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# Macro Determinants of Nonperforming Loans in Portugal

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**Abstract**

This study uses a VAR methodology to evaluate the impact of the macroeconomic conditions and money supply in the fluctuation of nonperforming loans for the Portuguese economy. Additionally, the feedback effect of nonperforming loans growth to the economy and specially to the credit supply is analised. The study is motived by the hypothesis that loan quality is procyclical and that the fast growth of credit supply has a positive relation with the growth of nonperforming loans. The hypothesis that nonperforming loans reinforce economic fragilities and credit market frictions is also tested. Empirical results corroborate both hypothesis presented. Hence, it was possible to establish that the macroeconomic conditions - measured by GDP and unemployment - and the fast growth of credit supply contribute to the development of nonperforming loans. Furthermore, the growth of nonperforming loans reinforces the economic cycle, as it contributes to the deterioration of macroeconomic conditions and creates frictions in the credit market that may results in a credit crunch.

# 1 Introduction

The macroeconomic conditions following the 2008 crisis have been favourable to the deterioration of the loan portfolio quality and consequently to the increase of the financial system fragilities. This crisis highlighted the necessity to link the macroeconomic conditions to the performance of the financial system. Hence, financial regulators have dedicated considerable attention to macroeconomic stress-testing[1] over the past decade.

Furthermore, the recent crisis has demonstrated that frictions in the credit market and financial system can exacerbate the cyclical fluctuation, contradicting the Modigliani-Miller (1958) theorem in which the financial structure is irrelevant to the real economy outcomes. Thus, those frictions on the credit market - higher number of doubtful loans and bankruptcies, rise of debt burden, declining asset and collateral values and bank failures - are not only a consequence of the downturn but a factor contributing to the economic slowdown. This effect may be materialized directly through the Gross Domestic Product (GDP) or indirectly through the credit supply chain. The direct effect is explained by the probability of higher number of insolvencies, bankruptcies or foreclosures, hindering the aggregate supply. The indirect effect is explained by the credit squeeze that might be felt during recession periods. As credit supply is partially responsible for demand of goods and services a shortening of credit induces aggregate demand to tank. For instance, these frictions have been cited as sources of the economic contractions felt during the Great Depression (Fisher, 1933). In his study the author atributes the severity of the crisis to the high debt burden and subsequent financial distress.

Hence the study of the dynamics of nonperforming loans is a relevant topic[2] as they serve as an indicator of financial imbalances and can contribute to the retrenchment of the economic performance. Moreover, the recent crisis demonstrated the necessity of properly managing credit risk in relation with the macroeconomic environment.

Using a VAR methodology this study evaluates the impact of the economic environment and the money supply on the loan portfolio quality for the Portuguese economy. The proposed hypothesis is that the retrenchment of economic performance and the fast growth of credit supply may translate

[1] Macroeconomic stress-testing refers to the techniques used to evaluate the vulnerability of the financial system to adverse developments in the economy. To a complete review of macro stress-testing methodology see Sorge (2004).

[2] Many authors have considered the importance of nonperforming loans to assess financial system fragilities. Reinhar and Rogoff (2010) show that nonperforming loans can mark the onset of a financial crisis and Diamond and Dybvig (1983) established in their model that a liquidity shock can raise the level of doubtful loans, which may originate bank runs.

into the deterioration of asset quality harming banking performance. Additionally, the feedback effect of nonperforming loans to the economy and especially to credit supply is analysed. The hypothesis that higher levels of bad loans may reinforce the economic cycle is also tested.

The empirical results indicate that the macroeconomic environment and credit supply are key determinants for asset quality fluctuations. Furthermore, results demonstrate that an increase in the growth rate of nonperforming loans creates frictions that exacerbate the macroeconomic vulnerabilities.

The structure of the study is as follows: In the following section a brief analysis of the Portuguese macroeconomic environment and the dynamics of nonperforming loans is presented. The third section summarizes some of the existing empirical literature on the determinants of nonperforming loans. In the fourth section the endogenous variables and the econometrics methodology applied are described. The fifth section discusses the results obtained and presents a robustness check for the VAR model. The sixth section entails a robustness check for the model and the last section concludes this study with some final remarks.

# 2 Nonperforming loans

Ever since Portugal joined the European Economic Community (EEC) – precursor of the European Union – there has been a considerable growth of the financial system. The accession of Portugal was a corner stone for the liberalization and modernization of the financial sector, due to an alignment of the Portuguese legal framework to European law. Furthermore the reshaped legal framework allowed for the entry of new financial intermediaries, either through private initiative or foreign investment. The new paradigm of financial system increased competition which, aligned with favourable economic conditions, provided a new impetus to the credit supply.

Banking activity grew considerably during the last decades, for instance, loans to non-monetary agents went from 77% of GDP in 1997 to 167% in 2008. By 2014 loans to individuals and non-financial corporations reached 170% of the GDP. This rise in debt burden made debtors more exposed to adverse shocks to their income, increasing the likelihood of default. The steep increase in domestic credit was most likely due to a rightward shift of the supply and demand curve. On the demand side, higher expectations of future income provided incentives for firms to invest and lead individuals to smooth their consumption through borrowing. Therefore, the cyclical behaviour of borrower's net wealth is essential to explain the fluctuations of credit supply. Furthermore, the raise in housing prices and the introduction of incentives to mortgage loans, through low interest rates, were also important factors. These conditions made the demand curve shift to the right. As for the supply side, the increasing competition for market share may provide the necessary explanation for this boost. Principal-agent problems can contribute to this expansion, specially for new players, as managers seek higher market share and short-term profitability extending loans to higher risk borrowers.

Additionally, the financial sector was characterized by a high concentration of credit in certain industries. The construction sector accounted for almost 50% of the credit supply by 1997, followed by the wholesale/retail sector with 38%. Nonetheless, this tendency has been inverted and by 2008 only 13.5% and 12%[3] of the loan supply was allocated in each industry, respectively. Overall, by the crisis period, aggregated credit supply was allocated almost evenly among industries[4]. This fact contributed to a reduction of credit risk in the financial sector, taking into consideration that diversification in loan supply and nonperforming loans have a negative relation [5]. As for the credit to individuals, by 1997, 70% of the accumulated supply was allocated in mortgages, with the remaining 30% in consumption loans. By the crisis period mortgage loans increased by 15%, in respect to 1997, reaching 81% of the loan supply and consumption loans were only 19% of the total supply.

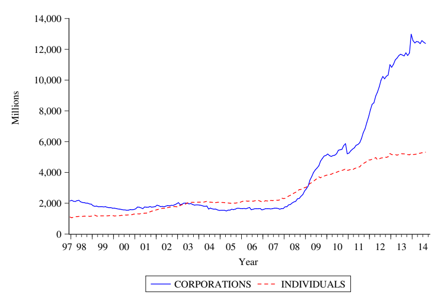



Figure 1: Nonperforming loans for individuals and non-financial corporations

[3]Debt-to-GDP data retrieved from Bank of Portugal.

[4]In 2007 the accumulated credit supply to non-financial corporations was as follow: Real Estate 16%, Construction 15%, Transformation Industry 13%, Wholesale/Retail 12%, Financial Holdings 9% and others 25%.

[5]Salas and Saurina (2002) demonstrated that causality link by using bank size as a proxy for diversification opportunities.

During this period nonperforming loans of household reached a maximum of 2 334 Million Euros by November 2007 while for non-financial corporations the highest value was 2 190 Million by May 1998. For the period comprehended between 2003 and 2008 the non-financial corporations loan quality registered an improvement, reaching an all time low of 1 494 Millions by April 2005. During the same period household nonperforming loans rose above the level registered by non-financial corporations. After the financial crisis of 2008 both indicators exhibit an upwards trend, resulting in an all time high of 12 980 Millions for non-financial corporations in December 2013 and 5 318 Million for households in August 2008. From these values it is clear that the financial crisis had a much harder impact on the level of nonperforming loans for non-financial corporations than for households. The differences observed in the level of nonperforming loans for households and companies might be explained by a higher sensitivity of the latter to the business cycle. Nevertheless, the illustrated behaviour seems to corroborate the notion that the level of credit risk is built up during economic booms and materializes in downturns (Borio and Lowe, 2002).

The economic slowdown felt in Europe after the crisis had a significant impact and by 2014 the EU area average of nonperforming loans ratio spiked to 8%, while before the crisis period it represented less than 3%. This reality was much more evident for countries where the economic deterioration was stronger such as for the so called PIIGS. By 2014 in Portugal the nonperforming loan ratio was estimated to be over 11%, corresponding to an average annual growth rate of 30% since 2008. Italy recorded a value of 17%, a 31% average growth, Ireland 25%, Spain 9%, with an average growth of 192% and 34% respectively and Greece with a record high of 33%, representing an average growth of 900%[6].

Nevertheless, these figures need to be interpreted with caution considering that there is no euro-area wide classification for nonperforming loans which compromises the comparability of the aforementioned values. The distinct national regulation and supervision practices create a bias across different countries. For instances, the Portuguese classification presents a slight downward bias in nonperforming loans classification when compared to other EU countries, due to the fact that only the amount overdue is considered as nonperforming (Barisitz, 2013).

[6]The figures presented for Italy, Ireland and Spain are referent to 2013. Nonperforming loan ratio data retrieved from World Bank.

# 3 Literature review

The literature on the subject has been mainly divided by the type of variables considered to explain the fluctuation of asset quality. The determinants generally included in the models studying loan quality are bank-level, macroeconomic factors or a mix of both. While the former considers a set of bank level variables - idiosyncratic factors - in order to describe asset quality variability, the second takes into consideration variables that measure the macroeconomic environment – systematic factors – regarding those as core drivers of loan quality fluctuation. As for the latter a set of idiosyncratic and systematic factors are consider to explain these fluctuations.

One example of bank level analyses is the work of Salas and Saurina (2002) which studies the effect of inefficiency, measured through the ratio between operating expenses and operating margin, and capital-to-asset ratio on problem loans, for the Spanish financial system. The authors established that while inefficiency exhibits a positive correlation with nonperforming loans, capital-to-asset ratio displays the opposite effect. Furthermore, Berger and DeYoung (1997) and Podpiera and Weill (2008) found that the decrease in cost efficiency entails an increase in nonperforming loans, in line with the "bad management" hypothesis [7]. Other studies conclude that bank-level variables, such as bank size, capital ratio, equity-to-asset ratio, return on equity (ROE)[8], were also significant determinants of loan quality.

In the systematic approach authors consider that macroeconomic conditions affect borrowers' capacity to repay debt, thus affecting loan quality and the performance of the banking sector; such analysis can be recovered in the work of Ali and Daly (2010), Bofondi and Ropele (2011) and Pesola (2005). Hence, macroeconomic variables are often good indicators of loan quality.

One of the main drivers of risk is GDP - an indicator of the cyclical position of the economy. For instance, Baboucek and Jancar (2005) established the relationship between economic cycle and bank risk through an unrestricted VAR model. The empirical results exhibit a negative correlation between GDP growth and nonperforming ratio (nonperforming over total loans), thus an acceleration of GDP lead to a deterioration of the nonperforming loan ratio. In line with these findings, Beck et al. (2013), Fofack (2005) and Blaschke and Jones (2001) also established that as economic conditions worsen, during downturn periods such as recessions, the quality of banks' assets tend to deteriorate. Consequently, the business cycle, and the economic environment emerges as key drivers

[7] This hypothesis links 'bad' management with poor skills in credit scoring, appraisal of pledged collaterals and monitoring borrowers.

[8] The study of such variables can be found in Makri et al. (2014), Klein (2013) and Espinoza and Prasad (2010).

affecting credit quality. Another relevant point is the possible feedback effect stemming from the financial sector to the economy. In order to evaluate this effect, Klein (2013) studied the determinants of nonperforming loans for Central and Eastern and South-Eastern Europe (CESEE), through a VAR analysis. The results demonstrated that an increase in nonperforming loans has a significant impact on credit (measured as total credit as a percentage of GDP), GDP growth, inflation and unemployment with a lag of one quarter. Also in line with these findings, Nkusu (2010) explored the feedback effect of nonperforming loans for 26 advanced economies, through impulse response functions (IRFs) analysis. Both studies found that banking system fragilities and deterioration in economic activity reinforce each other, adversely affecting the economic environment.

Louzis et al. (2011) establishes the link between macroeconomic determinants and nonperforming loans across different loan categories – consumption, mortgage and business – for the Greek economy. This approach enabled the authors to disentangle the impact of the determinants for each type of nonperforming loan. Empirical evidence demonstrated that there are significant qualitative and quantitative differences among the effects of determinants under analysis. For instance, mortgages loans were found to be the least responsive to shifts in macroeconomic conditions. The authors also determined that unemployment was one of the factors influencing all loan categories, in particular business loans. Therefore, a higher unemployment rate leads to an increase of nonperforming loans, considering that it affects borrowers' capability to repay loans, thus affecting asset quality negatively[9] .

Several empirical studies validate the importance of credit supply as a central driver of nonperforming loans. Keeton (1998) has established this hypothesis under the condition that credit growth departures from a supply shift. Such a shift, caused either by an increase in competition or an underestimation of credit risk during expansion periods, induces credit standards to fall, which in turn leads to a rise in nonperforming loans. On the other hand, if loan growth is due to a demand shift, caused for example by an increase in productivity, it may not imply an increase in loan losses. Thus, the author points to a positive correlation between variables, imposing that an increase in credit growth leads to higher loan losses, under a supply shift situation. Other studies analysing the relationship between nonperforming loans and credit growth, such as Festic et al. (2011) and Kiss (2006), also determined the same dynamics found by Keeton. All the aforementioned studies established that the increase in credit supply, alongside with an ease in credit standards, leads to an

[9]Similar results are presented in the work of Gambera (2000) Aver (2008) and Babihuga (2007).

increase in default rates. Nonetheless, a lagged relationship is established, considering nonperforming loans take longer to arise as individuals and companies only experience debt service problems after the first year.

Furthermore, the level of private indebtedness, savings, inflation and the exchange rate were found to have a significant impact on credit risk measures [10].

# 4 Data and Methodology

## 4.1 Data

The analysis in this study uses time-series data drawn from published information of Bank of Portugal as well as from Eurostat[11]. The sample covers monthly data from 1997 to 2014, capturing the dynamics of the Portuguese economy for two distinct periods; economic expansion from 1997 to 2008 and economic contraction from 2008 onwards. Although the data span is limited, it provides the possibility to isolate the specific macroeconomic determinants that drive nonperforming loans for the Portuguese economy.

For this study aggregate indicators are used instead of disaggregate indicators (bank individual data), the choice of aggregate data was made to overcome the risk of non-representativeness of the sample (Boudriga et al. 2009). Furthermore, the choice of variables included in the model reflects the vast empirical literature on the determinants of the loan portfolios quality. Hence this model specification includes four macroeconomic variables, GDP, captured by the coincident indicator of activity (ECOACT)[12], unemployment rate (UNEM), credit supply from monetary financial institutions[13], proxied by the monetary aggregate M2[14] and nonperforming loans of nonfinancial corporations and individuals (NPL). The choice of a parsimonious number of endogenous variables is justified by the fact that this study applies the VAR methodology for which the increase of variables erodes observations rapidly. Additionally a dummy variable was included in the model

[10]Empirical analyses on the impact of the aforementioned determinants can be found in Kaminsky and Reinhart (1999) Rinaldi and Arellano (2006), Festic et al. (2011) and English (1999).

[11]The source of each variable considered is presented in the Table B.1

[12]The coincident indicator of activity is a composite indicator compiled and published by Bank of Portugal. The input series reflect the demand and supply side of the economy, income and the conditions in the labour market. A plot of the coincident indicator of activity and the GDP can be seen in Figure A.1. For details regarding the methodology of the Economic Activity Coincident Indicator see Rua (2004).

[13]The monetary financial institutions considered include universal banks, savings banks, mutual agricultural credit banks and money market funds assets.

[14]M2 comprises deposits with an agreed maturity of up to and including two years or redeemable at a period of notice of up to and including three months. Currency in circulation is excluded.

to account for the financial crisis period. The variable assumes value one from the first month of 2008 onwards and zero otherwise. The dummy was introduced in order to capture the effect of the enconomic deterioration on the growth of nonperforming loans. The descriptive statistics and a detailed list of the variables considered can be found in the appendix (Table B.1 and B.2).

For this study nonperforming loans are considered as defined in article $4^{th}$ notice 3/95 of Bank of Portugal [15]. According to it, nonperforming loans are those with principal or interest 90 days or more overdue or that present a well defined weaknesses, compromising debtor capability to repay the loan, such as the declaration of bankruptcy, or debtor liquidation [16]. The figure below (Figure 2) displays the behaviour of the variables of interest for the sample period.

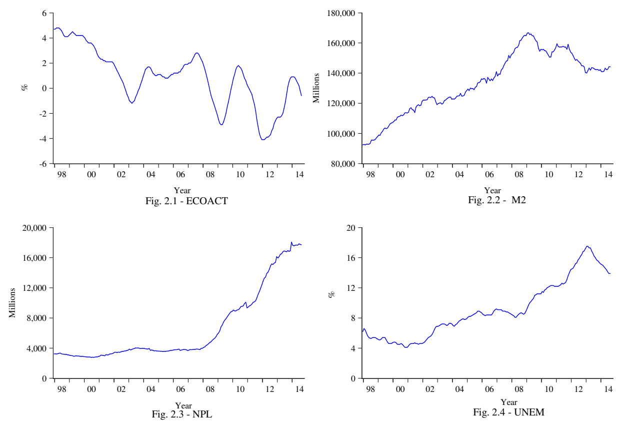



Figure 2: Data description

Figure 2.1 (ECOACT) presents the coincident indicator of activity and as expected it presents a relatively high rate for the years prior to 2000. For the following decade, the economic indicator starts to plunge, describing an irregular pattern from 2008 onwards. Although it records some improvements in economic conditions for the post crisis period, the series entails a significant fluctuation. Thus, a slight downward trend can be identified during this period, considering that the indicator never recovered to values reached by the end of 2007. The indicator reaches a record high of 4.8% in April 1998 and an all time low of -4.1% in January 2012. This series' mean is 0.84%, while it presents a standard deviation of 2.27.

[15] For further information see http://www.bportugal.pt/

[16] The amount registered as nonperforming reflects installments overdue for more than 90 days and amount considered to be of doubtful recovery. To be classified as doubtful, the loans as to present interest and capital arrears exceed 25% of the outstanding capital plus interest fallen due.

Figure 2.2 (M2) comprises the Portuguese contribution for the monetary aggregate M2. It exhibits a clear upward trend from 1997 to 2008 following the credit supply expansion which preceded the financial crisis. From 2008 to 2010 the expansionary trend is reverted. In 2010 there is a short lived improvement which retrenches significantly, thus from 2011 onwards the series decline again shifting to a downward trend. The monetary aggregate reaches 166 823 million Euros, the maximum value for the series, in February 2009 and a minimum of 92 357 by February 1998. The mean corresponds to 133 387 million Euros and the standard deviation to 20 122 millions.

Figure 2.3 (NPL) presents some interesting characteristics worth mentioning. The series exhibits a stable behaviour between late 1997 until 2007. Nevertheless, by 2008 an upward trend emerged which achieved its peak by December 2012, where the amount of nonperforming loans rose above 1 8055 million Euros. These features illustrates the highly cumulative and persistent character of the variable. The record low of 2 774 million Euros was reached in June 2000. Nonperforming loans present a mean of 6 586 million Euros and a standard deviation of 4 774 million.

The last variable, considered in Figure 2.4 (UNEM), describes the evolution of the unemployment rate for the sample period. It follows the expected pattern, in accordance with the phase of the economic cycle. Therefore, the series has a slight downward trend from 1997 to 2000, following the economic cycle and from 2000 onwards, the series has an upward trend, following the deterioration of the economic environment. The unemployment rate reaches an all time high of 17.5% in January 2013 and a record low of 4.1% in December 2000. The series presents an average of 9.1% and a standard deviation of 3.78%.

## 4.2 Model specification

For this study an unrestricted VAR($p$) model was specified as follows:

$$\boldsymbol{y}_t = \boldsymbol{c} + \sum_{j=1}^{p} \boldsymbol{\Phi}_j \boldsymbol{y}_{t-j} + \boldsymbol{\varepsilon}_t \tag{1}$$

where:

- $\boldsymbol{y}_t$ is a vector of endogenous variables
- $\boldsymbol{c}$ is a vector of intercepts
- $\boldsymbol{\Phi}_j$ are the coefficient matrices
- $\boldsymbol{\varepsilon}_t$ is a vector of disturbance terms

As described previously, the purpose of this study is to analyse the determinants that affect loan quality for the Portuguese economy. The choice of endogenous variables included in the model departed from the vast literature on the subject. Nonetheless, this choice was conditioned by the frequency of the data being this another reason bank level factors were excluded from this study. The variables were tested for seasonality and properly adjusted by the X-12 seasonal adjustment method [17].

In order to avoid spurious regressions and determine the level of integration of the time series an Augmented Dickey-Fuller test (Dickey-Fuller, 1979) was performed. Due to the results of the unit root tests, which can be seen in Table B.5, the endogenous variables NPL, Unemployment and Credit were differenced [18]. The lag length structure of the VAR under analysis was chosen based on the AIC information criteria (Akaike 1987). Therefore, a VAR model of order 4 was specified, accordingly to the results displayed in Table B.6. This specification allows for a sufficiently long lag structure in order to capture the well known delayed effects some variables might present. Thus, the vector of transformed endogenous variables is:

$$\boldsymbol{y}_t \equiv \begin{bmatrix} DLNPL_t & DLM2_t & DUNEM_t & ECOACT_t \end{bmatrix}$$

where:

- $DLNPL_t$ - growth rate of nonperforming long
- $DLM2_t$ - growth rate of the monetary aggregate M2
- $DUNEM_t$ - growth rate of unemployment
- $ECOACT_t$ - coincident indicator of activity

Furthermore, the Granger causality tests (Granger, 1969) was performed for the VAR model of length 4. Consequently, the results of the Wald test can be seen in Table 1. As it is possible to observe the endogenous variables, for which the null hypothesis of Granger non-causality was rejected are highlighted. It is relevant to mentioned that the variables for which the null was not rejected were kept in the model given that they do not vary independently of each other (Greene, 2013).

[17] With exception of unemployment all variables were seasonally adjusted.

[18] NPL and Credit were differenced in logarithms. As argued by Friedman and Schwartz (1963) this methodology enables an approximation to the monthly percentage growth.

Table 1: VAR - Granger Causality/Block Exogeneity Wald Tests

| Variable | DLNPL | ECOACT | DLM2 | DUNEM |
|---|---|---|---|---|
| DLNPL | - | 0.5518 | 0.2066 | 0.0187* |
| ECOACT | 0.0377* | - | 0.0010* | 0.2243 |
| DLM2 | 0.4331 | 0.0675** | - | 0.8655 |
| DUNEM | 0.3476 | 0.1711 | 0.1672 | - |
| Joint Wald | 0.0793** | 0.2062 | 0.0000* | 0.0340* |

Note: The null hypothesis in this case is: each variable in the rows does not Granger cause each variable in the columns. Significance levels are denoted as * significant at 5%,** significant at 10%.

The results of the Granger causality demonstrate that, at a 5% significance level, the coincident indicator of activity Granger causes nonperforming loan growth and the growth of credit supply, represented by the variable DLM2. At the same nominal dimension value, the growth of nonperforming loans causes the growth of unemployment. For a 10% nominal level, the credit supply Granger causes the coincident indicator.

As for the joint Granger causality the null hypothesis is rejected for three of the specifications. Thus the growth rate of nonperforming loans (DLNPL) is jointly caused by the remaining variables. Unemployment growth rate (DUNEM) and credit supply growth rate (DLM2) are equally jointly caused by the factors under analysis. Therefore, it is possible to establish that those variables are not weakly exogenous to the model. Regarding the coincident indicator of activity (ECOACT) the null hypothesis of non-Granger Causality is not rejected, being this variable weakly exogenous to the specification. Nonetheless, this variable is included in the model considering it is the closest proxy for the GDP of Portugal.

Granger-causality may not tell the complete story about the interactions between the variables of a system. In applied work, it is often of interest to know the responses of one variable to an impulse in another variable (Lutkepöhl 2005). Therefore, scrutiny of the results was divided in the analysis of the impulse response functions (IRF) and variance covariance decomposition, which can be seen in section 5. The IRF were estimated according to the decomposition of Pesaran and Shin (1998). This method utilizes generalized impulses which do not depend on VAR ordering. Lastly, the IRF confidence intervals were calculated based on the Monte Carlo approach with 100 repetitions. The results presented do not differ substantially from other methods available.

### 4.3 Diagnostic test

A battery of diagnostic tests was performed to ensure the model described the data appropriately and was correctly specified. Notably, the VAR approach requires the residuals to behave like Gaussian white noise. The heteroskedasticity of the residuals was tested through a White's test with cross terms. The null hypothesis of homocedasticity was not rejected at the usual nominal significance levels, thus providing indication of a well specified model.

Furthermore, an Autocorrelation LM test was performed for which the results are presented in Table B.12.1. Examining the serial correlation of the residuals is possible to observe that they are well behaved given that up until the 5th lag the null hypothesis of no serial correlation is not rejected. Additionally, an analysis through the display of pairwise cross-correlograms confirmed the absence of significant residual autocorrelation. Hence, the residuals seem to be independent over time with constant conditional variance. To account for the stability of the model an analysis of the inverse roots of the AR characteristic polynomial was also conducted. The results confirmed the stability of the model as all roots lie within the unitary circle[19].

## 5 Results and robustness test

### 5.1 Results and discussion

In this section a discussion of the results is presented. The analysis focus on the impulse response functions (IRF) and variance covariance decomposition.

Table B.7 presents the results of the VAR model by introducing the estimation output (coefficients, standard errors and t-statistics). As it is possible to observe from the results only a small number of coefficients are significant. According to Sims (1980) this result is to be expected bearing in mind that the VAR approach is not suitable to interpret directly the estimates neither the respective signs between variables due to multicoliniarity. The idea behind a VAR model analysis is to determine the responses of endogenous variables to impulses in other endogenous variable, establishing causality.

Uncovering the IRFs of the variables considered in the model, for a 12-month period, reveals the dynamics between nonperforming loans and the economic environment measured by the coincident indicator of activity, unemployment rate and credit supply. Examining the IRF it is possible to

[19]The results of the AR roots tests, LM Autocorrelation test, White's test and the correlogram are displayed in the appendix.

trace the effect of a one-time shock to the endogenous variables and trace its marginal effects through all equations in the system. Figure 3 presents the IRF, estimated from the VAR model, providing information regarding the dynamic interactions between the macroeconomic determinants and DLNPL according to the decomposition of Pesaran and Shin (1998).

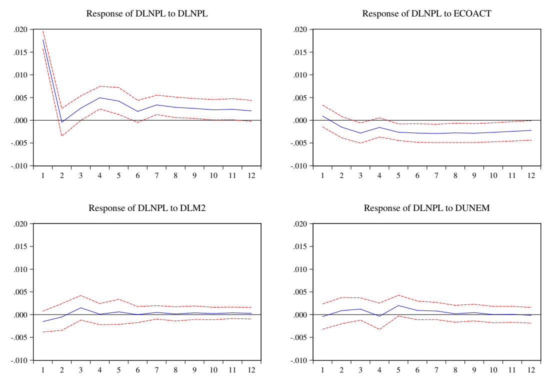



Figure 3: Impulse Response Function

Overall, the empirical results confirm the importance of indicators of general macroeconomic performance as drivers of credit risk fluctuations in the Portuguese economy. Moreover, following the existing literature on the subject, it was possible to verify the procyclical behaviour of loan quality. Thus, in a weak macroeconomic environment, such as recessions or downturns, the level of nonperforming loans tends to increase, while during strong and favourable macroeconomic conditions there is a reduction in the growth of nonperforming loans. The starting point of this analysis is the response of DLNPL to shocks in the remaining determinants.

As suggested by the empirical literature, nonperforming loans have a negative correlation with GDP growth. In this particular case, where the coincident indicator of activity growth served as a proxy for GDP, it was possible to validate this theory. Thus, a positive shock to the ECOACT leads to a negative response by DLNPL. An increase in the coincident indicator captures an economic upturn where cash flows of borrowers are expected to augment allowing them to meet their financial obligations. On the other hand, during a downturn period the coincident indicator registers low values, indicating a reduction of household and companies wealth, making it harder to meet their obligations. From the figure is also possible to see that a shock to DLNPL reinforces itself leading to positive reaction of DLNPL for the following periods.

Moreover, consistent with the existing literature, a positive shock to unemployment growth rate induces the nonperforming loans growth to spike. Thus, confirming the effect of the economic cycle over nonperforming loans, as adverse economic conditions deteriorate loan quality. Therefore, DUNEM exhibits a positive correlation with DLNPL, considering a positive shock in the former variable creates an increase in DLNPL. The unemployment rate is also closely related to borrower's wealth and their ability to serve debt. It affects negatively the future purchasing power of household and individuals and limits the production of goods and services. Hence, unemployment diminishes the cash flows of households and hinders effective demand. This effect causes a loss in non-financial firms' revenue, which in turn increases the debt burden.

The empirical results capture the expected dynamics of nonperforming loans and the macroeconomic background. The deterioration of the economic environment would lead to a drop of the coincident indicator and a rise of unemployment affecting the ability of households and non-financial corporations to serve their debt, undoubtedly increasing the amount of bad loans. With a strong economic growth, the wealth of household and non-financial corporations expands contributing to the decline of nonperforming loans.

As for the effect of the growth of credit supply the results show a positive correlation among the variables. Nonetheless, the effect of a positive shock to the credit supply growth is not clear for the first lags, only exhibiting a clear positive effect after the sixth period. This result is not a surprise considering the well documented lagged effect that credit supply has on nonperforming loans[20]. As a result, a positive shock to DLM2 has an unclear effect on DLNPL for the first five periods following the initial shock. The shock only exerts the expected effect after this initial phase, particularly after the sixth period, where the shock to DLM2 has a positive impact on DLNPL.

The empirical results corroborate the hypothesis that faster credit growth leads to a surge in bad loans. The loan growth effect might be explained by the aforementioned loosening of credit standards of financial institutions, during upturn periods, increasing the chances borrowers default in downturns. Hence the the low quality of the loans extended during upturns materializes during economic contractions. The factors contributing to the reduction of credit standards are two folded; first the increase in competition due to the liberalization of the market and entry of new players reduces standards as more lenders compete for the same business. Second, during expansion periods lenders may underestimate the risk associated with new loans becaming too optimistic about

[20] For a detailed analysis on the lagged effect of credit supply on credit risk view Jimenez and Saurina (2006).

borrowers capability to repay their debts.

As mentioned previously, the estimation of a VAR model was essential to enable the study of the feedback effect of nonperforming loans to the macroeconomic environment and specially to money supply. Hence, the figure below introduces the dynamic interactions of ECOACT, DUNEM, DLNPL and DLM2 to a shock on DLNPL.

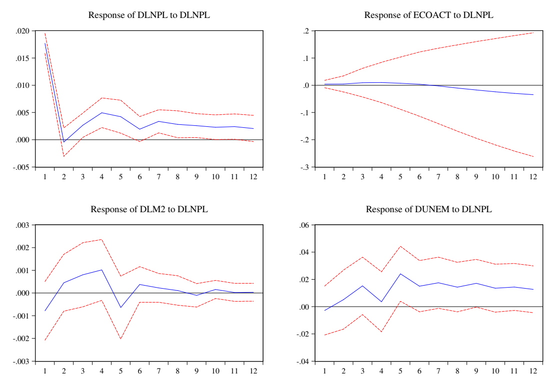



Figure 4: Impulse Response Function to a DLNPL innovation

From the IRF results it was also possible to access the feedback effect from nonperforming loans to the macroeconomic performance. Consequently, nonperforming loans growth has a positive correlation with the unemployment growth rate. Thus a positive shock to DLNPL generates a positive impulse in DUNEM. The feedback effect was fully established through the impulse of the variable ECOACT. A positive shock to DLNPL produces a negative impact in ECOACT. Thus, there is evidence that nonperforming loans growth reinforces the business cycle. Hence, during downturn periods higher growth of nonperforming loans contributes to the worsening of economic conditions. This relation suggests that the default in loans amplify unemployment, most likely through non financial corporations bankruptcies or insolvencies. The second effect described might be explained by the reduction of aggregate supply also caused by nonfinancial corporations bankruptcies.

Moreover, results show that the growth of nonperforming loans has a negative correlation with credit supply growth. Nonetheless, this relationship is not clear for the IRF depicted previously and it is only evident when considering a longer period for the IRF analyses, as in Figure 5. As a result, imposing a positive shock to DLNPL induces the DLM2 to fall but this effect only becomes negative after the $12^th$ period.

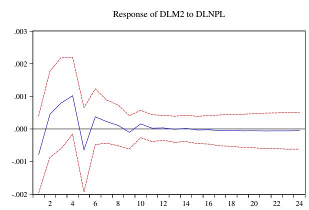



Figure 5: Impulse Response Function

The reduced ability to lend can be explained by the necessity of the financial institutions to adjust their provisions[21] for loan losses, which consumes capital that otherwise would be allocated for more productive purposes[22]. Futhermore the excess of bad loans in the institutions balance sheet might induce the lender to become risk adverse increasing credit standards. Although, it is not possible to disentangle which is the cause of the credit retrenchment, it is clear that the quality of loan portfolio contributes to the level of credit to the economy.

A second model was specified for which the variable Crisis was included to control for the financial crisis period and the structural break detected in the NPL times-series [23]. As expected the dummy variable coefficient as a positive and significant effect over DLNPL in the VAR estimation[24]. These results fall in line with the theoretical expectations and the results presented previously. Consequently, the deterioration of economic conditions harms the capability of borrowers to fulfill their obligations increasing the growth rate of nonperforming loans.

The empirical results obtained confirm the two hypotheses presented. The deterioration of macroeconomic environment and fast growth of money supply contribute to the worsening of credit quality. Furthermore, evidence that the growth of nonperforming loans represses credit supply is presented.

[21] Basel II agreement requires financial institutions to maintain the Tier 1 ratio equal or above 4%. The Tier 1 capital ratio is the ratio of a bank's core equity capital to its total risk-weighted assets (RWA).

[22] For a deeper analysis of the procyclicality of provision requirements see Keating et al. (2001).

[23] The results for the Quandt-Andrews Unknown Breakpoint test are presented in Table B.4.

[24] Estimation results for the VAR model with dummy can be seen in Table B.9.

The variance decompositions for DLNPL is displayed in Table B.11, providing information regarding the importance of each innovation and how it affects the variables in the VAR model. This analysis is limited to the Cholesky orthogonal factorizations, turning the results sensitive to the ordering of the endogenous variables. Therefore, the ordering criteria followed was: (1) NPL; (2) UNEM; (3) M2; (4) ECOACT. This ordering was motivated by the intention to capture the impact of the macroeconomic economic performance and the money supply to the growth of nonperforming loans. Hence, by this ordering criteria NPL is caused by the remaining three endogenous variables. The empirical results are in line with the conclusions for the analysis of the IRF. The economic environment - measured through ECOACT and DUNEM - has an important role in the variation of the nonperforming loans. Furthermore, the growth of credit supply (DLM2) also determines the variation of nonperforming loans, despite the effect being clearly smaller then the economic environment.

## 5.2 Cointegration Tests and VEC specifications

As described above the endogenous variables considered were not all integrated of order 1[25]. Hence, the Johansen Cointegration test (Johansen, 1995) could not be performed for all variables due to their different levels of integration. Nonetheless, it was possible to find two cointegrating relations among the $I(1)$ variables - M2, NPL and UNEM. The results of the Johansen Cointegration test are presented in Table B.7. From this results an error correction model (VEC) was specified in order to properly identify the long-run equilibrium relationship among variables as suggested by the Granger Representation Theorem (Engsted and Johansen 1997). In order to specify the VEC and properly capture the effect of the macroeconomic environment one adjustments was made to the initial endogenous variables. The stationary endogenous variable (ECOACT) was replaced by the Industrial Production Index (IPI)[26] , a integrated variable of order 1, as a proxy of GDP. A comparisson of the two variables can be foiund in the appendix, Figure A.7.

From the model is possible to attest the long run equilibrium of the endogenous variables - NPL, IPI, M2 and UNEM - and the significance of the adjustment effects for all three variables.

[25]See Table B.5 for Dickey-Fuller Augmented test

[26]Industrial production measures the output of businesses integrated in industrial sector of the economy such as manufacturing, mining, and utilities.

Results in Table B.10 indicate that the error correction terms are statistically significant. Hence, the long-run adjustment effect - which measure the speed of covergency to equilibrium - of NPL and M2 are 0,0059 and -0,003 respectively. Such an observation implies that while nonperforming loans respond with a positive variation to a positive equilibrium error, money supply displays the opposite behaviour, responding with a negative variation to a positive deviation from the long-run equilibrium.

The IRFs for the VEC model, presented in Figure A.8, exhibits a distinct behaviour from the one depicted in Figure A.6, considering that the impulses do not stabilize over time as in the VAR model. This is coherent with the non-stationary nature of the endogenous variables. From the same figure it is possible to conclude that the estimated model corroborate the main findings obtained for the VAR specification. LNPL exhibits a positive correlation with LM2 and UNEM and a negative causality link with LIPI. The IRF also confirm the positive relation between past realizations of LNPL and future LNPL. As for the impact of a shock to LNPL the endogenous variables present the same behaviour described previously. Therefore, LIPI and LM2 present a negative correlation, while UNEM has the opposite reaction. The clearer causality link established between LNPL and LIPI might be explained by the closer relationship of the variables of interest. Particularly, an increase in nonperforming loans of non-financial corporations may suggest higher bankruptcies which directly imply a retrenchment of industrial production and consequently a fall of the IPI.

With these empirical results corroborate the notion that the economic performance and the credit supply are relevant indicators of the evolution of nonperforming loans growth. Furthermore, the feedback effect of nonperforming loans to the economy is fully attested.

## 6 Conclusion

The 2008 crisis highlighted the importance to properly accessing the impact of macroeconomic conditions on the financial system vulnerabilities. Most of the literature on the subject has analysed the issue by assessing the impact of macroeconomic determinants on nonperforming loans or nonperforming loans ratio. Nonetheless, these studies usually entail a panel data analysis which may hide the different dynamics between macro conditions and doubtful loans for each country. Hence, this study examined the specific dynamics presented by nonperforming loans in the Portuguese economy.

Empirical results demonstrate that the macroeconomic environment and the credit supply are important drivers of asset quality in this economy. Furthermore findings corroborate the notion that periods of economic contraction - marked by high levels of unemployment and falling GDP - contribute to the growth of nonperforming loans. On the other hand, periods of economic expansion - marked by high GDP and low unemployment rates - imply a deceleration of the growth of nonperforming loans. Moreover, results suggest that credit supply expansion may lead to higher levels of doubtful loans, as riskier loans extended during expansion periods materialize into nonperforming loans in period of economic contraction.

It was also possible to establish that the growth of nonperforming loans entails a feedback effect to the economy. The feedback effect is two folded: firstly the adverse response of economic indicators - GDP and unemployment rate - to a increase in nonperforming loans creates a downward spiral in which economic distress and financial system fragilities reinforce each other. Secondly, the high level of nonperforming loans in banks' balance sheet leads to a retrenchment of the money supply to the economy. This credit squeeze compromises both aggregate demand and the funding of viable investment opportunities.

The findings of this study are relevant to stress testing, carried out by regulatory entities, to assess the vulnerability of financial institutions to a macroeconomic shock. Furthermore, the study highlights the importance of nonperforming loans as a source of frictions in the credit market. Hence, the importance of regulatory frameworks that prevent the formation of high levels of nonperforming loans and consequently the negative feedback loop to the economy is attested.

Further research on the subject may attempt to establish the causality link between macroeconomic determinants and nonperforming loans across different loan categories. This approach enable the study of the different dynamics for each type of nonperforming loan as they might present different responses to macroeconomic shocks. In particular, it would be of interest to disentangle the impact of the macro environment in nonperforming loans of individual and nonfinancial corporations.

## References


[1] Akaike, H. (1987). “Factor Analysis and AIC,” Psychometrika, 52(3), 317–332.

[2] Ali, Asghar, & Kevin Daly. (2010). "Macroeconomic determinants of credit risk: Recent evidence from a cross country study." International Review of Financial Analysis 19.3: 165-171.

[3] Aver, B. (2008). “An empirical analysis of credit risk factors of the Slovenian banking system.” Managing Global Transitions, 6(3), 317-334.

[4] Babihuga, R. (2007). “Macroeconomic and financial soundness indicators: an empirical investigation”. International Monetary Fund, No. 07/115.

[5] Babouček, I., & Jančar, M. (2005). “Effects of macroeconomic shocks to the quality of the aggregate loan portfolio”. Czech National Bank. No 1/15

[6] Barisitz, S. (2013). “Nonperforming Loans in Western Europe–A Selective Comparison of Countries and National Definitions”. Focus on European Economic Integration, (1), 28-47.

[7] Beck, R., Jakubik, P., & Piloiu, A. (2013). “Non-performing loans: what matters in addition to the economic cycle?”. European Central Bank, No. 1515.

[8] Berger, Allen N., & Robert DeYoung. (1997). "Problem loans and cost efficiency in commercial banks." Journal of Banking & Finance 21.6: 849-870.

[9] Blaschke, W., Jones, M., 2001. “Stress testing of financial systems: An overview of issues, methodologies and FSAP experiences”. International Monetary Fund, No. 01/88.

[10] Bofondi, Marcello, & Tiziano Ropele. (2011). "Macroeconomic determinants of bad loans: evidence from Italian banks." Bank of Italy Occasional, No 89.

[11] Borio, C., & Lowe, P. (2002). “Asset prices, financial and monetary stability: exploring the nexus”. Bank for International Settlements, No. 114.

[12] Boudriga, A., Taktak, N. B., & Jellouli, S. (2009). “Banking supervision and nonperforming loans: a cross-country analysis”. Journal of financial economic policy, 1(4), 286-318.

[13] Diamond, D. W., & Dybvig, P. H. (1983). “Bank runs, deposit insurance, and liquidity”. The journal of political economy, 401-419.

[14] Dickey, D. A., & Fuller, W. A. (1979). “Distribution of the estimators for autoregressive time series with a unit root”. Journal of the American statistical association, 74(366a), 427-431.

[15] English, W. B. (1999). “Inflation and financial sector size”. Journal of Monetary Economics, 44(3), 379-400.

[16] Engsted, T., & Johansen, S. (1997). “Granger’s representation theorem and multicointegration”, European University Institute, No. eco97/15.

[17] Espinoza, Raphael A., & Ananthakrishnan Prasad. (2010). “Nonperforming loans in the GCC banking system and their macroeconomic effects”. International Monetary Fund, No. 10/224.

[18] Festić, M., Kavkler, A., & Repina, S. (2011). “The macroeconomic sources of systemic risk in the banking sectors of five new EU member states”. Journal of Banking & Finance, 35(2), 310-322.

[19] Fisher, Irving (1933). “The debt-deflation theory of Great Depression”. Econometrica 1, 337-57.

[20] Fofack, H. (2005). “Nonperforming loans in Sub-Saharan Africa: causal analysis and macroeconomic implications”. World Bank Policy Research Working Paper, No. 3769.

[21] Friedman, M., & Schwartz, A. J. (1975). “Money and business cycles”. In The State of Monetary Economics. NBER, 32-78.

[22] Gambera, M. (2000). “Simple forecasts of bank loan quality in the business cycle”. Federal Reserve Bank of Chicago, SR 2000/3.

[23] Granger, C. W. J. (1969). “Investigating Causal Relations by Econometric Models and Cross-Spectral Methods,” Econometrica, 37, 424–438.

[24] Greene, W. (2003). “Econometric Analysis. New Jersey”: New York University, 5th edition

[25] Jesus, Saurina & Gabriel, Jimenez (2006). “Credit Cycles, Credit Risk, and Prudential Regulation”. International Journal of Central Banking 2: 65-98.

[26] Johansen, S. (1995). “Likelihood-based inference in cointegrated vector autoregressive models”. OUP Catalogue.

[27] Kaminsky, G. - Reinhart, M. C. (1999). “The twin crises: the causes of banking and balance of payments problems”, American Economic Review, vol. 89, 473-500.

[28] Keating, C., Shin, H. S., Goodhart, C., & Danielsson, J. (2001). “An academic response to Basel II”. Financial Markets Group, No. sp130.

[29] Keeton, William R., & Charles S. Morris. (1987). "Why Do Banks Loan Losses Differ?." Economic Review.

[30] Kiss, G., Nagy, M., & Vonnák, B. (2006). “Credit growth in Central and Eastern Europe: convergence or boom?” MNB Working Papers, No. 2006/10.

[31] Klein, Nir. (2013). "Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance.”, International Monetary Fund, No. 13/72.

[32] Louzis, Dimitrios P., Angelos T. Vouldis, & Vasilios L. Metaxas. (2012) "Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios." Journal of Banking & Finance 36.4: 1012-1027.

[33] Lutkepöhl, H. (2005). “New Introduction to Multiple Time Series Analysis”, Berlin: Springer.

[34] Makri, Vasiliki, Athanasios Tsagkanos, & Athanasios Bellas. (2014) "Determinants of non-performing loans: The case of Eurozone." Panoeconomicus 61.2: 193-206.

[35] Messai, A. S., & Jouini, F. (2013). “Micro and Macro Determinants of Non-performing Loans”. International Journal of Economics and Financial Issues,3(4), 852-860.

[36] Nkusu, Mwanza. (2011). "Nonperforming loans and macrofinancial vulnerabilities in advanced economies”. International Monetary Fund, 1/27.

[37] Pesaran, M.H., Shin, Y. (1998). “Impulse response analysis in linear multivariate models”. Economics Letters 58 (17-29).

[38] Pesola, J. (2005). “Banking fragility and distress: An econometric study of macroeconomic determinants”. Bank of Finland Research Discussion Paper, 13.

[39] Podpiera, Jiří, & Laurent Weill. (2008). "Bad luck or bad management? Emerging banking market experience". Journal of Financial Stability 4.2: 135-148.

[40] Rinaldi, L., & Sanchis-Arellano, A. (2006). Household debt sustainability: what explains household non-performing loans? An empirical analysis. EEC Working Papers: 570

[41] Salas, Vicente, & Jesus Saurina. (2002) "Credit risk in two institutional regimes: Spanish commercial and savings banks." Journal of Financial Services Research 22.3: 203-224.

[42] Sims, C. (1980): "Macroeconomics and Reality". Econometrica, Vol. 48.

# Appendix

## A.1 Figures

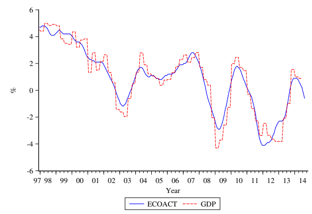



Figure A.1: GDP and ECOACT

Response to Generalized One S.D. Innovations ± 2 S.E.

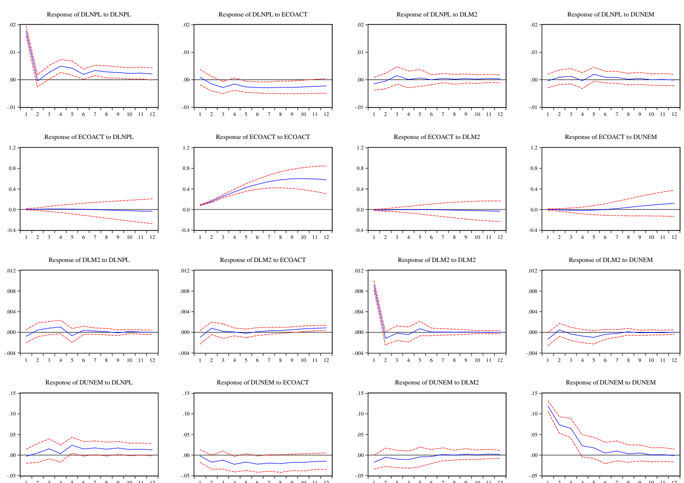



Figure A.2: VAR - Impulse Response Function

Response to Generalized One S.D. Innovations ± 2 S.E.

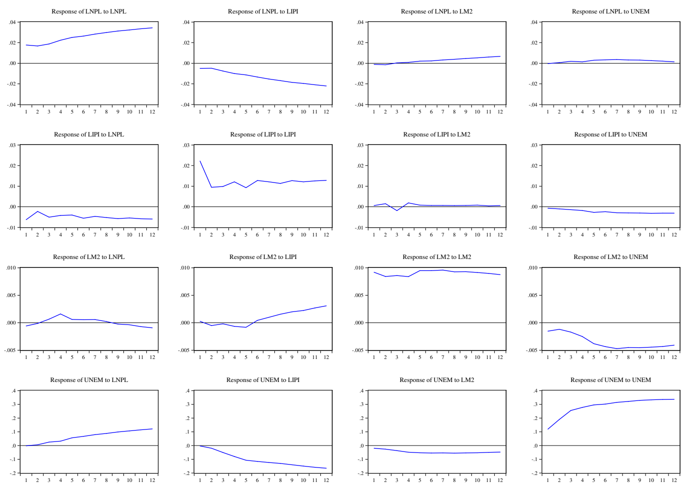



Figure A.3: VEC - Impulse Response Function

Autocorrelations with 2 Std.Err. Bounds

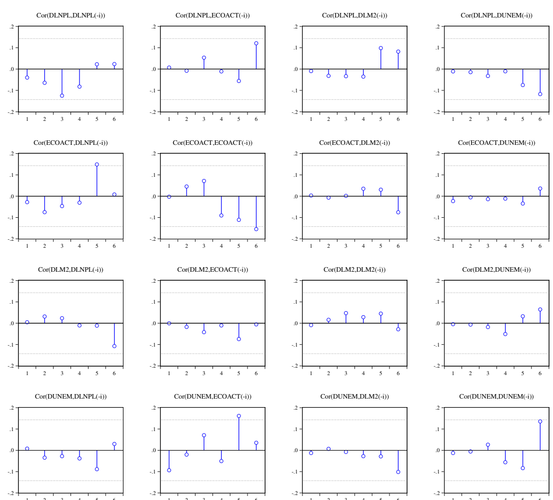



Figure A.4: VAR - Correlogram

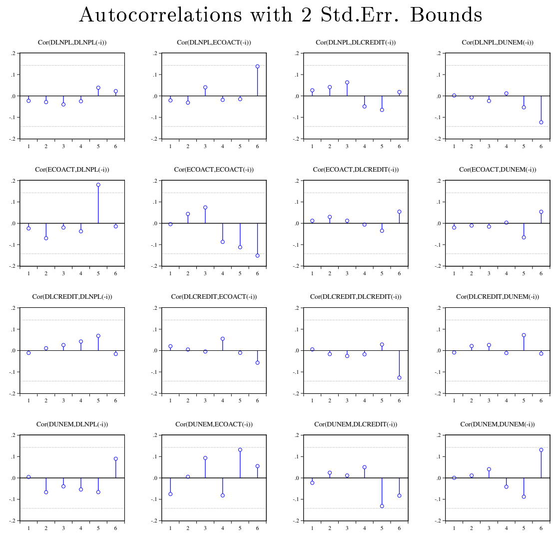



Figure A.5: VAR with dummy - Correlogram

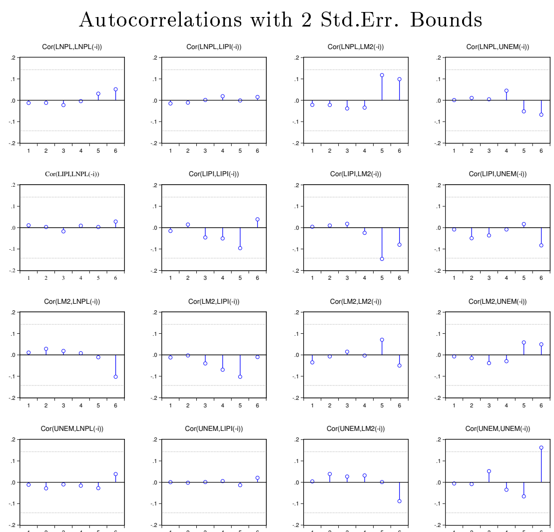
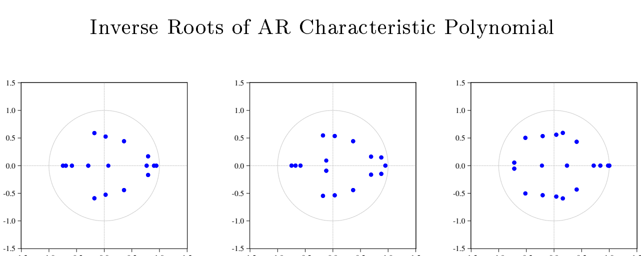



Figure A.6: VEC - Correlogram




(a) VAR (b) VAR with dummy (c) VEC

Figure A.7: Unit Root Test

## B.1 Tables

Table B.1: Variable description

| Vairables | Name | Description |
|---|---|---|
| Coincident indicator of activity | ECOACT | Year-on-Year rate of change of the Coincident indicator of activity |
| Industrial Production Index | IPI | Average through period. The Index is adjusted for working days |
| M2 | M2 | End of period National contribution for the euro area M2 monetary aggregates |
| Nonperforming loans | NPL | End of period outstanding amount of nonperforming loans of individuals and non-financial corporation. These amounts are adjusted for securities and do not exclude emigrants |
| Unemployment rate | UNEM | Unemployment rate seasonally adjusted |

Note: The coincident indicator of activity, Industrial Production Index, M2 and nonperforming loans data were drawn from Bank of Portugal. The unemployment rate was drawn from Eurostat.

Table B.2: Descriptive Statistics

| Variables | ECOACT | IPI | M2 | NPL | UNEM |
|---|---|---|---|---|---|
| Mean | 0.85 | 106.21 | 133387.40 | 6586.22 | 9.09 |
| Median | 1.10 | 108.98 | 135910.60 | 3843.07 | 8.40 |
| Maximum | 4.80 | 118.41 | 166823.30 | 18055.24 | 17.50 |
| Minimum | -4.10 | 90.13 | 92357.31 | 2774.05 | 4.10 |
| Std. Dev. | 2.27 | 7.60 | 20122.74 | 4774.14 | 3.78 |
| Skewness | -0.30 | -0.51 | -0.28 | 1.25 | 0.62 |
| Kurtosis | 2.52 | 1.95 | 2.11 | 3.11 | 2.32 |
| Jarque-Bera | 4.87 | 18.17 | 9.20 | 52.43 | 16.91 |
| Probability | 0.09 | 0 | 0.01 | 0.00 | 0.00 |
| Observations | 201 | 201 | 201 | 201 | 201 |

Table B.3: NPL Quandt-Andrews Breakpoint Test

Null Hypothesis: No breakpoints within 15% trimmed data.

| Statistic | Value | Prob. |
|---|---|---|
| Maximum LR F-statistic (2008M01) | 26.97281 | 0.00* |
| Maximum Wald F-statistic (2008M01) | 26.97281 | 0.00* |

Note: Probabilities calculated using Hansen's (1997) method.
Significance levels are denoted as: * significant at 5% ** significant at 10%.

Table B.4: Dickey Fuller Augmented test

Null hypothesis; Variable has a unit root.

| Variables | ECOACT | IPI | M2 | NPL | UNEM |
|---|---|---|---|---|---|
| Levels | -3.765063* | -0.863592 | -0.235952 | -0.839769 | -3.38361 |
| First differences | - | -15.72131* | -13.82439* | -5.125643* | -6.530936* |

Note: $p-value$ calculated with distribution of Mackinnon (1996).
Significance levels are denoted as: * significant at 5% ** significant at 10%.

Table B.5: VAR - Lag Order Selection Criteria

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 1 | 1225.43 | NA | 3.04e-11 | -12.86626 | -12.59082 | -12.75467 |
| 2 | 1417.02 | 366.8765 | 4.69e-12 | -14.73425 | -14.18337* | -14.51106 |
| 3 | 1438.47 | 40.15752 | 4.443e-12 | -14.79221 | -13.96588 | -14.45741 |
| 4 | 1472.66 | 62.56872 | 3.65e-12* | -14.98577* | -13.884 | -14.53937* |
| 5 | 1482.98 | 18.43754 | 3.89e-12 | -14.9253 | -13.54809 | -14.36731 |
| 6 | 1497.03 | 24.48939 | 3.98e-12 | -14.90442 | -13.25176 | -14.23482 |
| 7 | 1508.91 | 20.24499 | 4.17e-12 | -14.86073 | -12.93264 | -14.07954 |
| 8 | 1519.66 | 17.83923 | 4.43e-12 | -14.80488 | -12.60134 | -13.91209 |
| 9 | 1535.56 | 25.71829 | 4.46e-12 | -14.80386 | -12.32489 | -13.79947 |
| 10 | 1559.23 | 37.26129* | 4.14e-12 | -14.88541 | -12.131 | -13.76943 |
| 11 | 1569.29 | 15.42302 | 4.45e-12 | -14.82231 | -11.79245 | -13.59472 |
| 12 | 1580.91 | 17.29572 | 4.71e-12 | -14.77563 | -11.47033 | -13.43645 |

Note: LR: sequential modified LR test statistic (each test at 5% level) FPE: Final prediction error AIC: Akaike information criterion SC: Schwarz information criterion HQ: Hannan-Quinn information criterion. indicates lag order selected by the criterion indicated by *.

Table B.6: Johansen Cointegration Test

| Hypothesized No. of CE(s) | Eigenvalue | Trace Statistic | 0.05 Critical Value | Prob.** |
|---|---|---|---|---|
| None * | 0.141573 | 59.26378 | 35.19275 | 0.000* |
| At most 1 * | 0.098719 | 29.49639 | 20.26184 | 0.002* |
| At most 2 * | 0.046223 | 9.228468 | 9.164546 | 0.048* |

Note: $p-value$ calculated with distribution of Mackinnon (1996).
Significance levels are denoted as: * significant at 5% ** significant at 10%.

Table B.7: VAR - Estimation Results

| | DLNPL | ECOACT | DLM2 | DUNEM |
|---|---|---|---|---|
| DLNPL(-1) | -0.022366 | -0.183499 | 0.018961 | 0.459676 |
| | -0.07176 | -0.33678 | -0.03709 | -0.4839 |
| | [-0.31168] | [-0.54486] | [ 0.51128] | [ 0.94995] |
| DLNPL(-2) | 0.163557 | 0.226036 | 0.046295 | 0.665334 |
| | -0.06857 | -0.3218 | -0.03544 | -0.46236 |
| | [ 2.38535]* | [ 0.70242] | [ 1.30643] | [ 1.43898] |
| DLNPL(-3) | 0.280905 | -0.12994 | 0.055673 | -0.475387 |
| | -0.0688 | -0.3229 | -0.03556 | -0.46395 |
| | [ 4.08276]* | [-0.40242] | [ 1.56571] | [-1.02465] |
| DLNPL(-4) | 0.230631 | -0.403485 | -0.0308 | 0.943085 |
| | -0.07225 | -0.33906 | -0.03734 | -0.48716 |
| | [ 3.19234]* | [-1.19002] | [-0.82492] | [ 1.93587]** |
| ECOACT(-1) | -0.018633 | 1.8875 | 0.007753 | -0.19335 |
| | -0.01417 | -0.0665 | -0.00732 | -0.09555 |
| | [-1.31496] | [ 28.3833]* | [ 1.05873] | [-2.02357]* |
| ECOACT(-2) | 0.002901 | -0.458463 | -0.011232 | 0.343974 |
| | -0.03031 | -0.14224 | -0.01566 | -0.20437 |
| | [ 0.09573] | [-3.22317]* | [-0.71711] | [ 1.68306]** |
| ECOACT(-3) | 0.034161 | -0.881792 | -0.002034 | -0.179621 |
| | -0.03062 | -0.14371 | -0.01583 | -0.20649 |
| | [ 1.11557] | [-6.13578]* | [-0.12850] | [-0.86987] |
| ECOACT(-4) | -0.019556 | 0.445597 | 0.007581 | 0.026241 |
| | -0.01459 | -0.06849 | -0.00754 | -0.09841 |
| | [-1.34003] | [ 6.50588]* | [ 1.00515] | [ 0.26665] |
| DLM2(-1) | -0.067099 | 0.421258 | -0.113154 | 0.477735 |
| | -0.14583 | -0.6844 | -0.07537 | -0.98337 |
| | [-0.46011] | [ 0.61551] | [-1.50139] | [ 0.48581] |
| DLM2(-2) | 0.178669 | 1.727707 | -0.032356 | -0.115086 |
| | -0.1437 | -0.67441 | -0.07427 | -0.96901 |
| | [ 1.24333] | [ 2.56181]* | [-0.43568] | [-0.11877] |
| DLM2(-3) | 0.107717 | -0.698288 | -0.070759 | -0.920124 |
| | -0.14259 | -0.66921 | -0.07369 | -0.96154 |
| | [ 0.75541] | [-1.04345] | [-0.96018] | [-0.95693] |
| DLM2(-4) | 0.170371 | -0.542988 | 0.043298 | 0.272717 |
| | -0.14176 | -0.66532 | -0.07326 | -0.95594 |
| | [ 1.20179] | [-0.81613] | [ 0.59098] | [ 0.28529] |
| DUNEM(-1) | 0.006344 | -0.045565 | 0.002892 | 0.619597 |
| | -0.01097 | -0.05151 | -0.00567 | -0.07401 |
| | [ 0.57809] | [-0.88464] | [ 0.50992] | [ 8.37221]* |
| DUNEM(-2) | 0.008166 | 0.041591 | -0.004168 | 0.151276 |
| | -0.01239 | -0.05814 | -0.0064 | -0.08353 |
| | [ 0.65921] | [ 0.71539] | [-0.65101] | [ 1.81096]** |
| DUNEM(-3) | -0.013092 | 0.028336 | -0.006221 | -0.265917 |
| | -0.01233 | -0.05786 | -0.00637 | -0.08314 |
| | [-1.06187] | [ 0.48971] | [-0.97631] | [-3.19844]* |
| DUNEM(-4) | 0.017091 | 0.061316 | -0.003814 | 0.12169 |
| | -0.01052 | -0.04939 | -0.00544 | -0.07096 |
| | [ 1.62413] | [ 1.24153] | [-0.70133] | [ 1.71487]** |
| R-squared | 0.31835 | 0.99869 | 0.207996 | 0.543859 |
| Adj. R-squared | 0.261546 | 0.998581 | 0.141996 | 0.505847 |
| Sum sq. resids | 0.056362 | 1.241403 | 0.015054 | 2.562839 |
| S.E. equation | 0.017695 | 0.083046 | 0.009145 | 0.119323 |
| F-statistic | 5.604342 | 9150.94 | 3.151445 | 14.30764 |
| Log likelihood | 520.987 | 217.9515 | 650.3651 | 146.9139 |
| Akaike AIC | -5.152928 | -2.06073 | -6.473114 | -1.335857 |
| Schwarz SC | -4.885327 | -1.793129 | -6.205512 | -1.068255 |
| Mean dependent | 0.008561 | 0.747449 | 0.00225 | 0.042347 |
| S.D. dependent | 0.020592 | 2.204784 | 0.009873 | 0.169744 |

Note: 196 observations included. $t - statistics$ presented in brackets.
Significance levels are denoted as: * significant at 5%,** significant at 10%.

Table B.8: VAR with dummy - Estimation Results

| | DLNPL | ECOACT | DLM2 | DUNEM |
|---|---|---|---|---|
| DLNPL(-1) | -0.082057 | -0.030901 | 0.016065 | 0.617602 |
| | -0.07319 | -0.34923 | -0.03871 | -0.50344 |
| | [-1.12117] | [-0.08849] | [ 0.41499] | [ 1.22677] |
| DLNPL(-2) | 0.083882 | 0.429721 | 0.042429 | 0.876131 |
| | -0.07246 | -0.34577 | -0.03833 | -0.49846 |
| | [ 1.15756] | [ 1.24278] | [ 1.10694] | [ 1.75768]** |
| DLNPL(-3) | 0.200743 | 0.074992 | 0.051783 | -0.263299 |
| | -0.07274 | -0.34709 | -0.03848 | -0.50036 |
| | [ 2.75969]* | [ 0.21606] | [ 1.34586] | [-0.52622] |
| DLNPL(-4) | 0.16932 | -0.246745 | -0.033775 | 1.105299 |
| | -0.0738 | -0.35214 | -0.03904 | -0.50764 |
| | [ 2.29431]* | [-0.70069] | [-0.86522] | [ 2.17732]* |
| ECOACT(-1) | -0.009517 | 1.864196 | 0.008195 | -0.217468 |
| | -0.01422 | -0.06788 | -0.00752 | -0.09785 |
| | [-0.66903] | [ 27.4649]* | [ 1.08921] | [-2.22252]* |
| ECOACT(-2) | -0.006978 | -0.433206 | -0.011712 | 0.370113 |
| | -0.02988 | -0.14258 | -0.0158 | -0.20553 |
| | [-0.23355] | [-3.03842]* | [-0.74102] | [ 1.80074]** |
| ECOACT(-3) | 0.024921 | -0.85817 | -0.002482 | -0.155174 |
| | -0.03016 | -0.14392 | -0.01595 | -0.20747 |
| | [ 0.82622] | [-5.96276]* | [-0.15557] | [-0.74792] |
| ECOACT(-4) | -0.009307 | 0.419396 | 0.008078 | -0.000875 |
| | -0.01472 | -0.07023 | -0.00778 | -0.10124 |
| | [-0.63238] | [ 5.97194]* | [ 1.03770] | [-0.00865] |
| DLM2(-1) | -0.069764 | 0.428071 | -0.113283 | 0.484787 |
| | -0.14286 | -0.68165 | -0.07556 | -0.98265 |
| | [-0.48835] | [ 0.62799] | [-1.49919] | [ 0.49334] |
| DLM2(-2) | 0.170261 | 1.749201 | -0.032764 | -0.09284 |
| | -0.1408 | -0.67182 | -0.07447 | -0.96849 |
| | [ 1.20927] | [ 2.60366]* | [-0.43995] | [-0.09586] |
| DLM2(-3) | 0.070248 | -0.602502 | -0.072577 | -0.820992 |
| | -0.14027 | -0.66929 | -0.07419 | -0.96484 |
| | [ 0.50082] | [-0.90020] | [-0.97822] | [-0.85091] |
| DLM2(-4) | 0.150405 | -0.491947 | 0.042329 | 0.32554 |
| | -0.13904 | -0.66343 | -0.07354 | -0.95638 |
| | [ 1.08177] | [-0.74152] | [ 0.57557] | [ 0.34039] |
| DUNEM(-1) | 0.008289 | -0.050537 | 0.002987 | 0.614451 |
| | -0.01077 | -0.0514 | -0.0057 | -0.07409 |
| | [ 0.76959] | [-0.98328] | [ 0.52421] | [ 8.29309]* |
| DUNEM(-2) | 0.009525 | 0.038117 | -0.004102 | 0.147681 |
| | -0.01214 | -0.05795 | -0.00642 | -0.08353 |
| | [ 0.78436] | [ 0.65782] | [-0.63860] | [ 1.76795]** |
| DUNEM(-3) | -0.013254 | 0.028749 | -0.006229 | -0.26549 |
| | -0.01208 | -0.05763 | -0.00639 | -0.08308 |
| | [-1.09736] | [ 0.49886] | [-0.97501] | [-3.19566]* |
| DUNEM(-4) | 0.01693 | 0.061728 | -0.003822 | 0.122116 |
| | -0.01031 | -0.04919 | -0.00545 | -0.07091 |
| | [ 1.64233] | [ 1.25492] | [-0.70094] | [ 1.72214]** |
| CRISIS | 0.008925 | -0.022817 | 0.000433 | -0.023614 |
| | -0.00305 | -0.01454 | -0.00161 | -0.02096 |
| | [ 2.92949]* | [-1.56952] | [ 0.26873] | [-1.12677] |
| R-squared | 0.349536 | 0.998708 | 0.208316 | 0.547071 |
| Adj. R-squared | 0.291394 | 0.998593 | 0.137551 | 0.506586 |
| Sum sq. resids | 0.053784 | 1.224551 | 0.015047 | 2.544789 |
| S.E. equation | 0.017334 | 0.082711 | 0.009169 | 0.119234 |
| F-statistic | 6.011751 | 8648.907 | 2.943765 | 13.51285 |
| Log likelihood | 525.5763 | 219.291 | 650.4047 | 147.6066 |
| Akaike AIC | -5.189554 | -2.064194 | -6.463313 | -1.33272 |
| Schwarz SC | -4.905228 | -1.779868 | -6.178987 | -1.048394 |
| Mean dependent | 0.008561 | 0.747449 | 0.00225 | 0.042347 |
| S.D. dependent | 0.020592 | 2.204784 | 0.009873 | 0.169744 |

Note: 196 observations included. $t - statistics$ presented in brackets.
Significance levels are denoted as: * significant at 5%,** significant at 10%.

Table B.9: VEC - Estimation Results

| LNPL(-1) | LIPI(-1) | LM2(-1) | UNEM(-1) | C |
|---|---|---|---|---|
| 1 | -21.9772 | 12.5432 | -0.688 | -47.7684 |
| | -7.3093 | -2.6958 | -0.1769 | |
| | [-3.0067] | [ 4.6528] | [-3.8874] | |
| **Error Correction:** | **D(LNPL)** | **D(LIPI)** | **D(LM2)** | **D(UNEM)** |
| CointEq1 | 0.00997 | -0.000491 | -0.001525 | 0.010678 |
| | -0.0021 | -0.00142 | -0.0006 | -0.00756 |
| | [ 4.74602]* | [-0.34590] | [-2.54410]* | [ 1.41209] |
| D(LNPL(-1)) | -0.203778 | 0.010842 | 0.007064 | -0.129007 |
| | -0.0746 | -0.0504 | -0.02128 | -0.26851 |
| | [-2.73175]* | [ 0.21510] | [ 0.33189] | [-0.48046] |
| D(LNPL(-2)) | -0.307599 | -0.066734 | 0.01855 | 0.535479 |
| | -0.07426 | -0.05017 | -0.02119 | -0.26729 |
| | [-4.14235]* | [-1.33006] | [ 0.87553] | [ 2.00339]* |
| D(LNPL(-3)) | 0.121312 | 0.025115 | 0.010278 | -0.33819 |
| | -0.07596 | -0.05132 | -0.02167 | -0.27341 |
| | [ 1.59711] | [ 0.48936] | [ 0.47424] | [-1.23694] |
| D(LNPL(-4)) | -0.185011 | -0.013626 | -0.006512 | 0.02974 |
| | -0.07415 | -0.0501 | -0.02116 | -0.26688 |
| | [-2.49525]* | [-0.27198] | [-0.30783] | [ 0.11143] |
| D(LIPI(-1)) | 0.212479 | -0.583015 | -0.067525 | -0.424836 |
| | -0.11835 | -0.07997 | -0.03377 | -0.426 |
| | [ 1.79535]** | [-7.29074]* | [-1.99965]* | [-0.99727] |
| D(LIPI(-2)) | 0.04054 | -0.338773 | -0.029006 | -1.009721 |
| | -0.13201 | -0.0892 | -0.03767 | -0.47518 |
| | [ 0.30709] | [-3.79799]* | [-0.77008] | [-2.12494]* |
| D(LIPI(-3)) | 0.05447 | -0.111918 | -0.046705 | -0.90542 |
| | -0.13004 | -0.08786 | -0.0371 | -0.46806 |
| | [ 0.41888] | [-1.27378] | [-1.25881] | [-1.93441]** |
| D(LIPI(-4)) | -0.036803 | -0.145329 | -0.056884 | -0.698105 |
| | -0.11015 | -0.07442 | -0.03143 | -0.39647 |
| | [-0.33413] | [-1.95275]** | [-1.81000]** | [-1.76082]** |
| D(LM2(-1)) | 0.134988 | 0.110202 | -0.03492 | 0.579333 |
| | -0.25801 | -0.17433 | -0.07362 | -0.92869 |
| | [ 0.52320] | [ 0.63215] | [-0.47435] | [ 0.62382] |
| D(LM2(-2)) | -0.100046 | -0.322486 | 0.041773 | 0.093031 |
| | -0.25448 | -0.17194 | -0.07261 | -0.91598 |
| | [-0.39315] | [-1.87552]** | [ 0.57531] | [ 0.10156] |
| D(LM2(-3)) | -0.016906 | 0.231872 | -0.010378 | -1.399438 |
| | -0.25268 | -0.17073 | -0.0721 | -0.90952 |
| | [-0.06690] | [ 1.35811] | [-0.14395] | [-1.53865] |
| D(LM2(-4)) | 0.030235 | 0.001025 | 0.151173 | 0.454517 |
| | -0.25519 | -0.17243 | -0.07281 | -0.91855 |
| | [ 0.11848] | [ 0.00594] | [ 2.07619]* | [ 0.49482] |
| D(UNEM(-1)) | 0.033237 | -0.008257 | 0.002969 | 0.607138 |
| | -0.02063 | -0.01394 | -0.00589 | -0.07426 |
| | [ 1.61113] | [-0.59237] | [ 0.50434] | [ 8.17616]* |
| D(UNEM(-2)) | -0.01842 | -0.008451 | -0.006763 | 0.18896 |
| | -0.0231 | -0.01561 | -0.00659 | -0.08315 |
| | [-0.79739] | [-0.54143] | [-1.02598] | [ 2.27249]* |
| D(UNEM(-3)) | -0.004025 | 0.010375 | -0.008244 | -0.304031 |
| | -0.02308 | -0.01559 | -0.00659 | -0.08307 |
| | [-0.17438] | [ 0.66530] | [-1.25188] | [-3.65972]* |
| D(UNEM(-4)) | 0.039589 | -0.014089 | -0.004562 | 0.146694 |
| | -0.01981 | -0.01338 | -0.00565 | -0.0713 |
| | [ 1.99848]* | [-1.05258] | [-0.80704] | [ 2.05730]* |
| C | 0.011523 | 0.0000218 | 0.00225 | 0.014687 |
| | -0.00325 | -0.0022 | -0.00093 | -0.0117 |
| | [ 3.54367]* | [ 0.00993] | [ 2.42522]* | [ 1.25483] |
| R-squared | 0.292831 | 0.328773 | 0.17767 | 0.55728 |
| Adj. R-squared | 0.225293 | 0.264667 | 0.099133 | 0.514997 |
| Sum sq. resids | 0.191986 | 0.08765 | 0.01563 | 2.487433 |
| S.E. equation | 0.032842 | 0.02219 | 0.009371 | 0.118213 |
| F-statistic | 4.335762 | 5.128591 | 2.262245 | 13.17999 |
| Log likelihood | 400.8757 | 477.7144 | 646.6827 | 149.8407 |
| Akaike AIC | -3.906894 | -4.690963 | -6.41513 | -1.345313 |
| Schwarz SC | -3.605843 | -4.389912 | -6.114078 | -1.044262 |
| Mean dependent | 0.008617 | -0.000601 | 0.00225 | 0.042347 |
| S.D. dependent | 0.037313 | 0.025878 | 0.009873 | 0.169744 |

Note: 196 observations included. $t-statistics$ presented in brackets.
Significance levels are denoted as: * significant at 5%,** significant at 10%.

Table B.10: VAR - Variance Decomposition of DLNPL

| Period | S.E. | DLNPL | ECOACT | DLM2 | DUNEM |
|---|---|---|---|---|---|
| 1 | 0.017695 | 100 | 0 | 0 | 0 |
| 2 | 0.017794 | 98.95556 | 0.745241 | 0.060566 | 0.238637 |
| 3 | 0.018355 | 95.11444 | 2.977715 | 1.184477 | 0.723367 |
| 4 | 0.019103 | 94.50468 | 3.65161 | 1.159988 | 0.683726 |
| 5 | 0.019904 | 91.54129 | 5.229174 | 1.495659 | 1.733881 |
| 6 | 0.020233 | 89.50475 | 7.119328 | 1.471165 | 1.90476 |
| 7 | 0.020769 | 87.57553 | 8.839099 | 1.598475 | 1.9869 |
| 8 | 0.021166 | 86.09738 | 10.39267 | 1.582207 | 1.927743 |
| 9 | 0.02154 | 84.57889 | 11.86147 | 1.6404 | 1.919236 |
| 10 | 0.02184 | 83.37568 | 13.11811 | 1.638675 | 1.867539 |
| 11 | 0.022126 | 82.41104 | 14.08896 | 1.677892 | 1.822105 |
| 12 | 0.022347 | 81.63188 | 14.89237 | 1.687688 | 1.788059 |

Note: The ordering for the Cholesky decomposition was specified as: DLNPL; DUNEM; DLM2 and ECOACT.
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Table B.11: Residual Serial Correlation LM Tests

| (a) VAR | | | (b) VAR with dummy | | | (c) VEC | | |
|---|---|---|---|---|---|---|---|---|
| Lags | LM-Stat | Prob | Lags | LM-Stat | Prob | Lags | LM-Stat | Prob |
| 1 | 22.96503 | 0.1147 | 1 | 20.32027 | 0.2061 | 1 | 16.77543 | 0.4003 |
| 2 | 18.74371 | 0.2822 | 2 | 22.28046 | 0.1344 | 2 | 20.44012 | 0.201 |
| 3 | 25.5373 | 0.0609 | 3 | 21.92216 | 0.1457 | 3 | 23.78587 | 0.0943 |
| 4 | 20.55443 | 0.1963 | 4 | 20.64779 | 0.1924 | 4 | 13.39299 | 0.6438 |
| 5 | 26.43225 | 0.0482 | 5 | 27.99077 | 0.0317 | 5 | 17.42183 | 0.3588 |
| 6 | 30.01779 | 0.0179 | 6 | 29.81096 | 0.019 | 6 | 20.92872 | 0.1813 |
| 7 | 19.69255 | 0.2344 | 7 | 19.7584 | 0.2313 | 7 | 4.260029 | 0.9984 |
| 8 | 34.64004 | 0.0045 | 8 | 33.6079 | 0.0061 | 8 | 21.09169 | 0.175 |
| 9 | 13.51376 | 0.6349 | 9 | 14.2668 | 0.5788 | 9 | 11.19567 | 0.7972 |
| 10 | 23.49853 | 0.101 | 10 | 23.34936 | 0.1047 | 10 | 16.50166 | 0.4185 |
| 11 | 21.7861 | 0.1502 | 11 | 22.58221 | 0.1254 | 11 | 17.55273 | 0.3507 |
| 12 | 20.95407 | 0.1803 | 12 | 21.12908 | 0.1736 | 12 | 112.8142 | 0 |

Note: Null Hypothesis: no serial correlation at lag order h. $Chi-square$ with 16 df.

Table B.12: Residual Heteroskedasticity Tests: Includes Cross Terms

(a) VAR

| Dependent | Prob. |
|---|---|
| res1*res1 | 0.945 |
| res2*res2 | 0.5821 |
| res3*res3 | 0.5658 |
| res4*res4 | 0.3009 |
| res2*res1 | 0.8168 |
| res3*res1 | 0.3941 |
| res3*res2 | 0.2867 |
| res4*res1 | 0.4496 |
| res4*res2 | 0.7302 |
| res4*res3 | 0.2931 |
| Joint test | 0.5233 |

(b) VAR with dummy

| Dependent | Prob. |
|---|---|
| res1*res1 | 0.8614 |
| res2*res2 | 0.4735 |
| res3*res3 | 0.5498 |
| res4*res4 | 0.3742 |
| res2*res1 | 0.7209 |
| res3*res1 | 0.4991 |
| res3*res2 | 0.3897 |
| res4*res1 | 0.5744 |
| res4*res2 | 0.4847 |
| res4*res3 | 0.4232 |
| Joint test | 0.5271 |

(c) VEC

| Dependent | Prob. |
|---|---|
| res1*res1 | 0.977 |
| res2*res2 | 0.2682 |
| res3*res3 | 0.521 |
| res4*res4 | 0.5836 |
| res2*res1 | 0.7489 |
| res3*res1 | 0.6672 |
| res3*res2 | 0.3752 |
| res4*res1 | 0.3631 |
| res4*res2 | 0.4056 |
| res4*res3 | 0.2227 |
| Joint test | 0.4721 |

Note: Residual Heteroskedasticity test includes cross terms.