Shocking the Borrowing Constraint over the Financial Cycle: Evidence of Non-linearities

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Abstract In this paper we ask how the propagation of shocks affecting the borrowing capacity of agents changes according to the tightness of borrowing constraints. In order to answer this question, we run a non-linear time series analysis, using local projections (Óscar Jordá [2007]) to extract impulse responses dependent on the level of the credit-to-GDP gap. Our cross-country analysis shows that the higher the credit-to-GDP-gap, the stronger and the more persistent are the impacts of housing, income and monetary policy shocks on the economy. These findings highlight the role which occasionally binding constraints on borrowings have in affecting the transmission of shocks and improving the forecasting performance with respect to linear specifications. Those results prove to be economically significant, largely outperforming standard VAR.

Keywords: Financial cycle, macroprudential policy, non-linear model, occasionally binding constraint.

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1 Introduction

In this paper we study how the tightness of borrowing constraints of agents affects the propagation of economic shocks. We find that the highly leveraged economies are generally more vulnerable to the shocks which directly impact the borrowing capacity of agents.

Since the financial crisis, a number of theoretical works (Guerrieri and Iacoviello [2016], Maffezzoli and Monacelli [2015]) pointed at the the high quantity of debt as one of the main amplification factors that explain the sever downturn of the Great Recession. According to these models, borrowers are subject to limited borrowing capacity, depending on their debt repayment capacity. The borrowing constraint is occasionally binding: when the level of debt hits its limit, the constraint becomes binding, amplifying the transmission of economic and financial shocks. According to these models, the amplification mechanism concerns in particular the shocks directly impacting on the borrowers' borrowing capacity (collateral, income, cost of debt).

In this paper, we empirically detect the presence of the Occasionally Binding Constraints on borrowing and quantify how these affect the propagation mechanisms of the economy. In order to do that, we implement a non-linear time series model where the key macroeconomic aggregates interact with the tightness of the borrowing constraint. To proxy this tightness of the indebtedness of the economic agents in the economy, we use the Credit-to-GDP-gap (Borio et al. [2013]), a measure of excessive credit growth diffused in the macro-prudential analysis. To extract non-linear impulse responses which depend on the level of credit-to-GDP-gap, we use the Local Projections method (Óscar Jordá [2007]). To detect the presence of the OBC, we focus on three shocks which directly affect the tightness of the borrowing constraint: 1) an housing shock, which increases the value of collateral, 2) an income shock, impacting on the borrowers' expected refunding capacity, 3) a monetary policy shock, affecting the cost of debt and the asset valuation. The analysis is run for a range of developed countries: US, UK and the four biggest countries of the Euro area. We find three general results. First, the effect of income, housing and monetary shocks produce stronger effects when the Credit to GDP is high. Second, we find that a negative housing shock has a stronger effect in absolute terms, compared to a positive one. Third, those effects are economically significant, more important than longer lags in a standard VAR: debt-fragility matters more than rich time effect.

These empirical results provide strong evidence for the presence of Occasionally Binding orrowing Constraints: when the level of debt is high, a larger fraction of agents is constrained, amplifying the vulnerability of the economy to the shocks hitting agents' borrowing capacity.

Our empirical analysis is founded on thee use of Local Projections (Óscar Jordá [2007]), permitting to easily include non-linear terms in the specification of the model. With local projections, the impulse responses of a shock to a macroeconomic variables are directly estimated by running, for each horizon, a regression of the macroeconomic variable on the explanatory variables. This approach sidesteps the inversion of the VAR into a Vector Moving Average representation. As a result, the possible errors deriving from the misspecification of the empirical model are not accumulated over the horizon, by potentially benefiting the estimation of the impulse responses for the longer horizon.

In order to proxy the tightness of indebtedness we use the Credit-to-GDP-gap, one of the most popular measures of risk in macroprudential analysis, to assess the evolution of cyclical risk (Borio and Lowe [2002, 2004], Borio and Drehman [2009], Juselius and Drehmann [2014]). The Credit-to-GDP-Gap is computed as the difference between the credit-to-GDP ratio and its long term trend. The trend is extracted with a Hodrick-Prescott filter. The *deviation* of the Credit to GDP ratio from this trend indicates credit excesses. In the robustness checks, we alternatively use the credit-to-GDP ratio and find similar results.

In our specification, the Credit to GDP gap is interacted with all the macroeconomic variables and with their squared values. This specification disentangle three types of non-linearities: 1) the non-linear effect associated to the level of indebtedness in the economy (state effect); 2) the asymmetric effects related to the sign of the shock (sign effect); 3) the presence of effects related to the size of the shock (size effect). To this extent, we find three main results. First, the state effect is the predominant source of non-linearity is the state effect (i.e. the level of indebtedness). Second, we detect significant size effect concerning the housing shock: the elasticities of income to an exogenous variation in housing prices increases with the size of the shock. Third, concerning the sign effect, we generally find that negative housing shocks have a larger negative effect in absolute terms, compared to positive shocks of the same size. These results are in line with the work by Guerrieri and Iacoviello [2016]. In their model positive shocks make the borrowers unconstrained, by allowing them to expand their debt according to their Euler equation. Instead, when house prices decrease, constrained borrowers are forced to deleverage, reducing their consumption accordingly.

Finally, we assess the in-sample forecast performance of the non-linear model with with respect to a linear VAR, by comparing the sum of squared residuals of the two models. The results show that non-linearities are crucial to improve the forecast performance of the model. [1]

Our paper builds on three main streams of literature. First, a stream of literature exploits empirical non-linear models to detect non-linear effects in the propagation of shocks (Óscar Jordá [2007], Óscar Jordá and Kozicki [2007], Óscar Jordá et al. [2016], Barnichon et al. [2016], Haug and Smith [2011]).

The paper by Barnichon et al. [2016] represents the closest work to this paper. In their analysis Barnichon et al. [2016] focus on the effect of the credit supply shock in the economy and its asymmetric effect. Also, they analyze whether the propagation of the shock changes according to the position of the economy in the business cycle (recession versus growth). Óscar Jordá et al. [2016] explore the role of financial crisis in affecting the business cycle. They study the role of debt overhang in the pre-crisis period as amplification factor of the recession. Instead, in our work, the main state variable is the tightness of the borrowing constraint. Furthermore, we focus on the effects of three different shocks: the housing shocks, of income shocks and of monetary policy shocks. This strategy aims at detecting the non-linear effects related to the OBC from different perspectives: the housing shock affects the value of collateral, the income shock affects the expected repayment capacity and the monetary policy shock has a direct impact on the cost of debt.

A second stream of literature (Guerrieri and Iacoviello [2016], Maffezzoli and Monacelli [2015]) focuses on the development of DSGE models with financial frictions to study the role of the occasionally binding borrowing constraint as amplification mechanism of the economic shocks. In these works, occasionally binding borrowing constraints are crucial to obtain asymmetric relations between financial and macroeconomic variables and the amplification of the financial shocks when the leverage in the economy is high. Our paper provides an empirical support to the

[1] In order to check that this result is not driven by the smaller specification errors of the Local projections, we compare the performance of the non-linear model with linear model run by local projections and we find similar qualitative results.

theories on OBC presented in these models. [2]

Finally, this paper relates to the works focusing on the measurement of the risks associated to high indebtedness (Borio et al. [2013, 2014], Juselius and Drehmann [2015]). To identify the excessive credit growth in the economy and assess the risk of financial crisis, Borio et al. [2013, 2014] Juselius et al. [2016] provide measures as such as the Credit to GDP gap or the Credit to GDP ratios. We contribute to this literature by using these risk indicators as state variable in our non-linear framework, showing how the the vulnerability of the economy varies according to the evolution of the risk measure. [3]

The rest of the paper is organized as follows. Section 2 presents the theoretical background which motivates the non-linear model specifications. Section 3 presents the empirical model. Section 4 presents the data, with a focus on the measures of the financial cycle. In Section 5, we present the results. In Section 6, robustness checks are housed. Last section concludes.

2 The theoretical background

Models featuring occasionally binding borrowing constraints have had an increasing importance in the recent economic debate (Guerrieri and Iacoviello [2016], Maffezzoli and Monacelli [2015]) and in central banking activity. The presence of the OBC for borrowers generates state dependency between macroeconomic variables and financial variables. [4]

In this paper we consider that agents (entrepreneurs or inpatient households) are subject to two types of occasionally binding constraint (OBC). The first OBC is a Loan-To-Value constraint:

$$\frac{D_t}{Q_t H_t} \leq ltv, \tag{1}$$

[2]Other seminal papers of this literature are Deaton [1991], Bernanke et al. [1996], Kiyotaki and Moore [1997], who develop economic models where a borrowing constraint amplifies the fluctuation of the economic shocks. Nevertheless, those models imply that the borrowing constraint is always binding: agents take as much debt as they can.

[3]Drehmann et al. [2012] finds that business cycle recessions are munch deeper when associated with fall in financial cycle.

[4]The OBC pushed economists to develop non-linear theoretical solution techniques to handle Occasionally binding borrowing constraints. These non-linear models have the feature of preserving state-dependent behaviour in the macroeconomic dynamics in the solution of macroeconomic theoretical models.

where D_t is debt, Q_t is the asset price (housing or capital), the H_t is the collateral detained by the borrower, ltv is the maximum loan to value ratio. According to this OBC, the borrowers can increase their debt up to a fraction of the worth of their collateral. The second OBC is on the Debt-to-Service Ratio:

$$\frac{D_t}{Y_t}\frac{i_t}{1-(1-i_t)} \leq dsr, \tag{2}$$

where Y_t is income, i_t is the interest rate, dsr is the maximum Debt to Service Ratio. According to this constraint, costs related to debt repayment can be raised up to a fraction of the agents' income.

A clear measure for the the tightness of the borrowing constraint is still missing in literature, due to the fact that dsr and ltv can be subject to variations, due to financial innovation or change in regulation. For this reason, in order to gauge time variation of tightness, we consider the evolution on a measure of credit excess, compared to long-term trend. When credit is high compared to this long term trend, we itnerpret it as a signal of credit excess also affecting the DSR and the leverage ratio, which thus become sensitive to three shocks: the housing shock, directly affecting the price of collateral Q_t, the income shock (Y_t) affecting debt repayment capacity, and the monetary policy shock, affecting the cost of debt (i_t). When the constraints bind, these shocks are expected to have an amplified effect on borrowers' spending capacity.

Negative shocks increase the existing debt ratios used by lenders to assess the riskiness of borrowers. This reduces their remaining debt capacity, and can even force them to deleverage, should they rollover their debt or because they come to breach some covenants, allowing banks to ask for immediate repayment. Borrowers thus have to cut back on their spending, both consumption and investment, and sell assets. At the macro level, this reduces profits and lowers asset prices, further increasing debt ratios.

By the same token, positive shocks increase debt capacity. Since agents were close to their maximum debt quantity, meaning they were keen on borrowing more if allowed to, they increase their debt to consume and invest, further increasing income and asset prices and thus debt capacity. The positive effect can be partially reduced by the transition from being constrained to unconstrained, which a fraction of borrowers go through after a positive shocks.

3 The empirical model

The empirical model is a non-linear vector auto-regressive process with interaction terms between the analyzed macroeconomic variables and a measure for tightness of the borrowing constraints. This model produces non-linear impulse responses, which are extracted by the local projections approach (Óscar Jordá [2007]).

With respect to the standard VAR approach, local projections deliver the impulse responses without the need of computing a VMA representation though the VAR inversion. Our choice is based on three reasons. First, the local projections easily allow the inclusion of non-linear terms and exhibit great flexibility in the choice of the model (i.e. specification of the interaction terms). Second, this procedure limits the accumulation of the errors over the impulse response horizon deriving from the discrepancy between the true data generating process and the empirical model. Third, non-invertibility and non-stationarity issues do not arise when computing the impulse responses by local projections.

For the sake of clarity, we first show the local projections in the linear case and then we expose the case with interaction terms.

In the standard linear local projection framework, the impulse responses of a shock in t on the variable in $t+h$, is obtained by directly running the regressions of the latter on the former. For each horizon $h = 1..H$:

$$Y_{t+h} = L_{h|1}Y_{t-1} + L_{h|2}Y_{t-2} + ... + L_{h|p}Y_{t-p} + v_{h,t} \tag{3}$$

where Y_t is the vector of endogenous variables, $L_{h|s}$ is the matrix of the estimated coefficients of the local projections of horizon h at lag s, $v_{h,t}$ is the vector of errors of the regression at horizon h; The impulse response for each horizon is then:

$$IR(t, h, D_t) = L_{h|1}D_t, \tag{4}$$

where D_t is the vector of reduced shocks, which can be obtained using different specification schemes. In the benchmark application, we apply the Choleski decomposition to the variance covariance matrix coming deriving from the first local projection.[5]

[5]This choice corresponds to select the VAR(p) as model to obtain the impact matrix to apply to the entire set of local projections. Barnichon et al. [2016] call this methodology "Mixed VAR Local projections".

In the non-linear case, we complement the auto-regressive process with a set of interaction effects. To capture the dependence of the responses to the state of the OBC, we interact all variables with the measure of the OBC. To capture asymmetry in the responses and make them dependent on the financial cycle, we also interact this measure with the square value of all variables. We specify those interactions only for the regressors at lag 1, for the sake of parsimony and because past interaction terms are unlikely to have large impact. Formally, for each horizon $h = 1...H$, we estimate the following regression:

$$Y_{t+h} = L_{h|1}y_{t-1} + Q_h y_{int,t-1}Y_{t-1} + S_h y_{int,t-1}Y_{t-1}^{\odot 2} + L_{h|2}Y_{t-2} + ... + L_{h|p}Y_{t-p} + \epsilon_{h,t} \quad (5)$$

where $y_{int,t}$ is the interaction variable at time t (scalar), Q_h and S_h respectively contain the estimated coefficients of the local projections for the state-dependent and asymmetric state-depend effects, $\epsilon_{h,t}$ is the vector of errors of the regression at horizon h. Here $\odot$ refers to point-wise multiplications, so $Y_{t-1}^{\odot 2} = (Y_{1,t-1}^2, ..., Y_{n,t-1}^2)$ As long as Q_h and S_h are different from zero, we have impulse responses which are dependent on the state of the economy (i.e. the OBC) and on the size of the shocks.

The non-linear impulse responses in the case with interactions are defined as:

$$\begin{aligned} IR(t,h,D_t,Y_{t-1}) =& L_{h|1}D_t + Q_h \left\{D_t \left(y_{int,t-1} + y_{int,t-1}\right) + d_{int,t-1}Y_{t-1}\right\} \\ &+ S_h \left\{\left(y_{int,t-1} + d_{int,t-1}\right)\left(2D_t \odot Y_{t-1} + D_t^{\odot 2}\right) + d_{int,t-1}Y_{t-1}^{\odot 2}\right\} \end{aligned} \quad (6)$$

where $d_{int,t}$ is the scalar of the shock to the interaction variable. We can rewrite this equation, separating the IRF in the 5 blocks:

$$\begin{aligned} IR(t,h,D_t,Y_{t-1}) =& D_t L_{h|1} \\ &+ Q_h \left(y_{int,t-1} + d_{int,t-1}\right) D_t \\ &+ 2S_h \left(y_{int,t-1} + d_{int,t-1}\right) D_t \odot Y_{t-1} \\ &+ 2S_h \left(y_{int,t-1} + d_{int,t-1}\right) D_t^{\odot 2} \\ &+ d_{int,t-1}\left(Q_h Y_{t-1} + S_h Y_{t-1}^2\right), \end{aligned} \quad (7)$$

where the first block contains the standard linear effect; the second term allows all shocks to have their impact depending on level and on the size of the shock of the interaction variable. The third block adds dependence on the level of the endogenous variables. The fourth block allows for asymmetric impacts depending again on the level of the interaction variable level and on the shock. Finally, in the fifth term the interaction shock triggers responses dependent on the level of all variables. In the benchmark specification, we assume the interaction variable to be exogenous. The IRFs thus simplify to:

$$
\begin{aligned}
IR(t, h, D_t, Y_{t-1}) =& D_t L_{h|1} \\
&+ Q_h y_{int,t-1} D_t \\
&+ 2 S_h y_{int,t-1} D_t \odot Y_{t-1} \\
&+ 2 S_h y_{int,t-1} D_t^{\odot 2}
\end{aligned}
\tag{8}
$$

This model captures complex and rich interactions between variables: the state effect, the sign, the size effect, and the extent through which the state effect influences the sign effect.

Other technical details on the regressions and the variance of coefficients estimates are provided in Appendix.

4 Data and identifying assumptions

To measure indebtedness, we rely on the Credit to GDP gap, one of the most popular used in the financial stability analyses, the so-called the *credit-to-GDP gap*, proposed by Borio and Lowe [2002, 2004], and then exploited, among others, in Borio and Drehman [2009], Juselius and Drehmann [2014]. The credit-to-GDP gap is defined as the difference between the credit-to-GDP ratio and its long term trend. The trend is extracted with a Holdrick-Prescott filter and is meant to capture long-term changes in sustainable credit-to-GDP ratio: demography, productivity, etc. The *deviation* of the Credit to GDP ratio from this trend indicates credit excesses. [6] We then rescale each country-specific Credit to GDP gap, in order to obtain values which fluctuate

[6] The Credit to GDP gap eases some of the issues related to the use of the Credit to GDP ratio. With respect to the simple credit-to-GDP ratio the Credit to GDP gap takes into account the possible differences in long term trends of the series of credit and GDP, which can result by structural changes in the economy (demography, technology, etc.). More details on the construction of this indicator are housed in the Appendix.

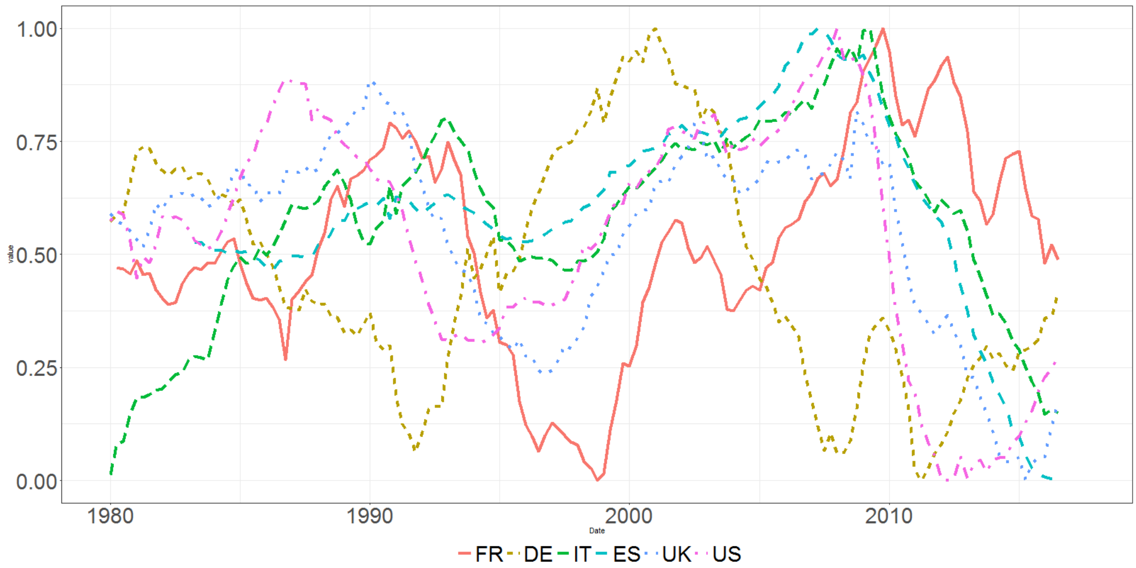


Figure 1: Credit-to-GDP gaps, rescaled between 0 and 1

between 0 and 1. By doing this, the interactions variables correspond to the stand-alone variables, rescaled by the level of the Credit-to-GDP gap. As shown in 1, the Credit-to-GDP gap displays a clear cyclical pattern and matches the leveraging and deleveraging periods. Except Germany, all countries in the sample experienced a rapid increase in the gap during the run-up to the crisis, pointing to a high degree of financial fragility. In all countries, the Great Recession triggered a steep fall in the gap that mirrors the rebalancing of balance-sheets from debt toward equity.

The rest of the data are: shadow 3-months interest rate, credit, output, inflation, house prices and output of the G20 (thereafter "world GDP"). Shadow 3-month interest rates are taken from Quandl. Residential real estate prices, output and inflation data come from the OECD dataset, while credit time series are taken from the Bank for International Settlement (thereafter BIS).

As in the standard VAR model, an identification scheme must be assumed in order to identify the structural shocks hitting the economy. We specify the world G20 and the credit-to-GDP gap as exogenous variables. For endogenous variables, we adopt a Choleski identification strategy for retrieving structural shocks. The benchmark ordering from the more exogenous to the more endogenous variables is the following: Credit, Output, Inflation, Housing prices, Interest rates. The ordering is motivated by the fact that prices and in particular financial prices, react more rapidly to economic information (and are considered as the most endogenous variables). It is worth to stress that the main results do not qualitatively change according to different Choleski ordering. For the sake of parsimony, in the benchmark application we specify a model with two lags, while longer lags are tested for robustness checks.

5 Results

In this section we expose the main results of the benchmark specification. Under this specification, we regress five endogenous variables (Credit, GDP, Inflation, house prices, short term interest rate) on their own lagged values and on two exogenous variables: World demand and Credit to GDP gap. The latter is also the main interaction variable.

We report the results for the four biggest economies of the euro zone (namely Germany, France, Italy and Spain), for the US and for UK. In the exposition of the results, we focus on the impulse responses generated by the housing prices shock, the income shock and the monetary policy shock, in order to assess whether higher indebtedness, proxied by a higher gap, makes the economy more fragile to shocks affecting the DSR or the leverage ratio. In particular, we highlight the non-linear effects generated by the state of the interaction variable (the tightness of borrowing constraints), the sign and the size of the shock. Finally, we compare the performance of this approach to a standard VAR.

5.1 The state effects

In order to compare the impulse responses across the different levels of the financial cycle, we report the impulse responses when the credit to GDP gap is at its 10th (green line) and at its 90th country-specific percentile (red light). Typically, the first percentile refers to largely negative gaps possibly due to recent large deleveraging and falling credit-to-GDP ratio; the second percentile refers to a condition of large gap, normally associated to an over expansion of debt with respect to GDP and to agents coming closer to their borrowing limits.

Overall, we find that when the economy is in a period of credit excess, it becomes more sensitive to shocks. The findings across the different shocks and across the countries analyzed are consistent with this statement (see Figures 2-4). For most countries, the differences, under the 10th and the 90th percentile for the Credit to GDP gap, turn out to be statistically significant for the housing shock, the monetary policy shock and income shock. Except the interest rate, when the credit to GDP gap is large, all endogenous variables display significantly higher persistent responses. This result is in line with theory on Occasionally Binding Constraint: when the level of debt is high, a larger fraction of agents will be borrowing constrained. Under this case, agents are sensitive to shocks and more time is needed to absorb a shock and to come back to equilibrium. In line with this theory, we find that both shocks have larger and longer impact when occurring in a phase of elevated credit to GDP gap, i.e. when a larger fraction of agents is borrowing constrained.

5.1.1 The housing shock

The housing shock (Fig. 2) can be interpreted as an exogenous variation of the value of collateral. When the shock is positive, an increase in house price is expected to produce a positive effect on the borrowing limit, by increasing the value of the collateral provided by borrowers.

Consistently with theory, when the level of Credit to GDP gap is high, the shock has statistically significant positive effects on GDP in all countries except Germany, which experienced very specific house price variations in the last twenty years. Instead, when the credit to GDP gap is at its 10th percentile, the effects are lower or insignificant, and even significantly negative for Spain and the US. It in interesting to note that those two countries, which display the largest indebtedness state-dependent effects of housing shock on GDP, went through a mortgage-financed housing bubble which is often pointed as one of the driving factors of the sustained economic growth featuring the pre-crisis period and the main cause of the severity of the crisis in those countries. Also, when the Credit to GDP gap is large, the housing shock generally favors an expansion of credit, consistently with higher GDP growth and with a more persistent increase of house prices.

5.1.2 The income shock

A positive income shock (Fig. 3) affects the limit of the borrowing constraint. When the number of agents who are borrowing constrained is larger, the shock is expected to be more persistent, because of the stronger amplification role played by the financial accelerator. A positive shock is more persistent for US, UK, Spain and

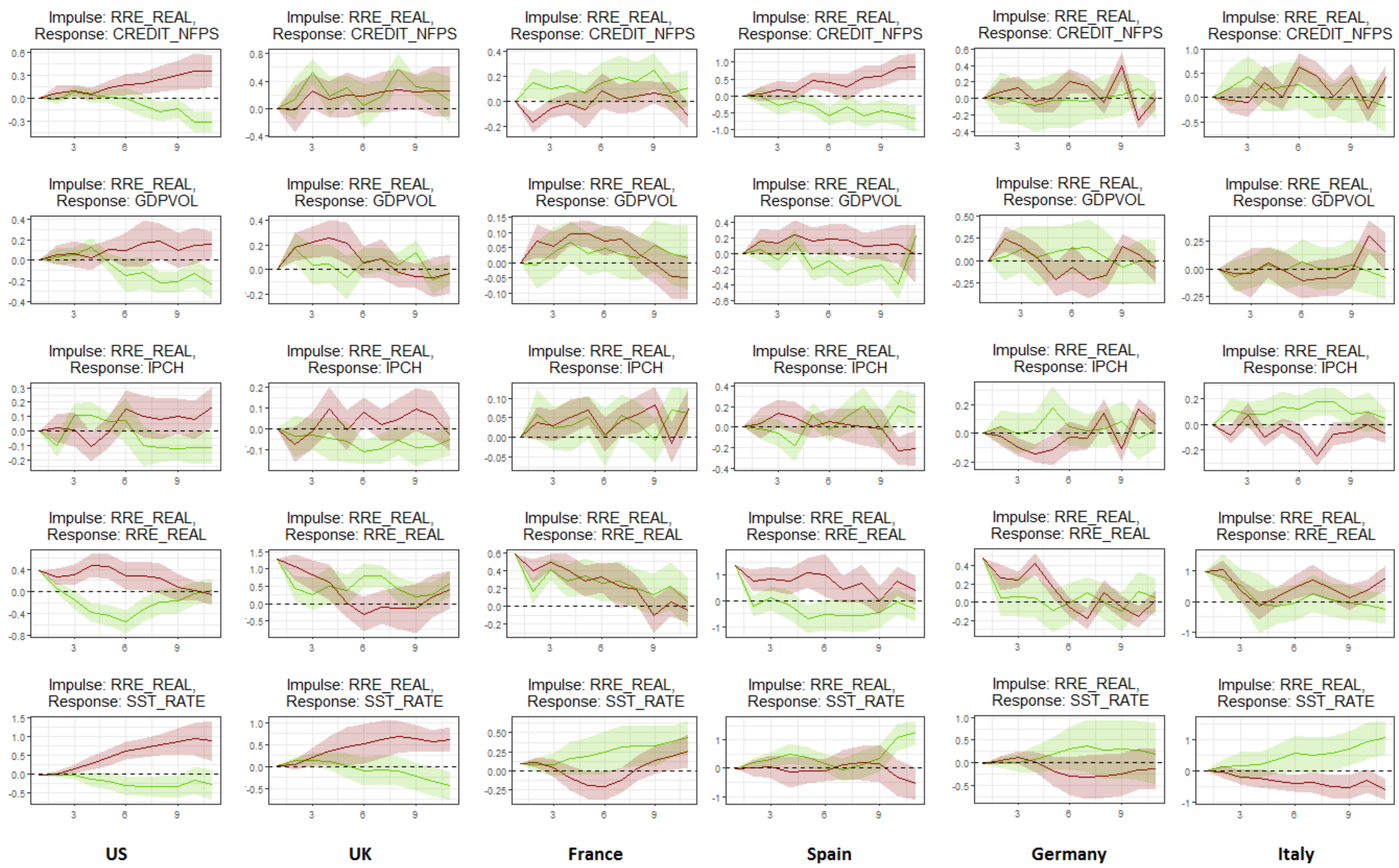


Figure 2: Impulse responses for a positive housing shock. The red (green) lines are the impulses at the 90th (10th) percentile of Credit to GDP gap. shaded areas represent the 66% confidence iterval.

Italy. Overall, the credit positively reacts to the shock. The reaction is stronger when the credit to GDP gap is at its 90th percentile than when it is at its 10th percentile, where effects are more ambiguous. Consistently, the shadow short term interest rate tends to react more positively and displays more persistence to positive GDP shocks at high credit to GDP gaps. Finally, house prices seem to react more in the US and UK than in the rest of the countries analyzed.

5.1.3 The monetary policy shock.

The monetary policy shock (Fig. 4) is generally expected to put recessionary pressures on the endogenous variables, hrough lower collateral value, higher repayment and lower income. We find that responses to monetary policy shock strongly depend on indebtedness of the economy: when the Credit to GDP gap is high, a change in monetary policy has larger effects, compared to the case of low level of Credit to GDP gap; growth in credit, GDP and house prices are all more affected. Overall, the results confirm the idea that the financial accelerator plays a different role according to tightness of the borrowing constraint, i.e. the fraction of borrowers who are vulnerable to variations in degt capacity. When the credit to GDP gap is high, a large fraction of agent is vulnerable to the variation of the limit of the borrowing constraint. Conversely, when the Credit to GDP gap is low, the fraction of agents which are borrowing constrained is smaller, reducing the role of the financial accelerator in the propagation of shocks.

5.2 The sign effect

In order to analyze the asymmetric effects of economic shocks, we report the responses to positive and negative shocks of one standard-deviation. To assess how this asymmetry changes depending on the state of the economy, we report the impulses when the Credit to GDP gap is at its 10th and 90th percentiles. We keep the other variables at their median values. To ease comparison, the impulse response functions of the negative shocks are plotted after having being multiplied by minus one.

Overall, we find that most IRFs display no asymmetric effects: positive and negative shocks have quantitatively similar impact. This implies that the state-dependent effects described above are not only driven by either type of shocks and

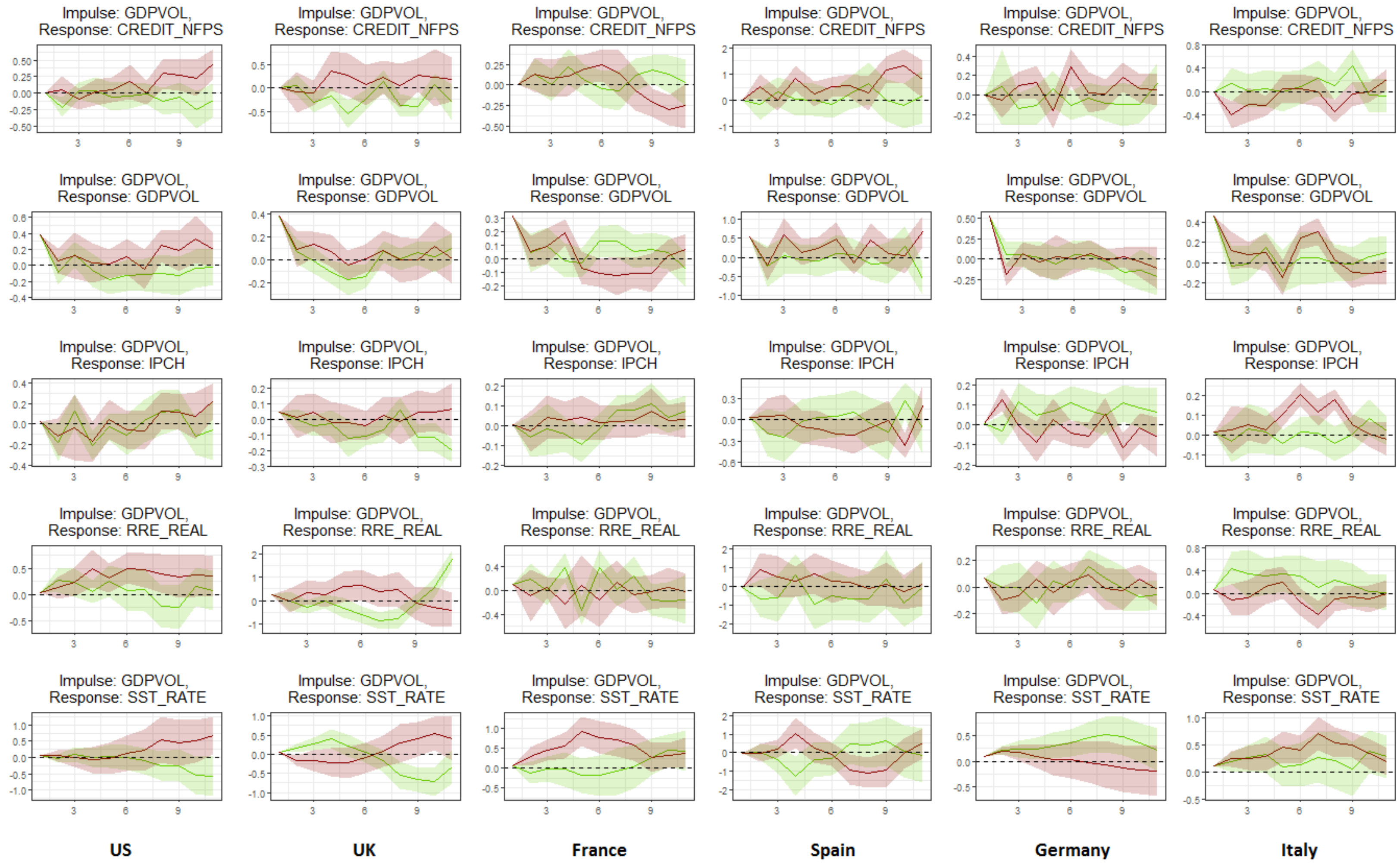


Figure 3: Impulse responses for a positive income shock. The red (green) lines are the impulses at the 90th (10th) percentile of Credit to GDP gap. shaded areas represent the 66% confidence interval.

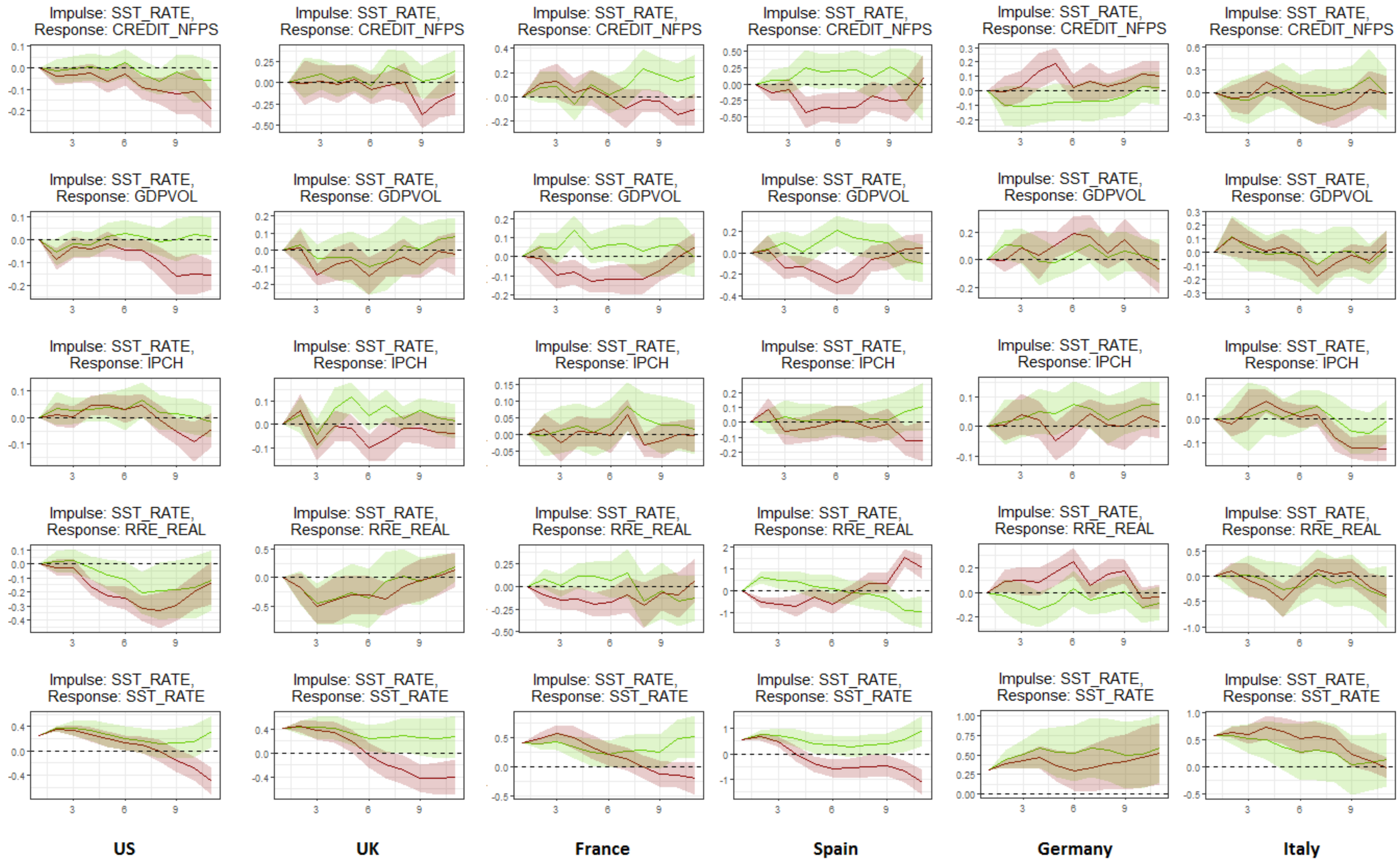


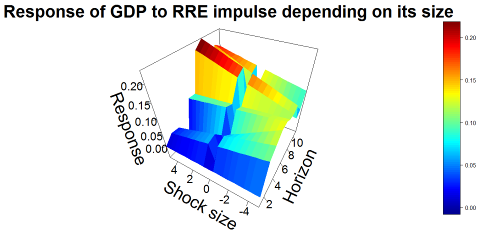
Figure 4: Impulse responses for a monetary policy shock. The red (green) lines are the impulses at the 90th (10th) percentile of Credit to GDP gap. shaded areas represent the 66% confidence interval.

that both side of the OBC story are credible: the negative debt-deflation and the positive higher debt capacity. In line with theory, borrowing-constrained agents facing a windfall, in the form of higher income or asset value, leverage on it to increase their debt, spending it on consumption and investment, further increasing profits and prices. On the contrary, agents confronted with a fall in their debt repayment capability have to cut back on spending, triggering a phase of Fisherian debt deflation. This implies that when the economy is loaded with debt, it is likely to suffer larger boom and bust cycles, as agents become more sensitive and responsive to exogenous shocks.

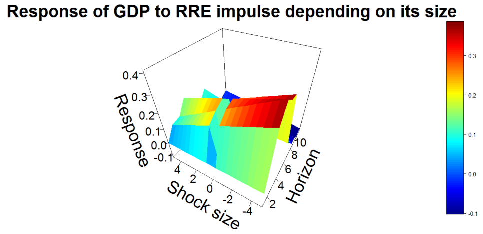
A noteworthy exception to the similarity between positive and negative IRF is the impact of housing shock on GDP : in most countries the negative impact lasts significantly longer than the positive one, in particular when the credit-to-GDP gap is high.

For what concerns the size and the sign effects, figure 5 provides further information for the housing shocks. The figures report the impulse responses of income to housing shocks for each country analyzed. Impulses are obtained at the 50th percentile of the Credit to GDP gap and are rescaled by the shock size, in order to ease comparison. Overall, we find that for the negative housing shocks, the elasticity of GDP increases with respect to the size of the shock itself for all the countries except US. Conversely, concerning the positive shock, we find a smaller size effect.

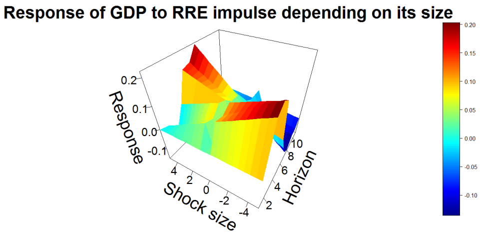
This asymmetry generated by the sign of the shock suggests that large negative housing cycles, in particular when financed with debt, have an overall negative impact on economic growth: the boost provided during the boom is more than compensated by the drag imposed during the bust. We see this result as a further validation of the theory of the OBC and the asymmetric effects of housing shocks (Guerrieri and Iacoviello, 2016). According to this approach, housing shocks have an asymmetric impact on the economy. When the housing shock is negative, constrained agents are forced to reduce their borrowings (and consumption and investments). Instead, with a positive housing shock, agents who become borrowing unconstrained, do not necessarily use all the slack to borrow (and consume or invest) more. With respect to their analysis, we also take into account the initial level of indebtedness of agents, making the assumption that when the credit to GDP gap is large, a higher fraction of agents will be borrowing constrained. Importantly in our analysis, we can disentangle the higher sensitivity deriving from having a large



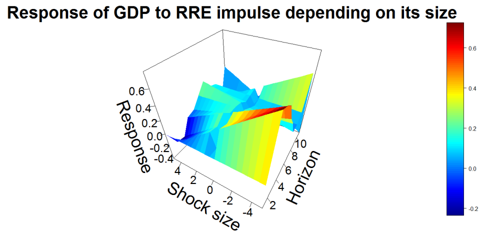
(a) US



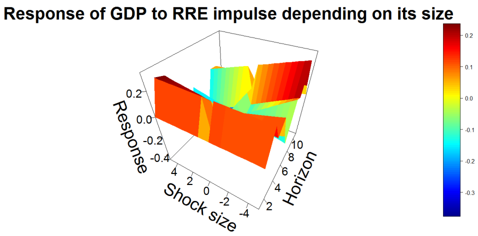
(b) UK



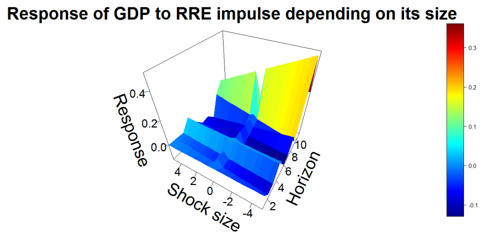
(c) FR



(d) ES



(e) DE



(f) IT

Figure 5: Elasticities of GDP to housing shocks, for different sizes of the shock and for different horizons. Elasticities are obtained by rescaling the impulses by the shock itself.

indebtedness of the economy (the state effect of being on a high credit to GDP gap) from the asymmetric effect related to the sign of the shock (a negative shock affects more than a positive because with the latter, a fraction of agents will not necessarily borrow up to the limit (transitioning to the unconstrained state). Another possible explanation for the asymmetric response is that housing booms encourage residential construction, partly crowding out more productive investment and triggering misallocation of resources. This suggests that policymakers should pay close attention to asset price cycles and prevent them from bubbling as this has an overall damaging effect on the real economy. [7]

5.3 Comparison with standard VAR

In order to assess the efficiency of our specification, we conduct a horse race between Local Projections and a standard VAR model. For the sake of comparability, we give the VAR as many coefficients as the Local Projections: the competing VAR has four lags to match the Local Projections, which have two lags, the interacted terms and the square interacted terms. It is possible to interpret this exercise as a competition between more lags, capturing richer time effects, and more interactions, capturing richer effects between simultaneous variables. We measure the relative performance of the Local Projections and the VAR by the ratio of their Sum of Square Residuals (SSR), for each variable at each horizon: the lower the ratio, the better the relative performance of the Local Projections.

Figure 6 shows the results for the US. Other countries have very similar results. At horizon one, some Local Projections underperform the VAR. Nevertheless, from horizon 2 to 10, all Local Projections outperform their counterparts from the VAR specification. The improvements are sizable, comprised in the 20% to 60% range. This confirms the economic significance of the effect of financial fragility on macroeconomic dynamics and the need to take them into account, in particular for longer horizons.

6 Robustness checks

To further assess the reliability of our results we conduct a range of robustness check. We increase the number of lags at three and four. As is sometimes specified

[7] A noteworthy exception is the US, for which the more positive the shock, the larger the elasticity. Two specific features of the American housing market can explain this. First, it is common for US households to secure consumption credits on the equity value of their houses. This means that any increase in property prices directly augments the debt capacity of households, without them having to sell the house to pocket those extra profits. So those higher prices are more likely than in other countries to support consumption credit and, in turn, GDP. Second, when for American households the value of their houses is lower than the capital being due to the bank, they can relatively easily write off their loans, either by negotiating with the bank of by abandoning the property and allow the lender to foreclose. This can be interpreted as a direct transfer of wealth from the bank to the household, supporting consumption. Foreclosure is rare in continental Europe, forcing households to make deep cuts in their spending and thus reducing aggregate demand.

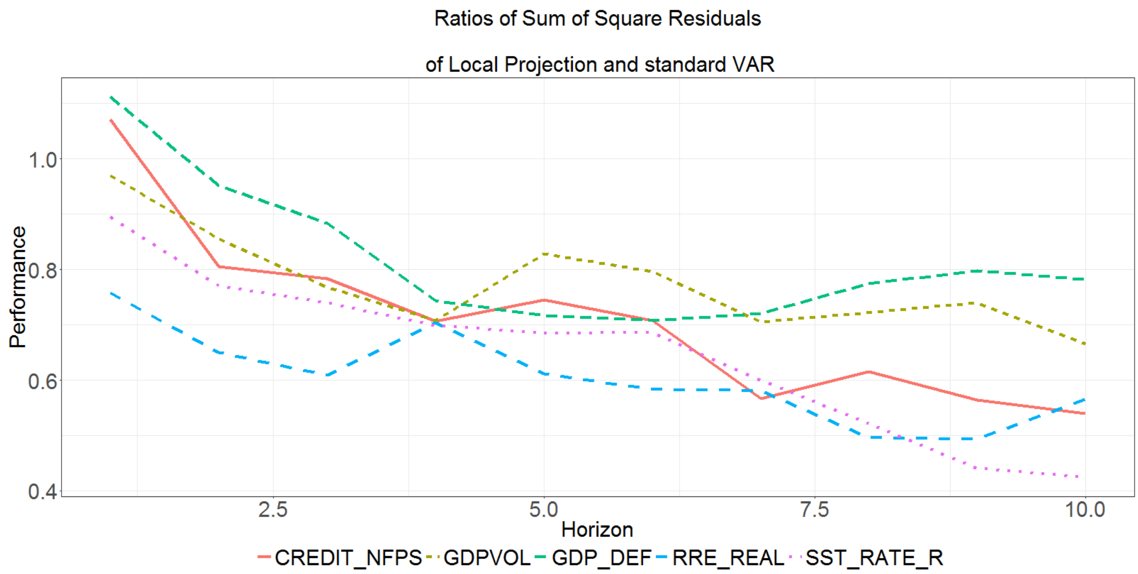


Figure 6: Ratio of Sum of Square residuals of Local Projections and Standard VAR
Note: Local Projections are performed with two lags, VAR with four lags

in monetary literature, we rank the shadow policy rate first instead of last in the Choleski ordering. We also use the credit to GDP ratio as an alternative measure of indebtedness. [8] Overall, results are qualitatively similar. Those regressions, which are available upon request, do not qualitatively affect our results.

7 Conclusion

In this paper, we show how the presence of Occasionally Binding Constraints affects the propagation of shocks in the economy. We find that when the Credit-to-GDP gap is high, shocks hitting the borrowers' debt limit have a stronger effect compared to the case where the Credit-to-GDP gap is low. More specifically, with high indebtedness, shocks which impact on the borrowing capacity (as the housing shocks, the income shock and the monetary shock) have a stronger impact on output and are more persistent. Concerning the housing shock, we detect asymmetric effects related to the sign of the shock: negative shocks have a stronger effect in absolute terms with respect to the positive ones. These elements play in favor of the theories relying on Occasionally Binding Constraints to explain non-linear dynamics in the

[8] The Credit to GDP ratio suffers from being non-stationary in some countries, with a clear upward trend blurring the results. Nevertheless, it provides an intuitive measure of indebtedness and can thus be used for robustness analysis.

transmission of economic shocks. Those effects prove to be economically significant and having a better performance with respect to linear VAR, in terms of forecast performance at longer horizon.

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8 Appendix

8.1 The financial cycle measures

The credit-to-GDP gap is the difference between the credit-to-GDP ratio and its long term trend. With respect to the simple credit-to-GDP ratio, the Credit to GDP gap takes into account the possible differences in long term trends of the series of credit and GDP, which can result by structural changes in the economy (demography, technology, etc.). The trend is extracted with a Holdrick-Prescott filter, which defines a trend as the result of the following minimization program:

$$\min_{\tau}\left(\sum_{t=1}^{T}(y_t-\tau_t)^2+\lambda\sum_{t=2}^{T-1}\left[(\tau_{t+1}-\tau_t)-(\tau_t-\tau_{t-1})\right]^2\right)$$

Where T stands for the last period of available data, y_t for the original time series and τ_t for the estimated trend. The parameter λ sets the equilibrium between two objectives of the trend estimate: (i) accuracy, captured in the first term of the equation, the sum of squared errors that penalizes deviation from original series, and (ii) smoothness of the trend, captured the second term of the equation. The larger λ, the more important is smoothness compared to accuracy the thus the more the trend looks like a straight line and can deviate from the original time series. Implicitly, each value of λ corresponds to a duration of the estimated gap cycle. The Basel Committee for Banking Supervision (thereafter BCBS) uses a particularly high λ of 400,000, that corresponds to a cycle of approximately thirty years, to be compared with the standard 1,600 used for the business cycle, estimated to last eight years. The BCBS justifies this choice by the frequency of financial crises in developed countries since the 1970s. The credit-to-GDP gap has both appealing economic interpretation, as a deviation to long-term, sustainable trend, and good in-sample performance as leading indicator of financial crisis. The credit to GDP gap has thus become a reference in macroprudential policy, first as a guideline in on Banking Supervision [2010] and then formalized in the euro area by the recommendation 2014/1 of the European Systemic Risk Board (thereafter ESRB), that prescribes national authorities to publish the gap in their quarterly decision on the CCyB rate.

8.2 Computing the HAC matrix of Local Projections

Local Projections use the same methods than standard VAR, except that we compute one VAR per horizon, and not only a one period-horizon VAR rolled over to compute longer horizons. Formally, we have:

$\underset{n.T}{Y}^{h} = \underset{n.nl+1}{\beta^h}\underset{nl+1.T}{X} + \underset{n.T}{\varepsilon^h},\ h\, in\, 1, ..., H$

with

$$Y^h = \begin{pmatrix} Y_{1,t+h} & ... & Y_{1,t-j+h} & ... & Y_{1,t-(T-1)+h} \\ & & ... & & \\ Y_{i,t+h} & ... & Y_{i,t-j} & ... & Y_{i,t-(T-1)+h} \\ ... & & ... & & ... \\ Y_{n,t+h} & ... & Y_{n,t-j+h} & ... & Y_{n,t-(T-1)+h} \end{pmatrix} = \begin{pmatrix} Y_{t+h} & ... & Y_{t-j+h} & ... & Y_{t-(T-1)+h} \end{pmatrix}$$

Which satisfies the standard shape of a VAR:

$\underset{m.T}{Y} = \underset{m.nl+1}{\beta} \underset{nl+1.T}{X} + \underset{n.T}{\varepsilon}$

with l the number of lags (the same values of x_i appear several times in the X matrix, at different lags), m the number of variables of interest and n the number of explanatory variables (including exogenous variables and possibly interaction variables).

The estimate of the β coefficients is thus given by the standard formula:

$\hat{\beta} = YX^T \left(XX^T\right)^{-1}$

For computing the confidence interval, we construct a HAC matrix adapted for VAR. Remember

$$\begin{aligned} \mathbb{V}(Vec(\hat{\beta})) &= \left(\left(XX^T\right)^{-1} \otimes I_m\right)(X \otimes I_m)\,\mathbb{E}\underset{mT.mT}{\left\{Vec(\varepsilon)Vec(\varepsilon)^T\right\}}\left(X^T \otimes I_m\right)\left(\left(XX^T\right)^{-1} \otimes I_n\right) \\ &= \left(\left(XX^T\right) \otimes I_m\right)^{-1} \phi \left(\left(XX^T\right) \otimes I_m\right)^{-1} \end{aligned}$$

with $\underset{m(nl+1).m(nl+1)}{\phi} = (X \otimes I_m)\,\mathbb{E}\underset{mT.mT}{\left\{Vec(\varepsilon)Vec(\varepsilon)^T\right\}}\left(X^T \otimes I_m\right)$.

Then the HAC matrix of a vectorized VAR is:

$$\begin{aligned} HAC_{VAR} = & HC + \frac{T}{T-n}\sum_{l=}^{L}\left\{\left(1-\frac{l}{L+1}\right) * \sum_{t=l+1}^{T}\left(\underbrace{\begin{pmatrix} w_{(t-1)m+1,} * \hat{\xi}_1^{l,t} \\ ... \\ w_{(t-1)m+m,} * \hat{\xi}_m^{l,t} \end{pmatrix}^T}_{nl+1,m}\underbrace{\begin{pmatrix} w_{(t-1-l)m+1,} \\ ... \\ w_{(t-1-l)m+m,} \end{pmatrix}}_{m,nl+1} + \right.\right. \\ & \left.\left.\begin{pmatrix} w_{(t-1-l)m+1,} * \hat{\xi}_1^{l,t} \\ ... \\ w_{(t-1-l)m+m,} * \hat{\xi}_m^{l,t} \end{pmatrix}^T \begin{pmatrix} w_{(t-1)m+1,} \\ ... \\ w_{(t-1)m+m,} \end{pmatrix}\right)\right\} \end{aligned}$$

with $HC = \frac{T}{T-n}\sum_{i=1}^{T} \hat{e}_i \left(\left(XX^T\right) \otimes I_{m,i}\right)^T \left(XX^T\right) \otimes I_{m,i}$

Where $w_{i,}$ is the i-th line of $\left(\underset{T.nl+1}{X^T} \otimes \underset{m.m}{I_m}\right)$. The element-wise multiplication is made to ensure that each coefficient of the HAC matrix is only affected by the residuals of the regression "at this line". Given the design of $\left(\underset{T.nl+1}{X^T} \otimes \underset{m.m}{I_m}\right)$ there is no interaction between the different regressions: when not from the same regression (i.e. of the same variable of interest), the multiplication of two lines of $\left(\underset{T.nl+1}{X^T} \otimes \underset{m.m}{I_m}\right)$ is null.