

"Real Sector and Banking System: First and Second Round Effects. A Non-Linear VAR Approach"*

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Short Abstract

We use a non-linear VAR model based on local projections approach, (Jordà, 2005), to study the relationship between real sector and banking system for the US economy. The non-linear VAR combined with local projections approach for estimating the impulse responses functions (IRFs) allows us to study the asymmetric behaviours of the macro variables in response to a positive or a negative shock. Moreover, it gives us more flexibility in determining the specification of the econometric model. In this way, we are able to capture first and second round effects: those going from the macro system to the banking sector and vice versa. We find that the traditional and the linear projection approaches for computing IRFs are similar in shape even if the former are not statistically significant. Moreover, we also find that IRFs based on linear and quadratic projection approaches lead to different results. Specifically, using the quadratic projection method we are able to find out first and second round effects. Finally, using a quadratic projection approach, we find that macro variables and banking indicators react asymmetrically in case of a positive and a negative shock.

Keywords: *Financial Stability, Non-Linear VAR, Local Projections Methods.*

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1-Introduction

Several empirical studies have focused on the relationship between the real sector and the banking system. Good economic conditions positively affect firms' profits, asset prices and customers' expectations. The expansion in the aggregate demand has two important consequences at the banking level. On the one hand, banking lending activity increases; on the other hand, also the economic system indebtedness increases. Banks may underestimate their risk exposure (Salas and Saurina, 2002), generating a deterioration process of borrowers' creditworthiness. An exogenous shock can lead to a worsening in customers' profitability and to a change in agents' opinion (from an over-optimism to an over-pessimism expectations). This in turn can trigger the fall of asset prices that further affects customers' financial wealth depressing the value of collaterals. Consequently, nonperforming assets appear and the number of firms in financial distress increases. This generates losses in banks' balance sheets. Banks' profitability and capital adequacy deteriorate, leading to a mechanism defined as first round effect going from the real sector to the financial system. Depending on banks' capital conditions, a second round effect can be generated. In fact, during a recession banks can overreact to a negative shock, drastically reducing credit supply, especially if they have thin capital buffers above the minimum capital requirement. If capital requirements are binding banks cannot expand lending without raising additional credit. In order to absorb a negative shock, a bank characterized by too thin capital buffers prefers reducing lending rather than raising capital, which is more costly in recessions (Peek and Rosengren, 1995). This implies that financial resources decrease or become more costly (Bernanke and Gertler, 1995). As a result, the net return of investments falls, the investment demand decreases and therefore, the economic downturn becomes more important.

The majority of the empirical contributions focus on the part of the relationship going from the macro variables to the banking indicators. Only in recent years, thanks to the implementation of new rules at the international level in order to prevent banking troubles due to borrowers insolvency, more attention has been given also to the study of the other side of the relationship, from the banking sector to the real economy. The recent global financial crisis has stressed the importance of studying the interrelationships between real economy, banking sector and financial system. Specifically, the financial crisis has showed that a shock hitting the financial market can have important consequences in the real economy and that it can rebound to the financial sector stronger and more important than before. This is the reason why it is important studying the interdependency between real economy, banking sector and financial system more closely. Such an analysis becomes even more important in the light of the fact that several governments are implementing policy measures in order to save the financial sector and to impart confidence to investors and shareholders. In order to understand the consequences of these policies, a thorough knowledge of the mechanisms linking the different pieces of the overall structure is needed.

In order to achieve this goal we implement a non-linear VAR model based on local projections for estimating impulse responses as proposed by Jordà (2005). We choose a non-linear VAR because it gives us more flexibility and because there is the suspicion that the unknown Data Generating Process (DGP) to be non-linear. As shown by Jordà (2005), if the DGP is a VAR then the local projection

method leads to consistent but not efficient impulse responses, while if the DGP is not a VAR then the local projection approach generates the best approximation at each horizon.

If the DGP is non-linear then, using the traditional approach for computing the impulse response functions can lead to important misspecification errors in case we want to study the impact of big shocks, larger than the classical one standard deviation, on the variables of interest. Moreover, the local projection approach is also recommended if we want to study the reaction of the variables of interest in case of positive and negative shocks. Using the traditional approach, considering negative rather than positive shocks of the same size, leads only to a symmetric but opposite in sign impulse response with respect to the original one. Misspecification errors, and the impossibility for asymmetric reactions to positive and negative shocks are avoided using the local projections approach.

Our study is based on US quarterly data and it covers a period of 23 years from 1984 to 2007. We find that the non-linear specification combined with the local projections approach can lead to important differences in results compared with those obtained using linear VAR and traditional techniques for estimating impulse responses. Specifically, we discover that that the traditional approach and linear projection impulse response functions are similar even if the former are not statistically significant. Moreover, we also find out that linear and quadratic projection impulse responses lead to different results. Specifically, using the quadratic projection we are able to find out first and second round effects. Finally, using a quadratic projection approach, we find that macro variables and banking indicators react asymmetrically in case of a positive and a negative shock.

The rest of the paper is organized as follows: section 2 analyzes the contributions from a theoretical and empirical viewpoint related to our study. In section 3 we discuss the advantages of using a non-linear model and a local projection approach for estimating impulse response functions. In section 4 we introduce our macroeconomic model and we analyze the main features of the data set used in this study. In section 5 we describe the main results, while in section 6 are reported the conclusions.

2-Literature Review

In the economic literature, the interaction going from the real economy to the banking sector is defined as first round effect, while the relationship going in the opposite direction is called second round effect. From a theoretical point of view, several models¹ have been constructed in order to take into account both the relationship going from the banking system to the macro variables and from the real economy to the banking sector. However, from an empirical viewpoint, there is a strong bias in favour of studies focusing above all on the first round effect. Only a marginal number of contributions investigate the second round effect. Moreover, the empirical literature is unsatisfactory about studies that, at the same time, combine first and second round effects analysis.

From an empirical point of view, it is possible to identify three generations of models. The goal of the first-generation models (FGM), based on standard linear regressions, is to measure the impact of changes in the macroeconomic variables on banking indicators and to analyze the cyclical nature of

¹ See for example Bernanke and Blinder, (1989), Bernanke et al. (1991) and Bernanke and Gertler (1995), Peek and Rosengren (1995), Bernanke and Gertler (1995);

the banking behaviours (in terms of provisions against loan losses). The main findings are that the economic conditions positively affect the quality of the banking system (pro-cyclical component) as well as the banks profitability has a positive impact on loan loss provisions (banking income-smooth behaviour). Arpa et al. (2001) develop a distributed lag model for analyzing the relationship between Austrian banks' provisions and Austrian real GDP growth. They find that real GDP growth negatively affects banks' provisions. Moreover, their results support the income-smoothing hypothesis. In particular, they find that banks increase provisions during increasing banks profitability periods. Pesola (2001) investigates the crises of the banking systems in Nordic countries developing a panel model over the period 1980-1999. He finds that macroeconomic shocks, such as the corporate and households' indebtedness, the interest rate as well as a GDP growth, and specific dummy variables, the deregulation dummy and lending growth play a crucial role in explaining banking distress in Sweden, Norway and Finland, measured by the banks' loan losses to lending and the enterprise bankruptcies per capita. Bikker and Hu (2002) estimate an unbalanced panel to evaluate the relationship between banking indicators (banks' profit and provisions) and a set of explanatory variables (GDP, unemployment, inflation, loans, net profits, failures) for a sample of 26 OECD countries between 1979 and 1999. Their findings show that capital and reserves accumulate much faster during a boom than in a recession phase, possibly because as a precaution. This result is opposite with respect to that found by Arpa et al. Salas and Saurina (2002) focus on the relationship between banking quality indicator (loans) and macroeconomic variables (economic cycle component) using a Spanish dataset for a period of 12 years. Their findings are coherent with the economic theory². An economic boom positively affects banks' lending activity in order to increase their market share. This goal is achieved by lending to borrowers of lower quality, once the high quality borrowers are attended. Moreover, bad economic performance positively affects bad loans. In a similar paper Jiménez, Salas and Saurina (2005), disentangling the relationship between past credit and current loans losses, find a lagged but clear relationship between the credit cycle and the credit risk. Current rapid increasing in loan portfolios is associated to future increase in non-performing ratios. Loans granted during the booming periods are more likely to default than those loans obtained during slow credit growth. They also show that there exist evidence for a change in credit supply policies: screening measures reduce during the booms and then they become more demanding during the busting phases. Pain (2003) analyzes the relationship between loan loss provision and business cycle for UK. On the one hand his results confirm previous contributions, specifically that provisions show a cyclical dependence. On the other hand, he finds that bank specific factors can help in explaining some banking features. In particular, results show that there is a strong positive correlation between size of provision and the sector riskiness. Specifically, mortgage banks provision less than commercial banks since their loans are typically collateralized. Finally, Quagliariello (2004) investigates how Italian banks' performance is affected by the changes of the general economic conditions, using an unbalanced panel of 207 Italian intermediaries whose accounting ratios are available for at least 5 years in the period between 1985 and 2002. The outcomes of the models are then used to carry out

² Rajan (1995), Ruckers (2004);

stress tests that simulate the impact of some macroeconomic shocks on the Italian banking system. His findings confirm that banks' loan loss provisions, bad debts and profits are affected by the evolution of the business cycle: bad economic conditions have a positive impact on the flow of new bad debts and the provisions against loan losses. About the resilience of the banking system, he finds that the Italian banks' earnings and capital buffers would be sufficient to absorb the shock, even in an unfavourable scenario as that experienced in 1993, in a 2002 background.

As stress above good economic conditions positively affect firms' profits, asset prices and customers' expectations. The expansion in the aggregate demand has two important consequences. On the one hand, at the banking level, banking lending activity increases; on the other hand, also the economy's indebtedness increases. Banks may underestimate their risk exposure, generating in this way a deterioration process of borrowers' creditworthiness. An exogenous shock can lead to a worsening in customers' profitability and to an agents change in opinion: from an over-optimism to an over-pessimism background which, in turn, can trigger the fall of asset prices that further affects customers' financial wealth depressing the value of collaterals. Consequently, nonperforming assets appear and the number of firms in financial distress increases. This generates losses in banks' balance sheets. Banks' profitability and capital adequacy deteriorate. Depending on banks' capital conditions a second round effect (feedback) can be generated. In fact, during a recession banks can overreact to a negative shock drastically reducing credit supply, especially if they have thin capital buffers above the minimum capital requirement. If capital requirements are binding banks cannot expand lending without raising additional credit. In order to absorb a negative shock, a bank characterized by too thin capital buffers, prefers reducing lending rather than raising capital, which is more costly in recessions (Peek and Rosengren, 1995). This implies that financial resources decrease or they become more costly (Bernanke and Gertler, 1995). As a result, the net return of investments falls, reducing their demand and reinforcing the recession. The second round effect also called credit crunch can amplify the cyclical fluctuations. The size of the second round effect is a function of the capital buffer available for the banks, the amount of credit reduction, the effects of such reduction on credit costs, the degree of substitutability between loans and bonds and the share of output accounted for by bank-dependent firms (Bernanke and Lown, 1991).

Even if the FGMs are easy to be implemented however they have the important limitation that the second effect, going from the banking sector to the macro variables, is totally ignored. In order to take into account at the same time first and second round effects a Linear Vector Auto-Regressive approach has been used. The main feature of this approach is that all the variables are endogenous where each variable affects all the rest of the variables in a system of n equations in n endogenous variables. Using a VAR approach it is possible to analyze the impact of the variables of interest in case of a particular shock. This analysis is based on the impulse response functions. There are two ways to look at the problem. On the one hand, it is interesting to analyze how many periods the variable of interest needs to go back to the original situation; on the other hand, it is also important to focus on after how many periods the peak is reached.

Alves (2004) develops a co-integrated VAR, using KMV's corporate expected default frequencies (EDFs) as endogenous variables. The macroeconomic factors included in the model are the change in

industrial output, the three-month interest rate, the oil price, and the change in the US stock market index. The EDF variable for each EU industrial sector is generated on the macroeconomic variables and the EDFs of other industrial sector are considered in order to take into account possible diffusion effects. The results show three main facts. First, the performance of the linear-VAR model can be substantially improved if risk dynamics across industries are taken into account; second, systemic and macroeconomic factors are important determinants of the steady state risk profile. Third, the model fails detecting a large shock coming from the macroeconomic variables, so that there is an important part of the variation in the risk that is not explained by the variables taken into account. Pesaran et al. (2005) use a global VAR for simulating firms' equity returns, which are then related to the loss distribution of a corporate loan portfolio. The global VAR is a more flexible approach because it leaves to take into account differences across regions and countries. They consider 11 countries for the period 1979-1999. The variables included in the global VAR are GDP, consumer prices, the nominal money supply, equity prices, exchange rates vis-à-vis the US dollar, nominal interest rate and crude oil price. They found that shocks to real equity prices and to the price of crude oil seem to have the most significant effect on implied credit losses.

Gerlach and Peng (2005) analyze the relationship between residential property prices and bank lending in Hong Kong, implementing a cointegrating VAR model in order to take into account short run adjustment and long run relationships. They focus on three variables: lending, property prices and a GDP indicator. The main evidences are that, even if their contemporaneous correlation is large, the causality direction between lending and property prices goes from latte to the former rather than conversely, excluding de facto the existence of a second round effect. Moreover, they find that the sensitivity of credit to property prices declines over time. One important determinant for explaining this fact is the banking tightness of the credit standards. Hoggarth et al. (2005) develop a hybrid linear VAR model in order to analyze the relationship between banking quality indicator and macroeconomic variables for UK. Specifically, they compute a VAR including write-off ratio as an indicator for the banking system (this variable represents a direct measure of the fragility of the banking system), and four macroeconomic variables such as the output gap, the nominal short-term interest rate, the annual RPIX inflation and the real exchange rate. At an aggregate level they find that changes in output (relative to potential) negatively affect the write-off ratio – although the opposite is not true, so that there is no evidence for a second round effect. Moreover, the bank write-off ratio is positively affected by a shock coming from the nominal variables such as annual rate of retail price inflation and nominal interest rates.

Also Marcucci and Quagliariello (2007) implement a linear VAR model for Italy in order to capture and quantify first and second round effects. They use the same specification of Hoggarth et al. (2005), considering the IS curve, the Phillips curve, the UIP equation, a modified Taylor rule and an equation for capturing the relationship between the banking system and macroeconomic variables. The analysis is based at aggregated and at sector level (corporate and households). Their results are coherent with the previous results in the literature. In particular, macroeconomic variables are important in explaining the default rate, while the inverse is not true: the banking system indicator does not help in explaining

the macroeconomic variables. In particular a positive GDP shock reduces the default rate. These results are confirmed at the sector level.

SGMs give a more appropriate picture of the effects going in both directions, from the macro to the banking system and vice versa. However, as pointed out by Drehmann et al. (2006), only in case of a linear underlying data generating process (DGP) the linearity assumption of the SGMs is correct. Linear models generate good forecast also in case of analysis about the impact of small shocks around the equilibrium of the process, even if the true DGP is non-linear. In these cases, linear model may be interpreted as a first-order Taylor series approximation to the true DGP. Nevertheless, the analysis of the first and second round effect must be focused on big shocks, or rare events. In this case, linear models are no more useful because may generate important misspecification errors. Moreover, linear models are no more useful also when we are interested in analyzing the behaviour of the variables of interest with respect to a shock of the same size but opposite sign. Non linear VARs combined with local projections impulse response functions represent a way for avoiding these problems. The non linear VAR models represent the third family of models for analyzing the relationship between macro variables and banking indicators. In our knowledge, Drehmann et al. (2006) are the first who use non-linear VAR in this context. Their non-linear vector auto regression model focuses on 3 macroeconomic variables: GDP growth, inflation and interest rate and it is based on the Jordà's (2005) method. Jordà's claim is that a standard VAR can be considered as a first-order approximation of the true unknown DGP. The specification of the GDP can be improved introducing quadratic or cubic approximation. They show that linear and no-linear models lead to different results, especially when large shocks are considered. Moreover, they show that a non-linear model leads to substantially different conclusions for credit risk projections in stressed conditions, specifically in the tails region of the credit risk distribution. The general results of this contribution confirm previous findings: a big shock in the interest rate positively affects credit risk, while an opposite effect is obtained when the economy experiences a big positive GDP shock. The results referring to the second round effect are puzzling and they depend on the sample selection. Moreover, when there is evidence of the second round effect, it works via interest rate instead of GDP.

Our analysis is similar in some aspects to Drehmann et al. (2006) but it contains important differences both from a methodological point of view, and in terms of results. First, our analysis is based on US data instead of UK data. Second, we use a longer series covering a period of 23 years, from 1984 to 2007, instead of only 12 years as in Drehmann et al. (2006). In particular, the variables included in our VAR are four. Three of them (output gap, nominal interest rate, inflation rate) refer to the real economy, while the last variable is an indicator of the quality of the banking system (loan loans over total loans). Third, we estimate a VAR directly including also a measure of the banking system in the main specification, instead of using a two steps estimation as proposed by Drehmann et al. (2006). Finally, we consider different specifications comparing the impulse responses obtained using the classical method with those generated using local projection techniques and that refer to linear and quadratic VAR specifications. Finally, differences arise also in terms of results: using a quadratic specification and a quadratic projection approach for computing the impulse response functions we find evidence supporting the first and second round effect.

Concluding we can say that non-linear VAR models represent the most advanced class of models that have been used in order to analyze the relationship between the real economy and the banking sector. Non-

linear VAR models belong to the so called third generation models (TGM). Non linear VAR models represent an improvement of the normal linear VAR models, which refer to the second generation models (SGM). As anticipated before the problems related with SGM are about the fact that in the majority of the cases the DGP is unknown and the analysis focuses on big shocks. However, SGMs are an advance of the standard linear regressions that belong to the first generation models (FGM). SGMs have the advantage to study at the same time first and second round effects in a system of equations where all the variables are interpedently. On the contrary, the goal of the FGMs is to analyze just one side of the relationship considering the other as given. In the majority of the cases, the FGMs focus on the first round effect, while they totally ignore the relationship going from the banking sector to the real economy.

3.1-The importance of non-linearities in estimating macroeconomic models

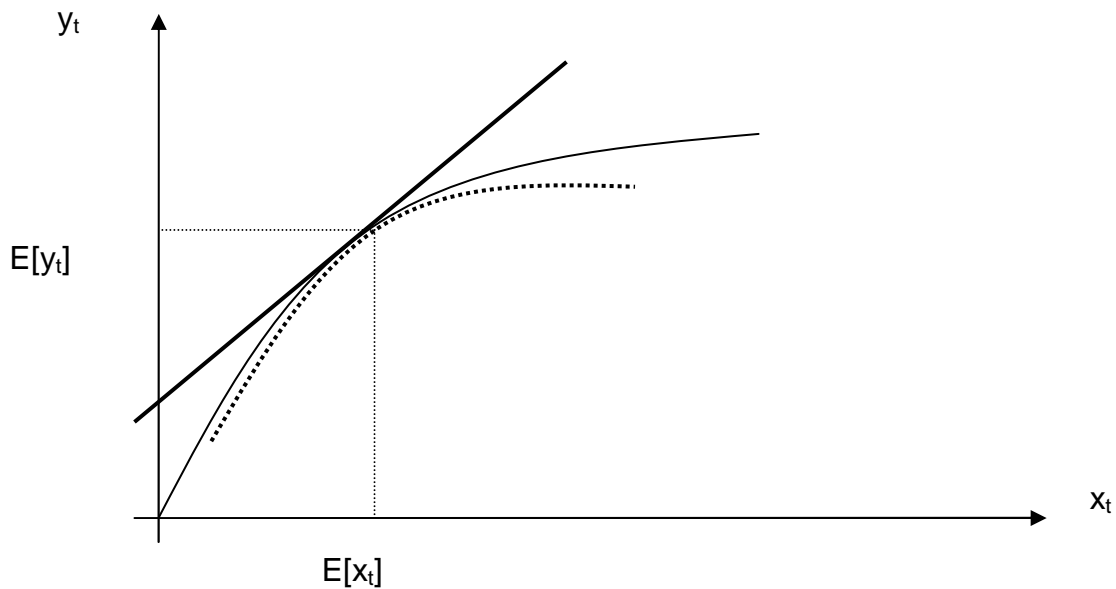
Impulse response analysis studies how a certain number of variables of interest react to a particular shock. Specifically, it is interesting to know the magnitude of the response and the time length needed in order to absorb the shock. Usually, the shock is equal to one standard deviation that represents small departures from the steady state. This means that one standard deviation shocks are not representative of rare events. Put in other terms, consider a random variable normally distributed. If we are interested in rare events, e.g. events with less than 1% of probability of occurring, then we have to consider departures from the mean larger than two standard deviations at least.

When we study the relationship between macro variables and banking sector, we want to see what happens when rare events occur. Using the framework of the classical linear VAR model and traditional methods for estimating impulse responses, one way to take into account rare events is to increase the size of the shock from one to two or three standard deviations. This procedure is neutral in case of linear DGP. However, if this is not the case, departing from the equilibrium may lead to important misspecification errors that increase over the horizon taken into account. Moreover, another issue related with the traditional estimating approach is that the impulse responses computed using a positive shock are mirror like the impulse responses generated using a negative shock. This means that the variables react in the same way, in absolute value, in case of a positive or negative shock. There is evidence that this is not the case.

Using the classical approach for computing impulse responses we are not able to capture qualitative differences due to shocks of opposite sign, and we incur in misspecification errors if we are interested in large shocks and the DGP is not linear. Non-linear approximation of DGP and the local projection method for estimating impulse response functions, as proposed by Jordà (2005), provide a credible alternative to linear models and traditional methods for computing impulse responses when we are interested in big shocks, and in case of shocks of the same size but opposite sign.

In case of one standard deviation shocks the issue of linear or non-linear approximation of the DGP is not so relevant, while it becomes crucial when we work with rare events. In order to understand the mechanism behind, consider a function $y_t = f(x_t)$ that depends on a random variable x_t normally distributed with zero mean and standard deviation equals to one. Moreover, assume that the $f_x(\cdot) > 0$ and $f_{xx}(\cdot) < 0$, so that $f(\cdot)$ is a concave function. As we can observe from the graph below, if we want to approximate around zero the function $f(x_t)$ by a linear function $g(x_t)$ and we are working in a small neighbour of zero, then the linear approximation lead to satisfactory results, with a small approximation error. However, the approximation of the concave function by a linear function when we want to study the impact of big shocks on the variable of interest can lead to important errors. Such errors may affect the impulse response function, generating misspecification errors, that are increasing over the time length considered.

Linear and Quadratic approximations



- Linear Approximation ———
- Concave Function ———
- Quadratic Approximation - - -

From Dhremman et al. (2005)

Small departure from the equilibrium corresponds to one standard deviation shock, while the larger departures represent the two or three standard deviation shock. The previous example can be used in order to explain why the linear VAR can lead to unsatisfactory results when the DGP is non linear and we are interested in big shocks.

3.2-A non-linear VAR model

In order to introduce a non-linear VAR, let us consider eq.[1] where a random variable Y_t is regressed against its own one period lagged value, y_{t-1} , and a constant.

$$y_t = \beta_0 + \beta_1 y_{t-1} + \varepsilon_t \quad [1]$$

Eq.[1] states that there exists a linear relationship between y_t and y_{t-1} . However, eq.[1] can be transformed in a more general way, such that y_t is a function $Z(\cdot)$ of its own one period lagged value y_{t-1} . Specifically we have

$$y_t = Z(y_{t-1}) + \varepsilon_t \quad [1.1]$$

Computing the first and second order Taylor approximation around zero of the function $Z(y_{t-1})$ we obtain

$$Z(y_{t-1}) \approx Z(0) + \nabla Z(0)[y_{t-1} - 0] \quad [1.2]$$

and

$$Z(y_{t-1}) \approx Z(0) + \nabla Z(0)[y_{t-1} - 0] + \frac{\nabla^2 Z(0)}{2}[y_{t-1} - 0]^2 \quad [1.3]$$

Moreover eq.[1.2] and eq.[1.3] can be rewritten as

$$Z(y_{t-1}) \equiv B_0 + B_1 y_{t-1} \quad [1.2.1]$$

and

$$Z(y_{t-1}) \equiv B_0 + B_1 y_{t-1} + Q_1 y_{t-1}^2 \quad [1.3.1]$$

where $B_0 \equiv Z(0)$, $B_1 \equiv \nabla Z(0)$ and $Q_1 \equiv \frac{\nabla^2 Z(0)}{2}$

If instead of using just one variable, we consider a macroeconomic model containing n endogenous variables and we want to estimate it using a VAR approach, we have a system of n equations in n unknowns. The explanatory variables are defined as one period lagged values of the dependent variables. For simplicity, assume that the VAR lag length equals to 1, so that the VAR model in standard form is given by

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \varepsilon_t \quad [2]$$

where now Y_t is a $nx1$ vector of dependent variables while Y_{t-1} is the $nx1$ vector of one period lagged dependent variables used as explanatory variables. As before, assume that Y_t is a function $Z(\cdot)$ of its own one period lagged value Y_{t-1} . Specifically we have

$$Y_t = Z(Y_{t-1}) + \varepsilon_t \quad [2.1]$$

In this case the corresponding expressions of eq.[1.2.1] and eq.[1.3.1] are given by

$$Z(Y_{t-1}) \equiv B_0 + B_1' Y_{t-1} \quad [1.2.2]$$

and

$$Z(Y_{t-1}) \equiv B_0 + B_1' Y_{t-1} + Q_1' Y_{t-1} \bullet Y_{t-1} \quad [1.3.2]$$

where $B_0 \equiv Z(0)$, $B_1 \equiv \nabla Z(0)$, $Q_1 \equiv \frac{\nabla^2 Z(0)}{2}$ and where the \bullet stays for the Schur product³. Because we assumed that the lag length equals to one, in the specification of eq.[1.3.2] there are not cross products. Combing eq.[2.1] and eq.[1.3.1] it is possible to rewrite the VAR for the quadratic specification in the following way:

$$Y_t = Z(Y_{t-1}) + \varepsilon_t = B_0 + B_1' Y_{t-1} + Q_1' Y_{t-1} \bullet Y_{t-1} + \varepsilon_t \quad [1.3.3]$$

Eq.[1.3.3] is a system of n equations that can be easily computed by standard OLS. Moreover if we define s as the horizon with $s=0, 1, 2, \dots, S$ we can estimate eq.[1.3.3] for S periods ahead. Specifically, we have

$$Y_{t+s} = B_0 + B_1^{s'} Y_{t-1} + Q_1^{s'} Y_{t-1} \bullet Y_{t-1} + \varepsilon_t^s \quad [1.3.4]$$

where $B_1^{s'}$ is the vector of coefficients that refer to variable Y_{t-1} and associated to the horizon $t+s$.

If we want to compute impulse responses for the variables included in model in eq.[1.3.3], iterating the model forward, we cannot use standard methods because if there exists a misspecification in the one period model, this may lead to misspecification error increasing in horizon s .

An alternative way to proceed is to follow the method based on local projection proposed by Jordà (2005). If the DGP is a VAR then the local projection method leads to consistent but not efficient estimations, while if the DGP is not a VAR then the local projection approach generates the best approximation at each horizon.

Even if the DGP is unknown, it is possible compute the impulse response function (IRF), that can be considered as the difference of two forecasts (see Koop et al. 1996). Specifically, we have

$$IR(t, s, d_i) = E(Y_{t+s} | \varepsilon_t = d_i; X_t) - E(Y_{t+s} | \varepsilon_t = \bar{0}; X_t) \quad \text{for } s=0, 1, 2, \dots, S \quad [3]$$

where $E(\cdot | \cdot)$ is the mean squared error predictor, Y_{t+s} is the $nx1$ vector of the dependent variables s periods ahead, X_t is the $nx1$ vector of explanatory variable. Specifically in our example $X_t \equiv Y_{t-1}$, ε_t

³ The Schur product or the Hadamard product of two $m \times n$ matrices A and B , $A \bullet B$, is formed by the element wise multiplication of their elements. The matrices must be the same size. $A \bullet B = B \bullet A$

is the $nx1$ vector of innovations expressed in the reduced form. Finally, d_i is the column i of the nxn matrix D that contains all the shocks. Combining eq.[1.3.4] and eq.[3] leads to

$$IR(t,s,d_i) = [\hat{B}_0 + \hat{B}_1^s (Y_{t-1} - d_i) + \hat{Q}_1^s (Y_{t-1} - d_i) \bullet (Y_{t-1} - d_i)] - [\hat{B}_0 + \hat{B}_1^s Y_{t-1} + \hat{Q}_1^s Y_{t-1} \bullet Y_{t-1}] \quad [3.1]$$

previous expression can be rewritten as

$$IR(t,s,d_i) = \hat{B}_1^s d_i + \hat{Q}_1^s (2Y_{t-1} \bullet d_i + d_i \bullet d_i) \quad \text{for } s=0,1,2,\dots,S \quad [3.2]$$

with the normalization $\hat{B}_1^0 = I$ and $\hat{Q}_1^0 = 0_n$, and with Y_{t-1} evaluated at its average values, so that $Y_{t-1} \equiv \bar{Y}_{t-1}$. The expression in eq.[3.2] gives us the reduce form of the IRFs. Moreover, we can also interpret the IRFs as structural responses. In order to achieve this goal, at each point in time of the length period taken into account, we generate a matrix A that takes into account both the endogenous order among the variables and also the size and the sign of the relation among the variables, at the impact. The matrix A must pre-multiply the vectors $Y_{t-1} \equiv \bar{Y}_{t-1}$ and d_i . More details about the construction of A matrix are given in the next section. In order to compute the IRF, the system of equations in eq.[1.3.4] can be estimated using normal OLS. At each time, if the estimated parameters are different from zero, then the IRF can vary depending on the sign and on the size of the shock. From the IRF expression, it is possible to construct a confidence interval working with the variance/covariance matrix of the estimated coefficients for all s .

4.1-Our macroeconomic models

In the second-generation models, the relationship between the real economy and the banking system is analyzed using a linear VAR approach. Two main results arise from this analysis: on the one hand, there is evidence for a first round effect going from the real sector to the banking system; on the other hand, there is no evidence for the second round effect going from the banking sector to the real economy. The suspect is that this result can be driven by the fact that non-linearities characterizing the DGP are not taken into account in the model specification.

In our contribution, we define a macroeconomic model including quadratic terms. In this way, it is possible to take into account possible non-linearities qualifying the Data Generation Function. The macroeconomic model is characterized by three variables capturing macroeconomic features and one variable summarizing the quality of the banking system. In particular, for the macroeconomic features we focus on output gap (GAP), nominal interest rate (INTE), inflation rate (INFL). Finally, for the banking sector the amount of loan losses over total loans (LSTL) has been used. Moreover, also the non performing loans over total loans (NPTL) has been taken into account for robustness tests. Linear and quadratic specifications have been used in order to define the shape of the VAR model. The non-linear specification is useful because it leaves the variables included in the model to react differently depending on the sign of the shock. The intuition behind is that the economic system is not supposed to react in the same way with respect to a positive or negative shock. Impulse response function computed using local projections are able to take into account this feature. Moreover, local projection are recommended also in case we are interested in big shocks, and there is the suspicious of non-linear DGP.

The VAR models, which can be estimated using normal OLS, take the following form:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \varepsilon_t \quad [4.1]$$

$$Y_t = B_0 + B_1' Y_{t-1} + Q_1' Y_{t-1} \bullet Y_{t-1} + \varepsilon_t \quad [4.2]$$

for the linear and quadratic specification respectively. Y_t is the vector of the dependent variables while Y_{t-1} is the vector of the one period lagged dependent variables used as explanatory variables. Because the lag length is equal to one quarter then in the quadratic specification there are not cross products. In this way, we also have a more parsimonious model. The choice of the length of only one lag for defining the set of the explanatory variables is justified by Akaike (AIC) and Schwarz (SC) information criteria for lag order. Moreover, the results found are also coherent with other empirical studies. Results are reported in the Appendix. Moreover, the VAR stability check shows that the VAR model satisfy the stability condition. Finally, the model in eq. [4.2] can be estimated via OLS.

Following Jordà (2005), we consider the linear VAR as a first Taylor approximation of the unknown Data Generation Process (DGP). In this way, our choice of using quadratic specification is supported

not only by the economic intuition but also by the fact that it can also be interpreted as a more flexible representation of the DGP. The cubic specification is not considered in this study, because it is difficult to find an economic intuition for this specification. As anticipated above, if the VAR is a first Taylor approximation of the DGP, then using the standard methods⁴ for computing impulse responses can lead to important mistakes. Specifically, if the one period model is misspecified then a forwarding process can generate misspecification errors. Alternatively, Jordà suggests to estimate, via OLS, a different model for each horizon and then to generate the correspondent impulse response. Using Jordà's approach two different situations are possible: on the one hand, if the DGP is a VAR then the Jordà's estimations are consistent but not efficient; on the other hand, if the DGP is not a VAR then the Jordà's estimations are the best approximations at each horizon. Based on this argument, in order to compute impulse responses we estimate a set of models for each horizon s .

Specifically for the quadratic specification we have:

$$Y_{t+s} = B_0 + B_1^{s'} Y_{t-1} + Q_1^{s'} Y_{t-1} \bullet Y_{t-1} + \varepsilon_t^s \text{ for } s=0,1,2,\dots,S \quad [4.3]$$

We take into account a horizon of 12 periods so that $S=12$. This implies that we estimate twelve different models, one for each period. Moreover, the estimated coefficients are then used in order to generate impulse responses using the expression in eq.[3.2]

$$IR(t,s,d_i) = \hat{B}_1^{s'} d_i + \hat{Q}_1^{s'} (2Y_{t-1} \bullet d_i + d_i \bullet d_i) \text{ for } s=0,1,2,\dots,12 \quad [4.4]$$

Eq.[4.4] represents a reduced form of the IRF. If we are interested in a structural interpretation of eq.[4.4] we have to generate a matrix A , taking into account the endogenous order of the variables. The endogenous order of the variables selected is the following: we claim that the stress variable can be affected contemporaneously by all the shocks of the model. The second more endogenous variable is the output gap that, at the impact, reacts after a shock coming from all the variables but stress. Finally, there are the variables referring to inflation and to the interest rate. The latter variable turns out to react at the impact only after its own shock. Moreover, we proceed imposing a structure about the sign and the magnitude of the relation among the variables, at the impact. In order to achieve this result we proceed in the following way. Given the endogenous order of the variables, we estimate the following system:

$$Y_{t+s} = B_0 + B_1^{s'} Y_{t-1} + Q_1^{s'} Y_{t-1} \bullet Y_{t-1} + C^{s'} X_t + \varepsilon_t^s \text{ for } s=0,1,2,\dots,S$$

⁴ Standard approaches for computing impulse responses are based on iterating n periods forward the one period model.

$$\text{where } X_t = \begin{bmatrix} \text{stress} \\ \text{output gap} \\ \text{inflation} \\ \text{interest rate} \end{bmatrix}_t \text{ and } C^{s'} = \begin{bmatrix} 0 & c_{12}^s & c_{13}^s & c_{14}^s \\ 0 & 0 & c_{23}^s & c_{24}^s \\ 0 & 0 & 0 & c_{34}^s \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The endogenous order of the variables is embed in the matrix $C^{s'}$. From this model, and for each point in time of the length period considered, we estimate the parameters of the matrix $C^{s'}$, and then we generate the matrix A, defined as

$$\hat{A}^{s'} = C^{s'} = \begin{bmatrix} 0 & -\hat{c}_{12}^s & -\hat{c}_{13}^s & -\hat{c}_{14}^s \\ 0 & 0 & -\hat{c}_{23}^s & -\hat{c}_{24}^s \\ 0 & 0 & 0 & -\hat{c}_{34}^s \\ 0 & 0 & 0 & 0 \end{bmatrix}^{-1}$$

Thereafter, the model is re-estimated dropping the vector X_t . Specifically, we have

$$Y_{t+s} = B_0 + B_1^{s'} Y_{t-1} + Q_1^{s'} Y_{t-1} \bullet Y_{t-1} + \varepsilon_t^s \text{ for } s=0,1,2,\dots,S$$

Matrixes $\hat{A}^{s'}$, $\hat{B}^{s'}$ and $\hat{Q}^{s'}$ are then used in order to compute the impulse responses:

$$IR(t,s,d_j) = \hat{B}_1^{s'} d_j + \hat{Q}_1^{s'} (2\tilde{Y}_{t-1}^s \bullet \tilde{d}_j + \tilde{d}_j \bullet \tilde{d}_j) \text{ for } s=0,1,2,\dots,12$$

where $\tilde{Y}_{t-1}^s = \hat{A}^{s'} \cdot \bar{Y}_{t-1}$ and $\tilde{d}_j = \hat{A}^{s'} \cdot d_j$

4.2-Data set

Our dataset is based on quarterly US-level data and covers the period from 1984.Q1 to 2007.Q3, for an overall of 95 observations. The dataset includes four variables: three of them refer to the real economy, while the last variable is an indicator of the quality of the banking system. Specifically, in order to describe the economic system we focus on output gap, nominal interest rate, inflation rate. Output gap has been generated taking into account the HP-filter component of the GDP defined as Real Gross Domestic Product. The original series is expressed in billions of chained 2000 dollars. The natural log of the consumer price index for all urban consumers has been used in order to describe price dynamics. Percent changes between quarters of two consecutive years have been considered. The series is seasonally adjusted. The original series was monthly based. We rearranged it taking the average values over each three months. The official discount rate has been used as the interest rate variable. Sometimes within a quarter, the discount rate changes several times. We report its value at the end of the third month of the quarter of interest. Finally, for describing the banking sector we focus on the natural log of the net loan losses over average total loans (LSTL), while the the natural log of

the non performing loans over total loans (NPTL) has been used for robustness checks. The dataset has been generated collecting information from the Federal Reserve of St. Louis. In the tables and graphs below, we report the main features of the variables included in our dataset.

Table 1: statistical features of the variables included in the dataset

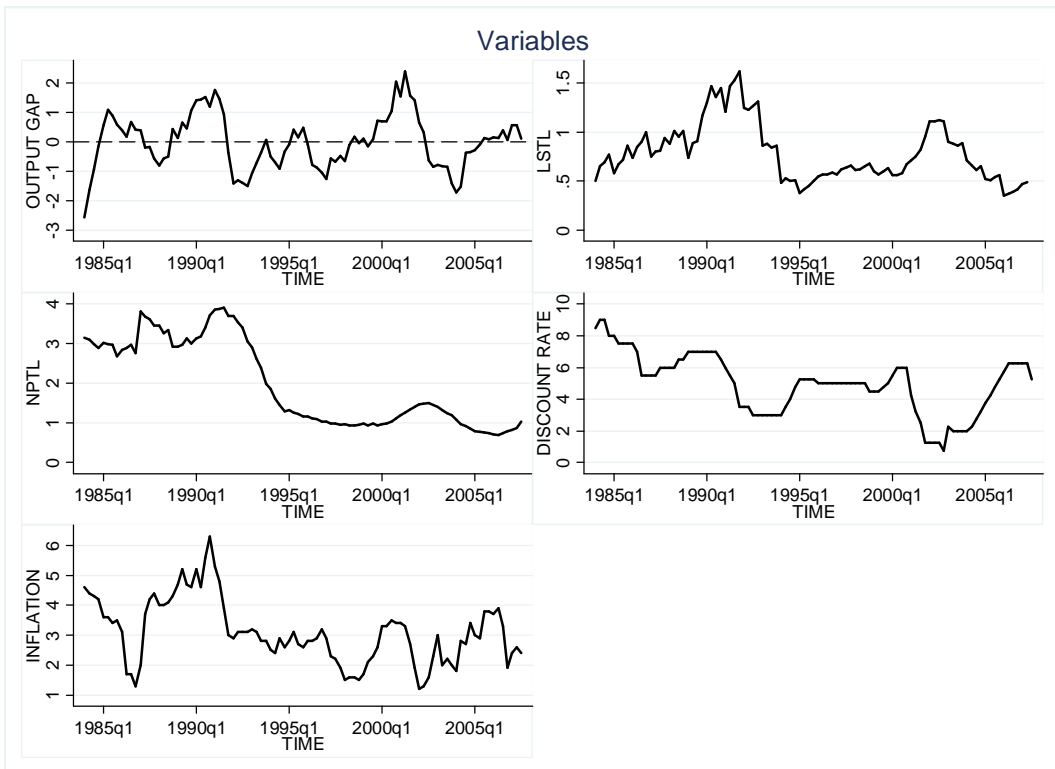
Variable	Obs	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
GAP	95	.00518	.9256	-.0900	2.931	-2.4	2.56
INFL	95	1.07	.36	-.3504	2.67	.1823	1.84
INTR	95	4.96	1.87	-.2157	2.549	.75	9
NPTL	95	1.974	1.08	.4102	1.494	.7	3.91
LSTL	95	.787	.295	.9043	3.1385	.35	1.62

Looking at the correlations between the variables, a first result is that output gap is negatively correlated with the rest of the variables included in the dataset. The highest and lowest correlations in absolute value are attained with the non performing loans over total loans, NPTL, and the loan losses over total loans, LSTL. Moreover, an opposite situation characterizes the correlations between the inflation rate and the interest rate and the banking sector variables: in all the cases there exist a positive correlation included between 31%, (LSTL) and 57%, (INTR). Finally, interest rate is negatively correlated with the loan losses over total loans (LSTL), while it is positively correlated with the non-performing loans over total loans, (NPTL).

Table 2: Correlations between the variables of the data set

Variable	GAP	INFL	INTR	NPTL	LSTL
GAP	1				
INFL	-0.4105	1			
INTR	-0.5373	0.5782	1		
NPTL	-0.8239	0.5595	0.3697	1	
LSTL	-0.3515	0.3095	-0.1423	0.6952	1

Graphs of the series



5-Results

Our analysis focuses on several aspects. First, we check whether the methods for computing the impulse response functions can significantly affect the results. In order to achieve this goal we compare the impulse response functions due to a positive shock (1 standard deviation), based on a traditional and local projection approaches, using a linear model specification.

Second, we are interested in analyzing whether the specification of the macro econometric model can have an impact on the results obtained. We analyze the impulse response functions, generated by a big positive shock (3 standard deviations), and based on local projection approach, using a linear and quadratic model specification.

Finally, we control whether there exists some evidence for asymmetric responses of the variables of interest in case of a shock of the same magnitude but of opposite sign. Using a local projection approach and a quadratic model specification, we compare the impulse response functions based on a positive and a negative shock.

Anticipating the results obtained, on the one hand, comparing the IRF depending on the model specification and the approach used for computing them, we can claim that there exist important differences in the results obtained using the classical approach and the local projection approach. Moreover, we find that the specification of the model affects the impulse responses shape. Finally, we find out that the variables included in our model react asymmetrically with respect to a positive and a negative shock. On the other hand, analyzing the impulse response, we find evidence for both first and second round effects. This means that there exists a link going from the macro variables to the banking sector and from the banking sector to the economic system. This is last evidence represents an important finding that in the majority of the others contributions is not found.

Linear specifications, Traditional (TA) vs Local Projection Approach (LP)

In order to check the importance of the approach used for computing the impulse response functions, IRF, we apply traditional and local projection approaches to a linear model. As shown in the figures below, there is evidence for claiming that the approach used matters in the shape and the statistical significance of the IRF. Even if there is a common path in the IRF, several times the two methods show important differences in the recovering path towards the steady state. For instance, this is the case, for the impulse response of the output gap due to an unexpected shock in the stress variable, the reaction of the stress variable after an unexpected shock in the interest rate variable and for the response of the output gap after a an unexpected shock in the inflation rate. Also focusing on first and second round effects there are clear evidence for important differences in the impulse responses obtained using the two methods. In particular, the first round effect measured by the LP is statistically different from zero for the entire horizon taken into account. This is not true analyzing the first round effect using the TA. Focusing on the second round effect, the TA leads to an IRF statistically not different from zero, while, using the LP, at least for the first two periods there is evidence for statistically significant IRF. Other differences arise also in terms of magnitude: the TA leads to responses that are smaller than those obtained using the LP.

Figure 1

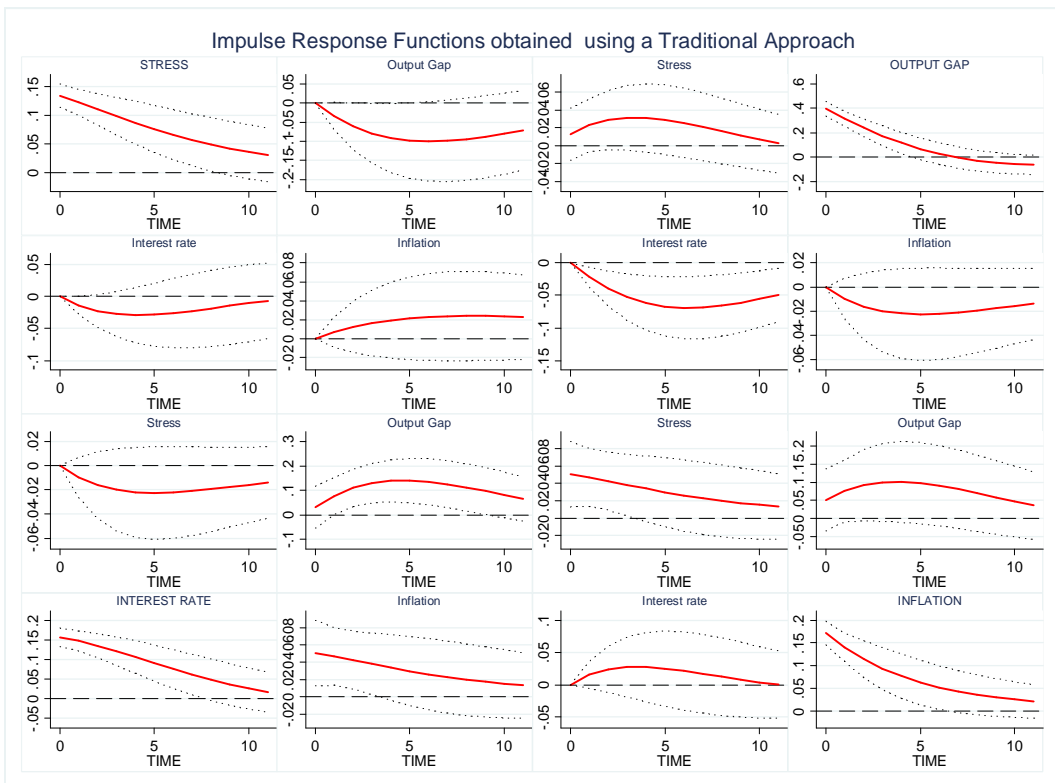
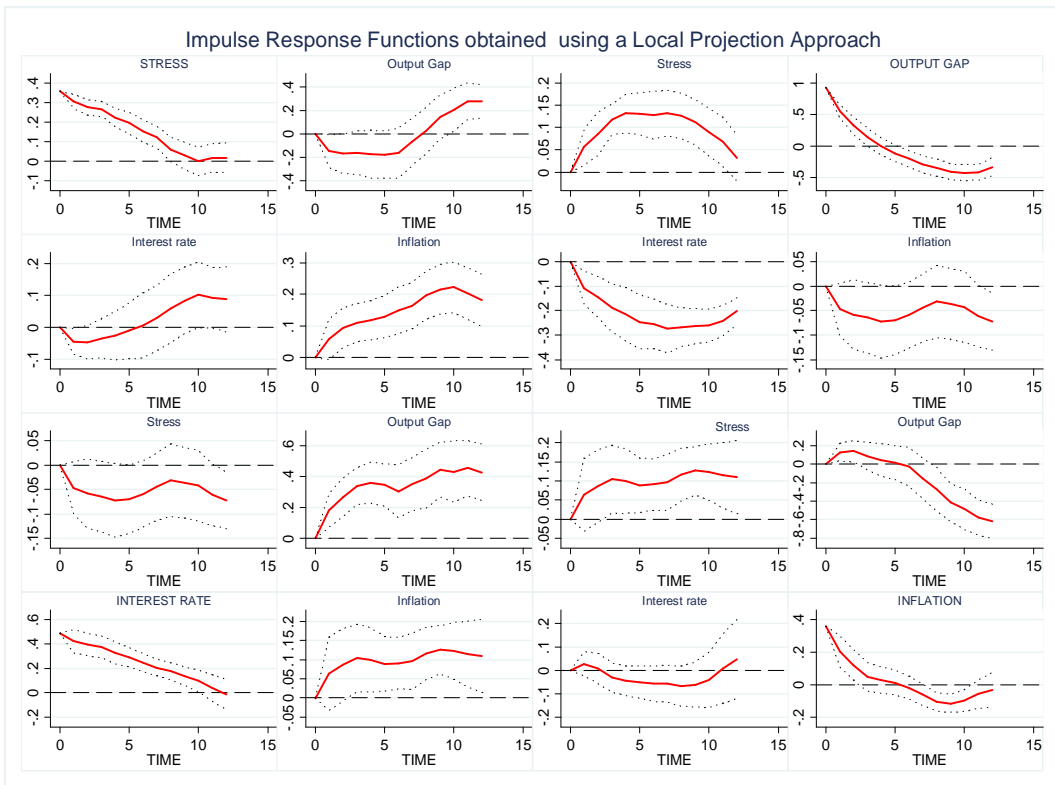


Figure 1: These figures show the responses of a 1 standard deviation shock. In capital letters the variable to which ascribe the shock. A linear specification has been used. The dot lines are the 95% confidence bounds on the impulse response. Variable used for describing the banking quality LSTL.

Linear vs Quadratic model specifications, Projection Approach

An issue that can arise working with linear and non-linear specifications of the macroeconomic model is about the role played by quadratic specification in terms of the shape of the IRFs, the magnitude and the statistical significance of the results obtained. In order to deal with this issue, we compare the IRFs obtained using linear and quadratic projections, in case of big shocks (3 standard deviations). As shown in table 2 there exist important differences depending on the model specification used. The only exceptions are represented by the impulse responses due to a shock in inflation: the IRFs are not statistically different using the linear or the quadratic specifications. In all the other cases, there are significant differences. Divergences can arise in terms of shape, magnitude and statistical significance of the impulse response functions. The IRFs obtained using the linear specification react less than those obtained using the quadratic specification. Analyzing some particular cases, significant divergences arise in the IRF of the output gap and the inflation due to a shock in the stress variable, the more important reaction of stress after a shock in the interest rate or in the output gap, in case of the quadratic specification. Finally, analyzing the statistical significance of the results it is clear that the quadratic specification strengthen the findings already found using the linear specification. In fact, the outcomes of the quadratic specification not only confirm the existence of a first round effect, but they also show that there is a second round effect going on. These findings are going to be analyzed in details in the next section. We can conclude claiming that the model specification matters in term of the shape and the magnitude of the IRFs.

Figure 2

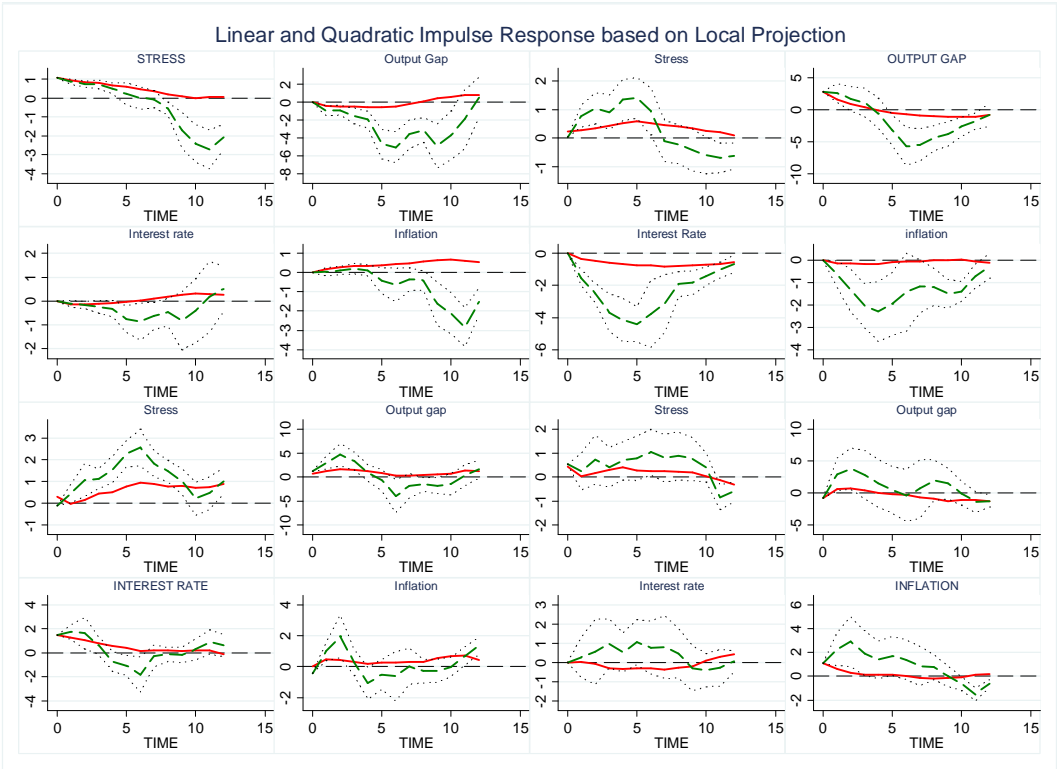


Figure 2: These figures show the responses of a 3 standard deviation shock. In capital letter the variable to which ascribe the shock. The solid and the dash lines are the impulse response obtained using the linear and quadratic projections, respectively. The dot lines are the 95% confidence bounds on the impulse response from the quadratic projection. Variable used for describing the banking quality LSTL.

Quadratic model specification, Projection Approach, Positive and Negative Shock

In this section, we discuss in details the results concerning the existence of a first and second round effect, characterizing the relationship between the macro variables and the banking system, and the possibility for the variables to react asymmetrically after a shock of the same size but opposite sign. In order to deal with these issues we focus on impulse response functions obtained by quadratic projections.

Focusing on the first round effect, the effect going from the macro system to the banking variable, the results included in figure 3 show that there exists a significant reaction of the quality of the banking sector. Specifically, at the impact there is no reaction. This implies that loan losses and total loans change at the same rate, so that the ratio does not change. Moreover, once the output gap decreases the loan losses increases reaching the peak after 5 quarters, and then eventually converges to the equilibrium. We can explain this finding in the following way. During booming phases, banks are less demanding in term of lending requirements. They expand their credits and so the fraction of bad loans does as well. At the same time, banks take more risk, financing projects that otherwise they would not finance. Therefore, as the economic conditions deteriorate, banks raise lending standards, reducing in this way, the capital amount lent and becoming more demanding with the current borrowers. That is why the loan losses arise once the economic conditions get worse. There is empirical evidence for the Spain economy supporting this result, see for instance Jiménez and Saurina (2005) Salas and Saurina (2002). Moreover, there are at least two theoretical contributions that can justify our findings. Specifically, Rajan (1994) predicts that banks may have a not-constant supply credit policy, due to the fact that bank managers are rational but short run looking, concerned about their reputation, and the information observable in the market is only about banks' earnings. These features of the managers, and of the market together with a to spread optimism and to the fact that for the market a common error is less relevant than a single error, may generate situations where credit requirements imposed by the banks to the borrowers change over time, and in particular decreasing over boom. Rucker (2004) uses similar arguments.

However, this result is in contrast with what found in other studies by Hoggarth et al. (2005), where the banking variable was approximated by write-off ratio, by Drehmann et al. (2006), where the liquidation rate decreases after a positive shock in output gap and Marcucci and Quagliariello (2006). In the last case, the results are not statistically significant. In the case of Drehmann et al. the results are not directly comparable with ours because they implement a two step estimations, and because they look at the probability of liquidation. Finally, the results of Hoggarth et al. can be driven by the implementation of linear VAR, and impulse responses computed using traditional methods.

First round effects work also via interest rate. An unexpected increase in the interest rate leads to an increasing in the stress level. The impulse response for loan losses reaches its maximum after 6 periods, and then converges to the equilibrium. Finally, shocks in inflation lead to unsatisfactory results.

Focusing to second round effect, a worseness of the banking system has a negative and statistical significance impact on the output gap, while there is no evidence for an effect of this shock on interest rate and inflation. The reaction of the output gap is delayed. After a zero reaction at the impact, the

output gap constantly decreases reaching its bottom, around 5 percentage points, after 5 periods, and it starts recovering some periods after that the quality of the banking system has already improved. The intuition behind this finding is that if loan losses drastically increase and banks have capital requirements that are binding, then they prefer reduce lending than raising new credit. This reaction of the banking sector is due to the fact that raising new credit becomes more costly, as pointed out by Peek and Rosengren (1995). In other words, financial resources decrease or they become more costly as found by Bernanke and Gertler (1995). These elements have a detrimental effect in output. Moreover, Bernanke and Lown (1991) claim that the size of the second round effect is a function of the capital buffer available for the banks, the amount of credit reduction, the effects of such reduction on credit costs, the degree of substitutability between loans and bonds and the share of output accounted for by bank-dependent firms.

Comparing the impulse response functions generated by a positive shock with those due to a negative shock of the same size, the results on figure 3 show important elements. On the one hand, also in case of negative shock, the existence of the first round effect is confirmed even if the stress level reacts more in case of a positive shock. At the impact, LSTL lies just below the steady state value. Then, as the output gap starts recovering, the quality condition of the banking sector improves as well. Moreover, interest and inflation rate show a zero reaction at the impact and then, as the output gap recovers they increase before converging again to the equilibrium. In general, the results are statistically significant. On the other hand, there is no clear evidence for the existence of the second round effect. The impulse response for the output gap is statistically significant only for some points in time, and in any case, it is not significant for the first three periods.

Summing up, there is evidence that the variables reacts differently in case of positive and negative shocks. In case of negative shock, the impact of the first round effect is reduced, while there is not sufficient evidence for supporting the second round effect.

Finally, looking at the rest of the impulse responses we can claim that the differences with those obtained after a positive shock, lie both in shape and in magnitude. This finding confirms that there exist asymmetric reactions to shock of the same size but opposite sign.

Figure 3

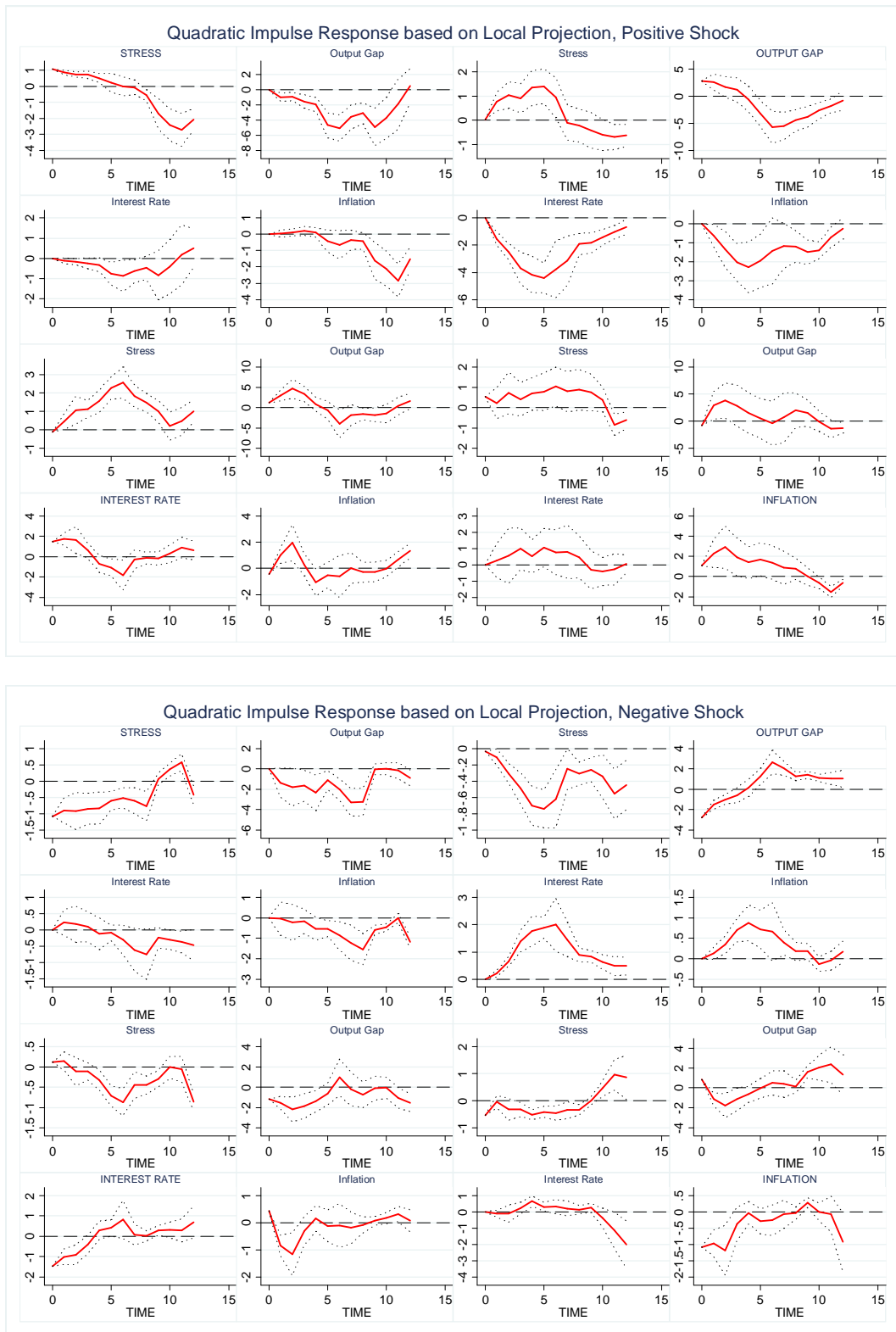


Figure 3: These figures show the responses of a 3 standard deviation positive and negative shock respectively. In capital letters the variable to which ascribe the shock. A linear specification has been used. The dot lines are the 95% confidence bounds on the impulse response. Variable used for describing the banking quality LSTL.

Robustness tests:

In order to check the robustness of our results we proceed in two directions. On the one hand, we replace the variable describing the fragility of the banking system. Specifically, we replace the loan losses over total loans by the non-performing loans over total loans. On the other hand, we select a new sample, excluding all those periods characterized by a recessions⁵. The results are reported in the Appendix. In both case, our results are robust to these modifications. In particular, there is evidence for first and second round effect. Moreover, the results attest the existence of asymmetric responses of the variables after a shock of the same size but opposite sign.

6-Conclusions

In this paper, we implement a non-linear VAR model estimating the impulse response functions using local projection approach, as proposed by Jordà (2005). The choice of a non-linear VAR is important because it allows us to introduce non-linearities in the specification of the model that can be useful for understanding the dynamic of the variables taken into account. Our preference for local projection instead of using traditional methods for computing impulse response functions is due to two main reasons. First, if the data generator process is non-linear, and we are interested in big shocks, then traditional methods may lead to important misspecification errors iterating forward the model. Second, it is not possible to study the reaction of the variables of interest in case of a shock of the same size but opposite sign using the traditional approach, while this is the case working with non-linear specifications and local projection method for computing the impulse response functions.

Our VAR model takes into account four variables of the US economy: output gap, nominal interest rate, inflation rate for describing the macro system, while the amount of loan losses over total loans has been considered in order take into account the fragility of the banking system. Data are quarterly and the period taken into account includes 23 years, from 1984 to 2007. The primary findings of our paper lie in three main results. First, the traditional approach and linear projection IRFs are similar even if the former are not statistically significant. This implies that the method used for computing impulse responses matters. Second, linear and quadratic projection impulse responses lead to different results. Specifically, using the quadratic projection it is possible to find out first and second round effects. This means that non-linearities matter in detecting first and second round effects. Finally, using a quadratic projection approach, we find that macro variables and banking indicators react asymmetrically in case of a positive and a negative shock. These results are robust to changing in variable for representing the banking fragility (the non-performing loans over total loans (NPTL) instead of the amount of loan losses over total loans (LSTL)), and to different samples selected.

⁵ In this case, we do not report the results that are in any case available under request.

APPENDIX

Information criteria for lag order: lags included 2

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-223.887	NA	0.001666	4.954066	5.063709	4.998319
1	80.69969	576.0662*	3.14e-06*	-1.319558*	-0.771344*	-1.098294*
2	94.39418	24.70962	3.31E-06	-1.269439	-0.282652	-0.871163

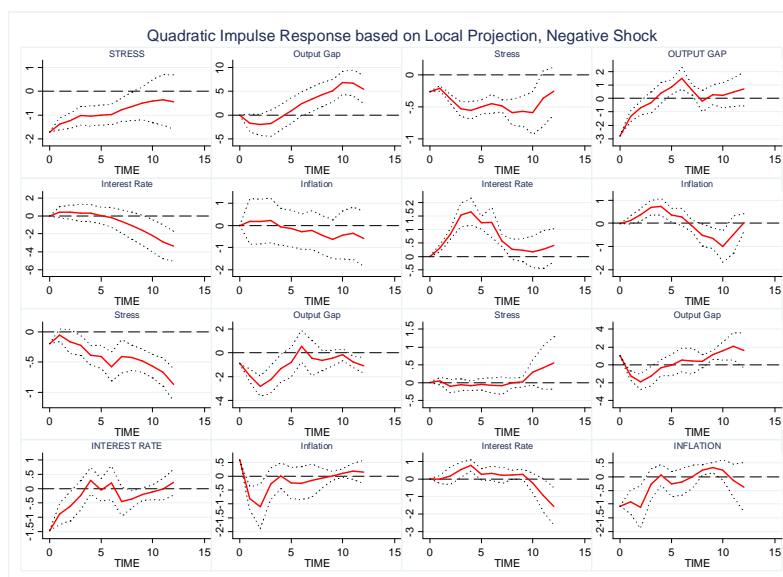
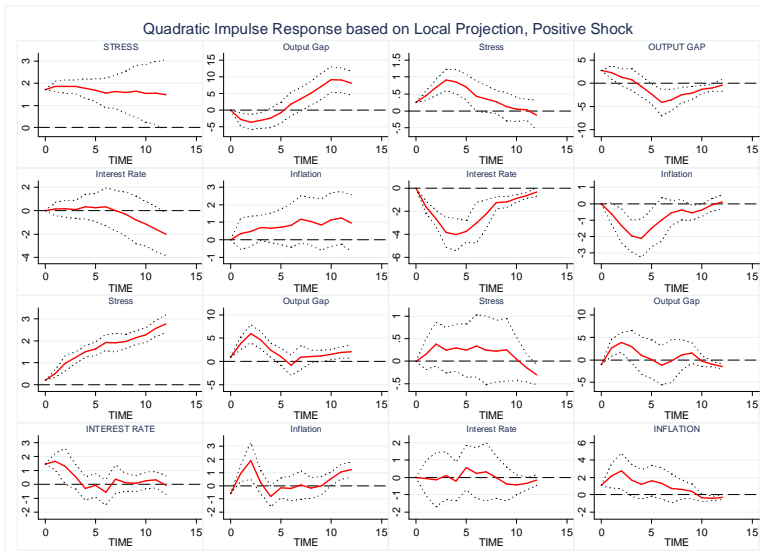
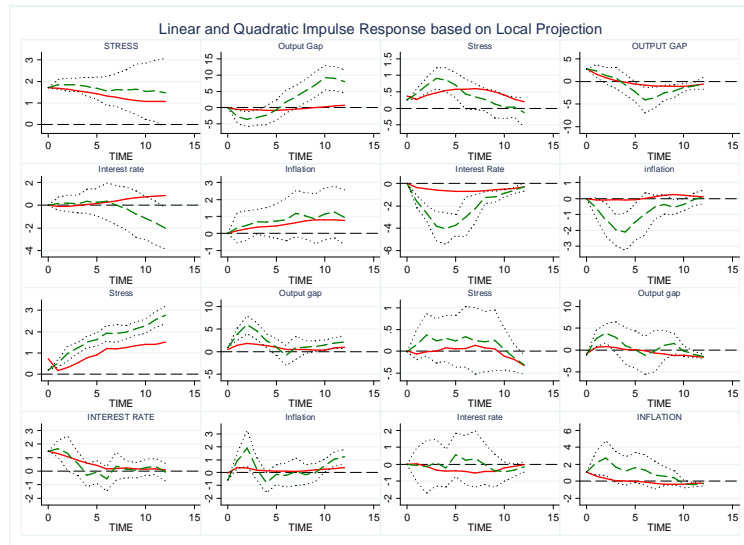
* indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

Information criteria for lag order: lags included 4

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-218.9125	NA	0.001665	4.953611	5.064713	4.998414
1	76.56459	558.1234	3.35e-06*	-1.256991*	-0.701478*	-1.032975*
2	91.73732	27.31092*	3.41e-06	-1.238607	-0.238683	-0.835379
3	103.8742	20.76746	3.74e-06	-1.152759	0.291576	-0.570318
4	119.4926	25.33666	3.81e-06	-1.144281	0.744464	-0.382628

* indicates lag order selected by the criterion. 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

Robustness check, using Non performing Loans over total loans NPTL



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