked to macroeconomic performance such as GDP growth and the unemployment rate, fiscal pressure imposed on the economy, as measured by changes in the cyclically adjusted primary surplus, constitute important determinants of Non-Performing loan formation. Also our specifications provide efficient out-of-sample one-step ahead forecasts combining effectively unobserved country heterogeneity with observed macro and fiscal determinants. Our analysis could be of great interest to policymakers since the assessment of credit risk in the banking sector is a crucial element of macro-prudential policy. In this framework, besides strict macroeconomic performance metrics one should also take into account the fiscal framework when trying to explain the key drivers behind NPL evolution.

Keywords: Non-Performing Loans; Fiscal Policy; Panel Data

JEL Classification: C22, C41, G01, G12, G14

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1. Introduction

During the years following the global financial crisis of 2007-2008, the credit quality of loan portfolios in most countries deteriorated mainly due to the economic recession (Beck et al, 2013). Yet, even though loan performance is tightly linked to the economic cycle, the deterioration of loan quality was uneven across countries. While US and Central European banks with exposure to US residential mortgage-backed securities experienced considerable asset quality deterioration in the initial phases of the Global Financial Crisis, countries on the periphery of the Eurozone Union are still experiencing very high levels of Non-Performing Loans (NPLs) which continued to increase in 2015. This situation is more pronounced in Eurozone countries where the financial crisis evolved into a sovereign debt crisis. For example, in Greece the ratio of NPLs to total loans is estimated to have risen from 6.3 percent in 2005 to 34.3 percent in 2014. This situation holds true also in other peripheral countries of the Eurozone (Spain, Italy, Portugal, Cyprus and Ireland) where it is accompanied by episodes of costly banking system distress and subsequent government-funded bank recapitalizations.

During the sovereign debt crisis, peripheral Eurozone countries were forced to follow a strict fiscal policy through austerity measures expressed in the form of tax increases and a reduction in government expenditures. This increased the fiscal burden of households and businesses, affecting at the same time their bank debt servicing capacity.

The objective of this paper is to uncover linkages between macroeconomic performance and Non-Performing loans (NPLs), especially examining the hypothesis that pressure stemming from fiscal policy measures constitutes an important determinant of Non-Performing loan formation even after accounting for macro performance indicators such as GDP growth and unemployment rate.

This paper contributes to the current literature by assessing empirically the existence of government fiscal policy effects on Non-Performing loans by using a unique data sample covering a large number of countries. In line with previous studies (Beck et al. 2013), we exploit cross-country variation in Non-Performing loan trends which is likely to yield more robust results than an analysis of individual countries. We argue that besides the macroeconomic performance of a country, fiscal policy measures affect the loan servicing capacity of the economy in total. Our work also contributes by setting and evaluating a predictive in nature model, along with the proposals of Granger and Huang (1997), with relevant practical implications for regulators and practitioners interested in predicting future bank asset credit quality for stress testing or business planning purposes.

At the most general level, a Non-Performing loan is a loan where a borrower is not making repayments in accordance with contractual obligations. In many jurisdictions a NPL is defined as a sum of borrowed money upon which the debtor has not made his or her scheduled payments for at least 90 days. However, the detailed definition of an NPL is not universal due to its heterogeneity across regulatory jurisdictions. These discrepancies complicate simple cross-country comparisons and make data aggregation challenging. One source of this variance is that detailed accounting standards and the classification of loans according to credit quality are a relatively recent phenomenon.

As a consequence, data on NPLs should be treated with caution because reporting countries compile these figures using different methodologies and definitions. The majority of countries classify loans as non-performing when principal or interest is 90 days or more past due and/or there are signs of unlikeness to pay (Barisitz, 2013). This unlikeness to pay element includes a different treatment for restructured loans, loans that go into default because the borrower breaches a contractual covenant or a product or customer view when determining if loans are performing or not. According to the recent ITS document 227/2015, in case of restructuring the loan remains non-performing for a probation period of one year and for another two years remains forborne before migrating to performing status. Unfortunately concerning past data in cases of restructuring there is ambiguity about whether once restructured, an exposure needs to continue being identified as non-performing. Also if the obligor falls behind repayment on one loan but is repaying on the other, there is debate about whether the performing loan should also be classified as non-performing since the delinquency on one loan implies that the obligor's overall financial state has deteriorated. Therefore there are other dimensions besides time (since last repayment) that matter in certain jurisdictions. As a result widely used data sources on bank asset quality can give slightly different representations of balance sheet health whereas International Financial Reporting Standards (IFRS) and US Generally Accepted Accounting Principles (GAAP) focus on the impaired and not on the Non-Performing loans. The introduction of expected loss provisioning methodologies (IFRS 9) that require loans to be classified into different categories adds further to the analysis of asset quality classification.

There are usually two directions in which difficulties on the financial and the macroeconomic side depend on each other. The one direction is from the macroeconomic towards the financial side. When an economy enters an expansionary phase the level of NPLs remains relatively low as consumers and firms produce an adequate stream of income to service their debts. However, during the booming period banks tend to extend credit to low quality debtors, in order to maintain or increase their market share, hence when recession hits, households and companies can more easily get into difficulties leading to an increase in NPLs.

However there may also be reverse causality related to a possible feedback impact from the developments in the financial system (banking sector) to economic growth (De Bock and Demyanets, 2012 and Espinoza and Prasad, 2010). As NPLs increase the funding costs for banks with bad loans on their books also rise, their cumulative provisions increase and the value of equity falls. Also when NPLs lead to bank and borrower insolvencies, with negative effects on third parties through interlinkages, systemic failures may occur. In this context, banks cannot adequately fulfill their role in channeling savings to investment and transmitting monetary policy to the real economy.

In our study we focus on the effects directed from the macro-economy to the banking sector, focusing on the effect of the loan servicing capacity of businesses and households caused by austerity measures of the government when it tries to control its fiscal deficit (Perotti, 1996). The identification of fiscal effects may be difficult due to potential endogeneity. Therefore we employ as fiscal indicator the cyclically adjusted budget balance, sometimes known as the full employment budget balance, which is the budget balance that would have been recorded if the economy were at a normal level of activity. A positive change in the cyclically adjusted budget balance is linked to increasing tax burden accompanied by public expenses reduction. This is expected to increase NPLs as the loan servicing capacity of the economy declines. Indeed from Figure 1 a positive relation between NPLs and the change of cyclical balance is observed.

In order to separate the fiscal effects from the general macroeconomic effects, we employ as control variables basic NPL drivers which have been recognized by relevant empirical studies. Therefore, following the associated literature on the subject, we focus on GDP growth and unemployment as indicators of the phase of economic cycle, capturing to a large extent underlying drivers such as revenues of households or companies along with negative net present value of business projects. It is expected and observed (Fig 1) that NPLs are negatively associated with real GDP growth and positively related to unemployment rates.

Inflation affects also borrowers' debt servicing capacity through different channels and its impact on NPLs can be positive or negative. Higher inflation can make debt servicing easier by reducing the real value of outstanding loans. However, it can also weaken some borrower's ability to service debt by reducing real income. Moreover in a variable loan rate environment, monetary policy actions to combat inflation are likely to reduce loan-servicing capacity, as lenders adjust rates to maintain their real returns or simply to pass on any increases occurring in policy rates.

We also include in our specification two country debt capacity indicators namely the change in public debt to GDP ratio and the deviation from the mean of 10 year sovereign debt yields[1] which measure market access, the latter, in conjunction with changes in public debt policy, measured by the former. The inter-linkages between sovereign debt crises and banking crises have been recognized especially after the financial crisis of 2008 and the consequent sovereign debt events

[1] For all countries Long-Term Government 10-year Bond Yields are used except for cases of data unavailability, which are Brazil, India and Estonia, where short-term interbank rates were used as a proxy.

(Reinhart and Rogoff, 2010). Finally we include as a covariate the change in Private Debt to GDP ratio. A fall in private credit is expected to be positively related to NPLs since it restricts the agents businesses and household potential to refinance their debt leading them to default.

From Figure 2 we gain valuable insight into the fact that increasing government debt and rising government debt yields are positively related to rising NPLs. By contrast, private credit is negatively related to NPLs.

2. Literature review

The empirical literature on the interaction between the macroeconomic conditions and asset quality is vast and diverse. Many studies approaching the statistical relationship between macroeconomic conditions and NPLs find a positive relation between GDP and unemployment and NPLs since both of these macro variables signal lower national income from which loans can be repaid.

Most of the empirical literature is based on country specific studies. Vogiazas and Nicolaidou (2011) applied time series modeling techniques to investigate the deterministic factors of NPLs in the Romanian financial system. Their empirical findings suggest that macroeconomic variables, specifically inflation, the unemployment rate, the external debt to GDP ratio and M2 influence the credit risk evolution in the Romanian banking system.

Louzis et al. (2011) examine the determinants of NPLs in the Greek banking sector and find that credit quality is explained mainly by macroeconomic fundamentals such as GDP growth, unemployment and interest rates along with management quality. Greenidge and Grosvenor (2010) focused on the NPL ratio of the commercial banking sector in Barbados on aggregate and at the individual bank level. Their empirical results support the view that macroeconomic factors, such as growth in real GDP, inflation rate and weighted average loan rates, have an impact on the level of NPLs.

Salas and Saurina (2002) use panel data models to compare the determinants of problem loans of Spanish commercial and savings banks in the period 1985-1997, taking into account both macroeconomic and individual bank level variables. The growth rate of GDP, firms and family indebtedness, credit expansion and specific bank metrics explain adequately NPL formation. Quagliariello (2007), using a large panel dataset of Italian banks over the period 1985-2002 analyzes banks behavior over the business cycle. His main finding is that loan loss provisions and non-performing loans show a cyclical pattern. Prasanna (2014) analyzed a panel dataset of 31 Indian banks with annual data that spans the period 2000 to 2012. His finding is that GDP growth is associated with lower NPLs whereas higher interest rates and inflation contribute positively to rising NPLs. Messai and Jouini (2013) tried to detect the determinants of non-performing loans for a sample of 85 banks in three countries (Italy, Greece and Spain) for the period 2004-2008. They point out that NPLs vary negatively with the growth rate of GDP and the profitability of banks assets and vary positively with the unemployment rate, the loan loss reserves to total loans and the real interest rate.

A second category of studies uses cross country data to identify specific determinants of asset quality. We follow this approach since exploiting the cross-country variation in Non-Performing loan trends is likely to yield more robust results than an analysis of individual countries. In the same framework Nkusu (2011) uses panel data techniques on a sample of 26 advanced economies that spans from 1998 to 2009, to quantify the relationship between the quality of banks' loan portfolio and macro-financial drivers. The study shows that deterioration in the macroeconomic environment as expressed by slow growth, high unemployment or falling asset prices is associated with rising NPLs. Also, a sharp increase in NPLs triggers disturbances that cripple macroeconomic performance.

Beck et al (2013) use an unbalanced panel of data for 75 countries over the period 2000 -2010 to study the macroeconomic determinants of NPLs. Real GDP growth, share prices, exchange rates and lending interest rates are found to significantly affect NPL ratios. In the case of exchange rates the effect is particularly high in countries with pegged or managed exchange rates whereas in the case of share prices, the impact is found to be larger in countries which have a large stock market relative to GDP.

Rinaldi and Arellano (2006) used a panel of seven euro area countries and estimated an error-correction model. They found that in the long-run, an increase in the household ratio of indebtedness to income is associated with higher levels of NPLs. Monetary conditions are also important because rising inflation and lending rates significantly worsen financial conditions.

Makri et al. (2012) used an unbalanced panel of 14 Eurozone countries for the period 2000-2008. The found that from a macroeconomic perspective, public debt, GDP and unemployment along with the rate of non-performing loans of the previous year seem to be factors that affect the NPL ratio, unveiling that the state of the economy of Eurozone countries is clearly linked to loan portfolio quality.

Fofack (2005) used an unbalanced panel of data for 16 countries in Sub-Saharan Africa for the period 1993-2003. The results highlight a strong causality between NPLs and economic growth, real exchange and interest rates along with net interest margins.

3. Panel data models

Most of the studies which focus on the determinant factors of NPLs employ panel data models applied upon unbalanced datasets, which have the advantage of including more observations, whereas their results are less dependent on a particular period (Rinaldi and Sanchis-Arellano, 2006).

The basic linear panel data model can be described as α restriction of the following general model.

$$y_{it} = \alpha_{it} + \beta_{it} x_{it} + \varepsilon_{\mathrm{it}} \qquad (1)$$

where $\mathrm{i} = 1, \dots, \mathrm{n}$ is the individual (country) index, $\mathrm{t} = 1, \dots, \mathrm{T}$ is the time index and $\varepsilon_{\mathrm{it}}$ is a random disturbance of zero mean. A number of assumptions are made about the errors, the parameters and the exogeneity of the regressors which give rise to a taxonomy of models for panel data.

The most common assumption relies on parameter homogeneity among individuals which is described as $\alpha_{it} = a$ and $\beta_{it} = \beta$ for all i, t. The resulting model

$$y_{it} = a + \beta x_{it} + \varepsilon_{\mathrm{it}} \qquad (2)$$

is a standard linear regression model which pools all the data across $\mathrm{i, t}$ (Pooling model). If we assume parameter heterogeneity across individuals then the error component is separated in two components, one of which is specific to the individual.

$$y_{it} = a + \beta x_{it} + \mu_i + \epsilon_{\mathrm{it}} \qquad (3)$$

The idionsyncratic error ϵ_{it} is usually assumed well-behaved and independent of the regressors $\mathrm{x_{it}}$ and the individual error component $\mathrm{\mu_i}$. Based on the properties of the individual error component $\mathrm{\mu_i}$, different estimation methods are adopted. If $\mathrm{\mu_i}$ is correlated with the regressors the ordinary least squares estimator of β would be inconsistent, so $\mathrm{\mu_i}$ is treated as an additional set of n parameters to be estimated. This is called the fixed effects model (FE) which is estimated by OLS on transformed data and provides consistent estimates for β. The case of fixed effects corresponds to the restriction that the slopes in the general model are constant across individuals ($\beta_i = \beta$). These individual error components $\mathrm{\mu_i}$ stand for all unobserved aspects that distinguish the individuals from each other. For example, in our country panel this may capture differences in the NPL management regulatory framework across countries, local bank level of aggressiveness towards foreclosures or differences in the write-off policy.

If the individual error component $\mathrm{\mu_i}$ is uncorrelated with the regressors, the overall error also is also uncorrelated with the regressors so the OLS estimator is consistent. The OLS estimator nevertheless is inefficient since the common error component over individuals induces correlation across composite error terms, so one has to resort to feasible generalized least squares estimators. This model is usually termed Random Effects (RE). Contrary to the fixed effect case, where all individual-specific characteristics that are constant over time are absorbed in the constant terms, in the random effects case the constant terms are assumed to be drawings from an underlying population. This is a realistic assumption in the case where the individuals (countries) are drawn randomly from a larger population of individuals with varying frameworks of NPLs management policies.

Introducing the lagged dependent variable in the set of regressors leads to the Dynamic Panel Data model

$$y_{it} = \alpha y_{it-1} + \beta_{it} x_{it} + \mu_i + \epsilon_{\text{it}}, |a| < 1, i = 1, \dots, n, t = 1, \dots, T \quad (4)$$

The DPD model is consistently estimated utilizing the Generalized Method of Moments (GMM) as proposed by Arellano and Bond (1991) and generalized by Arellano and Bover (1995) and Blundell and Bond (1998). OLS estimation methods will produce biased and inconsistent parameter estimates since the individual error component μ_i is correlated with the lagged dependent variable, y_{it-1}. The GMM estimation method of Arellano and Bond (1991) is based on first differencing the above of equation to eliminate country-specific effects

$$\Delta y_{it} = \alpha \Delta y_{it-1} + \beta_{it} \Delta x_{it} + \Delta \epsilon_{\text{it}}, |a| < 1, i = 1, \dots, n, t = 1, \dots, T \quad (5)$$

The lagged dependent variable Δy_{it-1} is correlated with the error term $\Delta\epsilon_{\text{it}} = \epsilon_{\text{it}-}\epsilon_{\text{it}-1}$, leading to biased estimators. Nonetheless Δy_{it-2}can be used as an instrument in the estimation since it is expected to be correlated with Δy_{it-1} but not correlated with $\Delta\epsilon_{\text{it}}$ for $t = 3, \dots, T$

$$E[y_{it-s} \Delta\epsilon_{\text{it}}] = 0, t = 3 \dots T, s \geq 2 \qquad (6)$$

We also assume weakly exogenous explanatory variables, where lagged values of x_{it} are used as valid estimation instruments.

$$E[x_{it-s} \Delta\epsilon_{\text{it}}] = 0, t = 3 \dots T, s \geq 2 \quad (7)$$

Arellano and Bond (1991) propose another variant of the GMM estimator, namely the two-step estimator, which utilizes the estimated residuals in order to construct a consistent variance covariance matrix of the moment conditions. However this estimator does not seem to be preferred in empirical panel data studies of Non-Performing loans (Louzis et al, 2010) since it imposes bias in standard errors (t-statistics) due to its dependence on estimated residual values, especially in the case of data samples with relatively small cross section dimension.

4. Empirical application

Our dependent variable (NPL) is the ratio of defaulting loans (interest and principal payments past due by 90 days or more) to total gross loans. The use of NPL in the remainder of the paper refers to this definition. The loan amount recorded as non-performing includes the gross value of the loan as recorded on the balance sheet, not just the amount that is overdue.

The dataset is comprised of annual Non-Performing loan ratios and macroeconomic data for 31 countries taken from the website of the Federal Reserve Bank of Saint Louis[2]. The perimeter of the sample includes 23 European countries (of which 14 in the Eurozone), Brazil, Canada, USA, Chile, Australia, India, Japan and Russia. The wide scope of countries used in the study has the purpose of securing a wide and extended macroeconomic dataset which provides us with the opportunity to investigate potential common global patterns in the Non-Performing loan formation. The dataset covers different periods for each country, depending on the data availability. The resulting unbalanced panel has in total 398 yearly observations with a maximum range of 16 years (1998 to 2013) to a minimum range of 6 years of observations (Table 1).

Cross country comparisons of the levels of NPL should be interpreted with caution due to differences in regulation, supervisory practices and accounting procedures. For instance, NPL levels may not reflect the full extent of impaired loans, some banks may preemptively restructure loans when they consider that the obligor is unlikely to repay its credit obligations whereas there might also exist differences in times till write-offs. In order to examine the fiscal pressure effects inherited from the real economy and their adverse impact on the Non-Performing loans (**NPL**), we employ as a fiscal indicator the cyclically adjusted budget balance (**CSUR.GDP**), which is the budget balance that would have been recorded if the economy were at a normal level of activity. In principle, the cyclically adjusted measure better measures the stance of fiscal policy, as it removes the endogenous components of spending

[2] Data for the cyclically adjusted primary surplus were obtained from OECD economic outlook (Annex Table 32) whereas Private Debt to GDP data were obtained from World Bank website (World Development Indicators).

and revenues showing the underlying fiscal position when cyclical or automatic movements are removed.

It is expected that austere fiscal policy measures as expressed in positive changes of the cyclically adjusted budget balance will limit the loan servicing capacity of business and households leading to an increase in Non-Performing loans. We also include in our specification two country debt capacity indicators namely the change of public Debt to GDP (**DEBT.GDP**) ratio and the deviation from the mean for 10 year sovereign debt yields[3] (**YIELD.DEV**) which measure changes in public debt policy and countries access to markets. We finally employ as control variables basic macroeconomic indicators such as **GDP** growth, the unemployment rate (**UNR**) and inflation (**INFLAT**) and changes in Private Debt to GDP (**PDEBT.GDP**) so as to separate fiscal pressure from the rest of macroeconomic performance. The low cross - correlation of the regressors (Figure 3) allows us to rely on the asymptotic standard errors when interpreting regression results.

According to Wooldridge (2002) a simple way of testing for serial correlation in the pooled and the random effects case is to apply a standard serial correlation test to the original and the quasi-demeaned data respectively. The Fixed Effects case needs some qualification since in short FE panels the test gets severely biased towards rejection. Therefore we employ the Breusch-Godfrey autocorrelation test in the pooled and Random Effects case, whereas for the FE case we use Woolridge's serial correlation test which is applicable to FE models on "short" panels with small T and large n. All tests reject the null of no-serial correlation probing us into using a robust to autocorrelation covariance matrix (Arellano, 1987).

Due to the presence of serial correlation we cannot use the Hausman test for selecting between the Fixed Effects and Random Effects model, since the test statistic depends on the variance matrix of the estimators. Therefore we present the results for both specifications along with the pooled OLS model for comparison reasons. Finally given the AR(1) effects detected we also include the parameters of a

[3] For all countries Long-Term Government 10-year Bond Yields are used except for cases of data unavailability, which are Brazil, India and Estonia, where short-term interbank rates were used as a proxy.

Dynamic Panel Data model based on the one-step GMM estimation method.

Coefficient signs (Table 2) are in line with our expectations whereas their statistical significance does not differ much across specifications, validating the robustness of our results to alternative model assumptions. The selected macro variables explain a maximum of 59% of the cross-sectional variation of Non-Performing loan ratios on a global level.

We notice that most of the one-year lagged variables affect significantly the NPL ratio indicating that the selected factors can provide useful insights in setting a forecasting model for Non-Performing loans evolution. Especially the changes in fiscal policy effect indicator (CSUR.GDP) appear to significantly affect NPL formation, validating the hypothesis that the fiscal policy has a definite impact on the loan servicing capacity of households and businesses. Regarding macro performance our findings indicate that changes in economic activity, as expressed in low GDP growth and high unemployment are main drivers of deterioration in bank asset quality. Also increases in the country Debt to GDP ratio, rises in sovereign yield and a fall in the Private Debt to GDP affect adversely NPL levels.

In the dynamic model, the coefficient of the lagged dependent variable is positive and statistically significant, implying that NPLs are likely to increase when they have increased in the previous year. Following the dynamic panel data literature, we test the overall validity of the instruments using the Sargan specification test proposed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundel and Bond (1998). Under the null hypothesis of valid moment conditions, the Sargan test statistic is asymptotically distributed as chi-square. Also, since serial correlation in the level of the error term leads to inconsistent GMM estimates, we assess the assumption that the errors are serially uncorrelated by testing for the hypothesis that the differenced errors are not second order autocorrelated. In our case neither the null of valid moment conditions can be rejected nor the null of no second order autocorrelation (m2).

In order to test the out-of-sample performance of our specification, forecast errors are generated using a cross-validation procedure (Granger and Huang (1997)). We select randomly 25% of the countries (Test sample) which are left out of the sample and estimate the models on the remaining 75% of the countries (Development sample) thus providing the out-of-sample forecast errors. This process is repeated 4 times (Grouping 1 to 4) until it covers the entire sample[4]. The relative groupings are shown in Table 3.

We additionally evaluate the post sample performance of our specifications by estimating our model using all country data for the period 1998-2009 and keeping the 2010-2013 periods for validation purposes. Finally we proceed to a cross post sample -out of sample validation by estimating our model using data for the period 1998-2009 for each group of countries (Table 3) and using the rest of the periods and remaining countries for cross validation purposes.

Granger and Huang (1997) and Romer and Romer (2000) propose the use of a Mincer-Zarnowitz (1969) regression for testing forecast efficiency. This method consists of regressing forecast errors on a constant by using autocorrelation-corrected standard errors and testing whether the latter is equal to zero. In that regression what is being tested is if the forecast errors have a zero mean, that is, if there is no systematic bias in the forecasts. Efficient forecasts should not systematically over or under-predict because simply adding the constant to the forecasts improves them. We also evaluate the models based on the variance of the residuals along with the usual forecast metrics of Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE), Correlation (CORR) between the realized and fitted values.

From Table 4 we deduce that in all cases there is no systematic bias in the forecasts. There is a slight bias in DPD model forecasts only in the post sample testing which has been dealt by adding back the Mincer-Zarnowitz regression constant before comparing across models. The findings that are related to the post sample – out of sample have to be interpreted with caution given the low number of observations in the validation sample. In the out of sample case the DPD model among specifications exhibits the lowest residual variance and error evaluation

[4] The application of the coefficients calculated based on the Development sample to the Test sample is straightforward except for the case of Fixed Effect model due to the country specific effects. Granger et Huang (1997) propose to use the Development sample country specific effects average in the fitted values calculation.

metrics whereas the results are mixed in the other cases.

In order to facilitate model comparison we apply the Diebold and Mariano (1995) test to couples of forecasts. A negative realization of the Diebold–Mariano test statistic indicates that the first forecast is more accurate than the second forecast.

From Table 5 we note that in the out of sample case the null hypothesis of equal predictive accuracy is rejected for all comparisons at a 1% confidence level, since all the test statistics are above the critical value of 2.33. Moreover, the statistical superiority of the DPD forecasts is confirmed as the realizations of the Diebold and Mariano (1995) statistic are negative. In the post sample and post – out of sample case the test in general does not reject the null hypothesis of equal predictive accuracy among specifications.

In summary incorporating fiscal variables provides useful insight when setting up a predictive in nature model for NPLs. More precisely our specifications produce cross validated forecasts which do not exhibit systematic bias whereas in the out of sample case the dynamic specification outperforms the static ones. In the post sample and post – out of sample testing all specifications have similar forecasting performance, a finding which has to be interpreted with caution given the low number of observations in the validation sample.

5. Conclusions

In this paper we are empirically testing the hypothesis that the fiscal stance in an economy may have a significant impact on the Non-Performing loans (NPLs) through the imposition of austerity measures which limit the loan servicing capacity of households and businesses. We employ panel data methodologies on a global data set spanning 31 countries covering a 15 year period, whereas we control also for other macroeconomic performance factors so as to distinguish the effects stemming only from fiscal policy measures. The fiscal-related indicator appears to significantly affect NPL formation, validating the hypothesis.

We also examine the one period ahead forecasting performance of our macro based models in line with the cross sample panel data validating suggestions of Granger and Huang (1997). Our findings imply that macroeconomic and fiscal factors explain much of the deterioration in bank asset quality whereas a dynamic panel specification may improve the out-of-sample performance.

Our analysis could be of great interest to policymakers since the assessment of credit risk in the banking sector is a crucial element of macro-prudential policy. We deduce that supervisory authorities should not focus only on macro performance factors but also on the fiscal stance of an economy so as to gain important insights on the vulnerabilities of the financial sector. Our findings may also apply to stress testing for credit risk which is based on macroeconomic assumptions in order to provide common scenarios for all participating banks. In this framework our results, besides shedding light on the interlinkages between the fiscal, macroeconomic and banking environment can serve as guidance in developing satellite models for credit risk regulatory stress testing.

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Tables and Figures

Table 1: Panel Dataset structure - Countries and time periods

	Country	Sample
AT	AUSTRIA	1998 - 2012
AU	AUSTRALIA	1999 - 2012
BE	BELGIUM	1998 - 2012
BR	BRAZIL	2006 - 2011
CA	CANADA	1998 - 2013
CH	SWITZERLAND	2002 - 2011
CL	CHILE	2005 - 2013
CZ	CZECH	2001 - 2012
DE	GERMANY	1998 - 2012
DK	DENMARK	1998 - 2012
EE	ESTONIA	2000 - 2012
ES	SPAIN	1999 - 2012
FI	FINLAND	1998 - 2012
FR	FRANCE	1998 - 2012
GB	UNITED KINGDOM	1998 - 2012
GR	GREECE	1998 - 2013
HU	HUNGARY	2000 - 2012
IE	IRELAND	2000 - 2012
IL	ISRAEL	1998 - 2013
IN	INDIA	1998 - 2012
IS	ICELAND	1998 - 2011
IT	ITALY	1998 - 2012
JP	JAPAN	2005 - 2012
LU	LUXEMBOURG	2001 - 2006
NL	NETHERLAND	1998 - 2009
NO	NORWAY	2000 - 2012
PT	PORTUGAL	1998 - 2012
RU	RUSSIA	2005 - 2012
SE	SWEDEN	2001 - 2012
SK	SLOVAKIA	2003 - 2012
US	USA	2001 - 2013

Table 2: Estimation results for Pooled regression (POOL), Fixed Effect Model (FE), Random Effect Model (RE) and one-step dynamic panel data model (DPD).

	POOL	**FE**	**RE**	**DPD**
Intercept	0.000		0.003	
	(0.007)		(0.007)	
lag(YIELD.DEV,1)	**0.583*** **	**0.670*** **	**0.671*** **	**0.339*** **
	(0.096)	(0.102)	(0.093)	(0.128)
lag(INFLAT,1)	**0.417*** **	0.104	0.173	**0.303*** **
	(0.111)	(0.148)	(0.130)	(0.059)
lag(UNR,1)	**0.351*** **	**0.447*** **	**0.415*** **	0.125
	(0.122)	(0.133)	(0.113)	(0.116)
lag(D(log(GDP)),1)	**-0.186* **	**-0.159*** **	**-0.161*** **	**-0.078** **
	(0.100)	(0.058)	(0.059)	(0.039)
lag(D(CSUR.GDP,1)	**0.130*** **	**0.089** **	**0.095** **	**0.076** **
	(0.032)	(0.045)	(0.042)	(0.034)
lag(D(PDEBT.GDP,1)	**-0.030** **	**-0.054*** **	**-0.051*** **	**-0.030*** **
	(0.013)	(0.013)	(0.012)	(0.010)
lag(D(DEBT.GDP,1)	**0.179*** **	**0.106* **	**0.117** **	0.042
	(0.059)	(0.056)	(0.056)	(0.034)
lag(NPL,1)				**0.571*** **
				(0.129)
Adj. R-Squared	0.49	0.56	0.59	-
Sargan-p value				1.000
Autocorrelation test (m1) p-value:				0.080
Autocorrelation test (m2) p-value:				0.260

***p<0.001,**p<0.01,*p<0.05

Table 3: Out of sample evaluation Country Groups

Sample	Group1	Group2	Group3	Group4
Development	AT	AT	AT	AU
Development	BE	AU	AU	BE
Development	CH	BE	BR	BR
Development	CZ	BR	CA	CA
Development	DE	CA	CH	CH
Development	DK	CL	CL	CL
Development	EE	CZ	DE	CZ
Development	ES	DE	DK	DK
Development	FI	EE	EE	FI
Development	FR	ES	ES	GB
Development	GB	FI	FR	IE
Development	GR	FR	GB	IL
Development	HU	GR	GR	IN
Development	IE	HU	HU	IS
Development	IL	IE	IL	IT
Development	IS	IN	IN	JP
Development	IT	IT	IS	LU
Development	LU	JP	JP	NL
Development	NL	LU	NO	NO
Development	NO	NL	RU	PT
Development	PT	PT	SE	RU
Development	SE	SK	SK	SE
Development	SK	US	US	US
Test	AU	CH	BE	AT
Test	BR	DK	CZ	DE
Test	CA	GB	FI	EE
Test	CL	IL	IE	ES
Test	IN	IS	IT	FR
Test	JP	NO	LU	GR
Test	RU	RU	NL	HU
Test	US	SE	PT	SK

Table 4: Cross validated out-of-sample evaluation. Mincer-Zarnowitz regression (MZ), Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE), Correlation (CORR) between forecasted and actual values.

Out-of sample (obs 364)	**POOL**	**FE**	**RE**	**DPD**
MZ – a	0.001	-0.001	0.000	0.004
MZ- p value	68%	85%	97%	12%
Var(res)	0.094%	0.106%	0.103%	0.039%
MSE	0.0009	0.0011	0.0010	0.0004
RMSE	0.0306	0.0326	0.0321	0.0201
MAE	0.0219	0.0241	0.0236	0.0129
MAPE	1.7165	1.9617	1.8959	0.7811
CORR	0.6902	0.6454	0.6544	0.8963
Post sample (obs 31)	**POOL**	**FE**	**RE**	**DPD**
MZ - a	0.025	0.030	0.028	0.045
MZ- p value	20%	6%	9%	0%
Var(res)	0.501%	0.345%	0.367%	0.202%
MSE	0.0055	0.0042	0.0043	0.0020
RMSE	0.0740	0.0650	0.0660	0.0442
MAE	0.0413	0.0369	0.0362	0.0312
MAPE	0.9696	0.7083	0.7185	1.0989
CORR	0.4209	0.7549	0.7393	0.9603
Post, Out-of sample (obs 4)	**POOL**	**FE**	**RE**	**DPD**
MZ - a	0.058	0.035	0.040	0.083
MZ- p value	27%	22%	22%	9%
Var(res)	0.752%	0.195%	0.274%	0.467%
MSE	0.0090	0.0027	0.0037	0.0102
RMSE	0.0949	0.0516	0.0607	0.1011
MAE	0.0736	0.0415	0.0482	0.0825
MAPE	1.4219	0.7600	0.8558	1.2945
CORR	0.9865	0.9987	0.9974	0.9922

Table 5: Diebold – Mariano competing forecast accuracy equality test. (* p<0.005, ** p<0.01, * p<0.05)**

Out-of sample (obs 364)	
DPD-POOL	-11,76***
DPD-FE	-12,89***
DPD-RE	-12,76***
POOL-FE	-4,23***
POOL-RE	-3,89***
FE-RE	4,4***
Post sample (obs 31)	
DPD-POOL	-1,54
DPD-FE	-1,01
DPD-RE	-0,87
POOL-FE	1,55
POOL-RE	2,32*
FE-RE	0,72
Post, Out-of sample (obs 4)	
DPD-POOL	1,14
DPD-FE	2,39**
DPD-RE	2,17*
POOL-FE	1,81
POOL-RE	1,58
FE-RE	-1,51

Figure 1: Dispersion chart of Non – Performing Loans to Fiscal Policy and Macroeconomic Indicators.

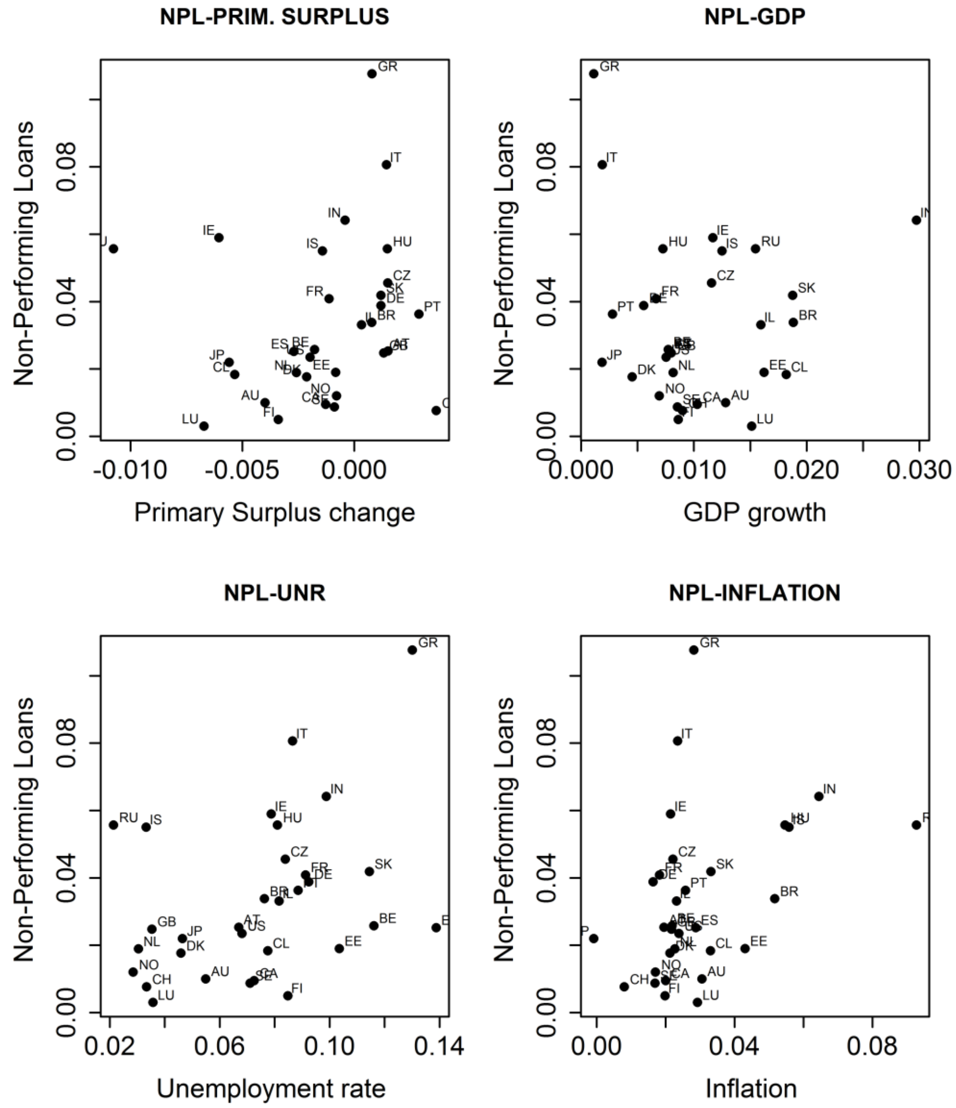


Figure 2: Dispersion chart of Non – Performing Loans to Public Debt Policy, Sovereign Yield and change in Private Debt to GDP.

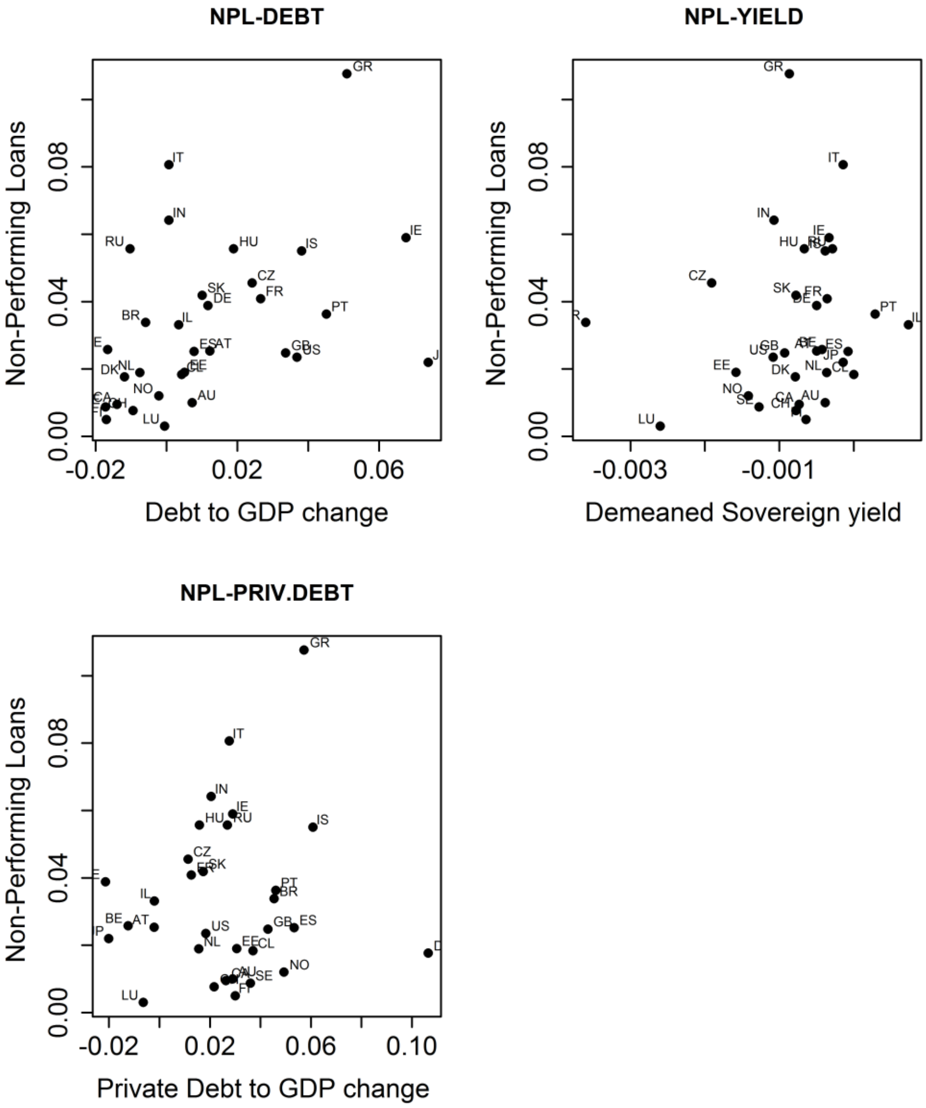
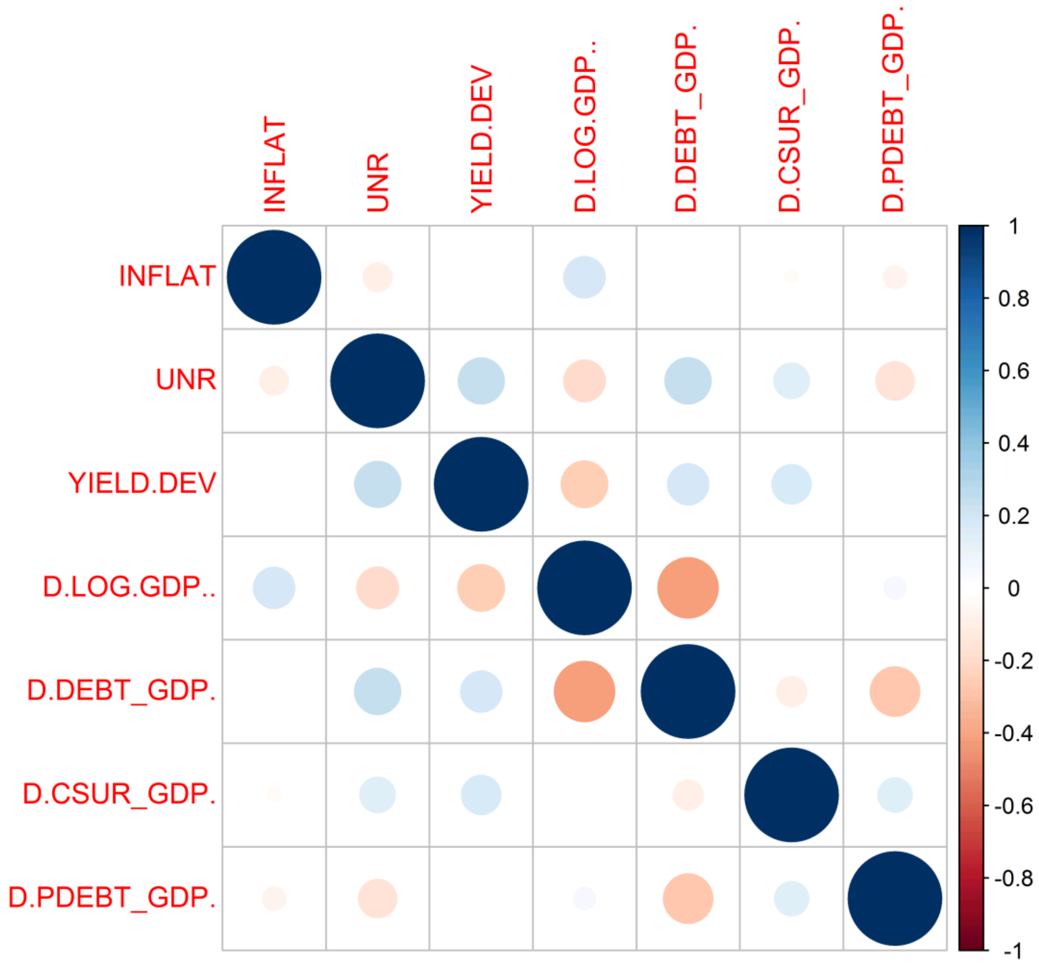


Figure 3: Cross correlation matrix of regressors



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