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Macro-Financial Linkages and Heterogeneous Non-Performing Loans Projections: An Application to Ecuador

By Francesco Grigoli, Mario Mansilla, and Martín Saldías

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Macro-Financial Linkages and Heterogeneous Non-Performing Loans Projections: An Application to Ecuador[1]

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Abstract

We propose a stress testing framework of credit risk, which analyzes macro-financial linkages, generates consistent forecasts of macro-financial variables, and projects non-performing loans (NPL) on the basis of such forecasts. Economic contractions are generally associated with increases in NPLs. However, despite the common assumption used in the empirical literature of homogeneous impact across banks, the strength of this relationship is often bank-specific, and imposing homogeneity may lead to over or underestimating the resilience of the financial system to macroeconomic woes. Our approach accounts for banks' heterogeneous reaction to macro-financial shocks in a dynamic context and potential cross-sectional dependence across banks caused by common shocks. An application to Ecuador suggests that substantial heterogeneity is present and that this should be taken into account when trying to anticipate inflections in the quality of portfolio.

JEL Classification Numbers: C53, E44, G21

Keywords: banks; cross-sectional dependence; heterogeneity; macro-financial linkages; non-performing loans; stress test

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I. INTRODUCTION

One of the legacies of economic crises is the surge in nonperforming loans (NPL) in the financial system. The empirical literature unambiguously uncovered the negative relationship between economic activity and asset quality, both for advanced and developing economies.[2] Even with appropriate macro-prudential regulation, the impact of a deteriorating economic cycle on the accumulation of NPLs is almost unavoidable. In turn, persistently high impaired assets pose significant challenges for policy makers as they threaten financial stability by jeopardizing the solvency of the system and slowing credit growth or affecting its quality. Thus, from the perspective of policy makers, regulators, and supervisors, accurately stress testing the resilience of the financial system's loan portfolio to a deterioration in economic growth, and assessing whether shocks would have a systemic impact is critical, as it provides information to anticipate recapitalization needs, elaborate financial regulation changes, and develop crisis preparedness tools.

There is a number of arguments that can explain NPL behavior via economic activity. Economic downturns are often accompanied by higher unemployment, which affects the ability of debtors to service their debt, ultimately leading to an increase in NPL. In contrast, economic growth allows households and corporations to keep their finances buoyant and stay current in their debt payments, which is reflected in higher quality of banks' loan portfolio. At any rate, changes in the macroeconomic context may take time to affect credit quality owing to many factors, including financial sector dynamics. For instance, NPL may increase sometime after the slowdown in economic activity as borrowers draw down savings to face payments. In some cases, financial crises were preceded by credit booms which, due to the accounting effect in the ratio, were accompanied by unusually low NPL ratios that upon the cycle reversal resulted in a delayed NPL response to the downturn. Also, the observed rise of NPL ratios may occur with a lag because some banks may concentrate lending in sectors which typically enjoy a grace period.

While the literature generally assumes that the impact of economic activity on NPL is homogeneous across banks, in reality these are likely to be affected heterogeneously by lower economic activity (and other shocks). For example, if some banks concentrate their lending into sectors whose performance is not correlated with GDP, the relationship may not be as strong. Alternatively, if real GDP growth is concentrated in a specific sector and a given bank has a well-diversified portfolio, it may not suffer the impact of economic contractions as much. In other words, the homogeneity assumption could severely bias the results, possibly leading to an over or underestimation of the extent to which a negative shock to economic activity could translate into a systemic financial crisis. Similarly, looking at the aggregate series of NPL for evaluating recapitalization needs can be problematic, as capital cannot be reallocated across banks.[3] At the same time, the presence of common shocks (e.g., the global financial crisis or

[2] See for instance Espinoza and Prasad (2010), Mwanza (2011), and Laeven and Valencia (2012) for empirical evidence across countries using alternative empirical approaches.

[3] This is less of a concern when disaggregating across business lines (or loan types) for a given bank, as capital can be reallocated.

financial sector regulations affecting all banks) could generate correlation across banks, making the cross-section independence hypothesis assumed in the literature unrealistic.

This paper proposes a three-stage stress testing framework to conduct credit risk assessments based on an econometric approach that takes into account dynamics, heterogeneity, and cross-sectional dependence (CSD). We present an application to Ecuador, which case is particularly interesting as the country is currently suffering from a worsening of its economic conditions due to mix of external and domestic shocks. The results identify the presence of macro-financial linkages, with interrelations and feedback effects between real and financial variables. Under July 2016 oil projections, the forecasts for GDP growth are expected to negatively affect the NPL ratio.[4] For the average bank, the short-run increase in NPL associated with one percentage point (pp) fall in real GDP growth is 0.15 pp, while the long-run effect reaches 0.55 pp. This would more than double the weighted average NPL ratio for the financial system over the next two years. However, such weighted average hides considerable heterogeneity, with banks reaching an NPL ratio between 2 and 15 percent over the next two years. Such segmentation could help increase effectiveness and accuracy to crises prevention efforts by helping supervisors focus on institutions that are more sensitive to cyclical fluctuations, especially those with relatively lower balance sheet buffers.

The rest of the paper is organized as follows. Section II places the paper in the literature on solvency stress testing, reviewing the main contributions in the literature. Section III presents the recent economic developments in Ecuador and shows some stylized facts. Section IV discusses the econometric approach and presents the results. Section V concludes.

II. LITERATURE REVIEW

Top-down credit stress testing has become increasingly popular over the past twenty years. Financial institutions as well as supervisory authorities periodically assess vulnerabilities to adverse macro-financial scenarios to evaluate the resilience of the financial system. Similarly, this stress testing approach has become common in multilateral surveillance, and has been widely used in the aftermath of the global financial crisis in macro-prudential assessments and to boost market confidence in advanced economies at the peak of the crisis.[5] It generally comprises four components.[6] The first is the macro-financial scenario design; the second looks at the impacts of the designed scenarios on banks' performance; the third consists of a solvency

[4] More favorable oil price projections would change the GDP forecasts and therefore the projected NPL ratios. With illustrative purposes, we use the most current oil price projections (July 2016) at the moment in which the paper is written.

[5] For instance, the Fed's Supervisory Capital Assessment Program in 2009 and the Committee of European Banking Supervisors in 2009 and 2010 conducted for the first time the so-called crisis stress tests (Ong and Pazarbasioglu, 2013) as an overall strategy to rebuild public confidence in a banking system in the aftermath of global financial crisis. They set the stage to use this type of stress tests as a tool in financial crisis management

[6] See Foglia (2009) and Henry et al. (2013) for a comprehensive overview of stress testing techniques across countries and recent developments.

(continued…)

calculation module; and the fourth analyzes the contagion and feedback effects. This paper focuses on the first two elements, carrying out a solvency stress test along the lines of Vazquez et al. (2012) and Wezel et al. (2014).[7, 8]

The macro-financial scenario design is usually based on statistical modeling. Jones et al. (2004) discusses advantages and disadvantages of structural models, including assumptions and restrictions. An alternative is the use of the vector autoregressive (VAR) models (or their vector error correction representation), which are sometimes preferred for their flexibility, smaller set of requirements, and ease of interpretation, as suggested by Åsberg and Shahnazarian (2008). Examples of these models are Hoggart et al. (2005), Van den End et al. (2006), Bank of Japan (2007), Jiménez and Mencía (2007), Vazquez et al. (2012), and Beck et al. (2013), where the selection of variables depends on the country's characteristics. A similar approach is the global VAR (GVAR) used by Castrén et al. (2008) and Haldane et al. (2007), in which domestic and foreign variables interact simultaneously. However, data requirements associated with this technique often turn out to be prohibitive and weak erogeneity assumptions are required.[9] A third approach to modeling macro-financial linkages is a pure statistical one based on simulations (Boss et al., 2006), which has the advantage of allowing for differences between marginal and multivariate distributions and changes in the correlation in stress scenarios. However, by nature it has limitations for policy analysis.

The models to map the macro-financial scenarios into stress scenarios at bank level can be divided into models based on borrower-level data and models assessing loan performance (Čihák, 2007). The former demands extensive information on the default risk at the household and corporate sector levels, and as a result is less common. The latter is often relying on NPL data (or loan loss provisions and default rates), and can be run at different degrees of aggregation (economy-, sector-, region-, or bank-level data, depending on availability). Our approach belongs to the latter group of models, given data availability for Ecuador.

Generally, the econometric approaches for loan performance rely heavily on panel data estimations of the determinants of loan impairment. The estimation technique ranges from ordinary least squares (OLS) with or without fixed effects, static and dynamic, and employing instrumental variables and cointegration techniques, to GMM-based methods (Arellano and Bond, 1991; Blundell and Bond, 1998). Applications of these sorts have the advantage of allowing for an easy mapping of the macro-financial forecasts and accommodating short samples

[7] As for the third and four elements, we do not provide results in terms of capital adequacy ratios for this paper but they can be easily obtained by applying assumptions on loan loss provisions, and the analysis of contagion and feedback effects is beyond the scope of the paper.

[8] See Drehmann et al. (2010) for an integrated approach for both solvency and interest rate risk.

[9] While VAR models (and their variations) are extensively used, many authors expressed concerns about the inability of these models to capture non-linearities.

(continued…)

and a large number of units. Recent examples are Vazquez et al. (2012) for Brazil and Wezel et al. (2014) for a small open economy with a large banking sector.[10]

The methods used in the literature only accommodate heterogeneity across banks by using fixed effects and do not commonly deal with issues of CSD caused by common shocks. However, both issues are likely to be present in bank-level data and impose a bias in the estimates if not accounted for. As an example, Memmel et al. (2014) show that common factors in Germany can represent a significant portion of credit losses. To address this issue, Pesaran et al. (2006) and Henry et al. (2013) propose using GVAR models, which require both the number of financial institutions and the timespan to be large. While being more flexible, these method requires large cross-section samples that are not generally available for emerging markets.

In the case of Ecuador, the dataset consists of a relatively small sample of banks and a somewhat long sample. Banks have different sizes in terms of assets, and they are heterogeneous in terms of their financial conditions and their ability to withstand shocks. Also, a high degree of cross-section dependence is likely to be present in the data, as banks are concentrated in certain credit segments (e.g., corporate and consumption) and at times geographically (e.g., coastal areas, possibly specialized in attending clients operating in the fishing or tourism sector).[11] An appropriate statistical method would then require to address CSD while keeping the model suitable for a relatively smaller cross-section dimension, and address heterogeneity across banks.

III. STYLIZED FACTS

In recent years Ecuador's economy and its financial system have come under pressure due to the combined fallout of two significant shocks: (i) the oil price fall, and (ii) a real appreciation of the US dollar. Figure 1 presents a series of charts that depict this deterioration. As shown in the top left panel, real GDP growth has been highly correlated with the real oil price over the past years, even if oil price movements affect the Ecuadorian economy with some delay. As of the end of 2015, real GDP growth fell to about zero percent.

Since 2004, average NPL declined substantially from about 10 percent to less than 4 percent before the global financial crisis. When the crisis hit, NPL rebounded to above 5 percent, but declined again thereafter. With the end of the commodity supercycle, NPL started to rise again and are now above the levels observed in the aftermath of the global financial crisis. During the first quarter of 2016, NPL reached 3.9 percent. The top right panel contrasts the NPL ratio with real GDP growth, and clearly depicts a negative correlation.[12]

The Ecuadorian banking system is highly concentrated and composed by small, medium, and large banks, and the asset quality varies considerably across them. The middle left panel shows

[10] Vazquez et al. (2012) additionally applies the model to disaggregated credit loan portfolios by economic activity and then compute aggregate NPL ratios for each bank and the whole system.

[11] For an account of concentration across credit lines, see Camacho et al., 2015.

[12] Negative correlation is even stronger when looking at non-oil real GDP growth, however, real GDP growth is preferred here because it is generally the measure used for generating forecasts by the authorities.

the median NPL ratio, along with the inter-quartile range and the 10th and 90th percentiles. At the beginning of the sample, only 10 percent of the banks had NPL ratios above 12 percent, but the median was as low as 6 percent. The deterioration started in 2014 presents much narrower bands around the median compared to previous critical periods, suggesting that NPL increased for all banks. The median NPL in the first quarter of 2016 reached 5.8 percent, close to the historical maximum in the sample.

Starting in early 2015, commercial banks experienced steady deposit withdrawals that lowered significantly their liquidity buffers. As suggested by the co-movement of real deposit and credit growth rates in the middle right panel, banks reacted by rationing credit. Interestingly, the real credit growth series seems to follow the deposit growth path with some delay, suggesting that banks have been able to lower lending in light of falling deposit levels. In this regard, the recent economic deterioration is not an exception.

At the same time, heterogeneity across banks in terms of deposit and credit growth is substantial. The lower left and right panels present the real credit growth and real deposit growth dispersion, respectively. These panels indicate that changes in real deposits and credit have become more homogeneous over time. However, while the recent fall in deposits has been a common factor to all banks, real credit growth varied, and for more than 10 percent of banks it was still above 10 percent.

IV. RESULTS

In this section we first describe the empirical strategy, and then present the results of the estimations.

A. Econometric Approach

We frame the empirical strategy in three stages. The first stage models the macro-financial linkages for Ecuador and generates forecasts that account for feedback effects between the real and the financial sectors. The second stage consists of a bank-level panel data estimation of the impact of real and financial variables on NPL. The third stage builds on the first two and simulates bank-specific NPL responses to the forecasted dynamics.

In the first stage, we estimate a VAR(p) representation of the macro-financial linkages by ordinary least squares (OLS) method for the aggregate financial system:

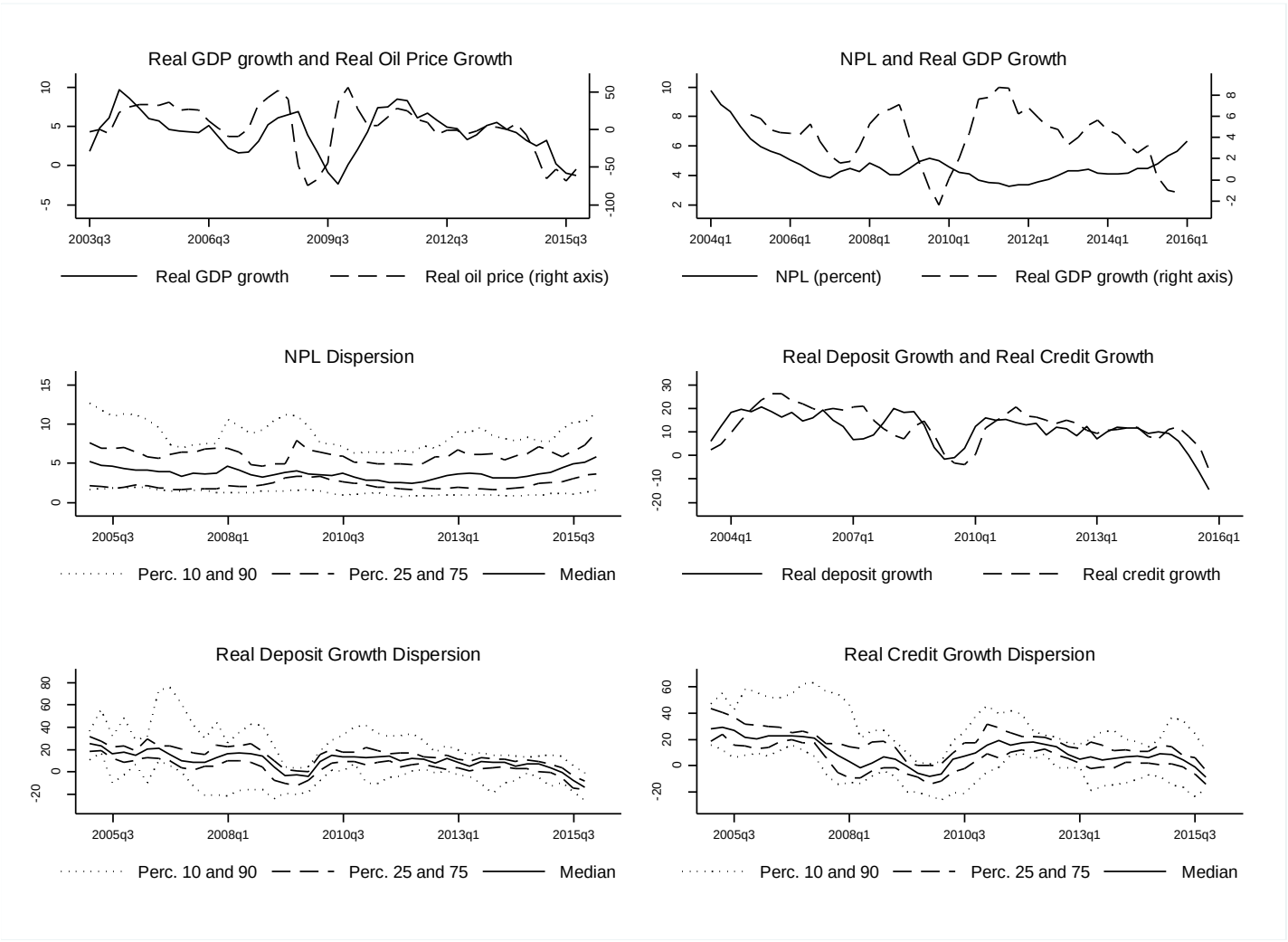
$$z_t = b + \sum_{j=1}^{p} D_j z_{t-j} + \sum_{j=1}^{p} F_j x_{t-j} + e_t \qquad (1)$$

where the vector z_t includes real GDP, real credit provided by private banks, and real deposits of private banks (all in logs); x_t denotes the exogenous variable (log of) real price of oil; b is a vector of intercepts; D and F are a matrix and a vector of coefficients, respectively; and e_t is a zero mean white noise vector of errors. Such parsimonious specification captures the linkages between real and financial variables, allowing for exogenous shocks coming from changes in real

oil prices. In the case of Ecuador, oil prices are a proxy of liquidity in the financial system through exports and through fiscal revenues.[13] We embed inflation in the system by expressing deposits and credit in real terms.

Figure 1. Variables' Correlation and Dispersion

(Percent, yoy, unless otherwise specified)



Source: Authors' calculations.

With variables integrated of order one, and in absence of cointegration, the VAR can still be estimated provided that the eigenvalues lie within the unit circle, i.e. the dynamic system is stable. We can recover the structural VAR (SVAR) representation from the reduced form in equation (1):

[13] Vazquez et al. (2012) include the yield curve slope in the model to account for relevant monetary policy shocks in Brazil, Bank of Japan (2007), Beck et al. (2013), and Hoggart et al. (2005) include stock prices, nominal or real exchange rates, and lending interest rates. Owing to Ecuador's full dollarization, capped interest rates, and a bank-based financial system, these variables do not add information to the model.

$$A_0 z_t = \alpha + \sum_{j=1}^{p} A_j z_{t-j} + \sum_{j=1}^{p} F_j x_{t-j} + \varepsilon_t \quad (2)$$

where ε_t is a vector of shocks. As shown in Fernández-Villaverde et al. (2005), since $A_j = A_0 D$ and $\varepsilon_t = A_0 e_t$, the mapping between e_t and ε_t is given by $e_t = A_0^{-1}\varepsilon_t$.

Given that A_0^{-1} contains nine parameters and we only have six distinct covariances in $\sum_e$, we need to impose restrictions on contemporaneous relations between variables. Thus, we assume the following Cholesky decomposition, with the variables set in the aforementioned order:

$$A_0^{-1} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{23} & a_{33} \end{bmatrix} \quad (3)$$

Such restrictions are plausible and have a sound economic meaning. Consistent with the stylized facts described above, the ordering of the variable assumes that real shocks affect the financial sector within the same period, and in particular, that increases (withdrawal) in deposits are reflected in credit expansion (rationing) during the same period. Thus, the impulse response functions help depicting the relationships among the endogenous variables of the VAR model and therefore the macro-financial linkages at work in the economy.

Finally, we generate forecasts of the endogenous variables, conditional on the evolution of the exogenous one. In other words, we obtain consistent projections for real GDP, real deposit, and real credit (and their growth rates) for a two-year horizon based on the IMF-World Economic Outlook (WEO) projection for oil prices.

The second stage of the empirical approach relies on a bank-level panel dataset of NPL to quantify the sensitivity of NPL to changes in macro-financial conditions. In particular, we model the growth rate of the logistic transformation of NPL for bank i at time t, $y_{i,t}$, with the following Autoregressive Distributed Lag (ARDL) specification:[14]

$$y_{i,t} = \alpha + \sum_{k=1}^{n} \beta_k x_{t-k} + \sum_{k=1}^{n} \delta_k z_{i,t-k} + u_{i,t} \quad (4)$$

where x_t is the real GDP growth and $z_{i,t}$ denotes the bank-specific variables real deposit growth and real credit growth; β and δ are the relative coefficients; α is the constant term; n is the maximum number of lags; and ε_{it} is the idiosyncratic disturbance term assumed to be independent across banks and serially uncorrelated. Other variables, including real salaries, real GDP growth of trading partners, and global interest rates resulted non-significant and were

[14] In line with Vazquez et al. (2012) and Wezel et al. (2014), we apply the logistic transformation to the NPL ratio $y_{i,t} = ln\left[n_{i,t}/\left(1 - n_{i,t)}\right)\right]$, where $n_{i,t}$ is the NPL ratio, to create an unrestricted variable to be used in the regression and therefore avoid non-normality of the error term.

dropped from the specification. The parsimonious model allows to create a direct mapping with the variables used in the first stage of the analysis.

We estimate equation (4) using pooled ordinary least squares (POLS) applied to the panel sample of quarterly observations, correcting standard errors for heteroskedasticity and autocorrelation. Such specification also deals with endogeneity by excluding the contemporaneous terms of the independent variables. However, this estimation suffers from other econometric issues: lack of dynamics, omitted variable bias, parameter heterogeneity across banks, and CSD.

Dynamics of the dependent variable are likely to be an important factor in the estimation because NPL is generally persistent. Thus, we specify a target adjustment model $y_{i,t} - y_{i,t-1} = (1-\gamma)(Y_{i,t} - y_{i,t-1})$, where γ is the adjustment parameter. Thus, if $\gamma = 0$, then $y_{i,t} = Y_{i,t}$, meaning that the adjustment takes place immediately. We then introduce dynamics in the following equation:

$$y_{i,t} = \alpha + \gamma y_{i,t-1} + \sum_{k=1}^{n} \beta_k x_{t-k} + \sum_{k=1}^{n} \delta_k z_{i,t-k} + u_{i,t} \quad (5)$$

where an incomplete adjustment for which $\gamma \neq 0$ leads to a form of state dependence where $y_{i,t-1}$ determines $y_{i,t}$. The omission of the lag of the dependent variable would result in unobserved heterogeneity from the correlation between $y_{i,t-1}$ and $y_{i,t}$ To further address the omitted variable bias, we modify equation (4) to include bank-specific fixed effects (OLSFE).

Most of the empirical literature in this area addresses endogeneity concerns by estimating some version of the Generalized Method of Moments (GMM) estimator (Vazquez et al., 2012; Klein, 2013; Wezel et al., 2014), instead of allowing for lagged effects. The difference GMM estimator assumes that the idiosyncratic error is serially uncorrelated and that past values of the endogenous variables are not correlated with the current error. These conditions allow the use of the second lag (and higher) of the dependent variable as instruments for its first lag, and second (and higher) lags of endogenous variables as instruments for the endogenous variables. Blundell et al. (2000) and Bond et al. (2001) show that the difference GMM estimator has poor finite sample properties and that the estimator performs weakly in samples with limited time dimension and when the dependent variable is persistent. Thus, Arellano and Bond (1991) and Blundell and Bond (1998) propose the system GMM (SGMM) estimator, which increases efficiency by estimating a system of two simultaneous equations, one in levels (with lagged first differences as instruments) and the other in first differences (with lagged levels as instruments). This estimator requires the additional identifying assumption that the instruments are exogenous to the fixed effects. Thus, we estimate the following equation with the asymptotically more efficient two-step SGMM:

$$y_{i,t} = \alpha + \gamma y_{i,t-1} + \sum_{k=0}^{n} \beta_k x_{t-k} + \sum_{k=0}^{n} \delta_k z_{i,t-k} + c_i + u_{i,t} \quad (6)$$

where c_i represents the unobserved bank-specific heterogeneity.[15]

All models discussed so far (and generally employed in the literature on NPL determinants) neglect parameter heterogeneity, which is likely to be a major issue in the data at hand. Pesaran and Smith (1995) and Haque et al. (1999) show that in cross-country panel data the assumption of slope homogeneity may not hold, and this leads to inconsistency of the estimates. Thus, they propose the mean group (MG) estimator for stationary panels by Pesaran and Smith (1995), which accounts for parameter heterogeneity and constructs simple mean estimates across the estimates derived from separate bank regression.

In addition, Phillips and Sul (2007) show that if CSD exists across units, then estimated parameters may be significantly biased and identification problems may be present. To deal with this, Pesaran (2006) present the common correlated effects MG (CCEMG) estimator, and Eberhardt and Bond (2009) and Eberhardt and Teal (2010) propose the augmented MG (AMG) estimator, both of which account for parameter heterogeneity and CSD, albeit in a different way. The CCEMG estimator augments the regression equation with cross-section averages of dependent and independent variables (to be interpreted as nuisance), as a way to control for the unobserved common factors, while the AMG regards the unobserved common factors as the common dynamic process and estimates it in two steps. First, it estimates a pooled difference OLS model with time dummy variables and saves the estimated coefficients as the common dynamic process. Second, the common dynamic process is added to the regression equation either by subtracting it from the dependent variable (I-AMG) or by including it in each of the bank-specific regressions. Finally, both for the CCEMG and the AMG estimators, bank-specific estimates are averaged as in Pesaran and Smith (1995). In this paper, we estimate the following equation using the AMG estimator:

$$y_{i,t} = \alpha_i + \gamma_i y_{i,t-1} + \sum_{k=1}^{n} \beta_{i,k} x_{t-k} + \sum_{k=1}^{n} \delta_{i,k} z_{i,t-k} + d_i \hat{\mu}_t^{\bullet} + u_{i,t} \quad (7)$$

where the vector $\hat{\mu}_t^{\bullet}$ contains the quarter dummy coefficients extracted from the pooled regression in first differences.

In the third and last stage of the empirical strategy, we follow Vazquez et al. (2012) and project NPL two years out of sample. While the AMG estimation of equation (7) provides the average coefficients α, β_k, δ_k, and d, the VAR provides a consistent set of forecasts for x_{t-k} and z_{t-k} that account for macro-financial linkages. Furthermore, we assume the common dynamic factor

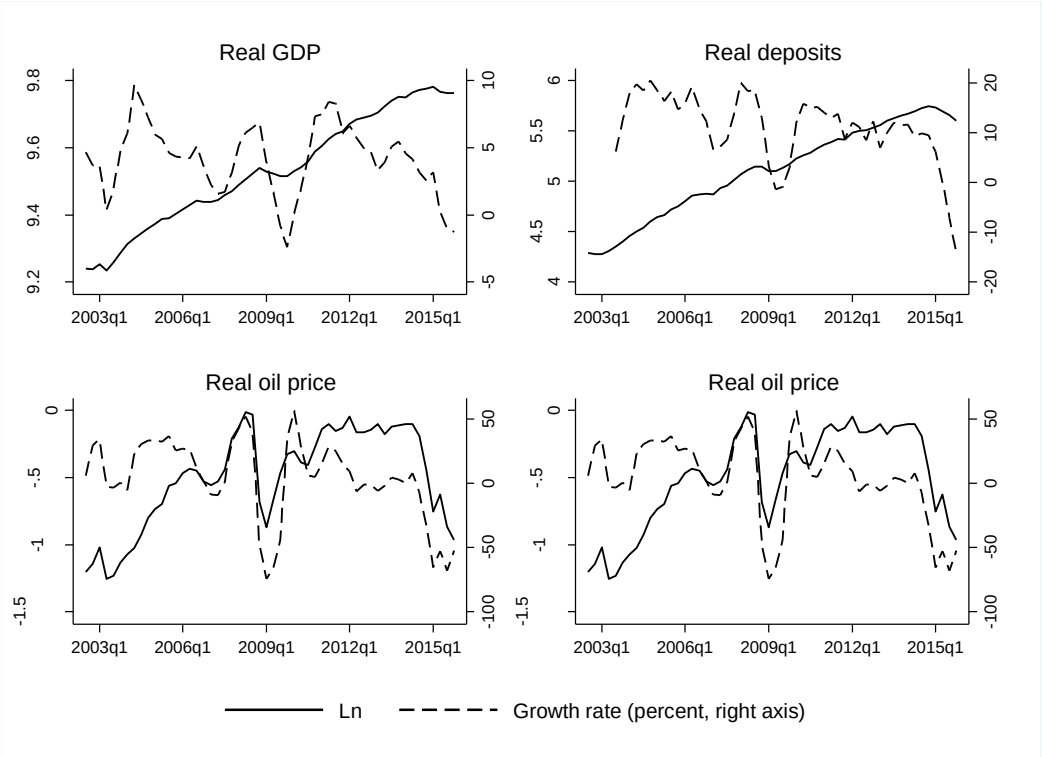
[15] The two-step variant presents estimates of the standard errors that tend to be severely downward biased (Arellano and Bond, 1991; Blundell and Bond, 1998). However, we implement the finite-sample correction of the two-step covariance matrix derived by Windmeijer (2005), which produces unbiased standard errors.

$\hat{\mu}_t^{\bullet}$ to maintain the same value as in the last observed period. Bank-specific NPL projections are then averaged using the stocks of credit as weights.

B. Analysis

We start by analyzing the stationarity properties of the series used in the VAR model.[16] Our sample starts in the third quarter of 2002 and extends to the fourth quarter of 2015. Figure 2 plots the logs of real GDP, real deposits, real credit, and real oil price, as well as the first differences in percent. A visual inspection suggests that first differences are stationary, while levels appear to be integrated of order one. We formally test for the presence of unit root with the augmented Dickey Fuller (ADF) test. In particular, we perform the tests excluding deterministic components, including the intercept, and including the intercept and a trend. The results corroborate the findings of the visual inspection.[17] Namely, variables in levels are non-stationary, while the first differences are stationary. Despite the presence of unit roots, however, the series in levels do not cointegrate.[18]

Figure 2. Stationarity of VAR Series



Source: Authors' calculations.

[16] All variables are seasonally adjusted using Census X-13.

[17] See Table A1 in Appendix II.

[18] See Table A2 in Appendix II.

(continued…)

Conventional tests reveal that the VAR model is well specified. Standard information criteria are used to select the lag length of the VAR. The likelihood-ratio test statistic, the final prediction error, the Akaike's and the Hannan and Quinn information criteria suggest two lags, while the Schwarz's Bayesian information criterion and suggests one lag.[19] Therefore, we opt for two lags. Despite the absence of cointegration, a VAR can still be specified in levels as long as it is stable. The test for VAR stability reveals that the eigenvalues lie in the unit circle.[20] While the normality of the residuals is not required for the generation of the impulse response functions (IRFs), these have still to be serially uncorrelated. Thus, we perform a Lagrange multiplier test and the Portmanteau test, which do not reject the null of no autocorrelation.[21]

We then estimate the IRFs, which describe the interactions among real GDP and financial variables over three years, thereby providing a picture of the macro-financial linkages. We first analyze the response of real GDP. As shown in Figure 3, real GDP reacts contemporaneusly to shocks in its level, and the effect tends to be persistent. A positive shock to deposits has a significant and short-lived impact on real GDP, as the effect dies out after six quarters. Finally, real GDP does not show a significant reaction to real credit.[22] We now turn to responses of real deposits. A one-standard deviation shock to real GDP produces an increase in real reposits that lasts about two years. The impact of real deposits on itself is strongly significant and takes longer than three years to set in. Shocks to real credit generate a short-lived significant effect on real deposits, which becomes insignificant after eight months. Finally, we analyze responses of real credit. A one-standard deviation shock to real GDP has a significant effect on real credit only after three quarters, and it lasts for about three years. Real credit also reacts positively to shocks in real deposits, however in this case the effects is immediate, and also sets in after three years. Finally, a shock in real credit has an immediate and short-lived effect on itself, as it phases out in three quarters.

Finally, we proceed to generate forecasts for the endogenous variables of the VAR model. The forecasts are conditional on the expected oil price projections of the IMF-WEO over 2016-17, and provide a consistent set of estimates that take into account the feedback effects among real and financial variables. Figure 4 presents the forecasts in growth rates. Under current oil price assumptions, real GDP growth is projected to remain in negative territory through the end of 2017, albeit recovering above current levels from the trough in the last quarter of 2016 due to higher projected oil prices. Real deposit growth is projected to continue falling until mid-2016 and recover thereafter. Real credit growth presents a somewhat delayed fall with respect to real deposits, hitting the bottom at the end of 2016.

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[19] See Table A3 in Appendix II.

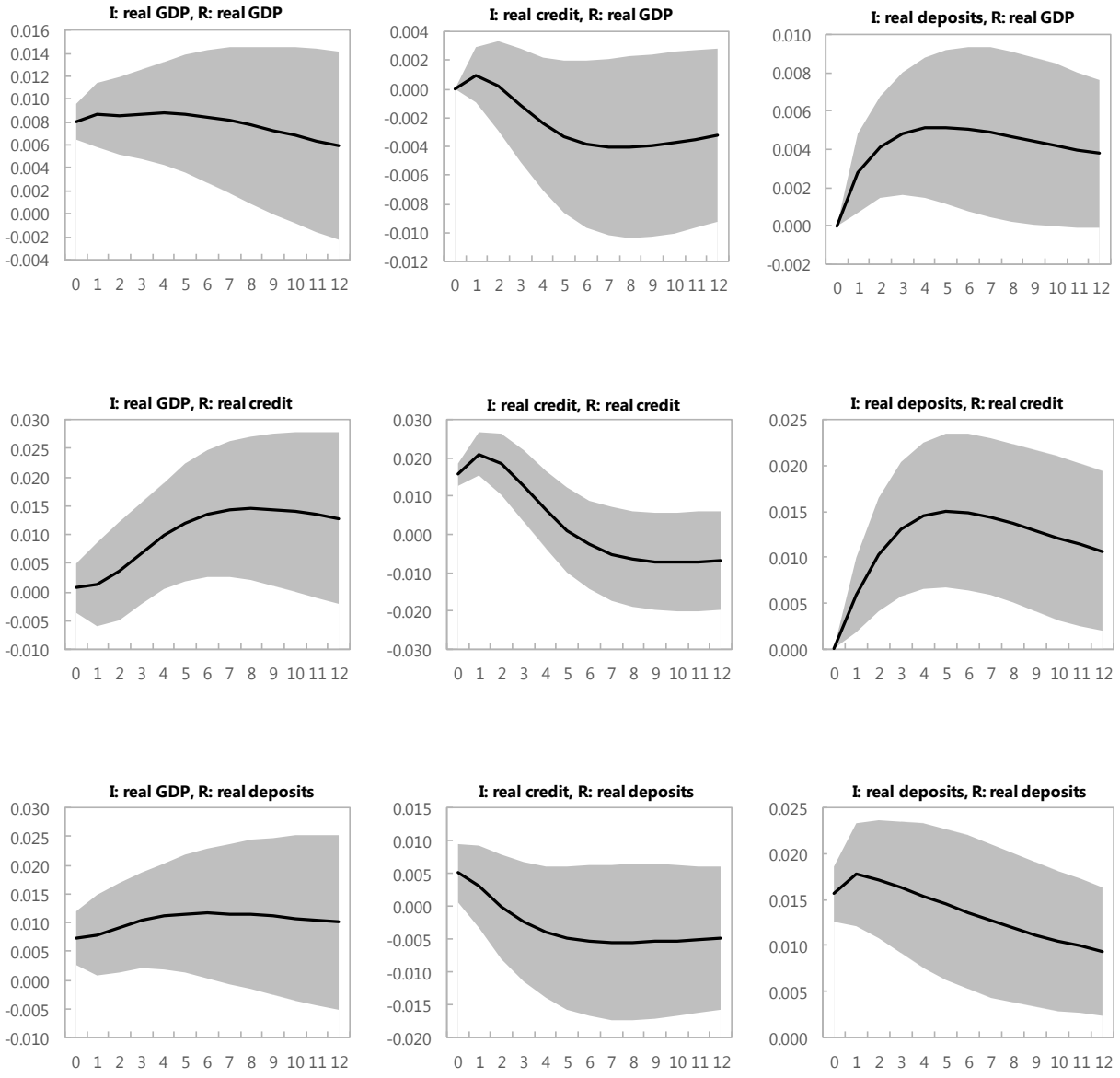
[20] See Table A4 in Appendix II.

[21] See Table A5 in Appendix II.

[22] This counterintuitive result might be associated to the fact that real deposits dynamics anticipate real credit ones, as shown in the previous section. Granger causality tests also confirm that changes in real deposits anticipate changes in real credit.

Figure 3. Macro-Financial Linkages

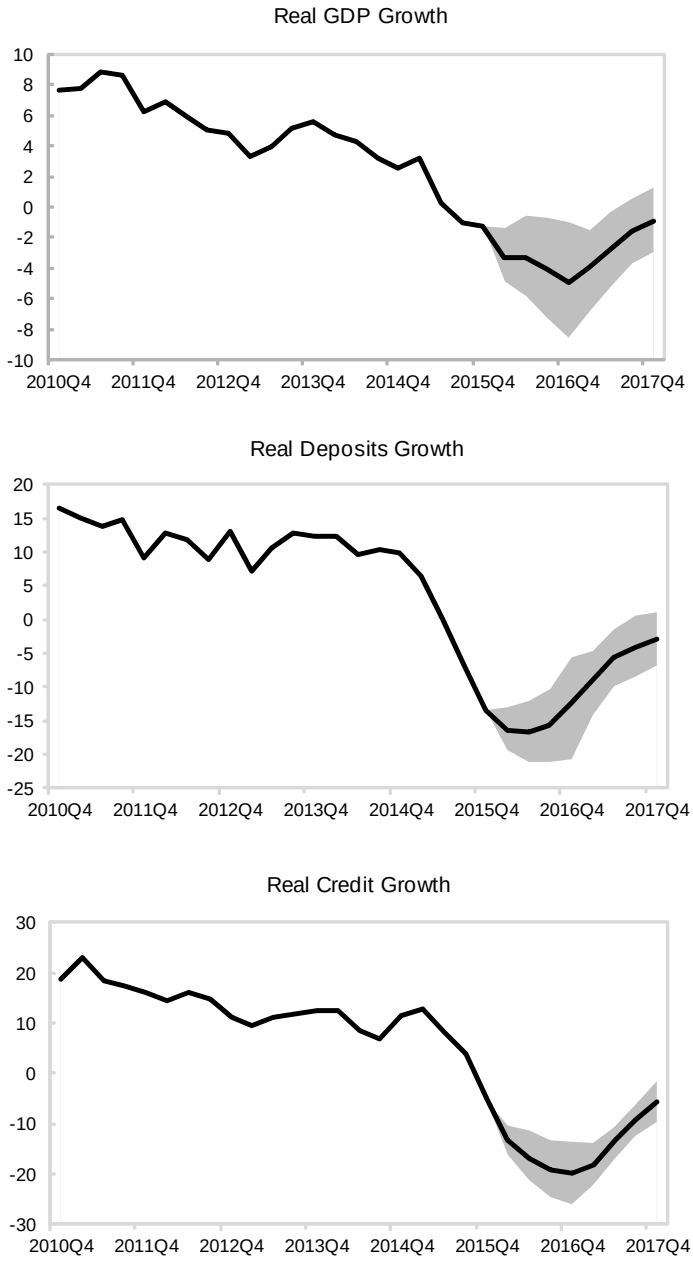
(Quarterly responses to one-standard deviation shocks with two-standard-deviation confidence intervals)



Source: Authors' calculations.

Figure 4. SVAR Conditional Forecasts

(Forecast in percent, yoy, with one-standard-deviation confidence intervals)



Notes: Forecasts are conditional on the IMF-WEO oil price projections.
Source: Authors' calculations.

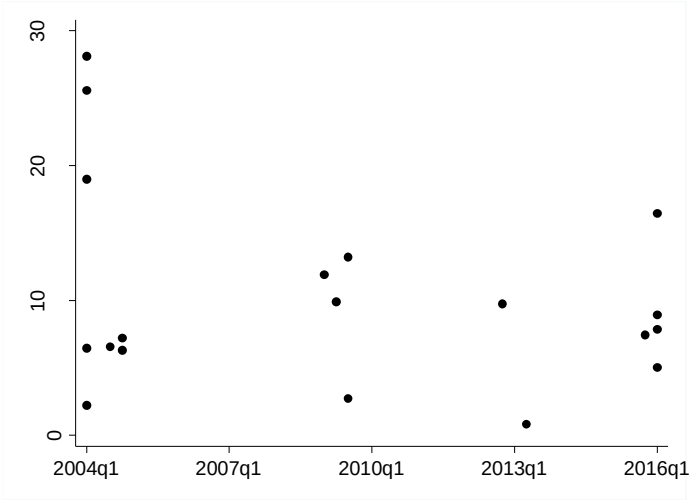
We now move to the second step of the analysis, which analyzes the relationship between the macro-financial variables and NPL using a bank-level panel dataset.[23] For this purpose, we rely on a sample that covers 22 banks over the decade 2005-15.

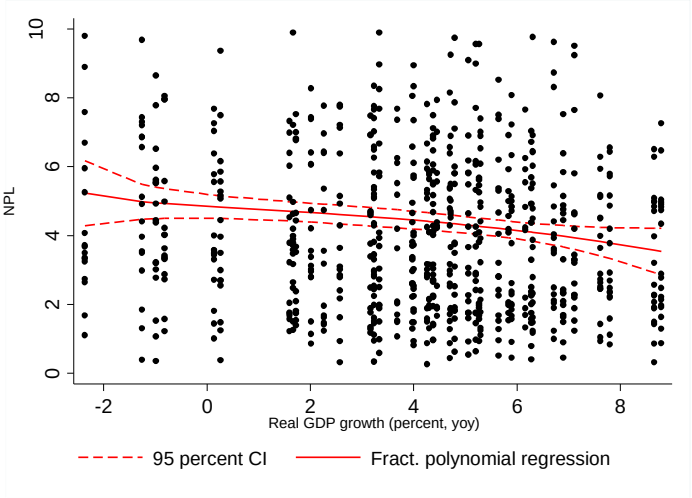
Common shocks in this context can be both external (e.g., the global financial crisis) and domestic (e.g., financial regulation changes affecting all banks) and, if not appropriately accounted for, can cause CSD, which can bias the parameters of interest (Philips and Sul, 2003; Andrews, 2005). Non-linearity can be observed if the deterioration in NPL accelerates when real GDP growth surpasses certain thresholds. For example, one could argue that NPL would increase faster when real GDP growth is in negative territory, or that the relationship would flatten out for high levels of real GDP growth. Similarly, it is very likely that banks react differently to shocks in real GDP growth. For example, as banks concentrate their lending into sectors whose performance is not necessarily correlated with GDP, the relationship may not be strong. Also, if real GDP growth is concentrated in, say, oil-related sectors and a given bank has a well-diversified portfolio, it may not suffer real GDP growth decelerations.

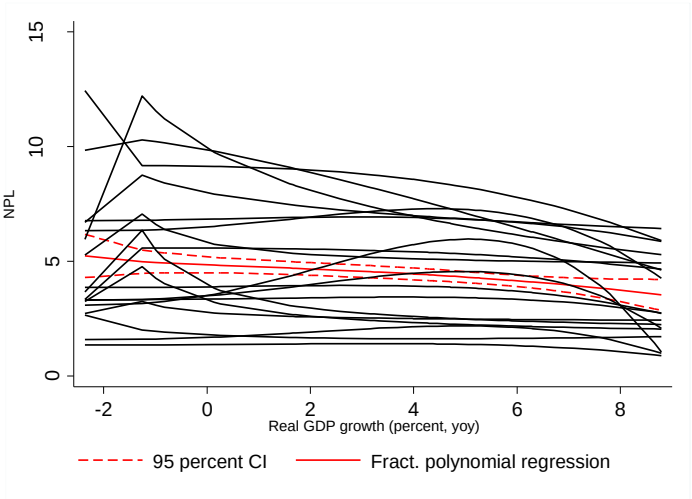
Figure 5 illustrates the potential for the distorting effects arising from common shocks, non-linearity, and CSD in the dataset. The upper panel shows the maximum NPL ratio by bank over time. There is a clear clustering around specific dates which can be associated to common shocks, e.g. the global financial crisis in 2009 and the recent worsening of economic conditions in 2016. While this is only a *prima facie* evidence, it suggests a remarkable presence of common shocks. The mid panel depicts a fractional polynomial regression line (along with a 95 percent confidence interval) for NPL against real GDP growth. While this descriptive analysis is highly stylized and there are other factors beyond real GDP growth that affect NPL, it still suggests that non-linearity is less of a concern for our dataset. Finally, the lower panel plots the same fractional polynomial regression for every bank, as a way to test whether departing from the assumption of homogeneous parameters is justified. The chart illustrates well the potential for misspecification in the NPL-real GDP growth relationship, and suggests that heterogeneous parameters need to be introduced.

[23] NPL, real deposit growth, and real credit growth are available at monthly frequency. We seasonally adjusted the monthly data using Census X-13 and calculated quarterly averages to match the frequency of the GDP series.

Figure 5. Relationship between NPL and Real GDP Growth
(Percent)







Notes: In the mid panel the maximum of the horizontal axis has been set to 10 o
ease the visual inspection of the data.
Source: Authors' calculations.

Table 1 presents the results of the panel estimations. Column 1 shows the results of the static POLS. In Column 2 we control for the persistence of NPL by adding its lag, and we also introduce bank-specific fixed effects to deal with omitted variable bias. In column 3, we report the results of the SGMM, which addresses endogeneity using a different instrumentation technique.[24] In Column 4, we allow for parameter heterogeneity using the MG estimator. Finally, in Columns 5 and 6 we also account for CSD. Column 5 presents the results using the AMG-I estimator, and Columns 6 using the AMG estimator. Our preferred model is presented in Column 6 for which the results from the empirical tests (Pesaran, 2004) suggest that CSD is effectively removed. Three of the 22 banks representing the private financial sector in Ecuador are dropped from the dataset due to their very short time series. Depending on the estimator used, the number of observations ranges between 704 and 718. In the case of the AMG estimators, a fourth bank is dropped due to the estimation technique.

Unsurprisingly, the results present some commonalities and some differences across estimators, consistent with the idea that they address progressively a larger set of econometric issues. The lag of the dependent variable is always significant, suggesting persistence in NPL. Real GDP growth is a strong determinant of NPL. In all estimations, the first lag of real GDP growth is negative and significant. The second lag is generally not significant, but in our preferred model that controls for CSD, it still has a negative and significant impact. The third lag is always positive but not always significant, suggesting some quick reversal following a shock. The results for other variables are not consistent across estimators, but the coefficients present much smaller magnitudes.[25]

The ARDL specification allows retrieving the short-run and the long-run impact. More formally, the former is calculated as $\sum_{k=1}^{n} x_{i,k}$, while the latter is equal to $\sum_{k=1}^{n} x_{i,k}/(1-\alpha)$. Figure 6 presents an overview of the average impact of a one pp shock in real GDP growth on NPL, calculated at the NPL ratio observed in 2016Q1 for every bank and using bank-specific coefficients. It is clear that the impact can be different by bank and that, in some cases, it contravenes theory. In our case, for example, the short-run and the long-run effects are counterintuitively positive in four banks, albeit close to zero. Bank-specific coefficients should be interpreted as merely indicative as individual estimates may provide weak signals, while averages represent very plausible estimates (Boyd and Smith, 2002; Baltagi et al., 2003).[26] Relying on average coefficients, we can calculate a rule of thumb in the case of Ecuador, for which in the short run NPL will increase by 0.15 pp for every pp fall in real GDP growth, while in the long run NPL would increase by 0.55 pp.

[24] Ideally, the SGMM specification could include the contemporaneous lags of the independent variables as long as the set of instruments is valid and exogenous. In any case, the results of the SGMM estimation should be taken with caution as the numbers of instruments is higher than the groups.

[25] Additional lags of the independent variables do not significantly change the results.

[26] Boyd and Smith (2002) also note that if there are omitted variables in units' estimates which are correlated with the observed covariates, these will lead to bias in these individuals' estimates of the observed covariates. However, averaging estimates across units would cancel out biases. The issue, however, will persist if the omitted variable bias is structural across all units of the panel.

Table 1. Panel Regressions Results

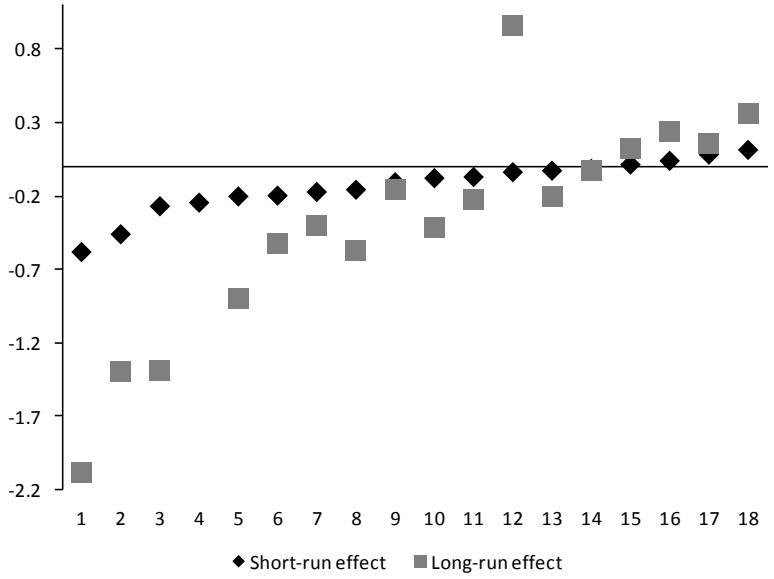
(Dependent variable: logistic transformation of NPL)

VARIABLES	(1) POLS	(2) FEOLS	(3) SGMM	(4) MG	(5) AMG-I	(6) AMG
Lag dependent variable	.	0.884***	0.943***	0.805***	0.676***	0.724***
	.	(0.016)	(0.021)	(0.050)	(0.050)	(0.046)
Lag real GDP growth (yoy)	-0.028*	-0.016***	-0.020***	-0.013**	-0.057***	-0.036***
	(0.014)	(0.003)	(0.005)	(0.005)	(0.005)	(0.008)
2nd lag real GDP growth (yoy)	-0.002	0.003	0.006	-0.005	-0.036***	-0.018**
	(0.010)	(0.005)	(0.007)	(0.009)	(0.008)	(0.007)
3rd lag real GDP growth (yoy)	0.006	0.011**	0.007	0.013**	0.052***	0.028***
	(0.012)	(0.004)	(0.006)	(0.006)	(0.006)	(0.007)
Lag real deposit growth (yoy)	-0.005**	-0.002***	-0.002***	-0.004**	-0.002	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
2nd lag real deposit growth (yoy)	0.002	0.002**	0.002*	0.003**	0.002**	0.002*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
3rd lag real deposit growth (yoy)	-0.002	-0.000	0.000	-0.001	-0.002*	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag real credit growth (yoy)	-0.001	0.002**	0.001	0.001	0.001	-0.000
	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)
2nd lag real credit growth (yoy)	0.001	-0.000	0.000	0.003*	0.003*	0.003**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
3rd lag real credit growth (yoy)	0.002	-0.001	-0.002*	-0.002	-0.003**	-0.002*
	(0.004)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Common dynamic factor	.	.	.	.	.	0.307***
	.	.	.	.	.	(0.085)
Constant	-3.204***	-0.378***	0.137	-0.588***	-0.847***	-0.671***
	(0.159)	(0.053)	(0.211)	(0.164)	(0.197)	(0.107)
Observations	718	716	716	716	716	704
Banks	.	19	19	19	18	18
Lags/instruments	.	.	1/21	.	.	.
AR(2) *p*-value	.	.	0.880	.	.	.
Hansen *J*-test *p*-value	.	.	0.154	.	.	.

Notes: Standard errors in parentheses are corrected for heteroskedasticity and autocorrelation of the error term. AMG estimations correct for cross-sectional dependence. The SGMM estimation uses a collapsed instrument matrix and performs the Windmeijer (2005) correction of the covariance matrix. The null hypothesis for the Hansen J -test is that the full set of instruments is valid. ***, **, * next to a number indicate statistical significance at 1, 5 and 10 percent, respectively.

Source: Authors' calculations.

Figure 6. Effect of Real GDP Growth Shock on NPL
(Impact of one pp real GDP growth shock evaluated at 2016Q1 NPL ratio)

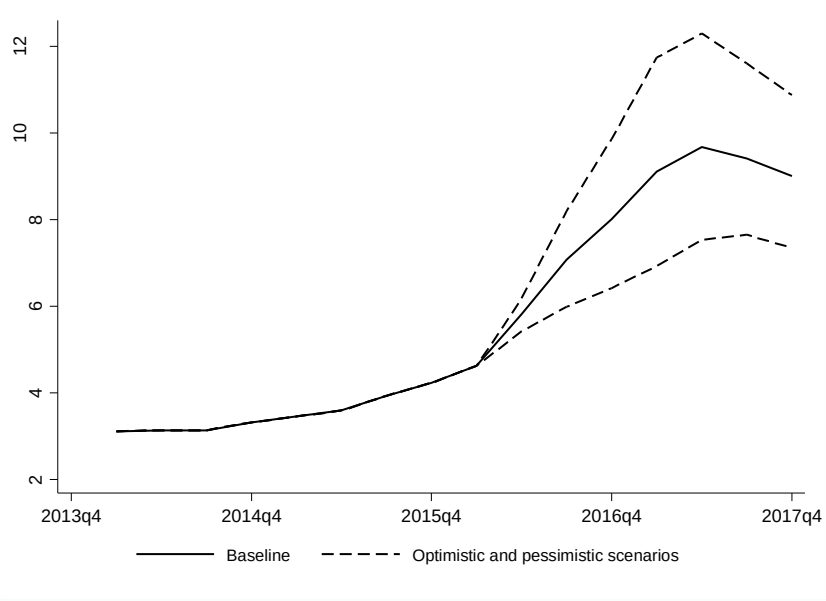


Notes: Banks are ordered by the magnitude of the short-run effect.
Source: Authors' calculations.

We finally move to project the path of NPL weighted average over the next two years. Figure 7 depicts the NPL projection through the end of 2017 using the variables forecasted in the first stage and the coefficients obtained in the second stage. The confidence intervals generated from the VAR estimation are used to project a pessimistic and an optimistic scenario. The results suggest that in the baseline scenario, under the July 2016 oil price projections, NPL may increase from 3.8 percent in March 2015 to 6.4 percent at end-2016 and 9.3 percent at end-2017, peaking up to 9.7 percent during the second quarter of 2017. These results can help authorities to enhance their preparedness against anticipated critical capital needs (or upcoming credit expansions) at the aggregate level.

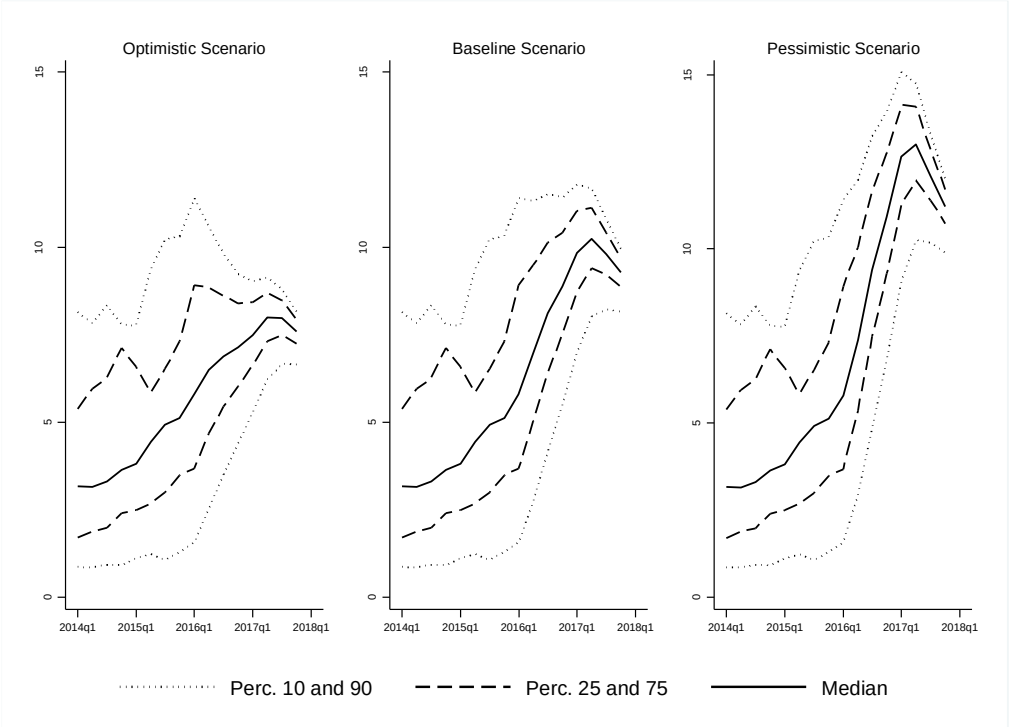
Weighted (or simple) averages hide heterogeneity across banks. Figure 8 shows the deterioration in the financial system for the three scenarios derived from the VAR forecasts. As shown, there is great heterogeneity across banks even under the baseline scenario, in which some banks reach an NPL ratio of almost 15 percent and others do not pass 2 percent. This more granular outcome would allow supervisors to better plan their activities at the micro level and map banks' strategies according to their expected NPLs paths.

Figure 7. Weighted Average of NPL Projections
(Percent)



Notes: Confidence bands of the VAR forecasts are used to build optimistic and pessimistic scenarios.
Source: Authors' calculations.

Figure 8. Heterogeneity in NPL Projections
(Percent)



Source: Authors' calculations.

V. CONCLUSIONS AND POLICY IMPLICATIONS

It is common to observe high NPL ratios during downturns, owing to the contraction in economic activity and the consequent reduced ability of borrowers to service their debt. In turn, high and persistent NPL ratios may eventually affect the stability of the financial system by raising solvency concerns and slowing down credit growth or affecting its quality. It is therefore crucial to measure to the best extent possible the resilience of banks to a worsening in economic conditions.

Stress testing to conduct solvency assessment became increasingly popular over the past twenty years. However, most econometric analyses assume homogeneity and independence across banks. In reality such assumptions are unrealistic due to many factors, including banks' varying degree of specialization and diversification across borrowers and sectors of activity. Such heterogeneity becomes particularly relevant when assessing recapitalization needs, as capital cannot be reallocated across banks, warranting a more granular approach. At the same time, shocks such as global crises or changes in the financial regulation are common to all banks, inducing CSD in the sample.

In this paper, we present an application of stress testing to Ecuador in line with the literature, but accounting for banks' heterogeneous reaction to shocks and CSD. After assessing the dynamics among real and financial variables, we generate forecasts for the same variables. Under July 2016 oil projections, the forecasts for macro-financial variables are expected to negatively affect the NPL ratio. Our results suggest that for the average bank, the short-run effect of a one pp fall in real GDP growth is 0.15 pp, while the long-run effect reaches 0.55 pp. This would more than double the weighted average NPL ratio for the financial system over the next two years. However, such weighted average hides considerable heterogeneity, with banks reaching an NPL ratio between about 2 and 15 percent.

From a policy perspective, this exercise is designed to supplement regular surveillance and provide more granularity to stress testing tools. Being able to appropriately anticipate inflections in the quality of portfolio allows a more efficient surveillance of the financial system, by focusing on the supervisory agenda to protect financial stability, engaging with the banks' management, and requiring mitigating measures in a timely manner, which could comprise additional provisions, new capital, better risk management, selective lending, among others. Also, the methodology presented would allow supervisors to target their efforts across institutions and possibly mitigate systemic risks via regulatory measures (e.g., by imposing generic provisions or enhancing macro prudential measures). Similarly, the methodology could serve to target efforts across different sub-segments of activity. For instance, to the extent information is available, the framework is adaptable to analysis by sector, business line, or region, which can help design and fine tune policy responses. In sum, the framework presented in this paper allows for a better quantification of NPL projections and therefore avoid over or underestimation of systemic risk.

Appendix I. VAR Specification Tests

Table A1. Augmented Dickey-Fuller Unit Root Test for VAR Series

	Levels			First differences		
Variable	No intercept, no trend	Intercept, no trend	Intercept, trend	No intercept, no trend	Intercept, no trend	Intercept, trend
Real GDP	3.546	-1.103	-2.510	-5.799***	-5.905***	-5.953***
Real deposits	2.006	-2.569	-0.157	-6.179***	-6.075***	-7.991***
Real credit	0.761	-1.989	-1.421	-8.206***	-8.093***	-7.991***
Real price of oil	-1.205	-1.951	-1.651	-6.711***	-6.635***	-6.563***

Notes: The null hypothesis is that the series has a unit root. The lagged differences are included in the specifications to obtain white noise residuals. The Schwartz Information Criterion is used to select the optimal lag length. ***, **, * next to a number indicate statistical significance at 1, 5 and 10 percent, respectively.
Source: Authors' calculations.

Table A2. Johansen Cointegration Test

Number of cointegrating equations	Trace Statistic	Max-Eigen Statistic
None	41.003	26.189*
At most 1	14.814	8.443
At most 2	6.370	5.154
At most 3	1.216	1.216

Notes: The null hypothesis is that the series do not have a cointegration relationship. The Schwartz Information Criterion is used to select the optimal lag length. The critical values are from MacKinnon (1991). ***, **, * next to a number indicate statistical significance at 1, 5 and 10 percent, respectively.
Source: Authors' calculations.

Table A3. VAR Lag Selection

Lag	Modified LR Statistic	Final prediction Error	Akaike Information Criterion	Schwartz Information Criterion	Hannan-Quinn Information Criterion
0		4.63E-08	-8.376	-7.898	-8.197
1	363.082	6.24E-12	-17.294	-16.459*	-16.981
2	20.258*	5.33e-12*	-17.465*	-16.273	-17.019*
3	8.234	6.30E-12	-17.324	-15.773	-16.743
4	7.018	7.71E-12	-17.166	-15.258	-16.451
5	8.823	8.78E-12	-17.102	-14.835	-16.253
6	7.055	1.07E-11	-17.004	-14.381	-16.022
7	4.857	1.44E-11	-16.844	-13.863	-15.727
8	10.495	1.44E-11	-17.036	-13.697	-15.785

Notes: * next to a number indicate the preferred lag lenght.
Source: Authors' calculations.

Table A5. VAR Stability

Root	Modulus
0.959518	0.959
0.818237	0.818
0.653693 - 0.131739i	0.667
0.653693 + 0.131739i	0.667
0.106625 - 0.050209i	0.118
0.106625 + 0.050209i	0.118

Source: Authors' calculations.

Table A5. VAR Residual Autocorrelation

	Lagrange Multiplier Test		Portmanteau Test				
Lag	LM Statistic	Prob.	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	9.340381	0.4065					
2	4.528068	0.8734					
3	4.610048	0.8669	10.8677	0.2849	11.36909	0.2513	9
4	8.060404	0.5281	19.34311	0.371	20.55078	0.3027	18

Notes: The null hypotheses of the Lagrange multiplier (LM) and Portmanteau Test is that there is no autocorrelation at the indicated lag. ***, **, * next to a number indicate statistical significance at 1, 5 and 10 percent, respectively.
Source: Authors' calculations.

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