Monetary Policy, Leverage, and Default

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PRELIMINARY and INCOMPLETE

Abstract

In this paper I argue that a monetary expansion increases the probability that firms default on loans. The mechanism works through a leverage effect. When the policy rate decreases, firms react to the lower cost of borrowing by taking on more debt and increasing leverage. This, in turn, decreases the relative buffer given by net worth to the risky loan and pushes up defaults. I use a Vector Autoregressive model to extent the two-step approach used by Basu, Fernald and Kimball (2006) to study technology shocks. I apply this empirical strategy to the US data and find that the delinquency rate of firms' loans and the aggregate leverage ratio of firms increase in response to a monetary expansion. I then show that the result is consistent with a standard New Keynesian model in which the contract between firms and lenders are modeled with the debt contract by Townsend (1979).

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1 Introduction

In this paper I study the effect that a monetary expansion exerts on the probability that firms default on loans. It would be sensible to expect that a monetary expansion reduces this default probability, because it boosts firms' revenues by lowering the cost of borrowing and by increasing aggregate demand. I argue, instead, that this revenue effect is dominated by a leverage effect. In fact, when the cost of borrowing decreases, firms have a higher incentive to take on debt. This, in turn, leads to a higher leverage ratio (i.e. a higher asset-to-equity ratio), which pushes up the default rate on loans because equity is now providing a lower buffer to the risky loan.

I first investigate the leverage effect empirically on US data. I use a Vector Autoregressive (VAR) model to extend the empirical strategy developed by Basu, Fernald and Kimball (2006) to study technology shocks. In particular, I first estimate candidate structural monetary shocks using a standard VAR model, which I identify with the popular Cholesky and the sign-restricted decompositions. I then compute the impulse responses of several variables of interest as the coefficients obtained by regressing each variable on the identified shocks. As will be explained, there are three main advantages of this approach relative to a standard VAR model: it handles deterministic control variables more efficiently, it improves the accuracy of least square estimates and it helps to impose prior information in Bayesian estimation. The Monte Carlo simulation exercise reported in Appendix A suggests that this approach is at least as valid as a standard VAR.

The key contribution from the empirical part of the paper relates to the effect on the default probability on loans and on the leverage ratio of firms. I measure the default probability on loans issued to non-financial firms as the ratio of delinquent loans over the stock of outstanding loans. This ratio covers the period between 1988Q1 and 2007Q2. I measure the leverage ratio of firms using aggregate data from the Flow of Funds for the period between 1955Q1 and 2007Q2. Several specifications of the model are considered in order to assess the robustness of the results. Overall, the data support the hypothesis that both the delinquency rate and the leverage ratio increase following a monetary expansion. The magnitude and timing of the effect on the delinquency rate depend on the exact model specification used, but the hypothesis that the delinquency rate increases is never rejected by the data. The effect on the leverage ratio, instead, is more robust across models, in part also due to the longer time horizon of the dataset. Both effects are quantitatively relevant. In response to a monetary shock that decreases the federal funds rate by 1%, both the delinquency rate and the leverage ratio increase by around 60 basis points, which is equivalent to around as much as 33% and 300% of the respective standard deviations. The increase in the delinquency rate equals around 20% of its average trough-to-peak variation observed along the business cycle.

Having found that the data do not reject the hypotheses that the delinquency and the leverage ratios increase in response to a monetary expansion, I show a standard New Keynesian model consistent with the causal interpretation proposed in the paper. The model draws from the general equilibrium model by Bernanke, Gertler and Gilchrist (1999), which in turn uses the optimal "costly state verification" model by Townsend (1979) to formalize the debt contract between entrepreneurs and lenders. In the model, the default probability on loans is endogenous, because it depends on the size of the loan and on the borrowing rate, which are both endogenous variables of the debt contract. The entrepreneur, who accumulates net worth from the previous period, anticipates that borrowing more allows to invest more only at the cost of accepting a higher default probability. This happens because the lender is willing to issue more credit only in exchange of a leverage premium against the increase in entrepreneur's leverage. The combination of a higher borrowing rate and a higher leverage ratio increases the default probability of the entrepreneur. It is the trade off between investing more and paying a leverage premium that pins down the equilibrium default rate. Although the Bernanke, Gertler and Gilchrist (1999) model and the debt contract by Townsend (1979) are well known in the literature, I am not aware of papers that use this framework to explicitly study the role of monetary policy in shaping the loan default probability of firms.

In the model, when a monetary expansion decreases the opportunity cost of lending, the default rate decreases on impact because leverage is predetermined from the previous period and because entrepreneurs enjoy an unexpected increase in their revenues. From the second periods onwards, instead, the entrepreneurs find it optimal to take advantage of the lower cost of borrowing by leveraging up their net worth, which ultimately leads to a higher default probability for several periods to come. While the consistency with the data of the prediction of the model with respect to the impact effect depends on the exact empirical model estimated, the following increase in defaults is consistent with the data. The effect is stronger if the central bank attaches a relatively small weight to inflation and to output in the Taylor rule, because in this case the borrowing rate takes longer to revert to steady state, generating a higher incentive to leverage up net worth.

The paper relates to several parts of the literature. The empirical exercise relates mainly to the VAR literature on monetary policy. The reduced-form model estimated in the first step of the analysis is standard and follows Bernanke and Blinder (1992), while the identification of monetary shocks extends Canova and De Nicoló (2002) and Rubio-Ramirez-Waggoner and Zha (2005). The methodological contribution consists of the extension of the approach used by Basu *et al.* (2006) for technology shocks. The approach goes along the lines of Romer and Romer (2004) and Van den Heuvel (2012). The main difference from their contribution is that they measure monetary policy either with a narrative approach or directly with the federal funds rate. Other authors have studied the role of monetary policy on firms' financing (for instance Eickmeier and Hofmann (2012) and Hu (1999)), but not with regard to the causal effect of monetary policy on the leverage ratio of firms and to their default probability on debt. To the best of my knowledge, this is the first paper that investigates the issue.

The theoretical part of the paper relates to the literature on general equilibrium models of monetary policy, although with an important twist. The paper centers around the qualitative investigation of the transmission mechanism of monetary policy, rather than on the ability of the model to capture the quantitative dynamics of the data. The relative simplicity of the model makes it a poor candidate as a structural model for quantitative policy analysis, especially if compared to seminal contributions like Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007). Instead, it serves the purpose of guiding the intuition behind a relatively unexplored and potentially relevant channel of monetary policy.[1] Several authors including Blanchard, Dell'Ariccia and Mauro (2010), Boivin, Kiley and Mishkin (2011) and Miles (2010) have recently encouraged research on non-neoclassical channels of monetary policy. The paper provides one step in this direction, while leaving a more quantitative analysis to future research.

The paper partially relates also to the literature on the risk-taking channel of monetary policy that follows Rajan (2006) and Borio and Zhu (2008). The predictions of the paper are consistent with the empirical analysis that uses credit registry data, survey data, Expected Default Frequencies, US credit spreads and various measures of risk.[2] Theoretical contributions in this literature include models with "rule-of-thumb" agents, partial equilibrium models and general equilibrium models.[3] The paper differs from these contributions along two dimensions.

[1]Chari, Kehoe and McGrattan (2009) provide an interesting and provocative assessment of the advantages of large-scale quantitative models relative to small models.

[2]For the analysis on credit registry data see Jimenez, Ongena, Peydró and Saurina (2010), Ioannidou, Ongena and Peydró (2009) and Lopez, Tenjo and Zarate (2011) respectively for Spain, Bolivia and Colombia; for the analysis on survey data on the US and on the European Union see Maddaloni and Peydró (2011); for the analysis on the EDF data on US and European banks see Altunbas, Gambacorta and Marquez-Ibanez (2010); for the analysis on US spreads see Paligorova and Santos (2012) and for the analysis on other measures of risk in the US see De Nicoló, Dell'Ariccia, Laeven and Valencia (2010).

[3]A model with "rule-of-thumb" agents is developed by Riccetti, Russo and Gallegati (2011). Related models in partial equilibrium can be found in Drees, Eckwert and Vardy (2012), Acharya and Naqvi (2012), Agur and Demertzis (2012), Challe, Mojon and Ragot (2012), Dubecq, Mojon and Ragot (2009), Dell'Ariccia, Laeven and

First, it uses an optimal debt contract in which rational agents price credit according to their expectation of future states of the world. Existing contributions, instead, usually assume the existence of a competitive credit market that is willing to lend borrowers any amount at the market rate. Second, it considers borrowers who are fundamentally equally risky and studies whether monetary policy affects their default probability through their optimal leverage ratio. Most of the existing literature, instead, focuses on how monetary policy affects whether credit is issued to risky versus safe borrowers, i.e. on a different yet complementary margin.

Section 2 explains the empirical strategy used and reports the main results. Some of the technical details and the robustness checks are reported in the Appendix. Section 3 develops the theoretical model. Section 4 concludes.

2 Empirical evidence

In this section I argue that US data are consistent with the hypothesis that a monetary expansion increases firms' default probability on loans due to an increase in their leverage ratios. Section 2.1 explains the dataset and provides some descriptive statistics. Section 2.2 outlines the empirical strategy. Section 2.3 comments the results.

2.1 Dataset

I use aggregate quarterly data on the US economy between 1955Q1 and 2007Q2. Data availability prevents from including the period before 1955Q1. The period after 2007Q2 is excluded from the analysis due to the significant effect that the subprime crisis had on the transmission mechanism of monetary policy (see for instance Ciccarelli, Maddaloni and Peydro (2013)). The transmission mechanism indeed evolved during the sample period considered, but it has overall remained qualitatively stable.[4] The results are robust across different sub-periods, as documented in figures ?? of Appendix C.

The macroeconomic variables are downloaded from the the National Income and Product Account (NIPA) of the Bureau of Economic Activity, tables 1.1.5 and 1.17.6. The rest of the dataset is downloaded from the Board of the Governors of the Federal Reserve System, Data Download Program. More precisely, the delinquency and the charge-off rates are downloaded from the main section of the download program. Interest rates are downloaded from section H.15. The balance sheet variables of the non-farm non-financial sector are downloaded from the Flow of Funds, section Z.1. In the Flow of Funds, tables B.102 and B.103 provide data separately for the corporate and for the non-corporate sectors. I aggregate the corresponding balance sheet items into a unique non-financial sector. The results hold for both sectors, as documented in figures 18 and 19 of Appendix C.[5]

The key variables used in the analysis are the delinquency rate, the aggregate stock values of firms' balance sheets (assets, debt, liabilities, equity) and the leading relative measures of firms' indebtedness (leverage, debt-to-GDP and liabilities-to-GDP ratios). The delinquency rate was explained in the introduction. Assets are reported by the Flow of Funds at either market value or replacement costs, depending both on the time period and on the individual firm.

Marquez (2010), Fahri and Tirole (2009), Valencia (2011), Stein (2012) and Bruno and Shin (2012). Related models in general equilibrium include Angeloni and Faia (2013), Cociuba, Shukayev and Ueberfeldt (2012).

[4]Bernanke and Mihov (1998) find that a model of federal funds rate targeting explains well the period between 1965M1 and 1996M12, expect for the short horizon of the Volcker monetary experiment in 1979Q3-1982Q2. Following many papers in this literature, I include this sub-period in the analysis without treating it differently. Part of the empirical literature on monetary policy, reviewed for instance by Boivin, Kiley and Mishkin (2011), finds that the the effect of monetary shocks on output has become weaker after the mid 1980s. Nevertheless, the conventional channels of the monetary transmission mechanism seem to still be at work.

[5]Figure 18 in Appendix C shows that the corporate sector is approximately twice as large as the non-corporate sector, and that the evolution of the leverage ratios is qualitatively similar across sectors. Figure 19 shows that the main results for the aggregate non-financial sector hold for both sub-sectors.

Debt is defined as the real value of outstanding debt, as also in Jermann and Quadrini (2011). Liabilities include both debt and non-debt financial liabilities, like tax and trade payables.[6] Leverage is defined as the ratio of assets over equity, as for instance in Adrian and Shin (2008). I compute two measures of leverage, depending on whether equity equals 'assets minus debt' or 'assets minus liabilities'.[7] I also use the ratios of debt over GDP and liabilities over GDP as relative measures of firms' indebtedness. All stock variables are deflated using the GDP deflator, as in Den Haan and Sterk (2011).

Figure 1 describes some key features of the most relevant variables included in the analysis. All variables are seasonally adjusted using the X-12 ARIMA algorithm from the US Census Bureau. Panel *A* reports the level of each variable in comparison to real GDP and, for the borrowing rate, to the federal funds rate. Panel *B* reports the product of the HP residual of each variable with the HP residual of real GDP. Panel *C* reports the standard deviations of the HP residual of each variable for four sub-periods: before Paul Volcker (1955Q1-1979Q2), under the Paul Volcker's new monetary regime (1979Q3-1984Q1), during Alan Greenspan and the so-called Great Moderation (1988Q1-2007Q2) and after the sub-prime crisis (2007Q3-2011Q4).[8] Standard deviations are reported both in absolute terms and relative to the standard deviation of real GDP. Figure ?? in Appendix C reports the same analysis also for the other variables in the dataset.

Figure 1 documents five main results of interest:

1. the size of the non-financial sector has progressively declined from around 14 times of GDP in the 1950s to 2.5 in 2011. Nevertheless, its indebtedness has increased. In fact, the stock of real debt displays an upward trend which markedly follows real GDP. Similarly, both the debt-to-GDP ratio and the leverage ratio increase steadily during the sample period, up to respectively 0.8 and 1.5. The increase in the stock of debt held by firms is in line with Jermann and Quadrini (2006);

2. low-frequency variations in the stock of assets and in the stock of equity are very similar. On the contrary, debt trends upwards irrespectively on the evolution assets. Adrian and Shin (2007) report a similar result for the banking sector, which they attribute to the stronger mark-to market accounting of banking assets relative to banking liabilities. A similar interpretation lends itself to the case of non-financial firms, as in this paper, although mark-to-market accounting is less established for such sector;

3. debt, assets and equity are largely procyclical. This is documented by the fact that their HP residual takes the same sign of the HP residual of GDP around 70% of the time. The debt-to-GDP, assets-to-GDP and the leverage ratios, instead, are mainly a-cyclical, if one excludes the recent crisis. The results on debt and equity are in line with the analysis on Compustat data by Covas and Den Haan (2011) respectively for all firms and

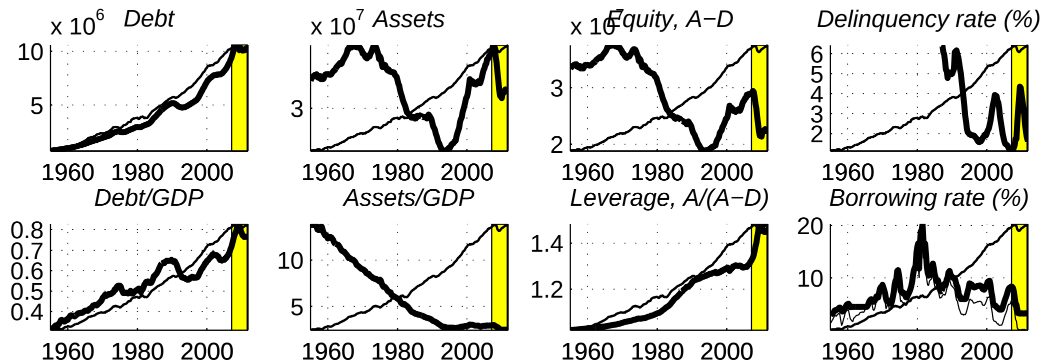
[6] Outstanding debt is defined as "credit market instruments" in the Flow of Funds, items FL104104005.Q and FL114104005.Q. For the corporate sector it mainly includes corporate bonds, credit loans and mortgages, which account respectively for around 50%, 30% and 15% of outstanding debt. For the non corporate sector it includes credit loans and mortgages, which account respectively for around 70% and 30% of outstanding debt. Non-debt liabilities account for approximately 30% to 45% of total liabilities, depending on the exact period considered.

[7] According to Jermann and Quadrini (2006), the former measure is more appropriate for the study of defaults, given that non-debt liabilities do not lead a company to default. I use both measures to assess the robustness of the results.

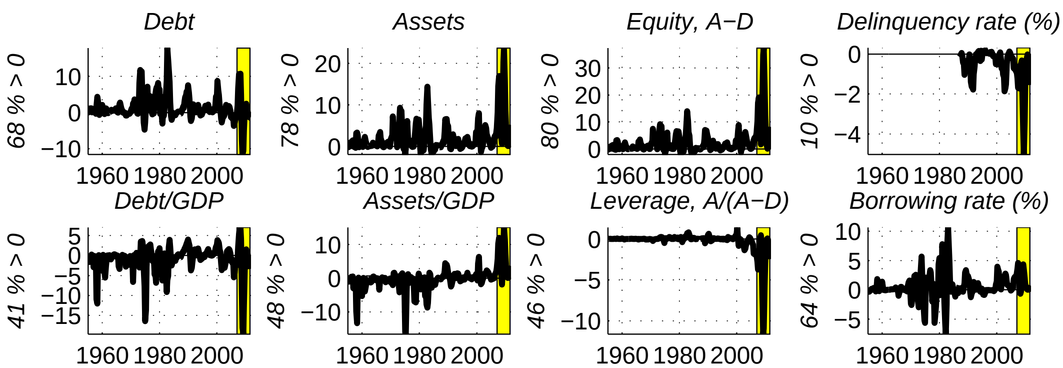
[8] The exact classification of the sub-periods considered follows Bernanke and Mihov (1998). 1979Q3 coincides with the appointment of Paul Volcker as Chairman of the Federal Reserve Bank and with the start of the regime of non-borrowed reserve targeting; 1984Q1 marks the official shift back to federal funds rate targeting; 1988Q1 indicates the beginning of the Greenspan era after the stock market crash; 2007Q3 separates the period of the Great Moderation from the beginning of the subprime crisis. A brief summary of the main events concerning monetary policy in the US can be found in Harvey and Huang (2002). The statistics reported in Panel *C* of figure 1 are mainly unaffected by the exact timing of these break points.

Figure 1: Descriptive statistics of the key variables

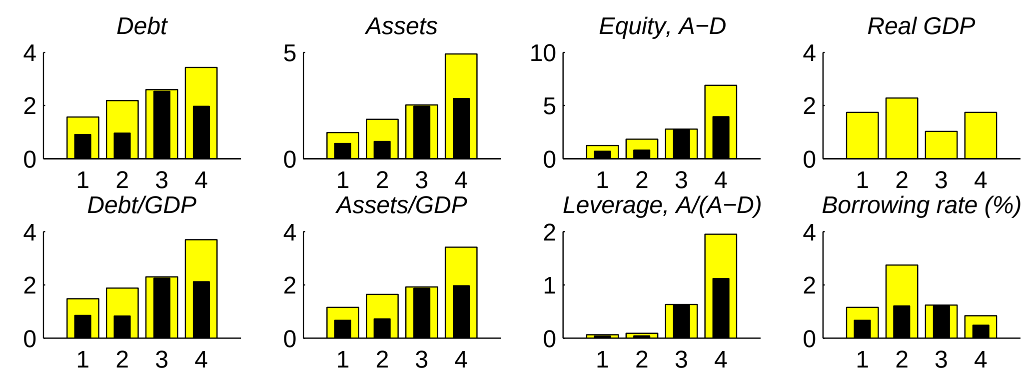
Panel A: Levels



Panel B: Cyclicality



Panel C: Standard deviations



Notes: All variables are seasonally adjusted. Panel A reports levels compared to the level of GDP and, for the borrowing rate, also to the federal funds rate. The shaded area indicates the period after 2007Q3 included. Panel B reports the product of the HP residual of each variable with the HP residual of GDP. Panel C reports the variance of HP residuals both in absolute terms (yellow, large) and relative to GDP (blue, thin) for 4 sub-periods: 1) Before Paul Volcker, 1955Q1-1979Q2, 2) Paul Volcker, 1979Q3-1984Q1, 3) Alan Greenspan and Great Moderation, 1988Q1-2007Q2, 4) Sub-prime crisis, 2007Q3-2011Q4.

for the bottom 95% of firms according to asset size. The borrowing rate is pro-cyclical, suggesting a stronger pro-cyclicality of credit demand relative to credit supply;

4. the delinquency rate is strongly counter-cyclical, and it peaks during the Gulf war recession in 1991, after the burst of the dot-com bubble in year 2001 and during the subprime crisis;

5. the absolute standard deviation of real GDP around its trend has decreased during the Great Moderation. Instead, the variability of most of the financial variables, including assets, debt and leverage, has increased both in absolute terms and relative to GDP. The result is in line with Jermann and Quadrini (2006).

2.2 Empirical strategy

The main empirical strategy of this paper consists of a modification of the two-step approach used by Basu, Fernald and Kimball (2006) to study the effects of technology shocks. As will be explained, this approach is particularly suitable for the research question at hand, because it separates the identification of monetary shocks from the computation of several impulse responses. As a robustness check, I also report the results from the more standard marginal vector autoregressive (VAR) approach by Christiano, Eichenbaum and Evans (1996) and Kim (2001). This approach consists of augmenting a small, standard VAR model with the additional variables of interest, one at the time. Monte Carlo simulations constructed on the estimates from the VAR model by Christiano, Eichenbaum and Evans (1999) suggest that the two-step approach is at least as valid as the standard VAR approach. See Appendix A for the details.

2.2.1 An application of Basu *et al.* (2006) to monetary policy

The empirical strategy consists of two separate steps. In short, I first use a parsimonious VAR model to identify candidate vectors of monetary shocks. The impulse response functions of the variables included in this first step are computed in the standard way. I then compute the impulse responses of the remaining N variables of interest by regressing each variable on the contemporaneous and $T-1$ lags of the identified shocks, in addition to deterministic controls. In this second step, the impulse response function of each of the N variables considered is computed as the T estimated coefficients on the shocks, multiplied by a scalar of the same magnitude and sign of the desired shock.[9]

More precisely, I first identify monetary shocks using a simple model in line with standard empirical models on monetary policy. The reduced-form model estimated is

$$Y_t = \alpha_t + A(L)Y_{t-1} + R_t. \tag{1}$$

The 3x1 column vector Y_t includes, in the following order, the GDP deflator, real GDP and the nominal federal funds rate. These variables are not filtered at any frequency before entering the model. The 3x1 vector α_t includes a constant, a linear trend with no time breaks and seasonal dummies. The 3x3 matrix $A(L)$ includes four lags of the endogenous vector Y_t. The model is estimated using equation-by-equation least squares. The variance-covariance

[9]The main difference from Basu *et al.* (2006) is that the relevant structural shocks are estimated from a VAR model with a relatively small set of structural assumptions rather than from a theoretical model. Following Bernanke and Blinder (1992) and Christiano, Eichenbaum and Evans (1999), most of the empirical literature on monetary policy uses one-step procedures consisting of a single structural VAR model with all variables of interest. More recent papers include an increasing number of variables, and address the consequent curse of dimensionality with Bayesian shrinkage (Banbura, Giannone and Reichlin (2010), ADD) or factor analysis (Bernanke, Boivin and Eliasz (2005), ADD).

matrix of R_t is Σ. Equation (1) captures the core ingredients of standard empirical models of monetary policy.[10]

Given the absence of variables at time t on the right-hand side, the contemporaneous relationships among the three variables included in Y_t are captured by the residuals, in the spirit of seemingly unrelated regression models. This implies that a shock to $R_{t,3}$, i.e. only to the federal funds rate, does not bear any structural interpretation, given that any structural shock underlying $R_{t,3}$ (say, an oil shock, a preference shock, etc.) could in principle affect also $R_{t\,j,j\neq 3}$. To extract a structural interpretation from the data, I follow the literature and assume that the reduced-form shocks are a linear combination of as many structural shocks S_t:[11]

$$R_t = P \cdot S_t. \tag{2}$$

Since the model is partially identified and only studies monetary shocks, the assumption that the vector S_t is 3x1 is without loss of generality, as the two non-monetary shocks in S_t can be viewed as a combination of all non-monetary shocks driving Y_t. By construction, S_t has a diagonal variance-covariance matrix. I normalize such matrix to the identity matrix, as in Christiano, Eichenbaum and Evans (1999).

An estimate of the matrix P is required in order to generate impulse responses and estimate structural shocks. The only condition imposed by the data on the estimation of P is

$$\Sigma = P \cdot P'. \tag{3}$$

Since there are infinite candidate matrices P that satisfy condition (3), there are infinite candidate structural interpretations of the same dataset. The literature solves this problem by introducing a limited set of theoretically-motivated assumptions. In this paper I use both the recursive (or Cholesky) identification and the sign-restriction identification, which are widely used in this literature.[12]

As in Den Haan and Sterk (2011), to compute the Cholesky identification I first compute the federal funds rate in the dataset as the average federal funds rate of the last month of the corresponding quarter. This adjustment reduces the risk of mistakenly ruling out contemporaneous effects in the event that such effects are actually consistent with the data. Instead, for the identification through sign restrictions, I measure the federal funds rate as the average rate of the corresponding quarter.

The identification through sign restrictions draws mainly from Canova and De Nicoló (2002) and from Rubio-Ramirez, Waggoner and Zha (2005), with some modifications. The algorithm proceeds in five steps. 1) generate L 3x3 orthogonal matrices Q, as explained in Appendix B; 2) compute L candidate matrices P_{cand} defined as $P_{cand} = P_{chol} \cdot Q$, where P_{chol} is the Cholesky-

[10] The inclusion of these variables is standard in the literature, as well as the use of a constant and a linear trend with no breaks. One exception is Canova and De Nicoló (2002), who use the slope of term structure instead of an interbank rate. The results are robust to using de-seasonalized variable instead of controlling for such frequencies using dummy variables. The inclusion of four lags in the right-hand side is also standard, as for instance in Den Haan and Sterk (2011). The Akaike, the Bayesian and the Hannan-Quinn information criteria suggested the use of respectively 6, 3 and 3 lags. The results remain unchanged, as documented in figures 13 to 16 in Appendix C. Kilian (2012) provides an excellent review of the literature on structural VARs.

[11] See Cooley and Roy (1985) for a discussion of the role of theoretical restrictions in the inference based on VAR models.

[12] The use of both approaches allows to avoid taking a stand on the debate regarding whether monetary policy generates contemporaneous effects on output or not, as the distinction turns out to be irrelevant for the results. There is a general disagreement in the literature regarding this issue. Bernanke and Mihov (1998) claim that one cannot rule out contemporaneous effects if the dataset used has quarterly data, and Canova and De Nicoló (2002) and Canova and Pina (1999) reject the hypothesis of no contemporaneous effects as inconsistent with a wide range of theoretical models. The assumption of no contemporaneous effects is instead accepted on quarterly data for instance by Christiano, Eichenbaum and Evans (1999), Den Haan and Sterk (2011) and Olivei and Tenreyro (2007), to mention a few.

identified matrix P;[13] 3) use $\{P_{cand,l}\}_{l=1}^{L}$ to compute $3 \cdot L$ sets of impulse responses, i.e. L responses to a structural shock to the first, to the second or to the third element of Y_t;[14] 4) to identify an expansionary monetary shock, restrict the identified responses by ruling out those that generate either an increase in the federal funds rate for the first two quarters, a decrease in output in the first two quarters or a price puzzle that lasts more than three years. This set of restrictions is very general and broadly in line with the existing literature;[15] 5) to further rule out poor candidate structural shocks, run an F-test on the exogeneity of the identified shocks with respect to the lagged variables, and run a Box-Pierce test on the serial correlation of the candidate shocks. These tests extend Coibion (2012). Rule out structural models corresponding to sign-restricted shocks that reject the null hypothesis of either the exogeneity or the serial uncorrelation at conventional type-I errors. Further details are provided in Section 2.3.

Call r the subset of the 3xL original candidate models that meet the restrictions. All in all, the above procedure generates $1 + r$ candidate structural representations of the data. The second step of the empirical strategy uses each of the corresponding $1 + r$ vectors of shocks. In particular, call s the generic vector of monetary shocks and call y_n the variable of interest not necessarily included in the first-step model. The m-period impulse response function of y_n to s is computed from the regression

$$y_{n,t} = \beta_t + \gamma_0 \cdot s_t + \gamma_1 \cdot s_{t-1} + ... + \gamma_{m-1} \cdot s_{t-m+1} + \epsilon_t. \quad (4)$$

β_t is a a time-varying scalar including deterministic controls, γ_i is a scalar coefficient on the $i - th$ lag and ϵ_t is the error term. The impulse response of y_n to a shock to s_t equals the vector $\gamma = (\gamma_0, \gamma_1, ..., \gamma_m)'$ multiplied by a scalar of sign and magnitude of the desired shock.[16]

[13] Canova and De Nicoló (2002) compute P_{cand} as $P_{cand} = P_{ee} \cdot Q$, where P_{ee} is eigenvalue-eigenvector decomposition of Σ. The wide set of orthogonal matrices Q that I use makes it irrelevant whether one starts from the Cholesky orthogonalization or from the eigenvalues and eigenvector decomposition, as shown in figure ?? of Appendix C.

[14] I do not impose that the monetary shock enters as the last element of S_t in the identification through sign restrictions. As argued by Canova and De Nicoló (2002), what makes an impulse response a plausible candidate for the true impulse response to a monetary shock is not that the shock is given to the equation of the interest rate, but that it generates responses consistent with the economic theory. This distinction is relevant because, in this application, a shock only to the last element of S_t significantly reduces the set of generated impulse responses despite the wide range of orthogonal matrices Q considered. Figure ?? in Appendix C provides the details.

[15] The restrictions on real GDP and the GDP deflator reduce the risk of mistakenly capturing supply shocks as monetary shocks, while the restriction on the federal funds rate reduces the risk of capturing real demand shocks and ensures that the monetary shock is expansionary. In principle, the identified reduced-form shock could be driven by a negative money demand shock instead of an expansionary monetary shock. In figure ?? of Appendix C I show the results of a model which includes also non-borrowed reserves, restricted to decrease for the first two quarters. The main results remain in place. Compared to the literature, the set of restrictions imposed is very general. Uhlig (2005) uses monthly data and identifies a monetary contraction by restricting the impact effect and the effect on the first 5 lags to display a decrease in prices, a decrease in non-borrowed reserves and an increase in the federal funds rate. Eickmeier and Hofmann (2012) identifies a monetary contraction by restricting both the impact effect and the effect on the first lag to display an increase in the federal funds rate, a decrease in real GDP, a decrease in the GDP deflator and a decrease in the M1 monetary aggregate. Canova and De Nicoló (2002) take a different approach. They base their restrictions on pairwise correlations across variables instead of the sign of the impulse response, and impose restrictions up to the lag that ensures the identification of only one structural representation of the data.

[16] The deterministic controls in equation (4) are a constant, a time trend and seasonal variables. While the exogeneity of the shocks in s_t suggests that the presence of a constant and of seasonal dummies do not affect the results because their omission does not imply an omitted variable bias, the inclusion of a trend was suggested by unreported Monte Carlo exercises. For consistency with the first-step estimation, the impulse response from equation (4) on the Cholesky-identified vector of shocks is computed by multiplying the estimates for $\{\gamma_i\}_{i=0}^{m-1}$ by the scalar used in the first step to generate a 1% decrease in the federal funds rate. Similarly, the impulse responses from equation (4) on the r sign-restricted vectors of shocks are computed by multiplying the estimates for $\{\gamma_i\}_{i=0}^{m-1}$ by the scalar used in the first step to generate a 1% decrease in the median target of the federal funds rate. Figure ?? in the on line Appendix shows that the results remain broadly in place when using the popular vector of monetary shocks estimated from Romer and Romer (2004).

Equation (4) can be estimated using either least squares or Bayesian methods. With the exception of the delinquency rate, all variables are available starting from 1955Q1. Least square estimation seems appropriate for these variables, given the relatively long sample period and the limited number of regressors included. Instead, the vector of the delinquency rate covers only the sample period from 1988Q1.[17] The significantly shorter time horizon suggests the need of Bayesian shrinkage. To do so, I follow Koop and Korobilis (2009) and assume that the error term ϵ_t is normally distributed according to $N(0, 1/h)$. I then take the following conjugate Normal-Gamma prior for the parameters $\delta = (\beta, \gamma')'$ and h:

$$\delta|h \sim N\big(\underline{\delta}, \frac{1}{h}\underline{V}\big) \quad , \quad h \sim G\big(\underline{s}^{-2}, \underline{\nu}\big). \tag{Prior}$$

As shown for instance on Koop (2003), the normality of the error term and the prior distributions of δ and h imply the following posterior distribution

$$\delta|h \sim N\big(\bar{\delta}, \frac{1}{h}\bar{V}\big) \quad , \quad h \sim G\big(\bar{s}^{-2}, \bar{\nu}\big). \tag{Posterior}$$

where $\bar{\delta}, \bar{V}, \bar{s}^{-2}$ and $\bar{\nu}$ are defined as

$$\begin{aligned}
\nu_{ols} &= T - k, \\
\hat{\delta}_{ols} &= (X'X)^{-1}X'y, \\
s^2_{ols} &= \frac{(y - X\hat{\delta}_{ols})'(y - X\hat{\delta}_{ols})}{\nu_{ols}}, \\
\bar{V} &= (\underline{V}^{-1} + X'X)^{-1}, \\
\bar{\delta} &= \bar{V}(\underline{V}^{-1}\underline{\delta} + X'X\hat{\delta}_{ols})^{-1}, \\
\bar{\nu} &= \underline{\nu} + T, \\
\bar{s}^{-2} &= \frac{\bar{\nu}}{\underline{\nu}\,\underline{s}^2 + \nu_{ols}s^2_{ols} + (\hat{\delta}_{ols} - \underline{\delta})'(\underline{V} + X'X)^{-1}(\hat{\delta}_{ols} - \underline{\delta})}.
\end{aligned}$$

T stands for the number of observations, k the number of regressors in equation (4) and X for the matrix of regressors. The calibration of the hyper-parameters $\underline{\delta}, \underline{V}, \underline{s}^{-2}, \underline{\nu}$ is explained in Section 2.3.3.[18]

The two-step empirical strategy explained above has two main advantages relative to standard structural VAR models:

1. It allows to select the set of deterministic controls that visual inspection suggests for each of the N variables of interest, considered one at the time. Take, for instance, the case in which such N variables display very heterogeneous breaks in an otherwise similar time trend, as will be in this paper. In a standard VAR model, one faces the trade-off of either including several breaks in the trend at the cost of losing degrees of freedom, or using a more parsimonious set of controls at the cost of not capturing potentially relevant breaks. The two-step approach improves this trade-off considerably: the inclusion of very few variables in the first-step model reduces the heterogeneity of time trends in the

[17] The time series is actually available from 1987Q1, but the result is not robust when including also these four initial observations. Figure ?? in Appendix C provides the detail.

[18] I also tried with an independent Normal and Gamma prior and a consequent posterior estimated using the Gibbs sampler. The results remain unchanged.

variables included, while the N second-step estimations can be run with different sets of control variables depending on the specific variable considered.

2. In the second step, the impulse responses coincide with the parameters estimated in equation (4), up to a scalar factor capturing the sign and magnitude of the shock. This is a non-negligible advantage relative to standard VAR models, where impulse responses are a non-linear function of the estimated parameters. In least-square estimation, it improves the quality of the estimates, since it avoids that the small-sample bias of the reduced-form parameters is magnified in the non-linear computation of impulse responses.[19] In the Bayesian estimation, it helps to impose prior information whenever, as in this paper, the researcher has more solid priors on the response to a shock than on the reduced-form parameters capturing the evolution of the data. For instance, in the case of the response of investment to a monetary expansion, one can impose the prior that investment is more likely to increase than to decrease following an expansionary monetary shock. Instead, in a standard VAR one would impose priors on the reduced-form model capturing the dynamics in the data, but this is arguably harder. The popular Minnesota prior, for instance, imposes that the mean of the parameter on the first lag of investment in the equation of investment equals one, and all the other parameters equal zero.[20] Literally speaking, this prior information implies the prior that, with a popular Cholesky decomposition, monetary policy has no effect at all on investment, unless it enters after the federal funds rate in the VAR model. Similarly, it implies that all variables which are taken as more exogenous than the federal funds rate, like for instance real GDP and the GDP deflator, do not respond to a monetary shock. The two-step approach used in this paper helps to impose prior information consistent with economic theory and reduces (bun does not eliminate) the set of prior information imposed on statistical convenience.[21]

2.2.2 Alternative empirical strategy considered for robustness

The above two-step approach constitutes the main empirical strategy used in the analysis. The alternative approach considered in this paper is the more popular marginal VAR approach used for instance by Christiano, Eichenbaum and Evans (1996) and Kim (2001). It consists of augmenting the first-step model from equation (1) with each of the N additional variables of interest, one at the time. The marginal variable enters after the federal funds rate, in order to allow for a possible contemporaneous response to the monetary shock. For consistency with the two-step approach, the N marginal VARs are estimated using the same set of controls used in the second-step estimation.

An additional robustness check considered regards the linearities in the VAR model. Jorda (2005) argues that if the true data generating process is not linear, then computing impulse responses from the Wald representation of the linear reduced-form VAR introduces a misspecification in the analysis. He suggests a local projection method to estimate the impulse response without imposing the linearity assumption. In figures **??** and **??** of Appendix C I show the impulse responses from the first-step estimation and from the marginal VARs estimated using local projection methods. The results from the standard approach are robust to the estimation through local projections.[22]

[19]For a similar reason, Kilian (1998) provides a bias-correction algorithm for VAR-based impulse responses, but not for the estimation of the structural shocks, which do not require non-linear computation from the estimated parameters.

[20]See, for instance, Ciccarelli and Rebucci (2003), Robertson and Tallman (1999) and Kadiyala and Karlsson (1997).

[21]The set of information imposed purely for statistical convenience remains quite large also in this paper, as for instance with regard to the Normal-Gamma prior. The details are provided in Section 2.3.2.

[22]In short, the approach consists of regressing the s-ahead lag of each variable with $s = (0, 1, ..., m)$ on the first p lags of itself, and to multiply the m coefficients obtained on the first lag by the impulse vector that

2.3 Results

I report the results in three sub-sections, depending on whether they relate to the variables included in the first step, to the delinquency rate of the second step or to the remaining $N - 1$ variables of the second step. The monetary shocks considered are always of the size that generates a 1% decrease in the federal funds rate in the first-step estimation, either on the Cholesky identification or on the median target à la Fry and Pagan (2011) of the sign-restricted estimation.

The impulse response of the variables in the first-step estimation (GDP deflator, real GDP and the federal funds) are widely consistent with the existing literature. The same holds for the response of other macroeconomic variables studied in the second step (consumption, investment, borrowing rates, etc.), as well as for the identified monetary shocks. I take such consistency with the literature as supportive evidence in favor of the validity of the empirical strategy used. The key contribution of the paper, instead, relates to the effect on the delinquency rate and on the firms' leverage ratio, which have attracted less attention in the literature. The main results are:

1. the delinquency rate on firms' loans increases, although the exact magnitude and timing of the effect crucially depend on the model used. The two-step approach predicts that the delinquency rate increases by around 80 basis points soon after the shock, and that the effect disappears within one year and a half. The marginal VAR approach, instead, predicts that the effect is half as strong, that it is delayed up to around three years after the shock and that it is actually negative on impact, although insignificantly. This divergence could be due to the relatively small time horizon of the sample available for the delinquency rate. Despite this, the hypothesis that the delinquency rate increases is never rejected by the data, lending support to the motivation of this paper.

2. the leverage ratio of firms increases. Contrary to the delinquency rate, this result is very robust across models, a fact that might be due to the much longer sample period available. The magnitude of the increase ranges between 50 to 80 basis points. The result is supported by the fact that other measures of firms' indebtedness increase, like the stock of real debt and the liabilities-to-GDP ratio. The effect on the leverage ratio is quantitatively significant, as it equals up to 3 times its standard deviation.

I now discus these and other results in more details.

2.3.1 First-step estimation

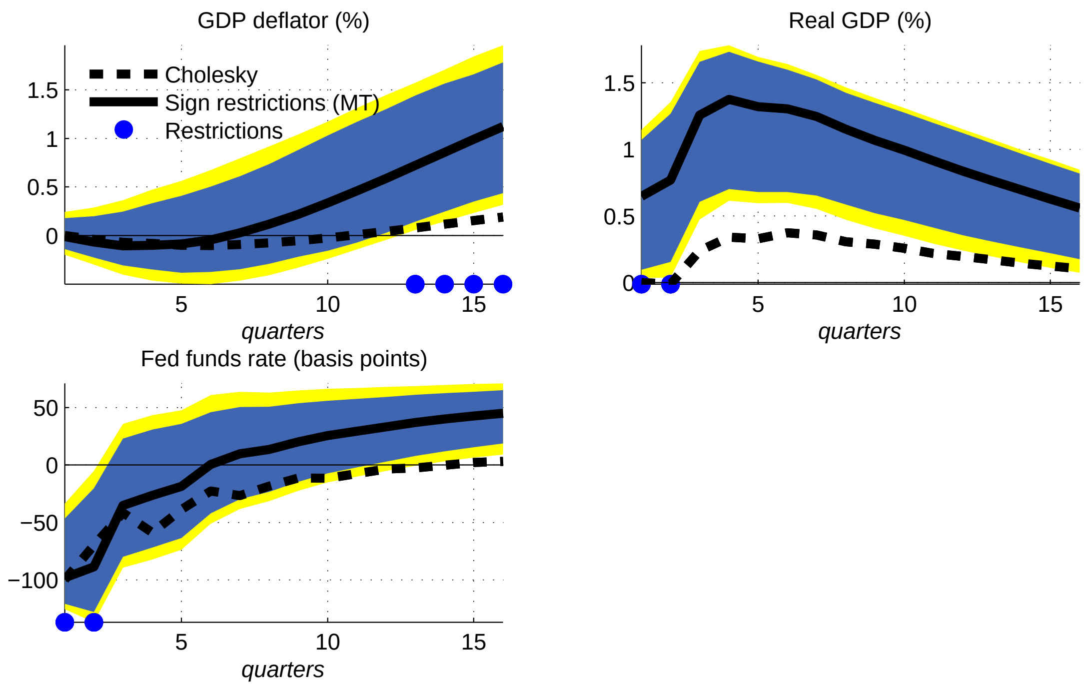
Figure 2 shows the impulse responses from the first-step estimation. The figure reports the results corresponding to 296 models, i.e. to one Cholesky-identified model and to $r = 295$ sign-restricted models. The time horizon is quarters. The dashed line shows the Cholesky-identified impulse response. The solid line shows the median target á la Fry and Pagan (2011). The light-yellow and dark-blue area cover respectively 95% and 80% areas of sign-restricted models. The sign restrictions imposed are in correspondence to the blue dots on the horizontal axis.

By construction, the impulse responses from figure 2 are in line with the literature. The GDP deflator displays a mild price puzzle, in line with several papers.[23] It then increases

captures the structural shock of interest. I only use local projection on the first-step estimations and for the marginal VAR models. In fact, the second-step regressions can already capture non linearities, as they do not impose restrictions to the data generating process of the variables considered.

[23]The price puzzle in VAR models was documented by Eichenbaum (1992). Christiano, Eichenbaum and Evan (1996) and Sims and Zha (2006) propose to include in Y_t the vector of commodity prices, which controls for the expectation that the central bank forms of future inflation. Several papers, for instance Uhlig (2005) and Olivei and Tenreyro (2007), document that the inclusion of commodity prices solves the price puzzle only for

Figure 2: First-step estimation



Notes: The figure shows the impulse response to a a monetary shock that generates 1% decrease in the federal funds rate. In the identification through sign-restrictions, the 1% decrease is intended on the median target. The shaded areas represent the 95% and 80% of the sign-restricted models. The reduced-form estimation includes four lags of the dependent variable, a constant, a linear trend and seasonal dummies.

after around 2 or 3 years. Output increases either on impact or with a lag, depending on the identification strategy used. The federal funds rate decreases by 100 basis points on impact and then reverts back. These variations are statistically significant, as shown by the bootstrap confidence interval in figure 28 of Appendix C.[24]

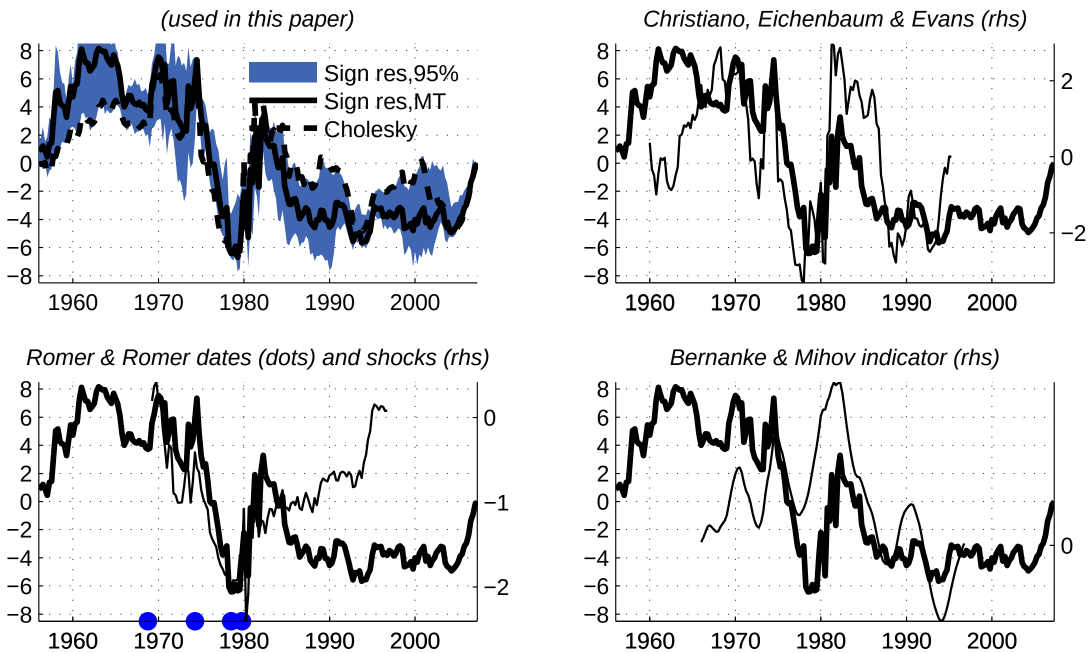
Each of the 296 models reported in figure 2 is associated with a candidate vector of monetary shocks. These vectors are crucial in the second-step estimation of Sections 2.3.2 and 2.3.3. The rest of this subsection reports several exercises that confirm the validity of such candidate shocks as structural monetary shocks.

Figure 3 shows the cumulated monetary shocks corresponding to the models identified and compares them to the literature. Such shocks are reported for the time horizon between 1956Q1 and 2007Q2, i.e. the sample period of the first-step estimation minus the number of lags included in equation (1). An increase in the cumulative monetary shock indicates a tightening of monetary policy. The top-left graph shows the cumulative time series of the Cholesky-identified shocks and the sign-restricted shocks used in the second-step estimation. These shocks are qualitatively very similar to each other and are consistent with the conventional view of the

datasets that include observations up to 1990s, but not afterwards. Boivin, Kiley and Mishkin (2011) show that the price puzzle might be the result of the misspecification of VAR models, and that it disappears in a FAVAR model. Barth and Ramey (2002) argue, instead, that the price puzzle is only the outcome of a working-capital channel that works through an increase in the cost of input factors of firms following a monetary contraction.

[24]The confidence interval is computed from 1000 pseudo-data generated by bootstrapping the reduced-form residuals. For simplicity, the bootstrap interval for the identification through sign restrictions is computed only on the median target impulse response.

Figure 3: Cumulative monetary shocks (increase = tightening)



Notes: The top-right graph shows the Cholesky and the median target, sign-restricted cumulative monetary shocks. These shocks are strongly correlated. The other graphs show that the median target shocks are consistent with the cumulative shocks in Christiano, Eichenbaum and Evans (1999), with the cumulative dates and shocks in Romer and Romer (1989, 2004) and with the monetary indicator by Bernanke and Mihov (1998). For comparability, the Bernanke and Mihov indicator enters the graph with inverted sign.

evolution of monetary policy in the sample period considered. In particular, they indicate a broadly contractionary monetary policy in the 1960s at the beginning of the chairmanship of William Martin, an expansionary monetary policy in the 1970s under Arthur Burns that contributed to the build up of inflationary pressures, an abrupt tightening in 1979 during the monetary regime by Paul Volcker, an expansionary monetary policy during most of the period under Alan Greenspan and a monetary tightening right before the 2007 crisis.[25] These shocks are in line with the cumulative structural shocks from Christiano, Eichenbaum and Evans (1999) and Romer and Romer (1989) (respectively top-right and bottom-left graphs), with the Romer and Romer (1989) dates (bottom-left graph) and with the Bernanke and Mihov (1998) monetary indicator (bottom-right graph).[26]

[25] As argued for instance by Bernanke and Mihov (1998), monetary shocks do not capture the most relevant component of monetary policy, and it is debated whether they are intrinsically meaningful or only convenient in order to identify causal effects with a minimal set of identifying assumptions. Bagliano and Favero (1998) discuss the alternative identification methods available in the literature. While the systematic component of the federal funds rate certainly plays a crucial role in the conduct of monetary policy, it is at least encouraging that the identified monetary shocks do not contradict the conventional and widely popular view of the stance of monetary policy during the sample period.

[26] Contrary to the other shocks in figure 3, the Bernanke and Mihov (1998) indicator includes the endogenous response of the the federal funds rate to contemporaneous non-monetary shocks, and is hence interpreted as a monetary index. The endogeneity of the index is not intended as the feedback effect of the federal funds rate to lagged endogenous variables. To compute cumulative Bernanke and Mihov index I invert its sign, in order to ensure comparability with the other graphs. The correlations of the Cholesky and of the median target of

Table 1: Tests on the identified monetary shocks

Panel A: Exogeneity with respect to lagged Y_t

	Cholesky	Sign restrictions			RR	CEE	BM
k	p-value	p-value, pc(5)	p-value, pc(95)	< 0.1	p-value	p-value	p-value
1	0.9996	0.9929	1	0%	0.4040	0.9974	0
2	0.9904	1	1	0%	0.0549	1	0
3	0.9996	1	1	0%	0.0955	1	0
4	0.9949	1	1	0%	0.1648	0.9997	0

Panel B: Serial correlation

	Cholesky	Sign restrictions			RR	CEE	BM
k	p-value	p-value, pc(5)	p-value, pc(95)	< 0.1	p-value	p-value	p-value
1	0.8942	0.4871	0.7266	0%	0.0584	0.5995	0
2	0.4194	0.5208	0.6706	0%	0.0507	0.8658	0
3	0.5870	0.5172	0.7899	0%	0.0590	0.8067	0
4	0.6730	0.1427	0.8215	0%	0.0535	0.9129	0

Notes: In panel A, I regress each shock on a constant and the first k lags of Y and I run an F-test on the joint hypothesis that the coefficients on lagged shocks are zero. For the Cholesky-identified shock I report the p-value. For sign-restricted shocks I report the 5th and 95th percentile, together with the percentage of identified shocks with a p-value lower that 0.10. For comparison, I also run the same test on the shocks by Romer and Romer (2004), the shocks by Christiano, Eichenbaum and Evans (1999) and the monetary indicator by Bernanke and Mihov (1998). Panel B reports the p-value for the Box-Pierce test on the serial correlation of the identified shocks. The Bernanke and Mihov index rejects exogeneity and serial un-correlation.

An additional heuristic check on the reliability of the identified shocks is shown in table 1. It reports the results of a test on the exogeneity of the identified shocks (Panel A) and on their serial-uncorrelatedness (Panel B). The exogeneity test draws from Coibion (2012). I regress each of the 296 vectors of shocks on a constant and on the first k lags of Y_t. I run an F-test on the hypothesis that the coefficients on the lags are jointly zero. For the Cholesky shocks I report the p-value, and for sign-restricted shocks I report the 5th percentile of the p-value, the 95th percentile of the p-value and the percent of p-values lower that 0.10. Encouragingly, the hypothesis that shocks are endogenous to lagged variables is rejected at standard confidence intervals. Additionally, these shocks reject the hypothesis of endogeneity at a higher significance level that for both the Romer and Romer shocks and the shocks implied in Christiano, Eichenbaum and Evans. The endogeneity of the monetary indicator by Bernanke and Mihov, instead, is not rejected. The test on serial correlation uses the Box-Pierce statistic for the same number of lags as in the tests in Panel A. The identified shocks reject the null hypothesis of serial correlation at a confidence interval slightly lower than for the Christiano, Eichenbaum and Evans shocks and at a confidence interval much higher than for the Romer and Romer shocks. The Bernanke and Mihov index rejects the hypothesis of serial uncorrelatedness.

Last, an additional check that the identified monetary shocks are sufficiently exogenous is suggested in figures 26 and 27 of Appendix C. It shows that the impulse responses from the second-step estimation are largely unaffected by the number of lags of the vector of shocks included in the right-hand side of equation (4). This would not be the case if the identified monetary shocks were not sufficiently exogenous, because the omission of lagged shocks would generate an omitted variable bias.

the monetary shocks with the Christiano, Eichenbaum and Evans (1999) shocks are respectively 0.74 and 0.59. The correlations with the Romer and Romer (2004) shocks are respectively 0.46 and 0.32, and they increase to respectively 0.85 and 0.70 for the sub-period between 1969Q2 and 1990Q1. The correlations with the Bernanke and Mihov (1998) indicator are respectively 0.36 and 0.38.

2.3.2 Second-step estimation (delinquency rate only)

Having estimated candidate vectors of monetary shocks, I now use them to estimate impulse responses from equation (4). The response of the delinquency rate is studied in figure 4. Panel A shows the result from the Bayesian estimation of the second-step approach either on the Cholesky shocks (left column) or on the median target of the sign-restricted shocks (right column).[27] Following Sims and Zha (1999), I report the 68% coverage interval for both the prior and the posterior distribution.[28] Panel B reports the impulse response computed with the marginal VAR approach. For the Cholesky decompostion, I compute a 95% bootstrap confidence interval. Figure 25 in Appendix C shows that the results are robust when measuring the loan default probability using the charge-off rate instead of the delinquency rate.[29]

I report three different cases for the Bayesian estimation, which differ depending on the exact prior information imposed. For all of them, I assume a non-informative prior on the deterministic control variables in equation (4).[30] The prior imposed on the mean value of $\{\gamma_i\}_{i=1}^m$ in *Case 1* and *Case 2* is that monetary policy has no effect on the delinquency rate. To constrain the imposition of this prior, I set a lower bound on the variance of the parameters $\{\gamma_i\}_{i=1}^m$ for the first year equal to 1.58^2%, where 1.58 is the standard deviation of the delinquency rate.[31] The variance then declines harmonically towards zero. Following the literature, all off-diagonal terms are set to zero for convenience.

The results from Panel A of figure 4 broadly suggest an increase in the delinquency rate of around 80 basis points within the first year after the shock. According to *Case 1*, the main effect occurs on impact, and after one year the probability attached to an increase in the delinquency rate is effectively the same as the probability attached to a decrease. *Case 2* constraints the impact effect by imposing a very small variance to γ_0. The result remains robust for the subsequent quarters. *Case 3* challenges further the result by imposing the prior information that the delinquency rate *decreases* by 400 basis points, which is as much as the trough-to-peak variation of the delinquency rate along the business cycle. The data seem to reject this prior. The posterior mean increases above zero right after the first quarter, and there is effectively a zero posterior probability attached to a negative response within the four subsequent quarters.

The results from the two-step Bayesian estimation of Panel A are only partially robust. The response from the more standard marginal VAR model reported in Panel B confirms the increase in the delinquency rate. The timing, though, is very different, suggesting a more sluggish effect. In particular, it suggests a small and insignificant impact effect and a subsequent increase one year after the shock. Also the magnitude of the increase is smaller, decreasing from around 80 basis points to 40 basis points.

While the results suggest that further research is required before drawing conclusions from the analysis, they also suggest that the data do not reject the hypothesis that the delinquency

[27] The figure remains essentially identical if the responses are computed on the 295 sign-restricted shocks instead of on their median target.

[28] The 68% coverage interval covers roughly one standard deviation on both sides of the expected value. Figure ?? in Appendix C reports the same analysis with a 95% coverage interval.

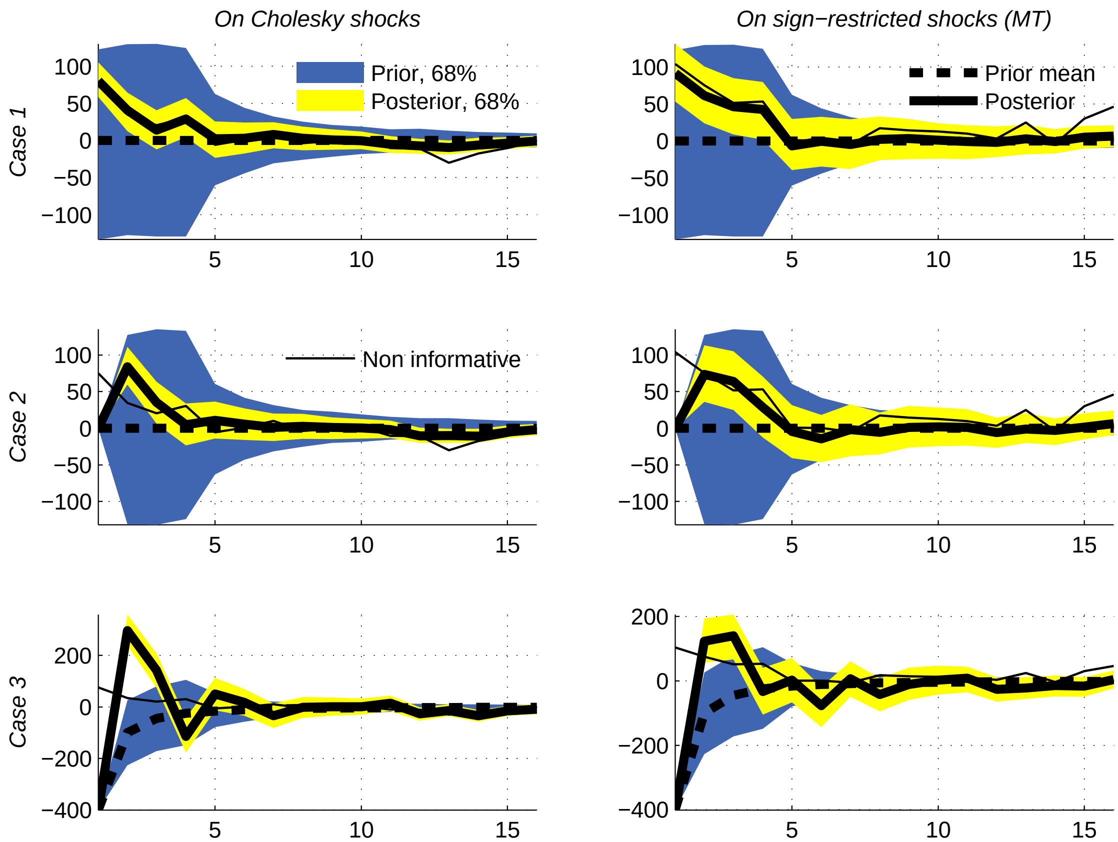
[29] The charge-off rate is defined as the stock of loans that are written off because they are *expected* to be uncollectable, relative to the stock of outstanding loans. By charging off a loan, the lender is allowed to book the loan in the "Profit and Loss" item of the income statement and hence deduct the loss from the corporations' tax return. The charge-off rate is closely related to the delinquency rate, as reported in figure ? in Appendix C.

[30] The control variables included are a constant and a linear trend in 2002Q2. The trend break is suggested by figure 1. The trend break in 1991Q1, apparent from figure 1, is instead excluded due to the loss of observations from the inclusion of 15 lags of the structural shocks to compute the 16-period impulse response. The loss of the first 15 observations of the delinquency rate is not strictly required because the estimates of the shocks cover a much longer time horizon than the vector of the delinquency rate. It is instead taken for computational convenience. The results are virtually identical when using also the observations of the delinquency rate from 1988Q1 to 1991Q3 and the corresponding vector of shocks.

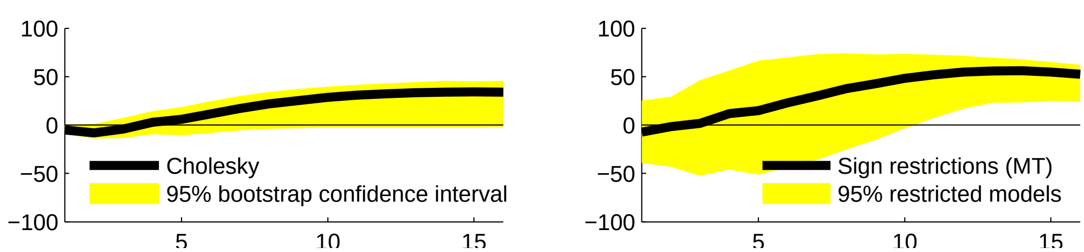
[31] The results are largely unaffected by this value, as shown in figure ?? of Appendix C.

Figure 4: Delinquency rate after a 1% decrease in the fed funds

Panel A: From the two-step approach



Panel B: From a small, standard VAR



Notes: Panel A shows the responses estimated with Bayesian methods. I use a non informative prior for the parameters capturing the deterministic controls. The prior variance of the coefficients on lagged shocks is 400 basis points, which is approximately the variation of the delinquency rate over the business cycle. Case 2 further restricts the impact effect on delinquencies to be zero. Case 3 stresses the result by assuming a prior mean of the impulse response on impact of -400 basis points. In all three cases the delinquency rate increases and reverts back within one year from the shock. The marginal approach, shown in Panel B, shows that the increase in the delinquency rate is robust, but with a very different timing.

rate increases following a monetary expansion. Additionally, and independently on its timing, the effect is quantitatively relevant, as it equals around one third of the standard deviation of the delinquency rate and around one fifth of the through-to-peak variation of the delinquency rate along the business cycle.[32] I find this result interesting because the dynamics captured by the responses reported in figure 2 reflect a combination of effects, some of which are likely to go against an increase of the default rate. For instance, it can be argued that the decrease in the borrowing rate and the increase in consumption and investment (figure 5 below) contribute towards a *decrease* of the delinquency rate because of a lower cost of borrowing and an increase in firms' profits. The fact that such effect does not emerge from figure 4 suggests that opposing forces like the one investigated in this paper could be relevant and worth the investigation of this paper.

The partial inconsistency of the results across different models used is likely to come at least in part from the relatively short period sampled by the data on the delinquency rate. This vector covers the period between 1988Q1 and 2007Q2 and has approximately only one third of the observations available instead for the analysis in the first-step estimation. To the best of my knowledge, there are no databases providing a proxy of the default probability on firms' loans for a longer period. Jimenez, Ongena, Peydro and Saurina (2010) use a huge dataset from 1985 to 2006 constructed from the Spanish credit registry which contains, for all issued loans, detailed information on the loan and on whether and when it defaulted. The US do not have such a detailed database. An alternative strategy could be to use Expected Default Frequencies from Moody's KMV, which are a measure of the default probability of firms. This measure only captures the default probability of firm, not of loans, and a delinquency on a loan does not lead mechanically to the insolvency of the entire firm.[33] In addition, it does not estimate a default probability as the ex-post default rate, but measures it using a structural credit risk model.[34] This means that EDFs crucially rely on the ability of market prices to properly discount the probability of future events, and of the structural model used to properly map such prices into a default probability.

2.3.3 Second-step estimation (all remaining variables)

The results for the remaining variables in the second-step estimation are shown in figure 5. The figure is divided in 5 panels, depending on whether the graphs refer to macroeconomic variables, interest rates, balance sheet variables, balance sheet ratios and interest rate spreads. The set of deterministic controls included in each regression is shown graphically in figure 17 of Appendix C.[35] The figure also reports the response computed from the marginal VAR approach (thin lines). The impulse responses of the other three variables (GDP deflator, real GDP and the federal funds rate) for each of the N estimations are reported in figures 21 to 24 in Appendix C.

Panels A and B show that the effect of a monetary expansion on the main macroeconomic

[32]Figure 1 shows that the delinquency rate increased by 3 percentage points during the recession after the dotcom bubble and by 4 percentage points during the subprime crisis. These variations are consistent with Covas and Den Haan (2011), who report an increase in the default rate on corporate debt after the Gulf war and after the dotcom bubble of around 4 percentage points.

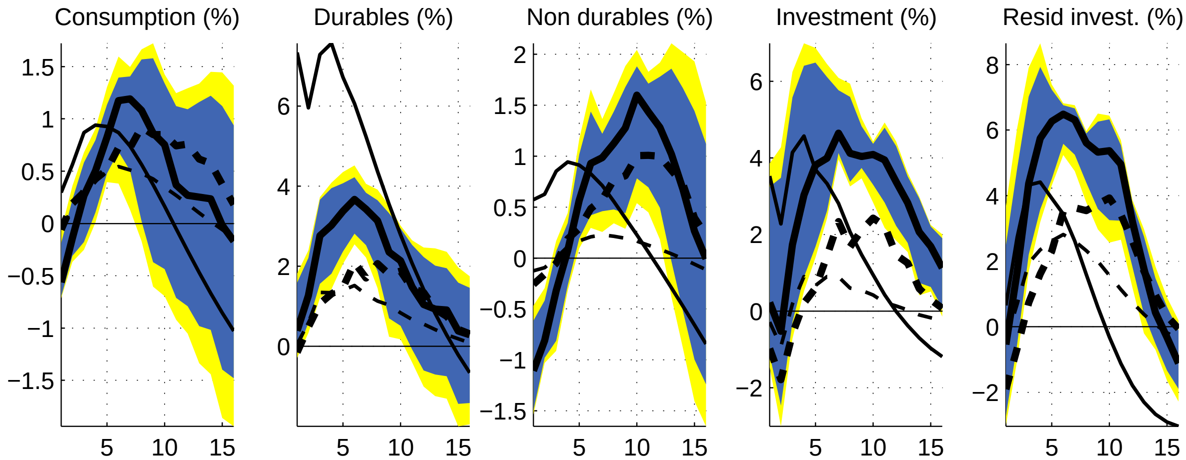
[33]For this reason, the default probability on a loan is likely to be higher than the probability that the firm defaults. Levin, Natalucci and Zakrajsek (2004) report an average Expected Default Frequency of US quoted non-financial firms in the period between 1997Q1 and 2003Q3 of 0.55%. The delinquency rate on loans to all non-financial firms in the same period is much higher (2.49%). Nevertheless, the difference could be also in part due to the difference in the samples spanned by the two datasets

[34]For an introduction to EDF data see http://www.moodysanalytics.com/ /media/Insight/Quantitative-Research/Default-and-Recovery/2012/2012-28-06-Public-EDF-Methodology.ashx.

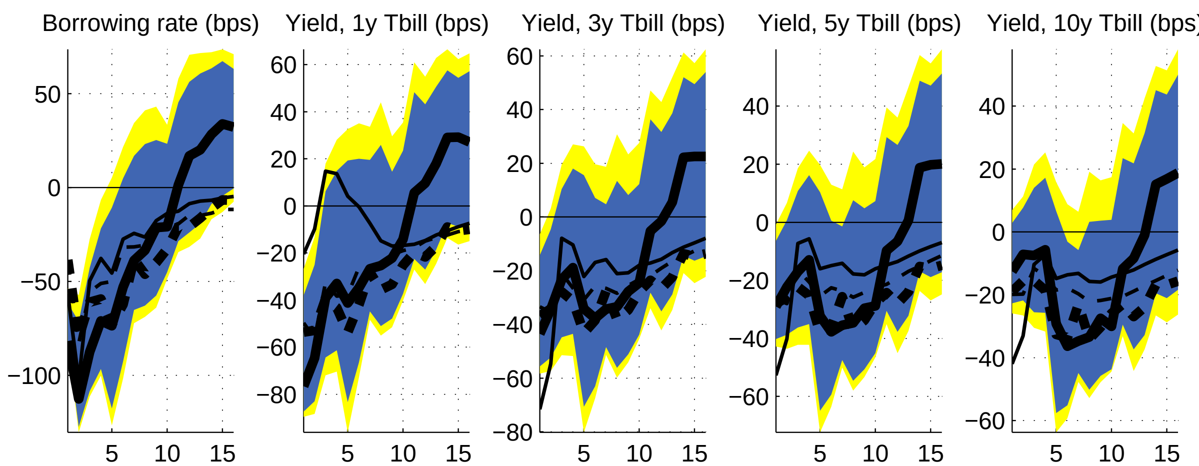
[35]The median target in the second-step is computed as the median target on the r impulse responses generated for each variable in the second step. This means that the median target response in the second step estimation does not necessarily correspond to exactly the same structural model that corresponds to the median target in the first step estimation.

Figure 5: Impulse responses from the second step

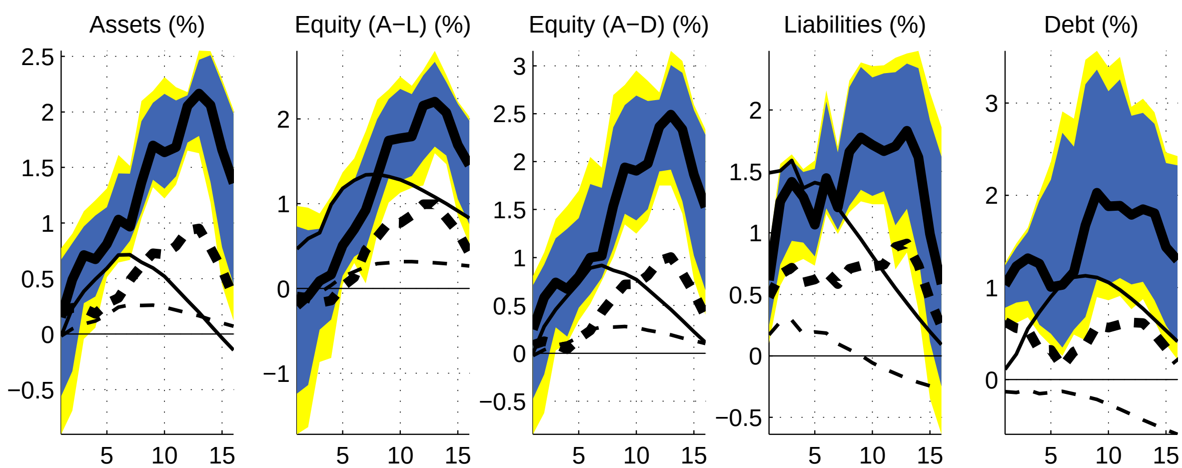
PANEL A: Macroeconomic Variables



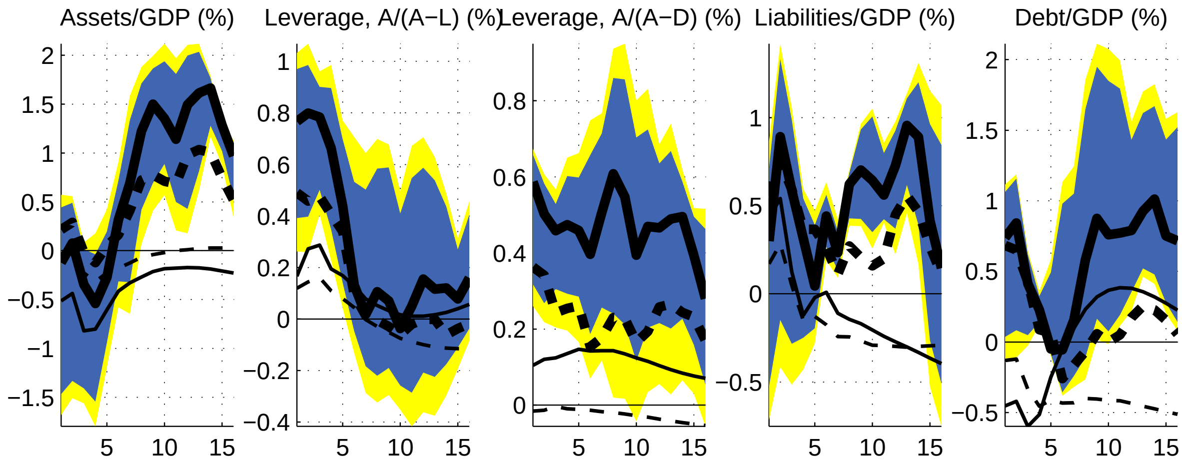
PANEL B: Interest rates



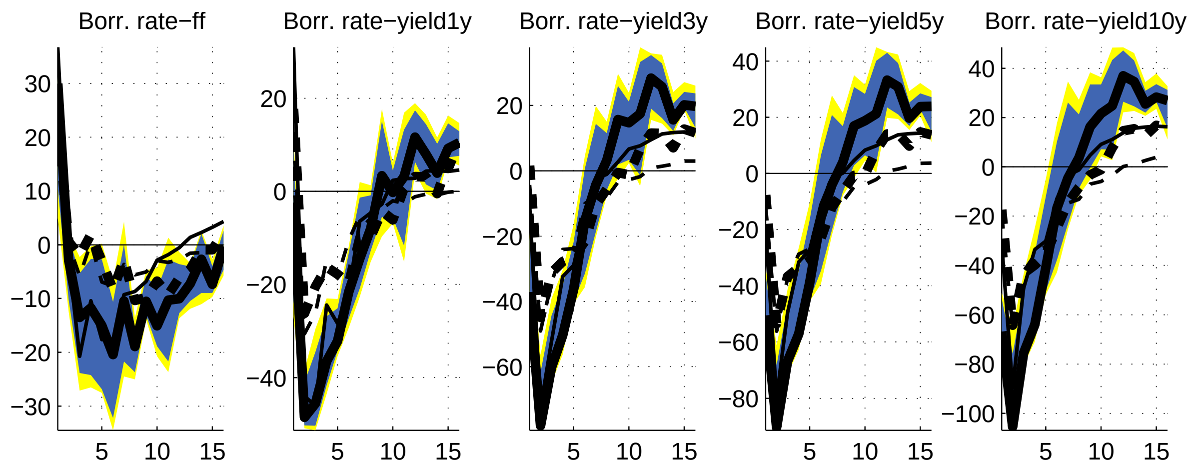
PANEL C: Balance sheet variables



PANEL D: Balance sheet ratios



PANEL E: Spreads



Notes: The figure shows the impulse responses to a monetary shock that generates a 1% decrease in the federal funds rate. It reports the responses computed on the second step using the vector shocks from the first step corresponding to Cholesky-identified shocks (dashed thick line) and sign-restricted shocks (thick solid line as median target). The shaded area reports the 95% and 80% interval on model uncertainty from the sign-restricted approach. The thin dashed and solid lines show the responses from the marginal approach respectively for the Cholesky and the sign-restricted (median target) identification. The deterministic controls in each of the 25 independent regressions and in the 25 marginal VARs depend on the specific variable and are explained in figure 17 in Appendix C.

variables and on interest rates is plausible and in line with the literature. Following a decrease in the federal funds rate, investment and consumption increase. In particular, investment react more than consumption, residential investment react more than total investment and durable consumption react more than total consumption. These results are in line with the literature reviewed in Christiano, Eichenbaum and Evans (1999). Regarding interest rates, the average borrowing rate of firms decreases, as well as several yields on Treasury bonds. This result is consistent with the standard interest rate channel of monetary policy (see for instance Christiano, Trabandt and Walentin (2011)).

Panels C and D show the effect on the key balance sheet variables and on several ratios. Assets, equity, debt and liabilities increase following a monetary expansion, as also documented by Eickmeier and Hofmann 2012). The leverage ratio and both debt-to-GDP and liabilities-to-GDP ratios increase. These results are consistent with the hypothesis of this paper, which is that a monetary expansion increases firms' default probability because it leads them to take on more debt and leverage up net worth. The magnitude of the effect is also relevant. In response to a 1% decrease in the federal funds rate, the leverage increases by 50 basis points or 80 basis points, depending on the exact measure of leverage, i.e. by as much as 2.5 to 4 times its standard deviation (20 basis points).

Panel E shows the effect of the spreads of the borrowing rate on the federal funds rate and on the Treasury yields from Panel B. Except for the impact effect for two of the five measures considered, spreads tend to decrease following a monetary expansion. The responses are consistent with the results on the spread on Commercial and Industrial (C&I) loans reported by Eickmeier and Hoffmann (2012). The decrease in the spread is not consistent with an increase in firm's default probability, unless one argues that such increase in the default rate is not priced accordingly into interest rates.

3 Structural DSGE model

This section uses a DSGE model to outline the relationship between monetary policy, leverage and defaults. The model draws from the Bernanke, Gertler and Gilchrist (1999) model, which features the main ingredients of a standard New Keynesian model. Many papers have extended this model along several dimensions, including Christiano, Motto and Rostagno (2008) and ??.

The model is populated by seven representative agents: households, lenders, capital producers, entrepreneurs, intermediate good producers, retailers and a central bank. In short, households supply labor to intermediate good producers and postpone consumption using saving accounts run by lenders. Lenders collect deposits and issue loans to entrepreneurs. Entrepreneurs have limited net worth from retained earnings, they borrow from lenders and buy capital from capital producers. They then rent capital to intermediate good producers on competitive markets. Intermediate good producers use capital and labor and sell their goods to retailers, who differentiate them and sell them to households. The central bank influences the borrowing conditions of entrepreneurs by having the opportunity cost of lending through a Taylor rule.

Given the research question at hand, the most relevant part of the model relates to the borrowing contract between the entrepreneur and the lender. For this reason, I focus most of the attention on this contract, while describing only very briefly the behavior of households, capital producers, intermediate good producers, retailers and the central bank very briefly. The behavior of such agents is very standard in this class of models and is well explained for instance by Galí (2008) and Christiano, Trabandt and Walentin (2011).

3.1 The full model

Households

Households are risk averse and derive utility from a basket of imperfectly substitutable consumption goods and from leisure. Households are infinitely lived, they discount future utility with the discount factor $\beta < 1$ and postpone consumption through the deposit services of lenders. These services take the form of deposits. In equilibrium, deposits pay the nominal risk-free rate R^n_{t-1} at period t because lenders perfectly diversify the idiosyncratic risk of entrepreneurs and because entrepreneurs bear aggregate uncertainty (more on this later). The households' maximization problem is

$$\max \sum_{t=0}^{\infty} \beta^t \Big\{ log(C_t) - \chi \frac{H_t^{1+1/\eta}}{1+1/\eta} \Big\},$$

subject to

$$P_t C_t + D_t \leq W_t H_t + R_{n,t-1} D_{t-1}, \, \forall t.$$

The first order conditions are

$$\beta^t \frac{1}{C_t} = P_t \lambda_t,$$
$$\beta^t \chi H^{\frac{1}{\nu}} = \lambda_t W_t,$$
$$\lambda_t = R_{n,t} \lambda_{t+1},$$

where λ_t stands for the shadow price on the budget constraint.

Capital producers

Each period, capital producers buy all non-depreciated capital from entrepreneurs, invest in new units of capital and sell the new stock to entrepreneurs. The technology that produces new units of investment goods is subject to investment adjustment costs. These costs capture disruption costs, replacement of installed capital and costly learning. The adjustment cost function is taken from Christiano, Eichenbaum and Evans (2005), Christiano, Motto and Rostagno (2008) and Smets and Wouters (2003):

$$K_t = (1-\delta) K_{t-1} + \left(1 - S\left(\frac{I_t}{I_{t-1}}\right)\right) I_t. \tag{5}$$

The adjustment costs are zero in steady state and have constant second derivative, i.e. $S(1) = S(1)' = 0,\ S(1)'' = \nu > 0$. These costs equal $S\big(\frac{I_t}{I_{t-1}}\big) = \frac{\nu}{2}\big(\frac{I_t}{I_{t-1}} - 1\big)^2$.[36]

Intermediate good producers

Entrepreneurs rent capital to intermediate good producers. Intermediate good producers use capital and labor in the following Cobb-Douglas production function to produce intermediate goods.

[36] The assumption of convex adjustment costs is justified by convenience rather than realism. Existing empirical evidence documents that investment decisions on micro data display lumpiness, periods of inactions and spikes that are inconsistent with the smooth behaviour of investment implied by convex adjustment costs. It appears, though, that the severity of these non-linearities is dampened by the aggregation, as argued by Caballero (1999) and Cooper and Haltiwanger (2006), and by general equilibrium effects, as argued by Veracierto (2002).

$$Y_t = K_{t-1}^{\alpha} H_t^{1-\alpha}. \tag{6}$$

In equilibrium, the first order conditions with respect capital and labour pin down the rental rate of capital and the wage rate:

$$r_{k,t} = \alpha\Big(\frac{K_{t-1}}{H_t}\Big)^{\alpha-1}, W_t = (1-\alpha)\Big(\frac{K_{t-1}}{H_t}\Big)^{\alpha}.$$

Retailers

Retailers buy intermediate goods, diversify them costlessly and sell them to consumers as final consumption goods. Retailers enjoy some price-setting power because households view final goods as imperfect substitutes. Under the assumption of Calvo price setting, prices are set as a mark-up over the weighted average of marginal costs over time. This nominal rigidity gives monetary policy real effects in the short term. The standard Dixit-Stiglitz aggregator combines the varieties of consumption into the consumption basket C_t of households.

Central bank

The key driver of the model is the monetary policy shock in the Taylor rule. The monetary shock enters at time t by changing the risk-free nominal interest rate R_t^n between t and $t+1$. In doing so, it affects the opportunity cost of lending and the investment decisions starting from period t onwards. The central bank sets the policy rule according to the following Taylor rule:

$$\frac{R_{n,t}}{R_{n,ss}} = \Big(\frac{R_{n,t-1}}{R_{n,ss}}\Big)^{\rho}\Big[\Big(\frac{\Pi_t}{\Pi_{ss}}\Big)^{\gamma_\pi}\Big(\frac{Y_t}{Y_{ss}}\Big)^{\gamma_y}\Big]^{1-\rho} e^{\epsilon_t}. \tag{7}$$

Equation (7) is similar to the Taylor rule used by Faia and Monacelli (2007) and Schmitt-Grohé and Uribe (2007), as it features inflation and output in deviations from their value in steady state.[37] Bernanke, Gertler and Gilchrist (1999) use a similar Taylor rule, except that γ_y is set equal to zero.

Entrepreneurs, lenders and the debt contract

The most relevant part of the model relates to the interaction between lenders and entrepreneurs. At the end of period $t-1$ the representative risk-neutral entrepreneur has limited net worth N_{t-1} and borrows $Q_{t-1}K_{t-1} - N_{t-1}$ from a risk-neutral lender. K_{t-1} stands for the stock of capital, while Q_{t-1} for the price of capital. The entrepreneur then rents capital at time t to intermediate good producers at the market rental rate $r_{k,t}$. In equilibrium, the unitary aggregate return to capital $R_{k,t}$ is pinned down by the capital gain and by the rental rate on capital, according to the equation

$$R_{k,t} = \frac{r_{k,t} + (1-\delta)Q_t}{Q_{t-1}}. \tag{8}$$

For simplicity, I assume for the moment that $R_{k,t}$ is deterministic and known to both parties at time $t-1$. In the full model this will not be the case, since $R_{k,t}$ is affected by the monetary shock through an unexpected variation in $r_{k,t}$ and Q_t. In this section, instead, I assume that

[37] It differs from the Taylor rule in Faia and Monacelli (2007) because it does not include the price of assets, and it differs from the Taylor rule in Schmitt-Grohé and Uribe (2007) because it considers the response of the policy rate to contemporaneous instead of future levels of inflation and output.

$R_{k,t}$ constant in order to simplify the intuition behind the leverage effect in the optimality condition. This assumption is relaxed later.

The revenues from the entrepreneur's investment equal

$$\omega_t R_{k,t} Q_{t-1} K_{t-1}. \tag{9}$$

The shock ω_t represents an idiosyncratic shock with support $[0, \infty)$, expected value of 1 and cumulative distribution function $\Phi(\omega_t)$. One can either think of ω_t as a shock affecting the market return to investment (as in Bernanke, Gertler and Gilchrist (1999) and Angeloni and Faiai (2013)) or as a structural shock affecting the effective capital rented out of the stock of capital (as in Christiano, Motto and Rostagno (2008)). Capital fully depreciates and cannot be consumed at the end of the production.[38]

Information is symmetric ex-ante but asymmetric ex-post. The contract is signed at the end of period $t-1$. The shock ω_t is realized at time t. If the shock could be costlessly observed by both parties, then state-contingent contracts would allow the borrowing rate of the contract to be some optimal function of the ex-post entrepreneur's revenues. Assume, instead, that ω_t is costlessly observed by the entrepreneur, but it is not observed by the lender unless he pays a fraction $\mu < 1$ of ex-post revenues $\omega_t R_{k,t} Q_{t-1} K_{t-1}$. This observation cost captures the idea that borrowers typically have a richer information set regarding their project relative to lenders. Given asymmetric information, the repayment scheme cannot be contingent on the shock, because it would lead the entrepreneur to opportunistically under-report ω_t in order to pay a lower interest rate.[39]

Entrepreneurs borrow from lenders in competitive markets. All agents have the possibility to invest in the risk free asset that yields $R_{n,t-1}$ at time t. Perfect competition takes the form of lenders competing among each other to provide loans to entrepreneurs. Under the assumptions of perfect competition among lenders and risk neutrality of all agents, the contract maximizes the expected profits of the entrepreneur under the condition that the expected return on lending equals the opportunity cost of lending.[40]

Townsend (1979) shows that in this setting the optimal contract is a simple debt contract, that is, the borrower either repays a fixed amount independently on the realization of the shock or defaults.[41] Let $R_{b,t-1}$ stand for the borrowing rate. When the borrower and the lender agree on $Q_{t-1}K_{t-1} - N_{t-1}$ and $R_{b,t-1}$ they indirectly agree on an endogenous threshold value $\bar{\omega}_t$

[38] The idiosyncratic shock is not truly a structural shock and enters the model in this way for practical convenience. The partial equilibrium result implicit in the debt contract remains unchanged if equation (9) is interpreted as a production function and ω_t as a productivity shock. The main results of the model do not depend on the linearity assumption of revenues in the stock of capital nor on the assumption of full depreciation, which only make the intuition clearer. See Covas and Den Haan (2012) for a study of non-linearities in production and capital depreciation in "costly state verification" models.

[39] Verification is assumed to be deterministic, although Townsend (1979) shows that it is dominated by stochastic verification. The assumption that the verification cost is proportional to ex-post revenues is without loss of generality. Townsend (1979) shows that the optimality of the debt contract holds irrespectively on whether this cost is constant or not in the realization of the revenues of the borrower.

[40] This form of perfect competition is taken from the original paper by Townsend (1979) and from several papers that draw from it, for example Covas and Den Haan (2012) and Faia and Monacelli (2007). The results do not rely on the assumption of perfect competition. In Dell'Ariccia, Laeven and Marquez (2010) a similar result emerges because a monetary expansion reduces the net return on lending by reducing the lending rate and increasing the monopolist bank's leverage ratio. These effects jointly reduce the incentive to monitor and increase the default probability of the firm. In Valencia (2011) the result is driven by the fact that a lower opportunity cost of lending leads the monopolistic bank to increase lending to firms in order to extract more surplus, and this increases firms' leverage ratios and defaults.

[41] The key intuition behind the optimality of the debt contract comes from the fact that it is optimal to limit the probability that the dead-weight observation cost will be incurred. To do so, the lender leaves no revenue to the entrepreneur in case of default in order to reduce the borrowing rate to be paid in case of no default. The debt contract is optimal if μ is an observation cost, i.e. a cost that the lender must pay to discover that the entrepreneur cannot afford to repay the debt. It is not optimal, instead, if μ is only a bankruptcy cost, i.e. a cost that the lender must pay to seize the revenues of the entrepreneur. In fact, if it was not costly to observe the revenue but only to organize, say, the dissembling of the firm and the sell of the entrepreneurs'

for ω_t below which the entrepreneur's revenues are insufficient to cover the debt repayment obligation. This threshold value is pinned down by $\bar{\omega}_t R_{k,t} Q_{t-1} K_{t-1} = R_{b,t-1}(Q_{t-1}K_{t-1} - N_{t-1})$. If $\omega_t > \bar{\omega}_t$, then the entrepreneur pays back $R_{b,t}(Q_{t-1}K_{t-1} - N_{t-1})$ and keeps profits $\omega_t R_{k,t} Q_{t-1} K_{t-1} - R_{b,t-1}(Q_{t-1}K_{t-1} - N_{t-1})$. If $\omega_t < \bar{\omega}_t$, then the entrepreneur defaults and the lender recovers $(1-\mu)\omega R_{k,t} Q_{t-1} K_{t-1}$.

The contract maximizes the expected profit of the entrepreneur subject to the participation constraint of the lender. The maximization problem is solved in $\bar{\omega}_t, R_{b,t-1}, K_{t-1}$ and is written as

$$\max_{\{\bar{\omega}_t, R_{b,t-1}, K_{t-1}\}} V_t = \int_{\bar{\omega}_t}^{\infty} \omega R_{k,t} Q_{t-1} K_{t-1} - R_{b,t-1}(Q_{t-1}K_{t-1} - N_{t-1}) d\Phi(\omega_t),$$

subject to

$$\bar{\omega}_t R_{k,t} Q_{t-1} K_{t-1} = R_{b,t-1}(Q_{t-1}K_{t-1} - N_{t-1}), \tag{10}$$

$$[1-\Phi(\bar{\omega}_t)]R_{b,t-1} + \Phi(\bar{\omega}_t)(1-\mu)\frac{E(\omega_t \mid \omega_t < \bar{\omega}_t) R_{k,t} Q_{t-1} K_{t-1}}{Q_{t-1}K_{t-1} - N_{t-1}} \geq R_{n,t-1}. \tag{11}$$

Equation (10) defines the threshold value $\bar{\omega}_t$ as a function of $R_{b,t-1}$ and K_{t-1}. Equation (11) gives the participation constraint of the lender. This constraint imposes that the expected return on lending (left-hand side) is not lower than the opportunity cost of lending (right-hand side). While equation (11) ensures that the lender covers the opportunity cost in expected value from each contract signed, the law of large number ensures that, on aggregate, the lender obtains exactly $R_{n,t-1}$ in any state of the world. The perfect diversification of idiosyncratic risk across entrepreneurs allows the lender to pay $R_{n,t-1}$ to depositors in any state of the world. [42]

It is convenient to simplify the maximization problem by substituting out the endogenous variable $R_{b,t-1}$ from equation (10) into equation (11) and into the objective function. This substitution reduces the maximization problem to

$$\max_{\bar{\omega}_t, K_{t-1}} F(\bar{\omega}_t) R_{k,t} Q_{t-1} K_{t-1},$$

$$\text{subject to } \frac{G(\bar{\omega}_t) R_{k,t} Q_{t-1} K_{t-1}}{Q_{t-1}K_{t-1} - N_{t-1}} \geq R_{n,t-1}, \tag{12}$$

where $F(\bar{\omega}_t)$ and $G(\bar{\omega}_t)$ are equal to

$$F(\bar{\omega}_t) = \int_{\bar{\omega}_t}^{\infty} \omega_t d\Phi(\omega_t) - [1-\Phi(\bar{\omega}_t)]\bar{\omega}_t,$$

$$G(\bar{\omega}_t) = 1 - F(\bar{\omega}_t) - \mu \int_0^{\bar{\omega}_t} \omega_t d\Phi(\omega_t).$$

assets, then in the event of a default it would be optimal ex-post to renegotiate the loan and avoid incurring the cost. This is not the case for an observation cost, because the lender needs to observe that the ex-post return on revenues is insufficient to cover the entrepreneur's repayment obligation before agreeing to renegotiate, otherwise entrepreneurs would demand to renegotiate irrespectively of the realization of ω_t. The above remark is pointed out, for instance, by Covas and Den Haan (2012).

[42] An equivalent way of writing down the participation constraint of the lender is

$$(1-\mu)\int_0^{\bar{\omega}_t} \omega R_{k,t} Q_{t-1} K_{t-1} d\Phi(\omega_t) + \int_{\bar{\omega}_t}^{\infty} R_{b,t}(Q_{t-1}K_{t-1} - N_{t-1}) d\Phi(\omega_t) \geq R_{n,t-1}(Q_{t-1}K_{t-1} - N_{t-1}).$$

To develop intuition behind the notation, use the expressions for $F(\bar{\omega}_t)$ and $G(\bar{\omega}_t)$ and the condition $E(\omega_t) = 1$ to derive the following equality:

$$\underbrace{\big[1 - \mu \int_0^{\bar{\omega}_t} \omega_t d\Phi(\omega_t)\big] R_{k,t} Q_{t-1} K_{t-1}}_{\text{net expected revenues}} = R_{k,t} Q_{t-1} K_{t-1} \big[\underbrace{F(\bar{\omega}_t)}_{\substack{\text{share to the} \\ \text{entrepreneur}}} + \underbrace{G(\bar{\omega}_t)}_{\substack{\text{share to} \\ \text{the lender}}} \big]. \tag{13}$$

This equality shows that $F(\bar{\omega}_t)$ and $G(\bar{\omega}_t)$ determine the shares of expected revenues $R_{k,t}Q_{t-1}K_{t-1}$ net of expected monitoring costs $\mu \int_0^{\bar{\omega}_t} \omega_t R_{k,t} Q_{t-1} K_{t-1} d\Phi(\omega_t)$ allocated to respectively the entrepreneur and the lender. These shares are implicitly pinned down by the debt contract, once the borrower and the lender agree on $Q_{t-1}K_{t-1} - N_{t-1}$ and $R_{b,t-1}$. Since the expected unitary monitoring cost $\mu \int_0^{\bar{\omega}_t} \omega_t d\Phi(\omega_t)$ is relatively small for any realistic calibration of μ, $F(\bar{\omega}_t)$ and $G(\bar{\omega}_t)$ approximately add up to one.[43] Borrowing conditions that indirectly imply a higher share of expected revenues to the lender $F(\bar{\omega}_t)$ imply a lower share of expected revenues to the borrower $G(\bar{\omega}_t)$ and vice-versa. The key result of the paper is driven by the positive first derivative of $G(\bar{\omega}_t)$ with respect to the default threshold $\bar{\omega}_t$.[44] An increase in the share of expected revenues promised to the lender $G(\bar{\omega}_t)$ is associated with an increase in the default threshold $\bar{\omega}_t$ because it is harder for the entrepreneur to meet the higher repayment obligation to the lender.

$$F(\bar{\omega}_t) + G(\bar{\omega}_t) \approx 1 \quad \text{with} \quad F'(\bar{\omega}_t) < 0 \text{ and } G'(\bar{\omega}_t) > 0.$$

By the law of large numbers, $F(\bar{\omega}_t)$ stands both for the expected share of revenues for the individual entrepreneur and for the share of aggregate revenues for the entire sector of entrepreneurs. Since entrepreneurs are risk neutral, they are willing to postpone consumption and retain their profits as future net worth. To avoid that the accumulation of net worth allows the entrepreneur to fully self-finance investment with retained earnings, I assume that an exogenous fraction $1-\gamma$ of non-defaulting entrepreneurs dies and the same mass of entrepreneurs is born. This assumption is standard in the literature. Reborn entrepreneurs enter their first debt contract with a positive net worth that can be made arbitrarily small, as in De Fiore, Teles and Tristani (2011) and in Carlstrom, Fuerst and Paustian (2012). Entrepreneurial net worth at the end of period t is given by[45]

$$N_t = \gamma V_t.$$

Return now to the simplified maximization problem. To understand the intuition of the model, note that the expected return on lending in equation (12) is affected by $G(\bar{\omega}_t)$ and K_{t-1} in opposite directions. It increases in the share $G(\bar{\omega}_t)$ to the lender because, given K_{t-1}, the lender receives a higher share of expected revenues. It decreases in K_t because, given $G(\bar{\omega}_t)$, an

[43] $F(\bar{\omega}_t)$ and $G(\bar{\omega}_t)$ add up to 0.9983 in the calibration of Section 3.2.

[44] More precisely, $G(\bar{\omega}_t)$ is increasing in $\bar{\omega}_t$ only in the lower support of $\bar{\omega}_t$. Since a level of $\bar{\omega}_t^*$ where $G(\bar{\omega}_t)$ decreases would be suboptimal (both parties would benefit from a reduction in $\bar{\omega}_t$) we can disregard the decreasing part of $G(\bar{\omega}_t)$ from the analysis. $\bar{\omega}_t^*$ will be pinned down by equation (14). Bernanke, Gertler and Gilchrist (1999) show that condition $G'(\bar{\omega}_t^*) > 0$ holds if $\Phi(\omega_t)$ is such that

$$\frac{d}{d\omega_t} \omega_t \frac{d\Phi(\omega_t)}{1 - \Phi(\omega_t)} > 0,$$

This condition is satisfied for standard distributions, including the log normal distribution used later.

[45] Note that, to simplify the analysis, the model does not allow firms to finance investment with outside equity, but only with retained earnings and debt. The empirical result on the leverage ratio suggests that the leverage effect would be in place even if equity financing was included in the model, because the data reject the hypotheses that equity increases more rapidly than debt. Covas and Den Haan (2012) develop an extension of the "costly state verification" contract to equity contracts.

increase in investment pushes up the entrepreneur's leverage and decreases the relative buffer provided by his net worth.

To solve the maximization problem, substitute for K_{t-1} using constraint (12) in the objective function and derive the optimality condition with respect to $\bar{\omega}_t$:

$$-F'(\bar{\omega}_t^*) = F(\bar{\omega}_t^*) \frac{G'(\bar{\omega}_t^*)}{Q \cdot \left(\frac{R_{k,t}}{R_{n,t-1}}\right)^{-1} - G(\bar{\omega}_t^*)}. \tag{14}$$

Equation (14) pins down the equilibrium default threshold $\bar{\omega}_t^*$ as a decreasing function of R for any parametrization of the model (see Covas and Den Haan (2012), appendix C).[46] The economic intuition behind equation (14) is the key result of the paper and is explained graphically in figure 6.

Panel a, shows combinations of K and $G(\bar{\omega})$ which differ for the implied expected profit of the entrepreneur and for whether they satisfy the participation constraint of the lender. The red dash-dotted lines represent iso-profit curves of the entrepreneur. Expected profits increase towards the top left part of the graph, where the entrepreneur invests more with a contract that implies a lower share of expected revenues to the lender. The participation constraint of the lender is shown in the solid, convex line. All combinations of $(K_{t-1}, G(\bar{\omega}_t))$ below the solid line satisfy the participation constraint of the lender, while all combinations above the line violate the participation constraint of the lender. The initial equilibrium is shown in point A, which is the point along the participation constraint which reaches the highest possible iso-profit curve of the entrepreneur.

The participation constraint of the lender is upward sloping in the space $(K_{t-1}, G(\bar{\omega}_t))$. This positive slope reflects the leverage effect that drives the result of the model. To see why, rewrite constraint (12) in terms of an upward limit to the entrepreneur's leverage ratio:

$$\frac{K_{t-1}}{N_{t-1}} \leq \frac{1}{Q_{t-1} - \frac{R_{k,t}}{R_{n,t-1}} G(\bar{\omega}_t)} = k(\bar{\omega}_t). \tag{15}$$

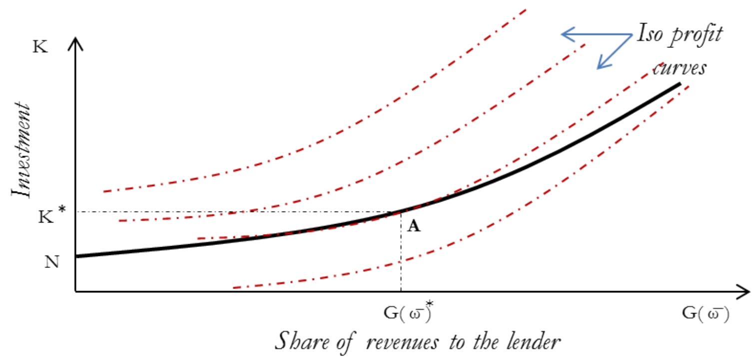
Equation (15) shows that the maximum entrepreneurial leverage compatible with the participation constraint of the lender is an increasing function of $G(\bar{\omega}_t)$. Given net worth N_{t-1}, and assuming that the constraint is initially binding, the entrepreneur can invest more only by borrowing more. For given $G(\bar{\omega}_t)$, this increase in borrowing violates the participation constraint of the lender. In fact, it increases the entrepreneur's leverage ratio, which reduces the relative buffer that the constant net worth provides to the risky loan. To compensate the lender for this leverage effect, the entrepreneur must pay a leverage premium that takes the form of a higher $G(\bar{\omega}_t)$, i.e. a higher share of expected revenues to the lender. The increase in $G(\bar{\omega}_t)$ has a negative effect on the expected profit of the entrepreneur because it decreases $F(\bar{\omega}_t)$. Nevertheless, it is necessary to move along the participation constraint and convince the lender to issue more credit.

Consider now what happens when the opportunity cost of lending decreases. A decrease in $R_{n,t}$ rotates the constraint upwards and expands the set of combinations compatible with the participation constraint of the lender. This happens because perfect competition pushes down the return on lending, pinning down a lower borrowing rate for any given level of lending. In principle, the entrepreneur could leave the level of investment unchanged and benefit from the lower cost of borrowing. This would push down the default probability, as shown in point B of

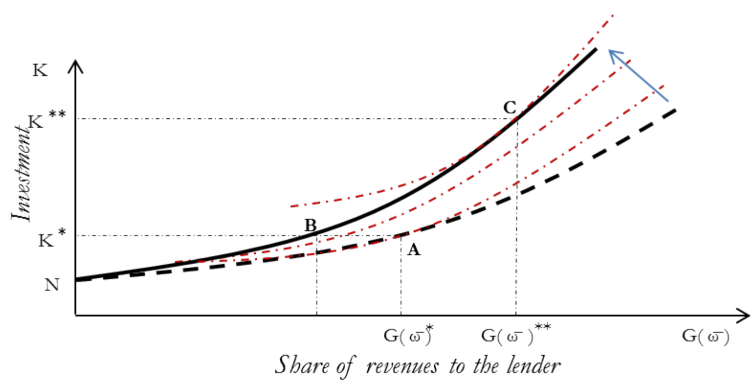
[46]Covas and Den Haan (2012) study the relationship between $\bar{\omega}_t^*$ and $R_{k,t}$. Their proof extends to the relationship between $\bar{\omega}_t^*$ and $R_{n,t-1}$, after accounting for how $R_{k,t}$ and $R_{n,t-1}$ affect the discounted return to capital $R_{k,t}/R_{n,t-1}$ in the optimality condition (14)Covas and Den Haan (2012), the equilibrium default threshold is independent on the entrepreneur's net worth due to the linearity in the production function.

Figure 6: Effects of a decrease in the opportunity cost of lending

panel a) Initial equilibrium



panel b) New equilibrium



Notes: A decrease in the opportunity cost of lending relaxes the participation constraint of the lender and reduces the cost of borrowing. The entrepreneur reacts to the lower cost of borrowing by leveraging up his net worth in order to invest more and reach point C. The equilibrium default probability is higher in point C relative to point A due to the leverage premium demanded by the lender.

Panel *b*. Interestingly, this is not optimal because the entrepreneur has an incentive to move along the new participation constraint of the lender. In fact, the decrease in the opportunity cost of lending pushes up the discounted return to capital $R_{k,t}/R_{n,t-1}$, making each unit of investment more productive in discounted terms. In this contract, the entrepreneur finds it optimal to leverage up his net worth up to the point that the default probability increases, despite the ultimate reduction in the borrowing rate. The entrepreneur is better off from doing so, while the lender is indifferent because his participation constraint is satisfied with equality.

The leverage effect commented above can be shown more formally by substituting equation (15) in the maximization problem and taking the first order condition in $\bar{\omega}$, which is

$$-\frac{dF(\bar{\omega})}{d\bar{\omega}}k(\bar{\omega}) = F(\bar{\omega})\frac{dk(\bar{\omega})}{d\bar{\omega}}. \tag{16}$$

Equation (16) states that, in an interior solution, the entrepreneur accepts a debt contract only if it implies that the marginal benefit and the marginal cost of a higher default threshold $\bar{\omega}$ are equal. The marginal cost of a higher $\bar{\omega}$ equals the foregone expected revenue implicit when accepting a higher share of revenues to the lender ($-\frac{dF(\bar{\omega})}{d\bar{\omega}}k(\bar{\omega})$). The marginal benefit of a higher $\bar{\omega}$ equals the benefit associated with the corresponding marginal increase in investment ($F(\bar{\omega})\frac{dk(\bar{\omega})}{d\bar{\omega}}$).

Define now the leverage premium as the increase in $G(\bar{\omega})$ associated with a 1% increase in the leverage ratio of the entrepreneur. The implicit function theorem gives

$$\frac{dG(\bar{\omega}_t)}{\frac{dk(\bar{\omega}_t)}{k(\bar{\omega}_t)}} = \underbrace{Q_{t-1}\cdot\left(\frac{R_{k,t}}{R_{n,t-1}}\right)^{-1} - G(\bar{\omega}_t)}_{\text{Leverage Premium}} > 0.$$

The leverage premium is strictly positive under the assumption that the maximization problem has an interior solution for K.[47] Substituting out $\frac{dk(\bar{\omega}_t)}{k(\bar{\omega}_t)}$ in equation (16) and rearranging the terms gives

$$-F'(\bar{\omega}_t) = F(\bar{\omega}_t)\frac{G'(\bar{\omega}_t)}{\text{Leverage Premium}},$$

which is the optimality condition of equation (14). As shown for instance in Covas and Den Haan (2011), equation (14) pins down a positive relationship between $\frac{R_{k,t}}{R_{n,t-1}}$ and $\bar{\omega}_t^*$. This means that, a decrease in $R_{n,t-1}$ pushes up the discounted return to investment and increases the marginal benefit of accepting a higher default probability.

So far I have assumed that the return to capital $R_{K,t}$ is known with certainty at time $t-1$ by both parties in the debt contract. This assumption was convenient in order to isolate the intuition behind the leverage effect. nevertheless, in the full model $R_{K,t}$ is affected by monetary shocks through unexpected variations in the rental rate of capital and in the price of capital. This has an important implication for the debt contract, because the uncertainty on $R_{K,t}$ potentially affects the aggregate return on lending for the lender and hence his ability to pay a risk free rate to the household. The risk neutrality of the entrepreneurs avoids this problem by ensuring that the entrepreneur is willing bear aggregate uncertainty.

Formally, the borrowing rate $R_{b,t-1}$ and the default threshold $\bar{\omega}_t$ become a function of the realization of the return to capital, and the maximization problem is rewritten as

[47] This assumption is satisfied if, in the optimum, $\bar{\omega}_t$ satisfies $R_{k,t} < Q_{t-1}\frac{R_{n,t-1}}{G(\bar{\omega}_t)}$. If this was not the case, the aggregate return $R_{k,t}$ would be high enough to make the asymmetric information irrelevant because the lender would supply an infinite amount of credit for any level of $\bar{\omega}_t$.

$$\max_{\bar{\omega}_t, K_{t-1}} \quad F(\bar{\omega}_t(R_{K,t}))R_{k,t}Q_{t-1}K_{t-1},$$

$$\text{subject to} \quad \frac{G(\bar{\omega}_t(R_{K,t}))R_{k,t}Q_{t-1}K_{t-1}}{Q_{t-1}K_{t-1} - N_{t-1}} \geq R_{n,t-1}, \tag{17}$$

The state contingency of the default threshold to the realization of $R_{K,t}$ is such that the left-hand side of equation (17) is not a function $(R_{K,t})$, so that the lender obtains the risk free rate $R_{n,t-1}$ in any state of the word. According to constraint (10), the borrowing rate becomes a function $R_{k,t}$ according to the equation

$$R_{b,t-1}(R_{K,t}) = \bar{\omega}_t(R_{K,t})R_{K,t}\frac{1}{1 - \frac{N_{t-1}}{Q_{t-1}K_{t-1}}}.$$

The intuition behind the leverage effect remains unchanged. The only difference is that, given the positive first derivative of $G(\bar{\omega}_t)$ with respect to $\bar{\omega}_t$, unexpected variations in $R_{k,t}$ move the ex-post threshold value $\bar{\omega}_t$ in the opposite direction. This means that an unexpected increase in the return to capital pushes down the default threshold and implies a default rate below expectation, given that the entrepreneur has benefited from an unexpected increase in revenues. After the impact effect, the leverage effect commented above takes place and the leverage ratio increases, pushing up the default rate.

3.2 Calibration

I calibrate the model using the dataset from Section 2. The moments matched by the model are the leverage ratio of firms, their average borrowing rate, their default probability and the risk free rate. The calibration is shown in table 2. The model is calibrated quarterly. For convenience, table 2 reports interest rates and the default probability in annualized terms. A wider range of parameter values is considered in Section 3.4 to assess the robustness of the results.

Parameters calibrated from the data

The discount factor β is calibrated at 0.9945. The value is chosen to match the annual risk free rate of 2.21%, which is the average real federal funds rate in the period between 1955Q1 and 2007Q2 (5.73% of average nominal federal funds rate minus the 3.52% average annual inflation rate). The literature typically uses a value of β equal to 0.99, equivalent to an annual real interest rate of 1%. Section 3.4 shows that the result remains in place with this alternative calibration.

The variance of the idiosyncratic shock, the aggregate return to capital R_k and the default observation cost μ are calibrated in order to match an average leverage ratio of 1.5705, an average annual default rate of 3.21% and an average real borrowing rate of 4.07%.[48] This calibration implies a variance of the idiosyncratic shock of 0.17, an annual return to capital of 9.8% and a default observation cost of approximately 46%. The values of σ and R_k are reasonable, but the value of μ is relatively high compared to the literature. Carlstrom and Fuerst (1997) review the related empirical evidence and report values of μ between 0.20 and 0.36, and Levin, Natalucci and Zakrajsek (2004) estimate a value of μ of around 0.45 during

[48] Levin, Natalucci and Zakrajsek (2004) document a wide dispersion in the leverage ratio of US non-financial firms, ranging from a minimum of 1.02 to a maximum of 16.9 (note that one needs to adjust for the different definition of leverage that they use, which is the ratio of debt over equity). Their median value of 1.55 is consistent with the value of 1.5705 used here. The dataset that they use coves the period between 1997Q1 and 2003Q3 and includes only quoted firms. Kalemli-Ozcan, Sorensen and Yesiltas (2012) report a higher median leverage ratio of around 2.3 across quoted and non quoted firms for the period between 2004 and 2009.

Table 2: Calibration

Moments matched by the model				
		Model	Data	Source
Leverage ratio	K/N	1.5673	1.5705	US flow of funds
Annualized default rate	$\Phi(\bar{\omega})$	0.0336	0.0321	FED, Board of Governors
Annualized risk free rate	R_n	1.0221	1.0221	FED, Board of Governors
Annualized borrowing rate	R_b	1.0401	1.0407	FED, Board of Governors
Parameters calibrated using the data				
		Parameter	Value	Target
Discount factor		β	0.9945	Risk free rate
Variance of the idiosyncratic shock e^{ω}		σ^2	0.3980	Leverage/defaults/borrowing rate
Observation cost of the lender		μ	0.4652	Leverage/defaults/borrowing rate
Annualized return to capital		R_k	1.0984	Leverage/defaults/borrowing rate
Probability that entrepreneur retires		$1-\gamma$	0.0324	SS net worth
Weight on disutility of labour		χ	5.0854	H = 33%
Parameters calibrated from the literature				
		Parameter	Value	Source
Policy rate persistence		ρ	0.97	Clarida *et al.* (1997)
Weight on inflation in the Taylor rule		γ_π	1.83	Clarida *et al.* (1997)
Weight on output in the Taylor rule		γ_y	0.56	Clarida *et al.* (1997)
Investment adjustment cost		ν	3.60	Christiano *et al.* (2005)
Elasticity of substitution across varieties		ϵ	10	Chari *et al.* (2000)
Marginal product of capital		α	0.35	Bernanke *et al.* (1999)
Depreciation rate		δ	0.025	Bernanke *et al.* (1999)
Frisch elasticity of labour		η	3	Bernanke *et al.* (1999)
Probability of Calvo price optimization		$1-\psi$	0.25	Bernanke *et al.* (1999)

Notes: The model is calibrated to match the average leverage ratio, the borrowing rate and the delinquency rate of the US corporate and non corporate non-financial firms. The data are extracted from the flow of funds and are described in Section 2.

the recession after the dotcom bubble, and of around 0.12 during normal times.[49] The high level of μ in the calibration is necessary in order to match the moment on the borrowing rate. Figures ?? in Appendix C shows that the results hold also for a calibration of μ consistent with the range reported by Carlstrom and Fuerst (1997), which comes at the cost of an annual borrowing rate around 40 basis points below target.[50]

The probability that entrepreneurs die is calibrated at 3.24% in order to ensure that the model has a steady state value of entrepreneurial net worth. The weight on the household disutility of labor is computed to ensure that, in steady state, households work 33% of their time endowment.

Parameters calibrated from the data

The remaining parameters are set according to the literature.

The Taylor rule is calibrated from Clarida, Galí and Gertler (1997). They report a persistence parameter of the federal funds rate of 0.97, a weight on inflation of 1.83 and a weight on output of 0.56. These values are in line with other empirical papers, including for instance Clarida, Galì and Gertler (2000) and Rudebush (2001).

The parameter ν is calibrated from Christiano, Eichenbaum and Evans (2005). The value implies an elasticity of investment to a temporary increase in the price of installed capital of 0.28. This elasticity is given by $\frac{1}{\nu}$, as shown in their paper. The elasticity to a permanent rather than a temporary increase in the price of installed capital is given by $\frac{1}{\nu\cdot(1-\beta)}$ and equals

[49]Covas and Den Haan (2011) argue that the debt contract by Townsend (1979) is optimal as long as μ is calibrated as an observation cost, but not also as a bankruptcy cost including for instance disruption costs and foregone sales, as in Carlstrom and Fuerst (1997), Bernanke, Gertler and Gilchrist (1999) and other papers.

[50]More precisely, the alternative calibration has $\mu = 0.3274$ and $R_b = 1.0372$.

50. For robustness, I consider values of ν up to 6.0526, which is the value required to generate a permanent elasticity of 30, the value implied by the calibration in Christiano, Eichenbaum and Evans (2005).

The elasticity of substitution across varieties of consumption goods ϵ is set equal to 10. This value is based on Basu (1996) and Basu and Kimball (1997) and is also used by Chari, Kehoe and McGrattan (2000). The literature tends to use lower values. Faia and Monacelli (2007) use 8, Schmitt-Grohé and Uribe (2007) use 5. I consider all these values for robustness.

The Frisch elasticity of labour supply η is set equal to 3, as in Bernanke, Gertler and Gilchrist (1999). This value is consistent with Cho and Cooley (1994) and King and Rebelo (1999), who report Frisch elasticities that range from 2.6 to 4. This is the range of values that I also consider in the robustness checks.[51]

As in Bernanke, Gertler and Gilchrist (1999) and Christiano, Trabandt and Walentin (2011), the probability $1-\psi$ that the retailer optimizes his price is set equal to 0.25, implying an average period for the adjustment of prices of 4 quarters. I will also consider values up to 0.5, implying an average price duration of half a year.

The parameter α for the marginal productivity of capital is set equal to 0.35. There is a general agreement on the plausible set of values for this parameter, at least in models with both capital and labour in the production (see Covas and Den Haan (2012), note 29).

The depreciation rate δ is set to 0.025, corresponding to a 10 % annual rate. There is a general agreement on the value of δ, at least within this class of models.

3.3 Results

The general equilibrium model delivers two main results:

1. A monetary shock that generates a 100 annual basis point decrease in the nominal interest rate leads to a reduction in the annual default rate of *outstanding* loans from the steady state level of 3.36% to 3.14%. It then leads to a subsequent prolonged increase in the default probability of *new* loans up to 3.61% annually, and it takes several years for the default probability to revert to steady state.

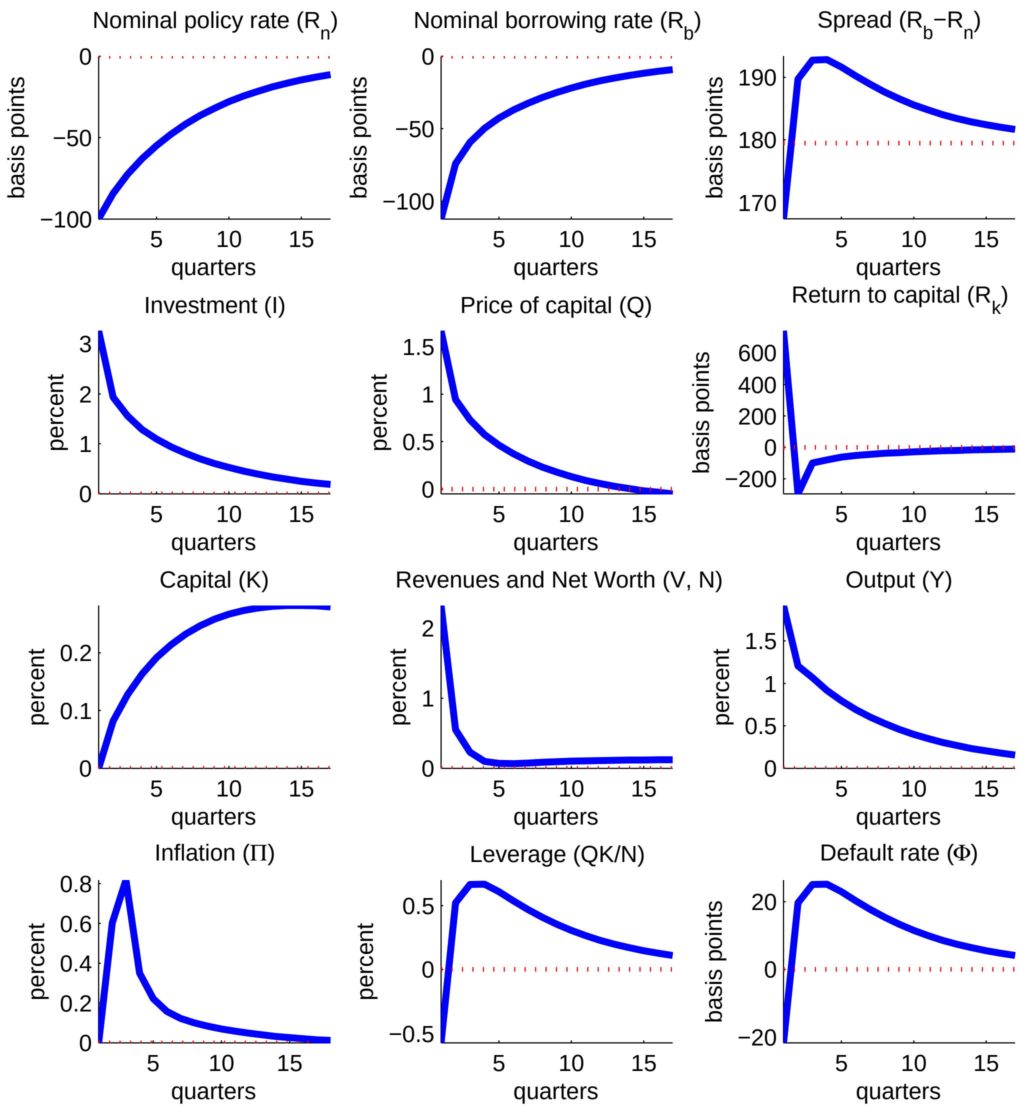
2. The increase in the default rate is reduced if the central bank avoids a high level of persistence in the policy rate or if it attaches high weights to the level of inflation and output in the feedback policy rule. This is due to the fact that the cost of borrowing decreases more when the policy rate is known to remain below the level of steady state for longer. In the exercises reported, this occurs either because agents know that the shock is persistent or because they know that the central bank reacts weakly to increases in inflation and output. The stronger decrease in the cost of debt leads the entrepreneurs to leverage up their net worth by more, and this increases the default rate on new loans by more.

Result 1

Figure 7 shows the effects of a 100 annual basis point decrease in the nominal interest rate R_t^n generated by a policy shock ϵ_t in the Taylor rule. The horizontal axis represents time, which is expressed in quarters. Variables are displayed in either basis point or percentage point deviations from the steady state, as specified for each variable. Interest rates, inflation and the default rate are reported in annualized terms. Except for the spread between R_b and R_n, all variables are reported in deviation from the steady state at the end of each period.

[51] Empirical estimates of the Frisch elasticity on macroeconomic data tend to exceed estimates based on microeconomic data, which are usually below 1. See Christiano, Trabandt and Walentin (2011) for an explanation of this divergence and Reichling and Whalen (2012) for a survey of different empirical estimates of the elasticity of labour supply.

Figure 7: Expansionary monetary policy shock of 100 basis points annually



Notes: All variables are shown in deviation from the steady state except for the spread $R_{b,t} - R_{n,t}$, which is in level. The interest rates, the spread, inflation and the default rate are shown in annualized terms. A monetary expansion that decreases the policy rate by 100 annual basis points reduces on impact the default probability from the steady state value of 3.36% to 3.14% due to a revenue effect generated by the unexpected increase in the aggregate demand of capital. From the first quarter after the shock, entrepreneurs react to the lower cost of borrowing by leveraging up their net worth. This increase in leverage increases the default probability up to 3.61%. It takes several quarters for defaults to revert to steady state.

The 100 basis point decrease in R_n pushes down the annualized borrowing rate from 4.01% to 2.89%. This pushes down the spread from 180 annual basis points to 167 annual basis points.

The decrease in the borrowing rate increases end-of-period investment by 3.26% and pushes up the price of capital by 1.66%. This is because capital producers anticipate that entrepreneurs will demand more capital starting from the end of the period. The unanticipated increase in the price of capital unexpectedly increases the return to capital R_k above steady state by 740 basis points from 9.84% to 17.25%. This increase is mainly driven by the capital gain on non-depreciated capital, but it also reflects a 90 basis points increase in the rental rate of capital and a 2.32% increase in labour (unreported in figure 7). Capital starts to increase from the second quarter.

The unexpected increase in the return to capital pushes up entrepreneurs' revenues by 2.32%. This decreases on impact the annualized default probability by around 22 basis points below steady state from 3.36% to 3.14%. On impact, the market value of leverage QK/N decreases because the unexpected increase in net worth dominates the increase in the price of capital. Output increases by 1.91% and inflationary pressures arise from the second period onwards, going from 0 up to 0.35% annually on the third period.

From the second period onwards, the nominal interest rate reverts to the mean. The accumulation of capital pushes the leverage ratio by 0.66% above steady state on the first period after the shock, carrying with it the default rate. In fact, the behaviour of defaults mimics the one of leverage. The default rate displays a hump that peaks at around 25 annual basis points above steady state 3 quarters after the shock, reaching 3.61%. This increase in defaults is reflected in the increase in the spread on the risk-free rate, which peaks at approximately 192 annual basis points 2 quarters after the shock. It is the increase in defaults that pushes revenues back to steady state. As the leverage ratio reverts to the mean, the default rate reverts to steady state. Note also that the ex-post return to capital decreases below steady state after the first period due to the capital loss on non-depreciated capital when Q_t decreases towards steady state.[52]

It is useful for the rest of the paper to summarize the behaviour of the default rate in terms of its magnitude and persistence. The *magnitude* of the effect on defaults is measured as the maximum variation of the default rate around steady state. In the baseline calibration the default rate decreases on impact from 3.36% to 3.14% and then increase up to 3.61%. This is equivalent to a maximum variation of the default rate of [-22, +25] basis points around the steady state. The *persistence* of the effect, instead, is computed using the "half-life" of the effect, as in Chari, Kehoe and McGrattan (2000). This measure is defined as the length of time after the shock before the increase in the default rate shrinks to half of the maximum increase. In the baseline calibration, the peak effect is reached 3 quarters after the shock, with a maximum increase in the default rate of 25 basis points. The 'half-life" of the effect is computed as the number of quarters after the shock that it takes for the default rate to decrease below $\frac{1}{2} \cdot 25 = 12.5$ basis points above steady state. In the baseline calibration it takes 6 quarters after the peak effect for half of the effect to fade away.[53]

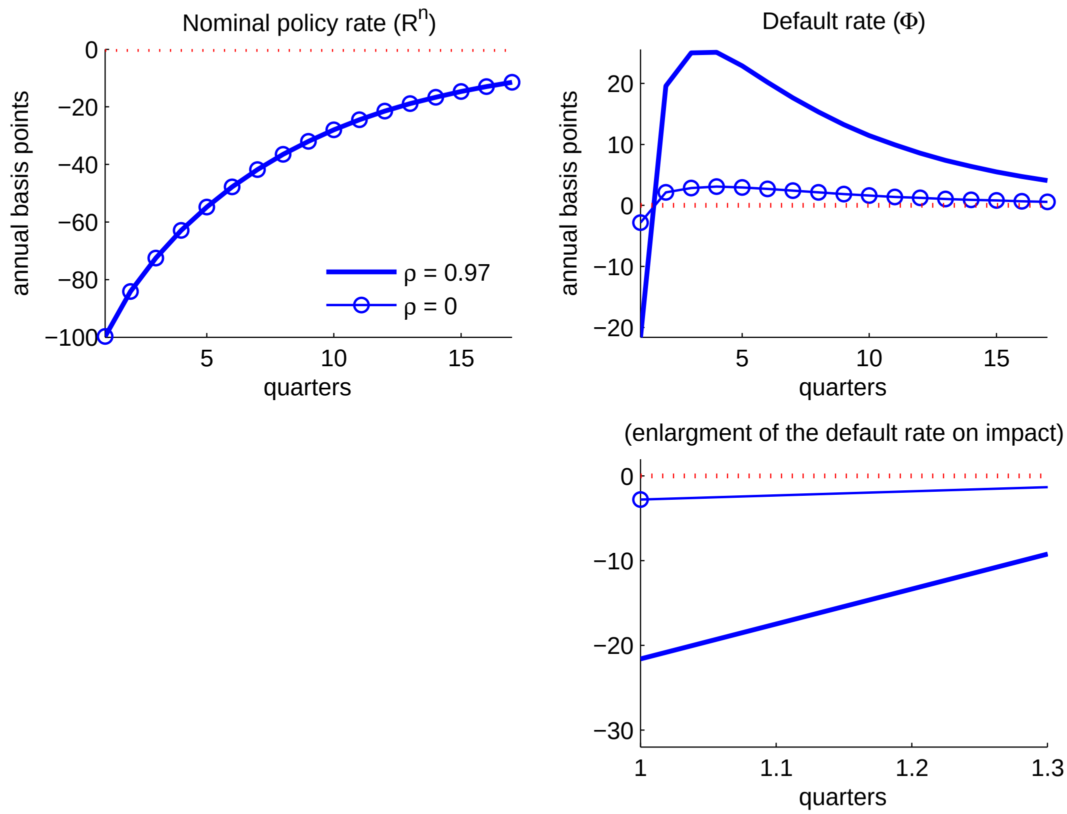
Result 2

I now consider what happens when the central bank follows a Taylor rule with different parameter values from the ones considered in the baseline calibration. The purpose of the exercise is to get an approximate idea of what would happen if the Federal Reserve Bank followed a Taylor rule with a lower persistence in the policy rate or with a higher weight to inflation and output.

[52]The increase in the credit spread is also generated by the model by Curdia and Woodford (2009), although for a very different reason. In the model presented here, the spread increases as a result of the increase in defaults. In their model, defaults are zero by construction, and the spread reflects the cost of intermediation. The increase in the spread in their model reflects the assumption of convex intermediation costs and is lost when this cost is assumed proportional. The empirical evidence on the behaviour of defaults is mixed. Eickmeier and Hofmann (2012) find that a monetary policy expansion decreases the spread on commercial paper and on commercial and industrial loans, increases the spread on consumer loans and does not affect significantly the Moody's corporate bond spread, i.e. the spread of BAA corporate yield over AAA corporate yield.

[53]Chari, Kehoe and McGrattan (2000) use a similar approach to measure the persistence of output under staggered price-setting, relative to synchronized price-setting.

Figure 8: Alternative values of the persistence in the Taylor rule



Notes: This figure compares the effects on the default rate of a decrease in the policy rate with and without persistence in the policy rate. The time series without persistence is generated by giving the exact monetary shocks in every period to generate the same time series of the policy rate with persistence. Given an identical variation in the policy rate, the increase in the default rate is higher the higher the persistence in the policy rate. This happens because entrepreneurs anticipate that the policy rate will remain below steady state and hence leverage up their net worth by more.

Figure 8 compares the effect on the default rate of a 100 basis point decrease in the nominal interest rate when the persistence parameter in the Taylor rule equals 0.97 (as in the baseline calibration) or 0. The case with no persistence in the policy rate is computed by generating a series of subsequent monetary shocks that replicate the exact policy rate generated by a single and persistent monetary shock. The exercise is designed to study the role of the expectation that entrepreneurs have regarding future variations in the policy rate. In the case of no persistence, agents are continually surprised by monetary shocks, while in the case with persistence they know the time path of the risk free rate from the second period onwards.

In general, with a positive persistence parameter in the Taylor rule, agents anticipate that the policy rate remains low for more than one period. Since the Euler equation prescribes an increase in consumption for many periods to come, entrepreneurs increase investment in order to satisfy the high demand from intermediate good producers. The increase in investment increases leverage and pushes up the default probability. On the contrary, when the persistence in the policy rate is zero, then agents do not anticipate a strong increase in consumption and leverage ratios increase by less.

Let us see this intuition in figure 8 and in table 3, top part. Compared to the baseline

Table 3: Effect of monetary shocks of different size on annualized defaults

Parameters in the Taylor rule			Magnitude		Persistence	
			default on impact	default at peak	time to peak	"half-life" of the effect
ρ	γ_π	γ_y				
0.97	1.83	0.56	3.14% (-22 bps)	3.61% (+25 bps)	3	6
0	1.83	0.56	3.34% (-2 bps)	3.40% (+4 bps)	3	7
0.97	1.83	0.56	3.14% (-22 bps)	3.61% (+25 bps)	3 2	6 6
0.97	1.33	0.26	3.05% (-32 bps)	3.70% (+34 bps)	3	7
0.97	1.001	0	2.38% (-98 bps)	4.17% (+80 bps)	3	11

Notes: Following Chari et al. *(2000), the 'half-life" is defined as the length of time after the shock before the deviation in the default rate shrinks to half of its maximum value at the peak. In the baseline calibration, the default probability decreases on impact by 22 basis points below the steady state annual level of 3.36% and then peaks 3 quarters after the shock to 25 basis points above the level in steady state. It then takes respectively 6 quarters for the default rate to decrease back to half the peak effect. The increase in defaults is smaller if the policy rate is less persistence or if it responds more aggressively to the level of inflation and output. See also figures 8 and 9.*

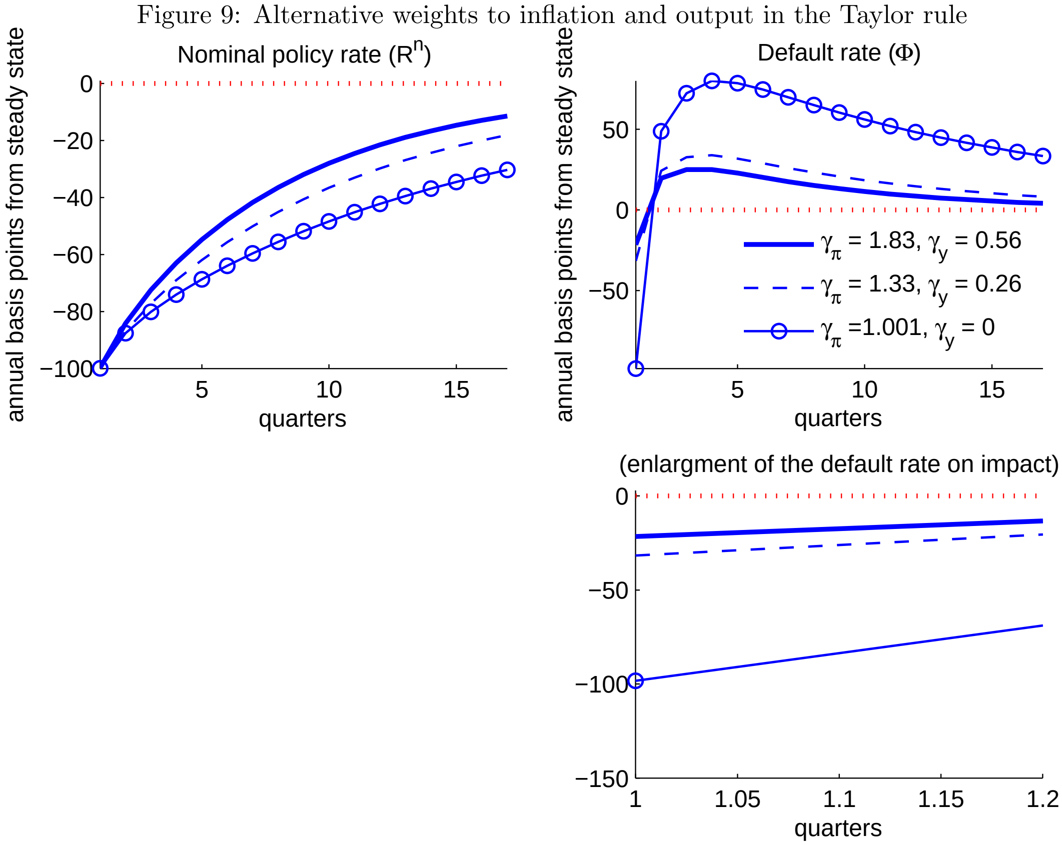
model of $\rho = 0.97$, a zero persistence effectively cancels the effect on the default rate. In fact, the default rate decreases on impact by only 2 basis points and increase afterward only by 4 basis points above steady state. I find this result interesting, since it suggests that, given an identical decrease in the nominal rate, the more agents know that it will take long for the central bank to revert the policy rate to steady state, the stronger the increase in the default probability. The reason is that the longer the nominal interest rate stays below steady state and the more the cost of debt decreases, giving a stronger incentive to take on leverage. If instead the monetary shock is not persistence, agents leverage up their net worth by less and this increases future defaults by almost nothing.

The other parameters in the Taylor rule have an equally important impact on the behaviour of the default rate. Figure 9 compares the effects on the default rate across different values of the weights attached in the Taylor rule to inflation and output. As discussed in section 3.2, the baseline calibration is $\gamma_\pi = 1.83$ and $\gamma_y = 0.56$. I now increase γ_π and γ_y to (1.33,0.26) and then to (1.001, 0). Compared to the baseline calibration both the impact decrease and the following increase in the default rate become bigger. Under the third Taylor rule considered, the default rate decreases on impact from 3.36% to 2.38% and then increases up to 4.17%. The effect also becomes more persistent. I find also this second result interesting. It suggests that the build-up effect on leverage and the following hike in defaults is less important in countries in which monetary policy is run with a stronger feedback to the economy, if compared to countries in which the policy rate is more exogenous to the current state of the business cycle. Although not appropriately captured in this framework, the model suggest that the variation in the default rate might be stronger in peripheral countries of a monetary union, which presumably matter less in the specification of the common monetary policy.

3.4 Robustness checks

[ADD]

Figure 9: Alternative weights to inflation and output in the Taylor rule



Notes: This figure compares the effects on the default rate of an identical decrease in the policy rate of 100 basis points depending on the weights that the central bank attaches to the levels of inflation and output in the Taylor rule. The stronger the weights attached to inflation and output and the faster the central bank reverts the policy rate to steady state. This leads entrepreneurs to leverage up their net worth less because they anticipate that the cost of borrowing decreases less.

4 Conclusions

In this paper I have argued that, when a central bank decreases the policy rate and engineers a monetary expansion, the probability that firms default on loans increases. The intuition evolves around a leverage effect. When the policy rate decreases, the cost of borrowing decreases and leads firms to increase debt. If this increases their leverage ratio, then the default probability on loans is likely to increase because net worth provides now a smaller buffer to the risky loan. In other words, it is true that debt becomes cheaper, but firms might take on more debt at a pace rapid enough to offset the beneficial increase in profits and ultimately imply a higher default probability.

I have shown empirical evidence consistent with the above intuition. In particular, I have argued that there is suggestive evidence that a monetary expansion increases the delinquency rate of loans in the US, although the relatively short time horizon of the available time series suggests to use caution in reading the result. There is, instead, a more solid empirical evidence on the increase in the leverage ratio of firms following a monetary expansion. Both of these results are consistent withe empirical evidence from existing contributions discussed in the Introduction.

The fact that the empirical evidence reported in both this paper and in related works reject the hypothesis that a monetary expansion decreases defaults is surprising, because it is apparently at odds with the widely documented result that a monetary expansion increases firms' profits through an increase in aggregate demand. Since these effects on profits reasonably lead towards a *decrease* in the default probability on loans, it seems that some forces within the transmission of monetary policy lead towards an increase in defaults at a sufficiently strong pace to dominate on the increase in profits. While this paper suggests one of these possible forces, much work remains to be done. In particular, I am currently working on two main extensions of the paper. The first extension consists of analyzing the leverage effect from a normative point of view. The current analysis, in fact, centers around a positive effect on the default rate, but does not develop any reason why the increase in defaults should or should not be taken into account by the central bank from a welfare perspective. The second extension consists of analyzing the existence of a leverage effect also for the other sectors of the economy, notably the financial and the household sectors. These and other extensions of the analysis are currently part of my research agenda.

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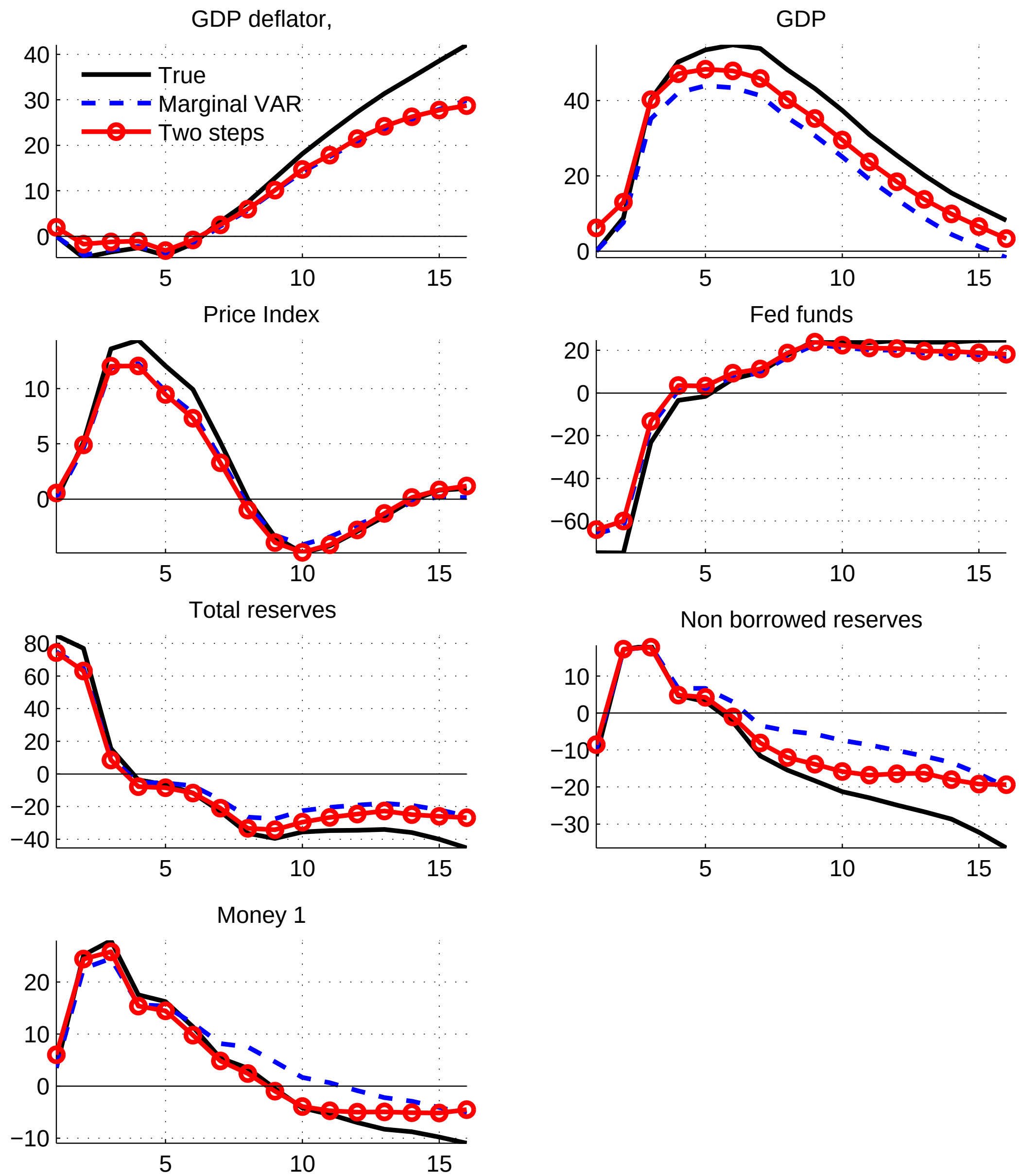
Appendix A: Monte-carlo simulation of the two-step approach

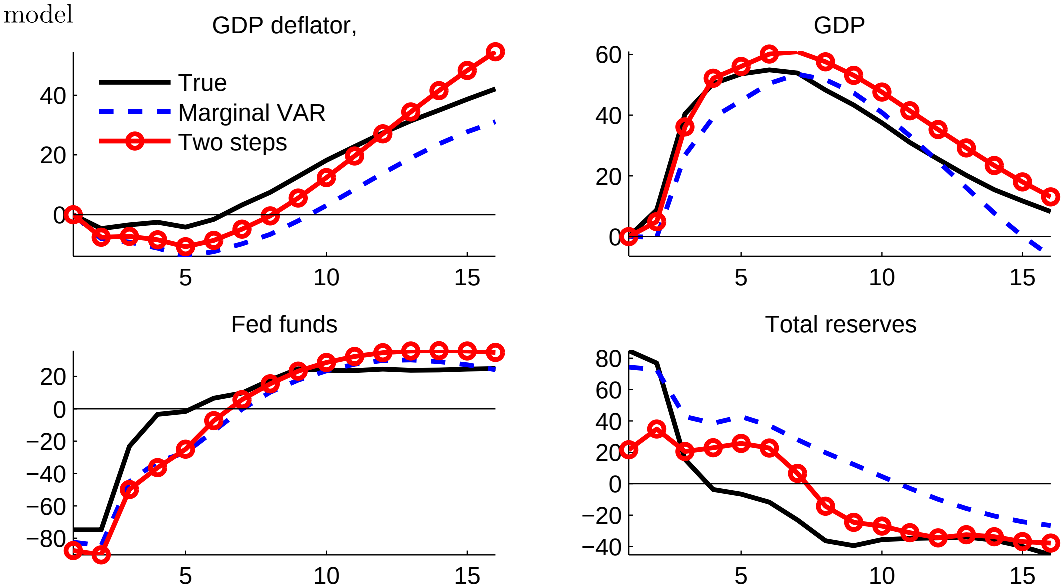
Figure 10: Monte Carlo simulations on Christiano, Eichenbaum and Evans (1999), full model



Notes: This figure shows the results from a Monte Carlo exercise comparing the performance of the marginal VAR approach relative to the two-step approach. As data generating process I take the model estimated by Christiano, Eichenbaum and Evans (1999). The figure shows the special case in which the researcher knows the exact set of variables entering the model.

In this appendix I show the results from a Monte Carlo simulation exercise on the relative efficiency of the two estimation techniques used in the paper. The true model is assumed to be the model estimated by Christiano, Eichenbaum and Evans (1999). I use their dataset and estimate the parameters of a VAR model with four lags, a constant and a time trend.[54] The monetary shocks are estimated under the recursiveness assumption. I then generate pseudo data by feeding into the model random draws for the structural shocks from a normal variable with zero expected value and standard deviation equal to the estimated standard deviation of the corresponding structural shock. All simulations use 210 observations, which equals the time horizon of the dataset used in Section 2. For simplicity, I only use the identification through Cholesky decomposition.

Figure 11: Monte Carlo simulations on Christiano, Eichenbaum and Evans (1999), partial model



Notes: This figure shows the results from a Monte Carlo exercise comparing the performance of the marginal VAR approach relative to the two-step approach. As data generating process I take the model estimated by Christiano, Eichenbaum and Evans (1999). The figure shows the more realistic case in which the researcher does not know the exact set of variables entering the model.

The estimation includes 7 variables, which are the GDP deflator, real GDP, the commodity price index, the federal funds rate, total reserves, non borrowed reserves and the monetary aggregate M1. Figure 10 shows the results from the special case in which the researcher knows the exact set of variables in the data generating process. The black solid line shows the true impulse response corresponding to the estimates by Christiano, Eichenbaum and Evans (1999). The blue dashed line shows the average impulse responses from 500 iterations of a VAR on pseudo data with all 7 variables, estimated with Cholesky decomposition. The red circled line shows the impulse responses of each variable estimated using the second-step estimation on the structural monetary shocks estimated in the VAR model with all variables. Both estimates replicate quite well the true underlying impulse response. The impulse responses converge to the truth as the sample size increases.

The case shown in figure 10 reports the fortunate case in which the reporter know the exact set of variables entering the true model. In real life such set of variables is very big and unknown to the researcher, which hope to capture the dynamics of the data by selecting the most representative variables for the isolation of monetary effects. To evaluate the relative efficiency of the estimation strategies used under this more realistic scenario, I start from the

[54] Say if they don't have the trend

same dataset generated above and computed the estimated impulse responses from a model that considers only three of the 7 variables in the true model. In accordance with model 1 from Section 2, I use the variables of the GDP deflator, real GDP and the federal funds rate as the key measures to capture monetary policy, and consider total reserves as the marginal variable of interest. The results are shown in figure 11. The black solid line shows the exact true impulse responses from figure 10. The blue dashed line shows the responses from the marginal VAR estimated from the 4 variables. The red circled line shows the responses from the two-step estimation. In particular, the responses of the first three variables are estimated with a VAR on these variables, as in Section 2, and the response of the marginal variable is computed using equation 4 on the vector of monetary shocks from the VAR with three variables. The estimates for the first three variables are very similar. Regarding the marginal variable, both empirical strategies seem plausible, although the VAR model tends to overestimate the length of the effect, while the two-step approach tends to underestimate the impact effect.

Appendix B: generating 3x3 orthogonal matrices

The computation of L candidate matrices P_{cand} that satisfy condition 3 from Section 2.2 requires the generation of L 3x3 matrices Q such that $QQ' = I$. Different Q matrices imply different structural representations of the data. Since there are infinite orthogonal matrices Q, the richer the set of Qs, the more likely it is that the true matrix P^* that has generated the data is actually replicated in the model.

Start by generating 3xM 2x2 orthogonal matrices. To do so, Rubio-Ramirez, Waggoner and Zha (2005) use the QR decomposition, while Canova and De Nicoló (2002) use Givens rotation.[55]

QR orthogonal matrices R_{qr} are generated using the orthogonal-triangular decomposition of a matrix. This operation decomposes any matrix $\tilde{A}$ into an orthogonal $\tilde{q}$ matrix and an upper triangular r matrix such that $\tilde{A} = \tilde{q}\tilde{r}$. To generate M QR orthogonal matrices I extract M 2x2 random matrices from a standard normal distribution. To each of them I apply the QR decomposition and save the generated orthogonal matrices $\tilde{q}$ in the set of R_{qr}.

Rotation matrices R_{rot} are defined as

$$R_{rot}(\theta) = \begin{pmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{pmatrix},$$

with $\theta \in [0, 2\pi]$.[56] Their orthogonality follows from the fact that $cos(\theta)^2 + sin(\theta)^2 = 1$ for $\forall\theta \in [0, 2\pi]$. To generate M rotation matrices I construct a grid of M points for the parameter θ in the space $[0, 2\pi]$ and then compute $R_{rot}(\theta)$ for each grid point. I extend Canova and De Nicoló (2002) and compute also M reflection matrices, which are defined as

$$R_{refl}(\theta) = \begin{pmatrix} cos(\theta) & sin(\theta) \\ sin(\theta) & -cos(\theta) \end{pmatrix}.$$

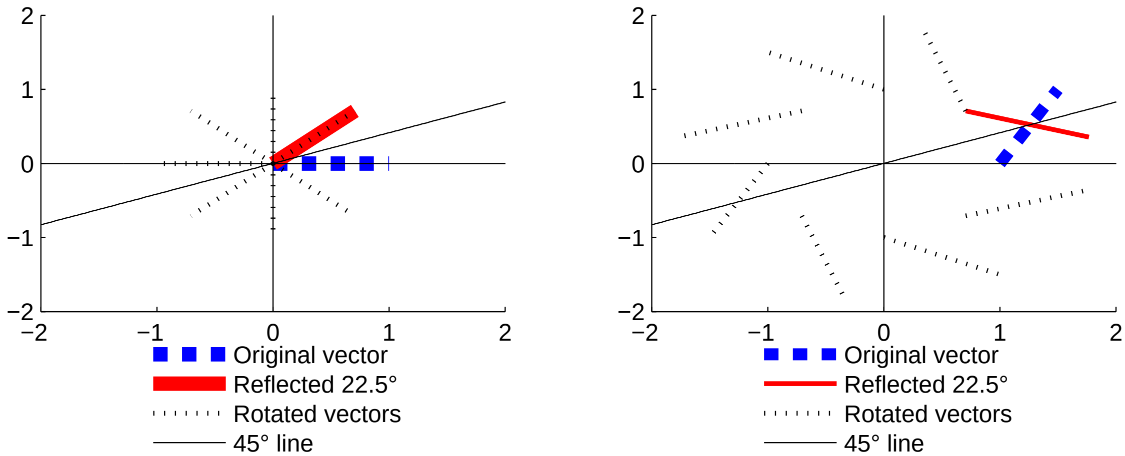
Rotation matrices generate a vector $y = x \cdot R_{rot}$ such that the vector x is rotated clockwise (or a vector $y = R_{rot} \cdot x$ such that the vector x is rotated counter-clockwise) by an angle of θ about the origin of the Cartesian coordinate system. Reflection matrices, instead, generate a vector $y = x \cdot R_{refl}$ such that the vector x is reflected around the line that goes through the origin of the Cartesian coordinate system with slope $\theta/2$. While for some special cases the transformed vectors coincide, the set of vectors generated through rotations does not fully overlap with the set of vectors generated by reflection matrices (figure 12 gives a simple illustration of this problem). It hence improves the analysis to account for both rotations and reflections in order to extend the set of structural representations replicated by the model. Figure ?? in Appendix C shows that accounting generating orthogonal matrices from only reflection, rotations or QR decompositions does affect the result, given that the set of structural representations replicated by the model is significantly reduced.

The 3xM 2x2 orthogonal matrices generated through rotations, reflections and QR decompositions need to be combined into 3x3 orthogonal matrices, in order to satisfy the dimensionality of the variance-covariance matrix Σ estimated from equation (1). This is achieved using the multiplication proposed by Canova and De Nicoló (2002). For each of the L 3x3 orthogonal matrices $Q(i)$ that needs to be generated, I extract three random numbers a, b, c from a discreet uniform distribution from 1 to $3M$. I use a, b, c to select three random matrices of the $3M$ 2x2 orthogonal matrices from the set $\{R_{qr}, R_{rot}, R_{refl}\}$ generated above. Once these three matrices are selected, I transform and multiply them as shown in equation (18), where $r_{z,ij}$ stands for entry (i, j) of the z-th matrix in the set $\{R_{qr}, R_{rot}, R_{refl}\}$.

[55] Fry and Pagan (2011) give an introduction to orthogonal matrices in sign-restricted models. See Paustian (2007) and Castelnuovo (2012) for an application of sign restrictions to New Keynesian models in a Monte Carlo experiment.

[56] Canova and De Nicoló (2002) construct the grid on $\theta \in (0, \pi/2)$.

Figure 12: Rotation vs. reflection matrices



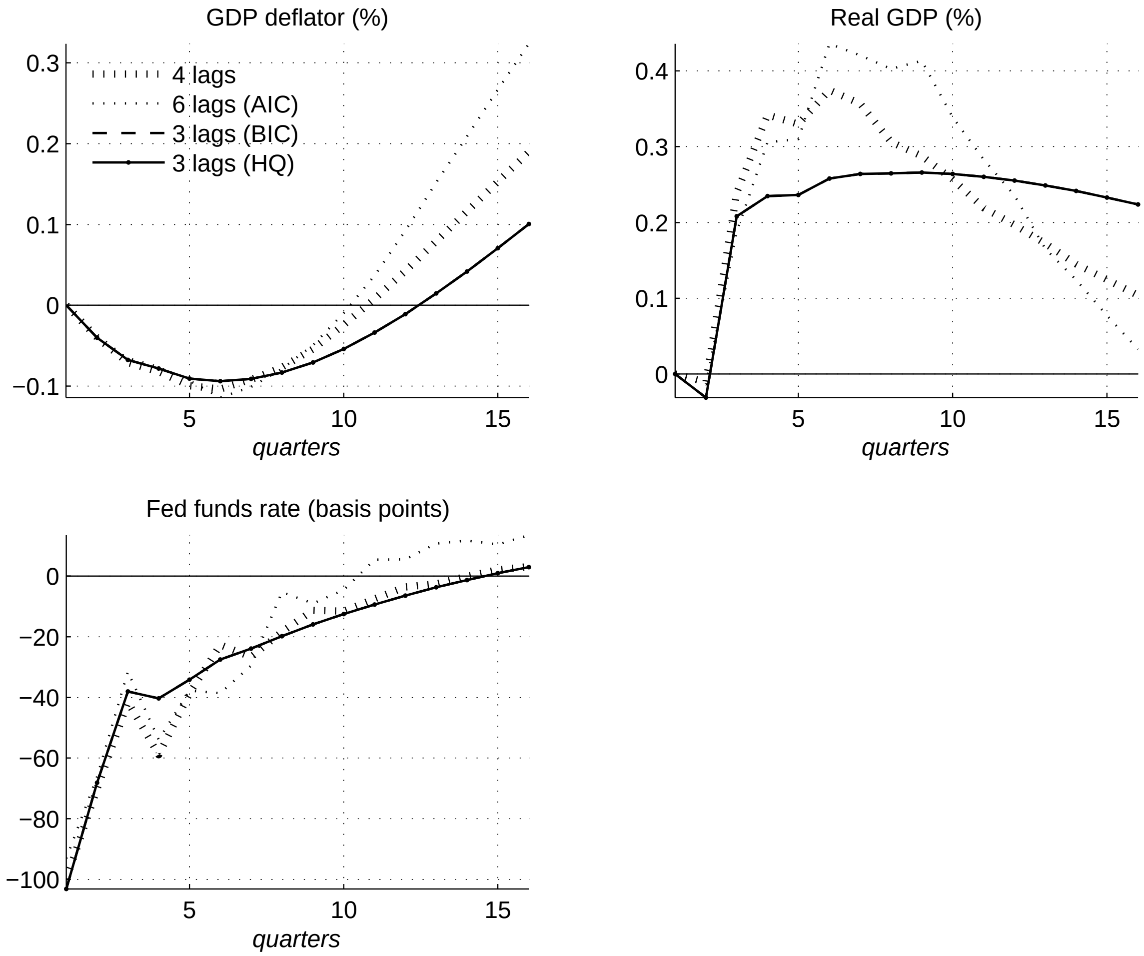
Notes: The left graph shows that the reflection around the 22.5 degree line of the vector between point (0,0) and point (1,0) (blue dashed line) gives the vector between point (0,0) and (0.7071, 0.7071) (red solid line). The same vector, though, is generate by a counter-clockwise rotation of the original vector of 45 degrees, or a clockwise rotation of the original vector of 315 degrees (black dotted line). The right graph, instead, shows the same case for the vector between (1,0) and (1.5,1). Reflection around the 22.5 degree line gives the vector between point (0.7071, 0.7071) and point (1.7678, 0.3536). No rotation can generate the same transformation achieved by the reflection.

$$Q(i) = \begin{pmatrix} r_{i_a,11} & r_{i_a,12} & 0 \\ r_{i_a,21} & r_{i_a,22} & 0 \\ 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} r_{i_b,11} & 0 & r_{i_b,12} \\ 0 & 1 & 0 \\ r_{i_b,21} & 0 & r_{i_b,22} \end{pmatrix} \cdot \begin{pmatrix} 1 & 0 & 0 \\ 0 & r_{i_c,11} & r_{i_c,12} \\ 0 & r_{i_c,21} & r_{i_c,22} \end{pmatrix} \tag{18}$$

In the paper, M is set equal to 500 and L is set equal to 1000. The results are robust to alternative values of M and L, as shown in figure ?? in Appendix C.

On-line Appendix: extra graphs

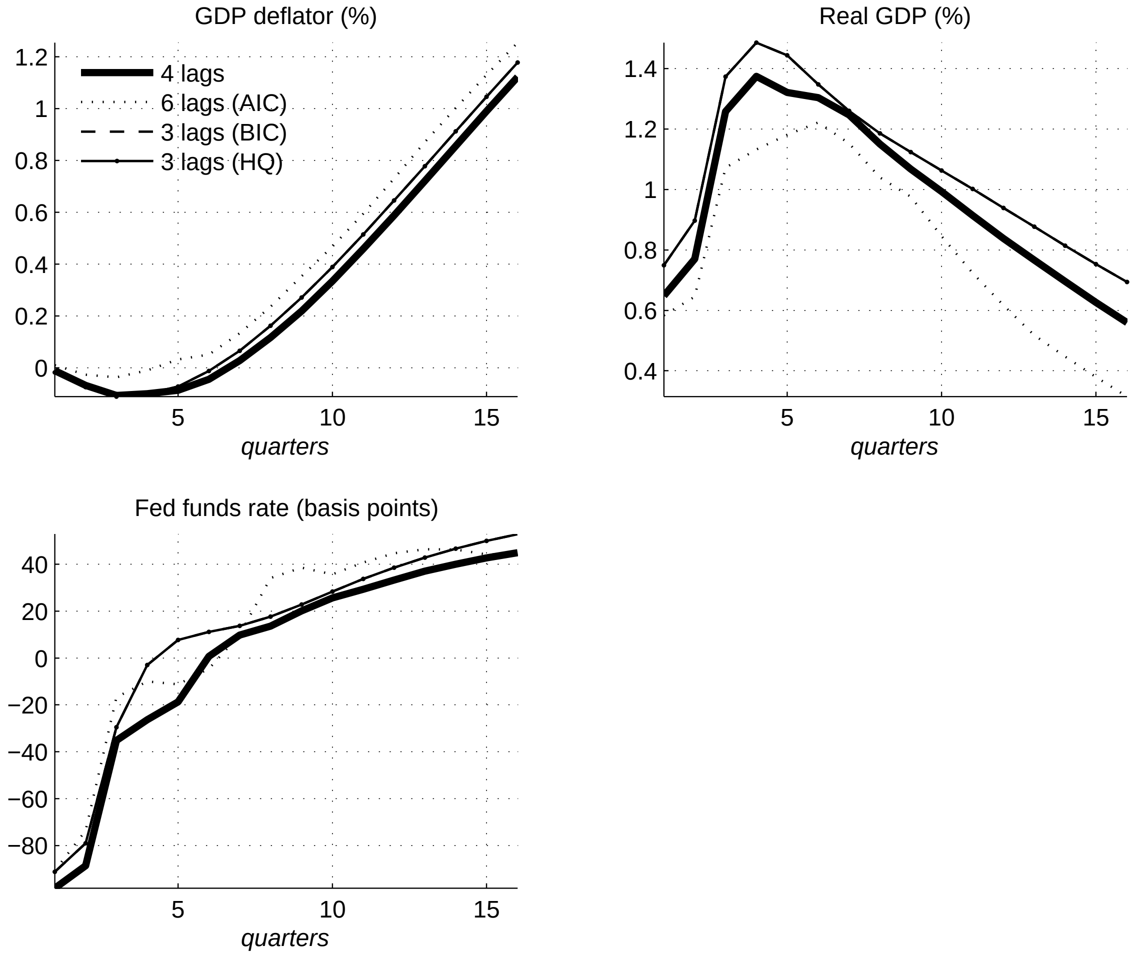
Figure 13: Robustness along number of lags in first-step VAR, Cholesky



Notes: This figure shows the robustness of the results in figure 2 along the number of lags included in the estimation in the first step, considering the identification through Cholesky decomposition. The Akaike, Bayesian and Hannan-Quinn information criteria suggest respectively 6, 3, and 3 lags. The main results are instead reported for 4 lags.

descriptive stats of all variables,not just the 8 ones / robustness of first stage with other trends, breaks, lags, constant ecc. / output innovation / first step, use eigenvalues decomposition / give

Figure 14: Robustness along number of lags in first-step VAR, Sign restrictions



Notes: ADD.

in relative measure of of corporate and non, need to give weighted average of leverage as well and then give both corporate and non, so that also get a feeling of relative weight of the two sub sectors

say that the two approaches are asymptotically equivalent

try also local projections to see if non linearities matter, maybe just report in appendix

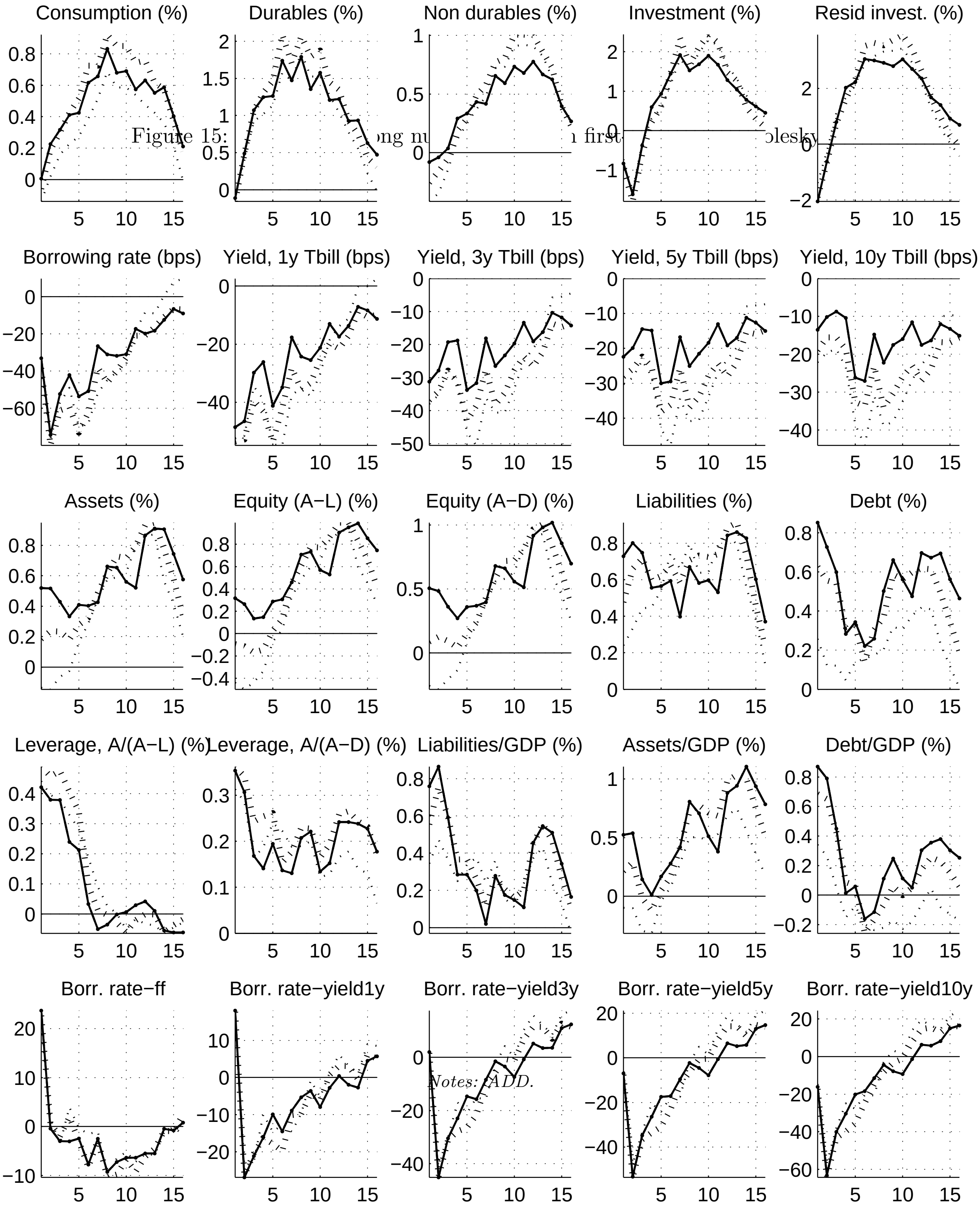


Figure 15: … ong nu … n first … olesky

Notes: ADD.

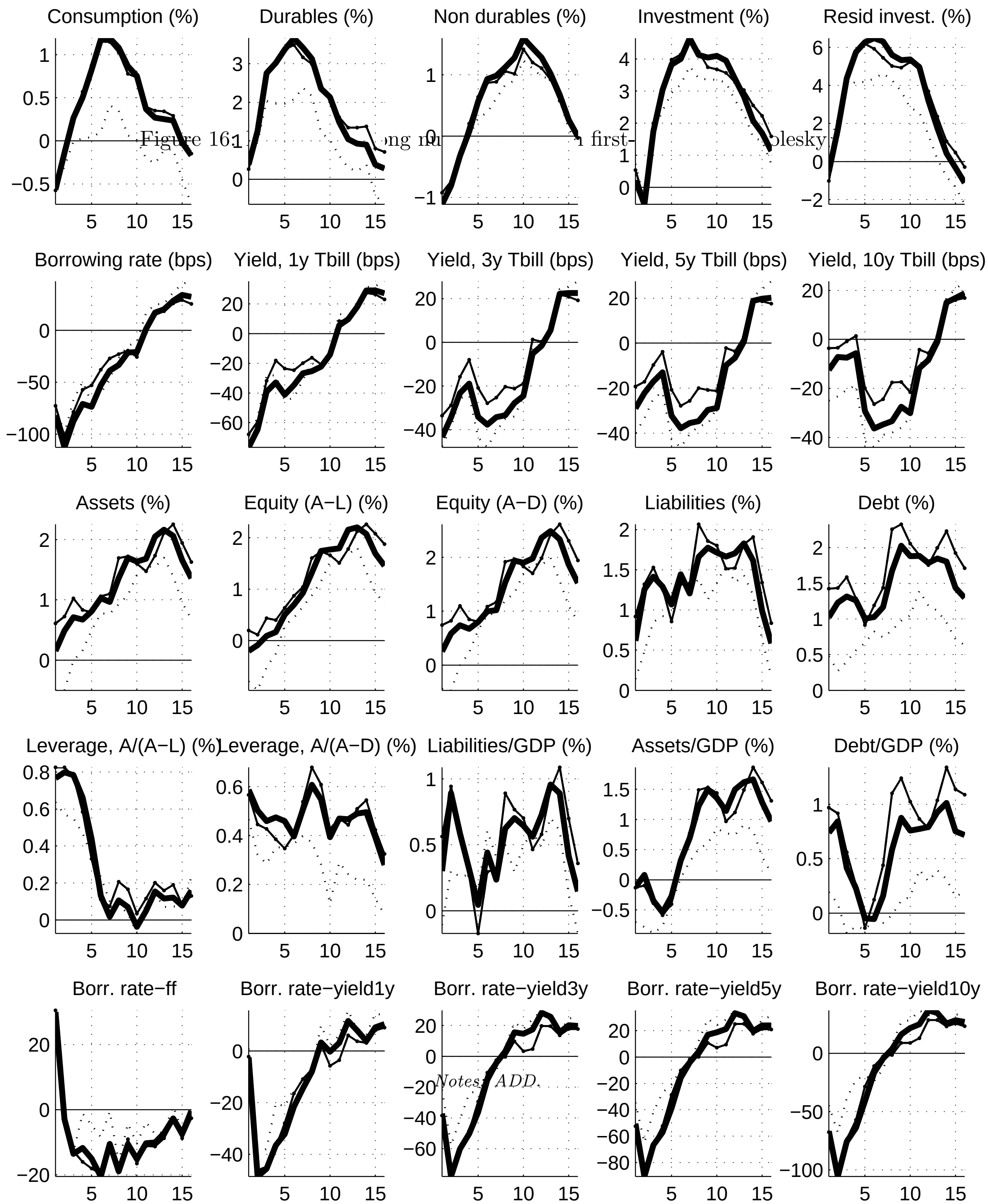
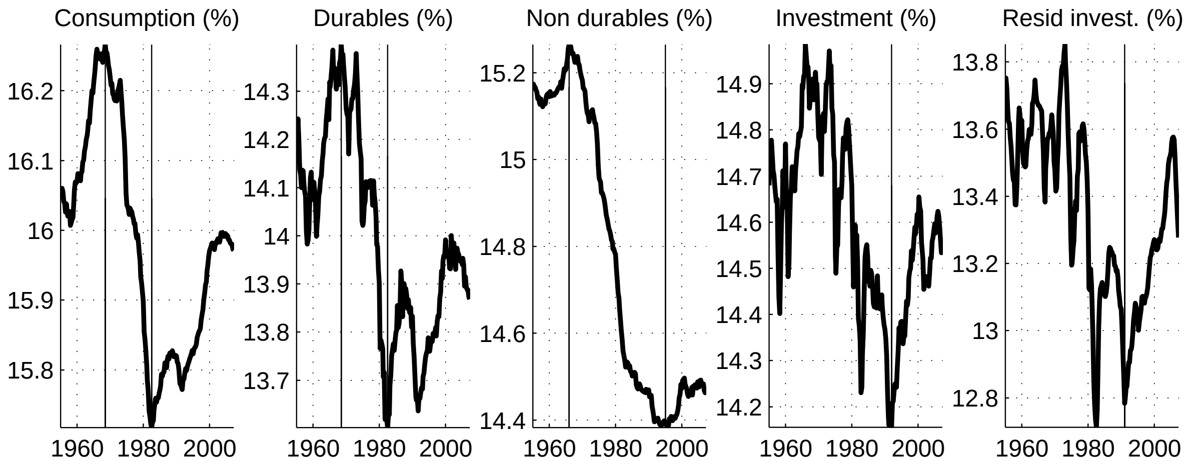


Figure 16: [illegible]ong m[illegible] first[illegible]olesky

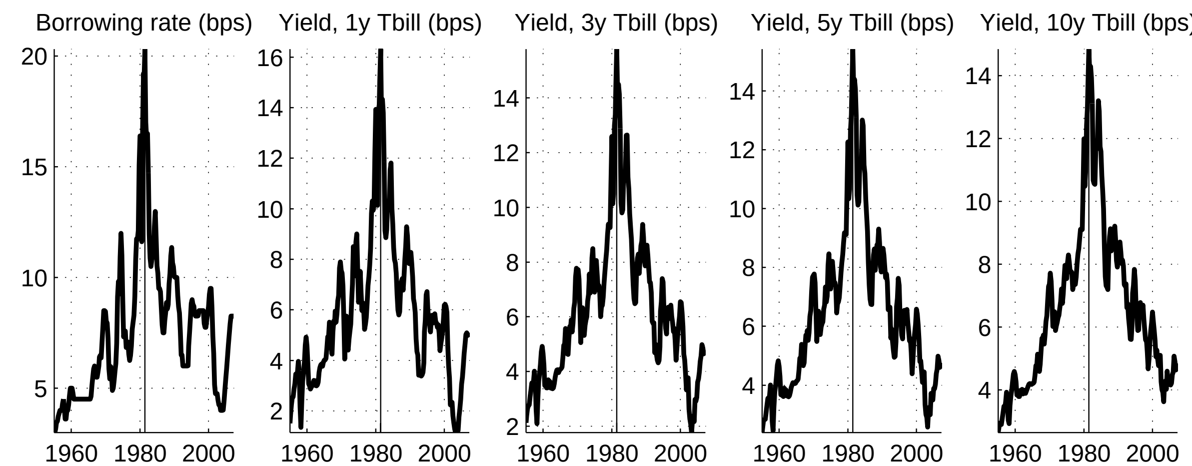
Notes: ADD.

Figure 17: Levels of the variables in the second-step estimation and corresponding control variables used

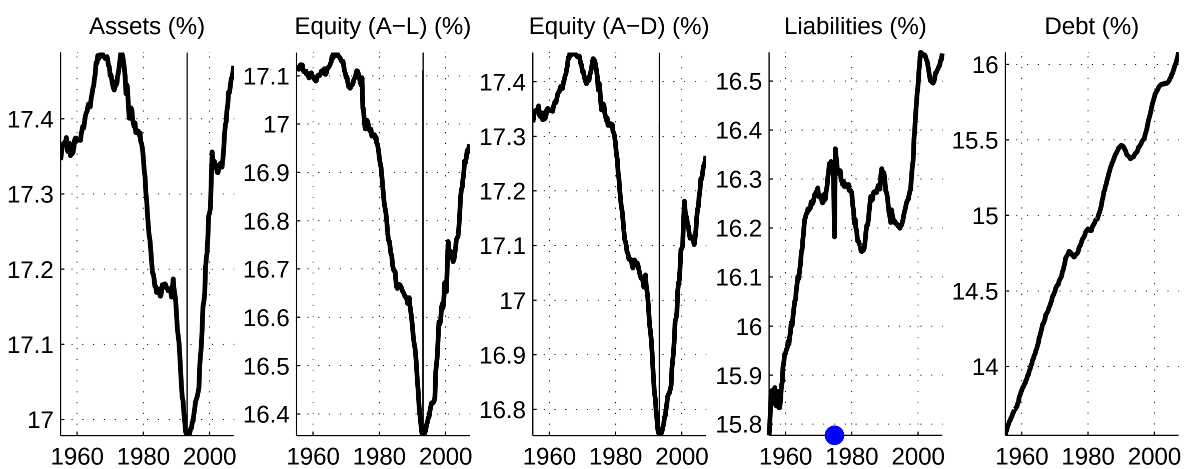
PANEL A: Macroeconomic Variables



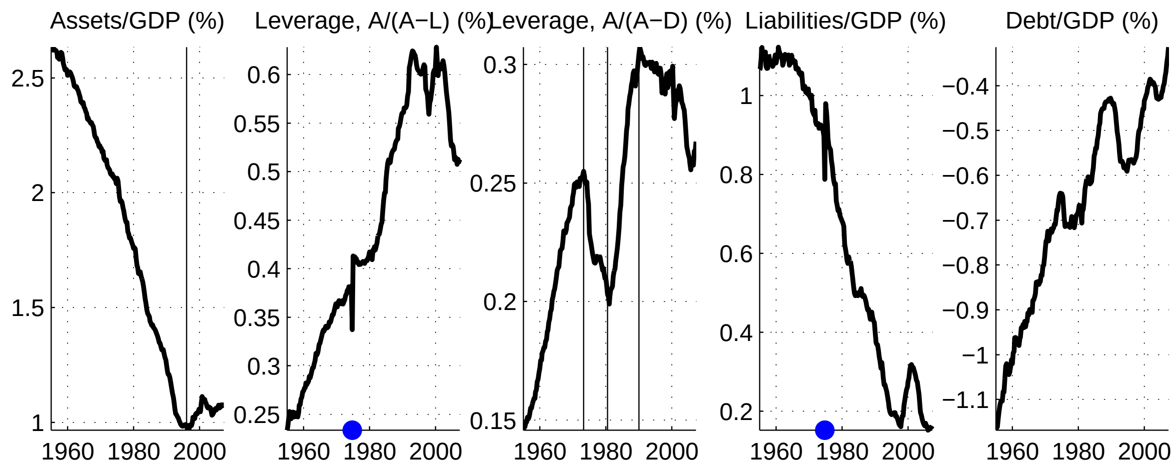
PANEL B: Interest rates



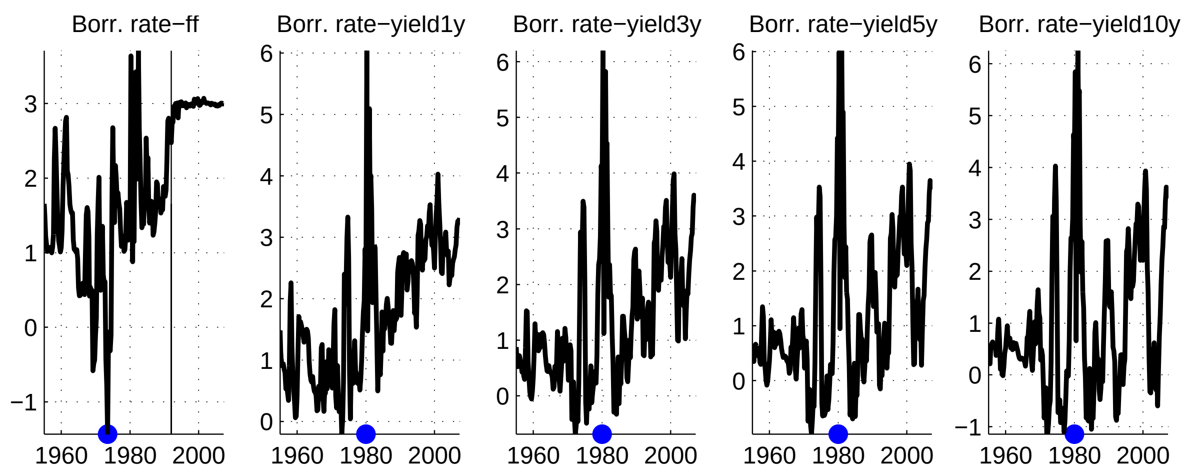
PANEL C: Balance sheet variables



PANEL D: Balance sheet ratios

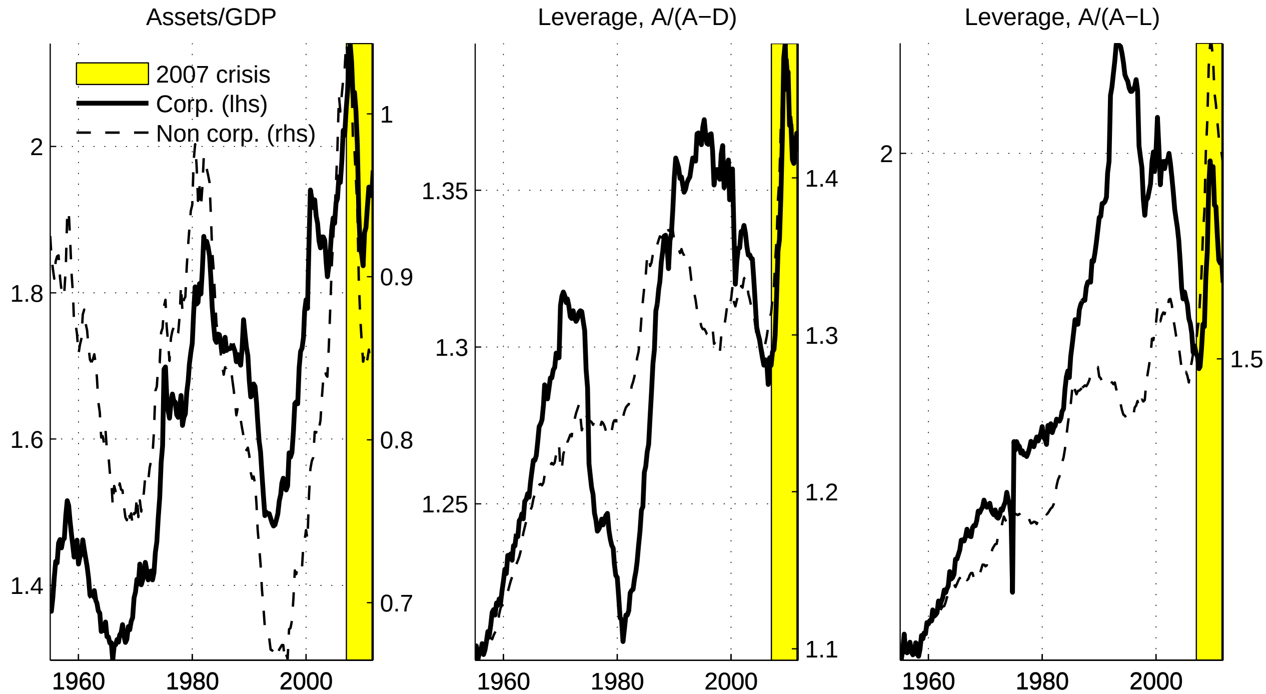


PANEL E: Spreads



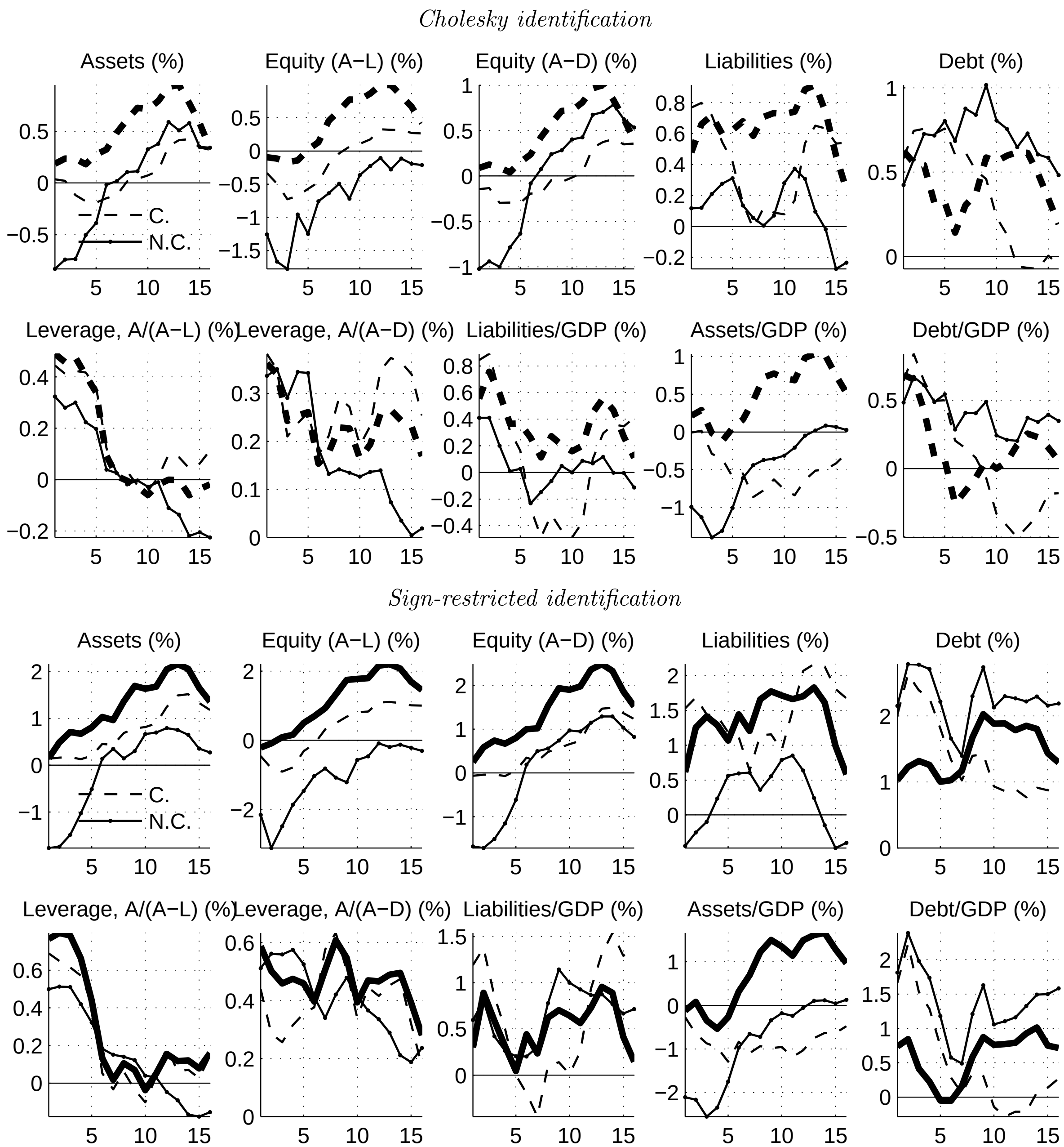
Notes: The figure shows the impulse responses to a 1% decrease in the federal funds rate. It reports the responses computed on the second step using the vector shocks from the first step corresponding to monetary innovations (dashed thin line), Cholesky-identified shocks (dashed think line) and sign-restricted shocks (thick solid line as median target). The shaded area reports the 95% and 80% interval on model uncertainty from the sign-restricted approach. Deterministic controls in each of the 25 independent regressions depend on the specific variable and are explained in figure 17 in Appendix ??.

Figure 18: Distinction between corporate and non corporate non-financial firms



Notes: The main results in the paper are shown for the aggregate sector of non-farm non-financial firms. The sub-distinction between corporate and non-corporate firms is addressed in this figure and in figure **??**. *The non-corporate sector is approximately half as large as the non-corporate sector, but the evolution of real assets over real GDP is qualitatively similar across subgroups. The corporate sectors has a higher leverage ratio. The drop in the leverage ratio measured with liabilities in 1974Q4 is explained by a sudden fall in trade payables and a following hike in miscellaneous liabilities. See note.*

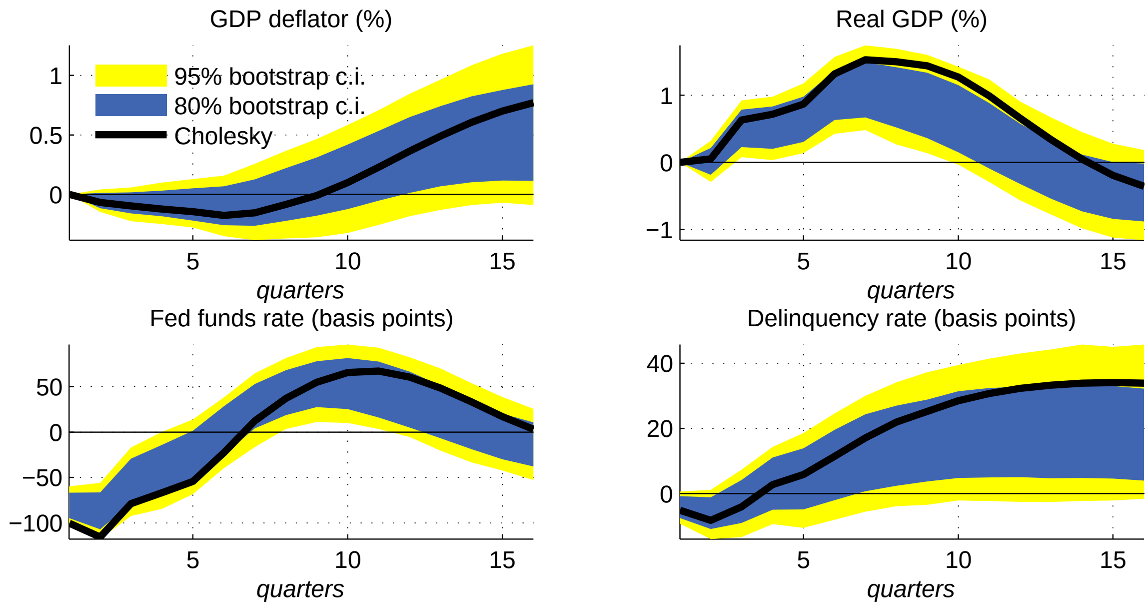
Figure 19: Second-step estimation: Corporate vs. Non corporate sectors



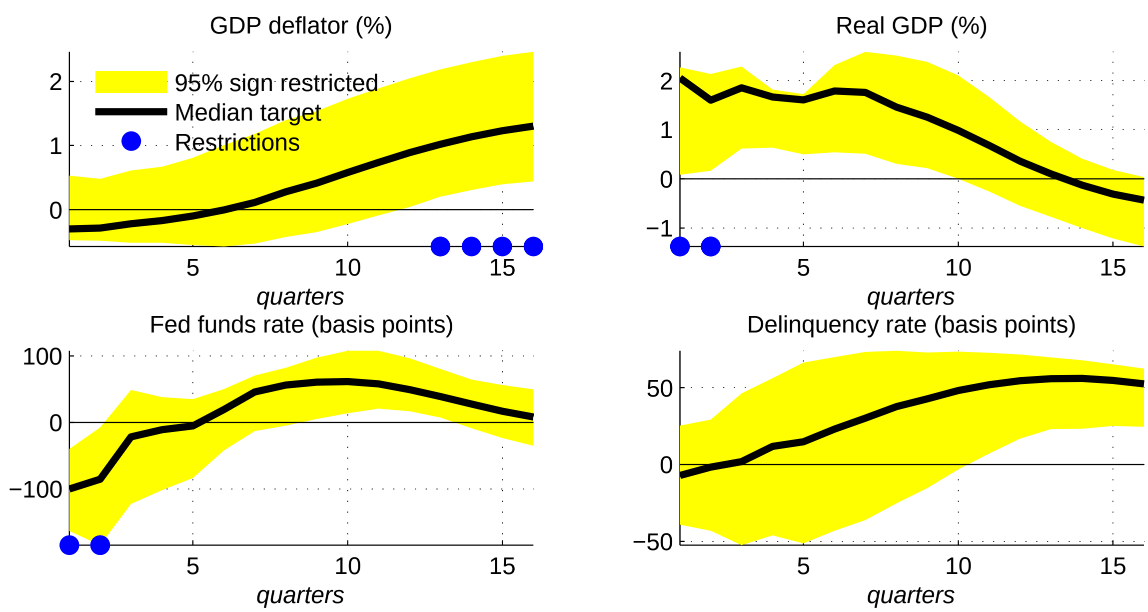
Notes: The main results were shown for the aggregate sectors of non-financial firms. This figure shows that the results on leverage and debt ratios are robust across the sub-groups of corporate and non-corporate sectors of non-financial sectors. Some of the other results are not robust on impact for the non-corporate sector, which for instance decreases for such firms and increases for the corporate sector and the aggregate sector. The evolution after the impact effect, instead, is robust. See note ?? in Section.

Figure 20: Marginal approach with delinquency rate

Cholesky identification

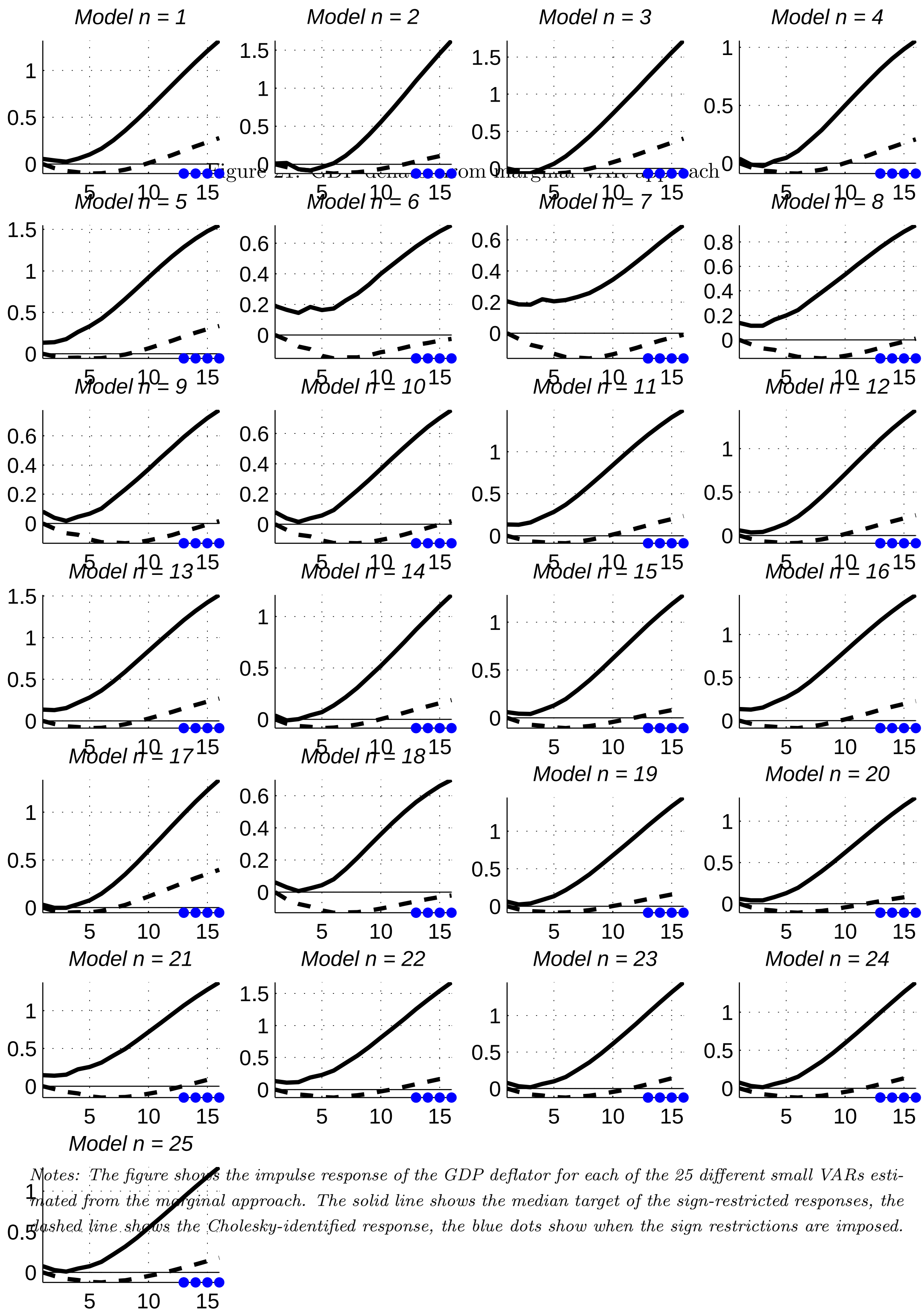


Sign-restricted identification



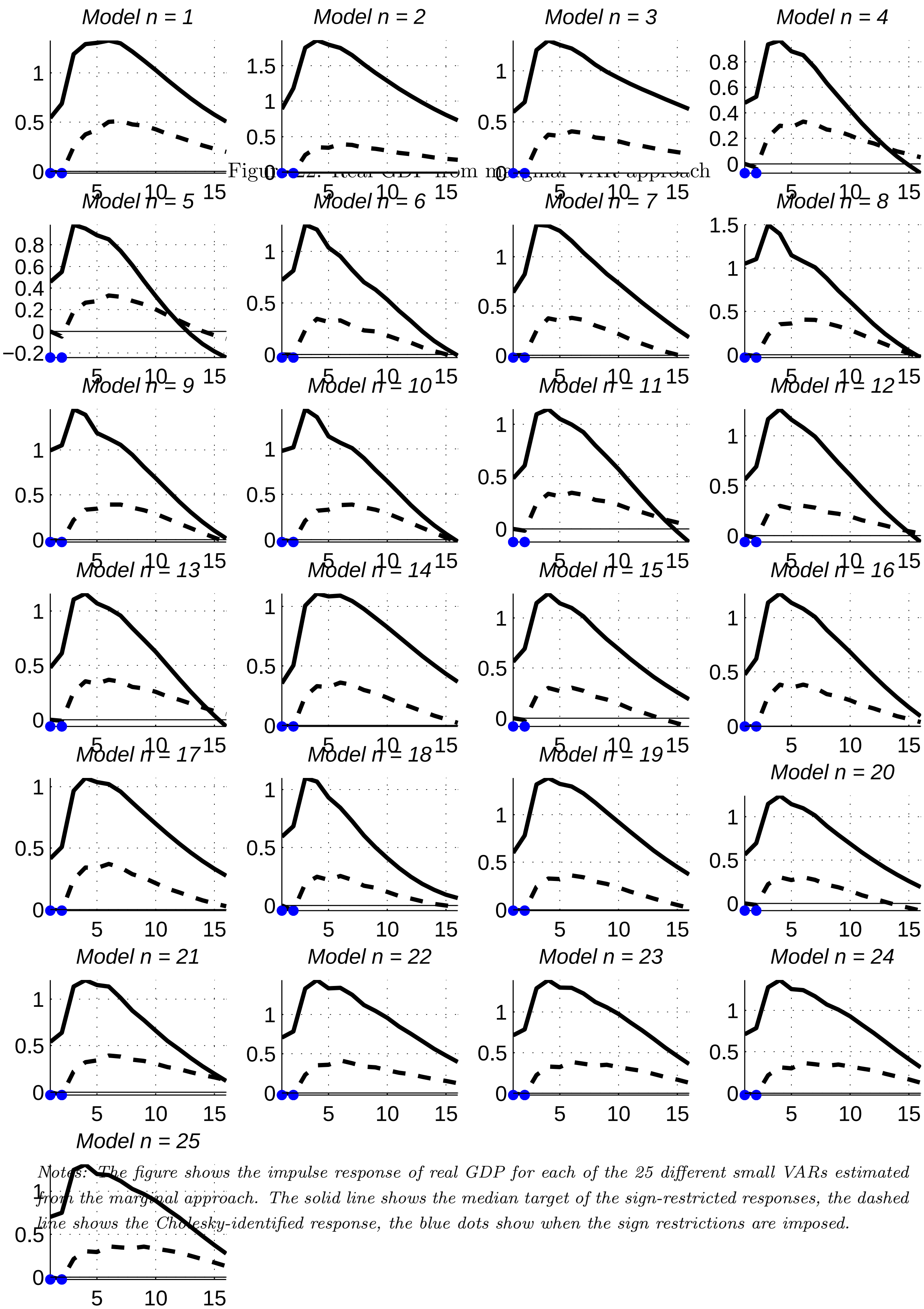
Notes: ADD.

Figure 21: GDP deflator from marginal VAR approach



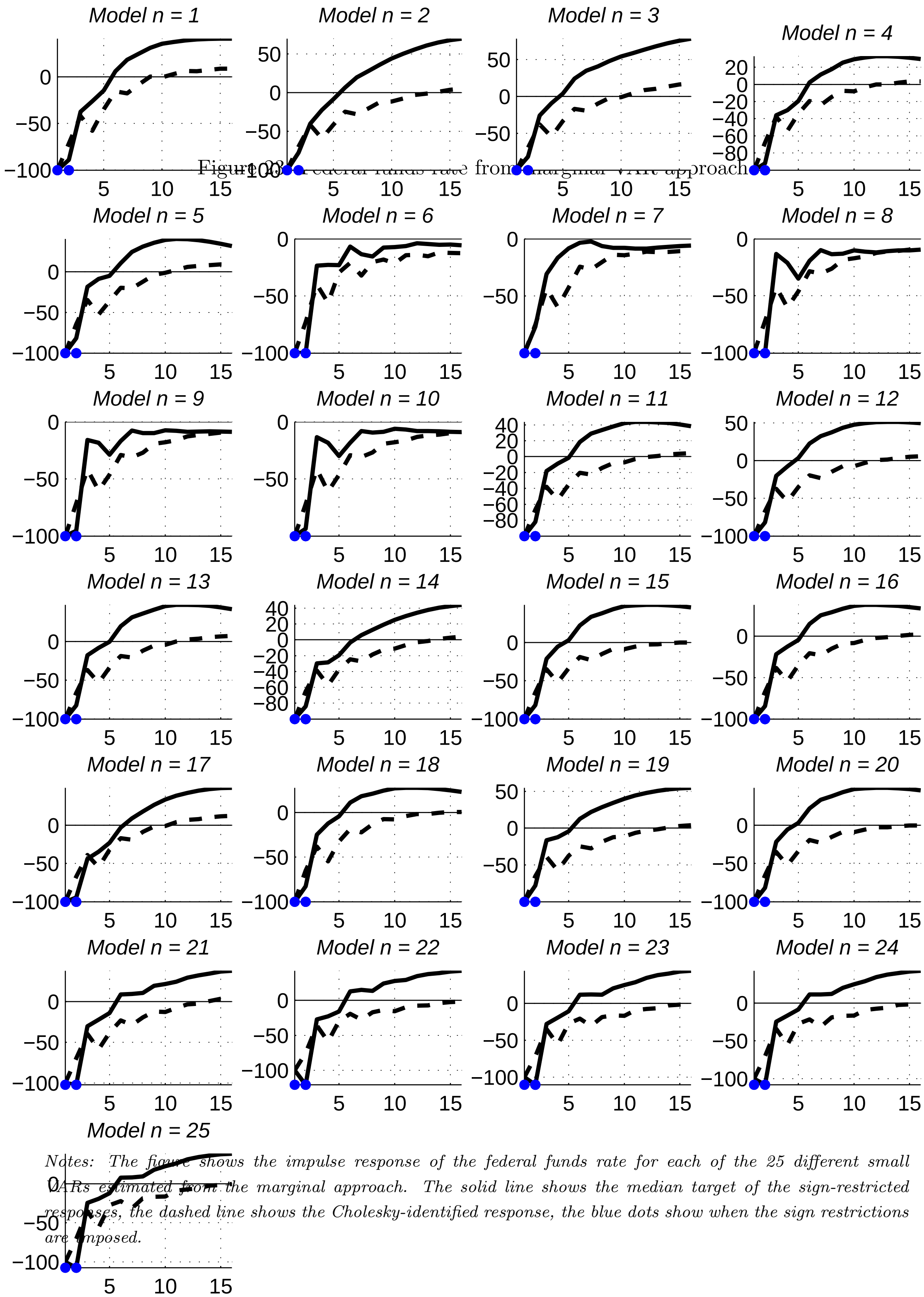
Notes: The figure shows the impulse response of the GDP deflator for each of the 25 different small VARs estimated from the marginal approach. The solid line shows the median target of the sign-restricted responses, the dashed line shows the Cholesky-identified response, the blue dots show when the sign restrictions are imposed.

Figure 22: Real GDP from marginal VAR approach



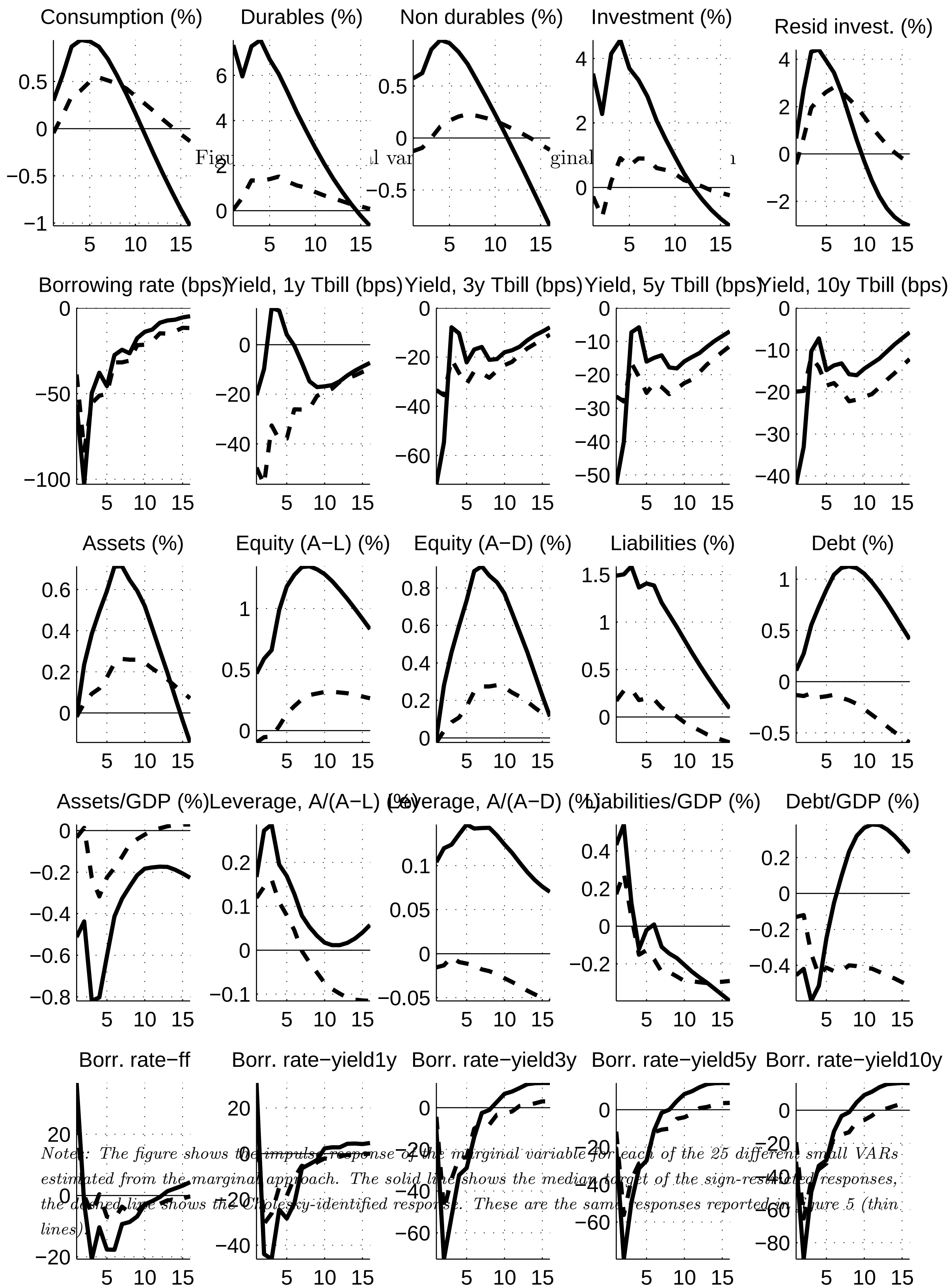
Notes: The figure shows the impulse response of real GDP for each of the 25 different small VARs estimated from the marginal approach. The solid line shows the median target of the sign-restricted responses, the dashed line shows the Cholesky-identified response, the blue dots show when the sign restrictions are imposed.

Figure 28: Federal funds rate from marginal VAR approach



Notes: The figure shows the impulse response of the federal funds rate for each of the 25 different small VARs estimated from the marginal approach. The solid line shows the median target of the sign-restricted responses, the dashed line shows the Cholesky-identified response, the blue dots show when the sign restrictions are imposed.

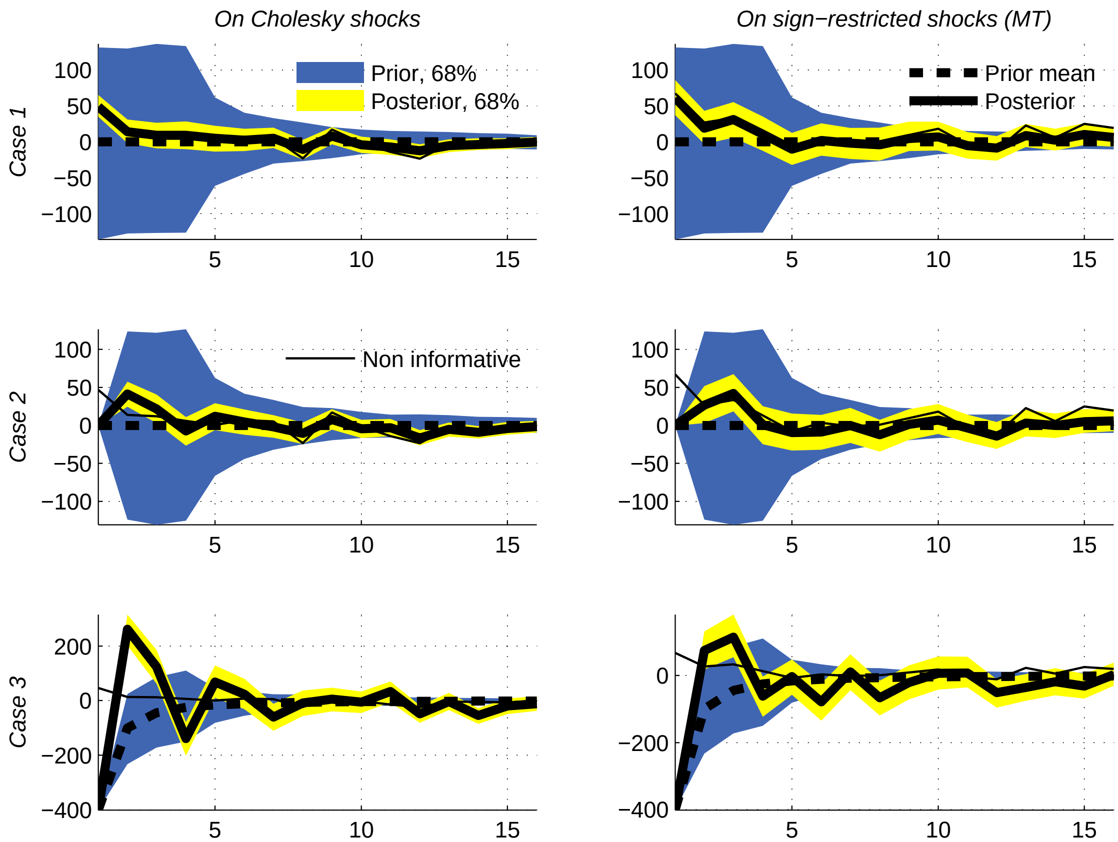
Figu l var ginal n



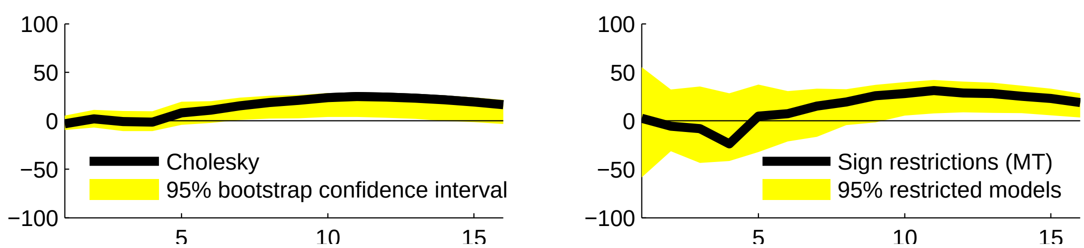
Notes: The figure shows the impulse response of the marginal variable for each of the 25 different small VARs estimated from the marginal approach. The solid line shows the median target of the sign-restricted responses, the dashed line shows the Cholesky-identified response. These are the same responses reported in Figure 5 (thin lines).

Figure 25: Charge-off rate after a 1% decrease in the fed funds

Panel A: From the two-step approach



Panel B: From a small, standard VAR



Notes: Panel A shows the responses estimated with Bayesian methods. The prior distribution of deterministic controls is non informative. The prior variance of the coefficients on lagged shocks is 400 basis points, which is approximately the variation of the delinquency rate over the business cycle. Case 2 further restricts the impact effect on delinquencies to be zero. Case 3 stresses the result by assuming a prior mean of the impulse response on impact of -400 basis points. In all three cases the charge-off rate behaves similarly to the delinquency rate in figure 4: it increases and the reverts back within one year from the shock. The marginal approach, shown in Panel B, shows that the increase in the charge-off rate is robust, but with a very different timing.

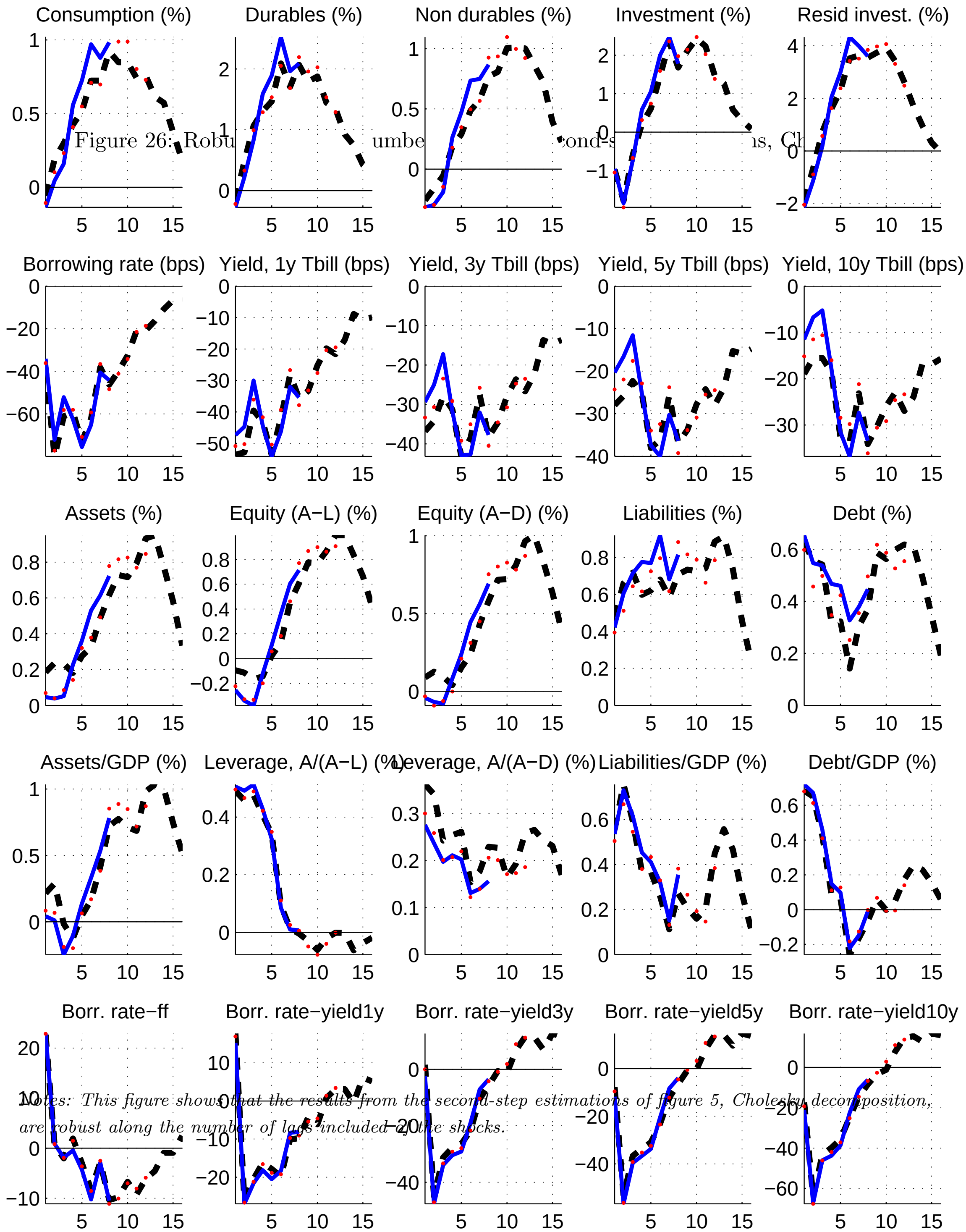
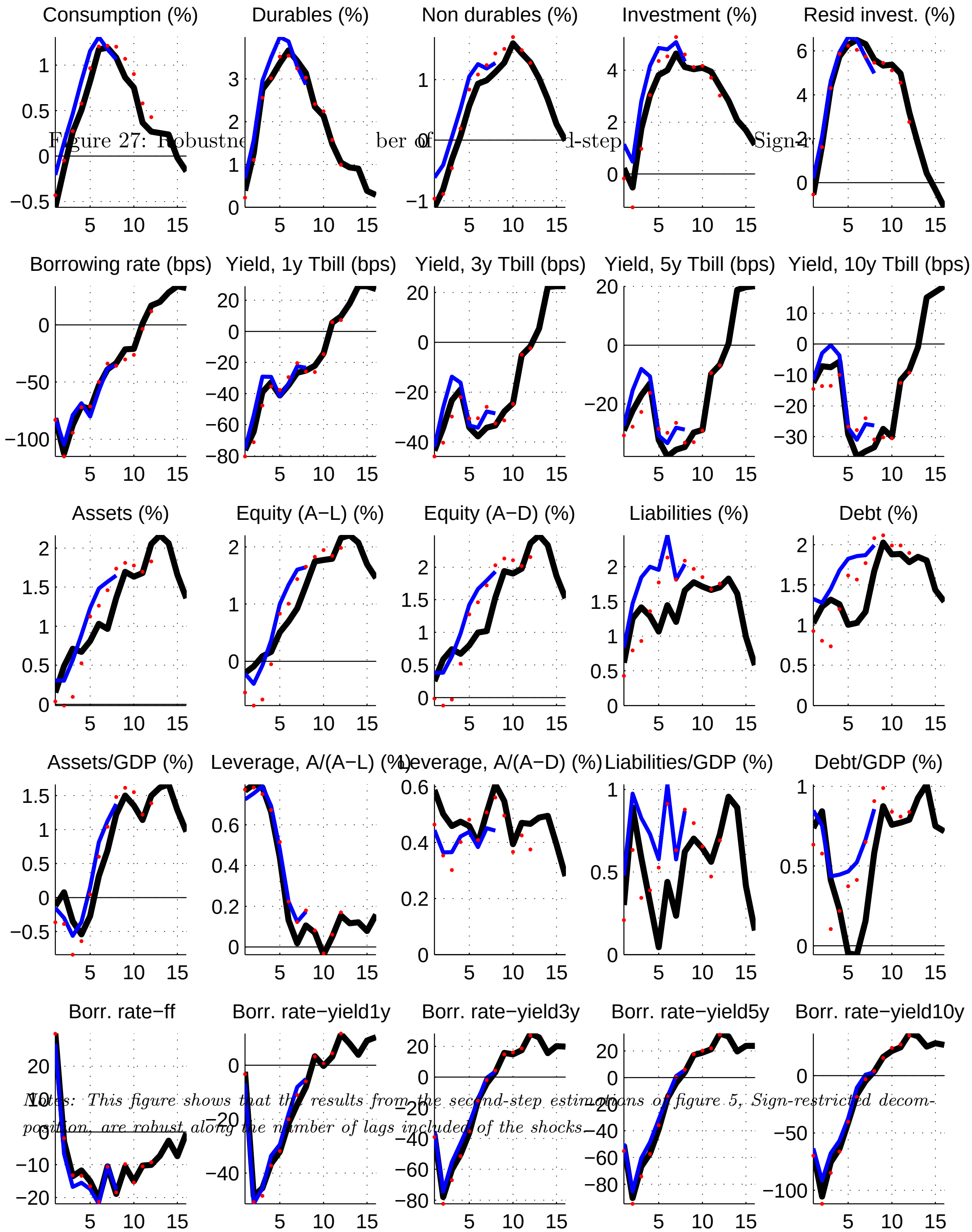


Figure 26: Robu... umbe... cond-s... ns, Ch...

Notes: This figure shows that the results from the second-step estimations of figure 5, Cholesky decomposition, are robust along the number of lags included in the shocks.

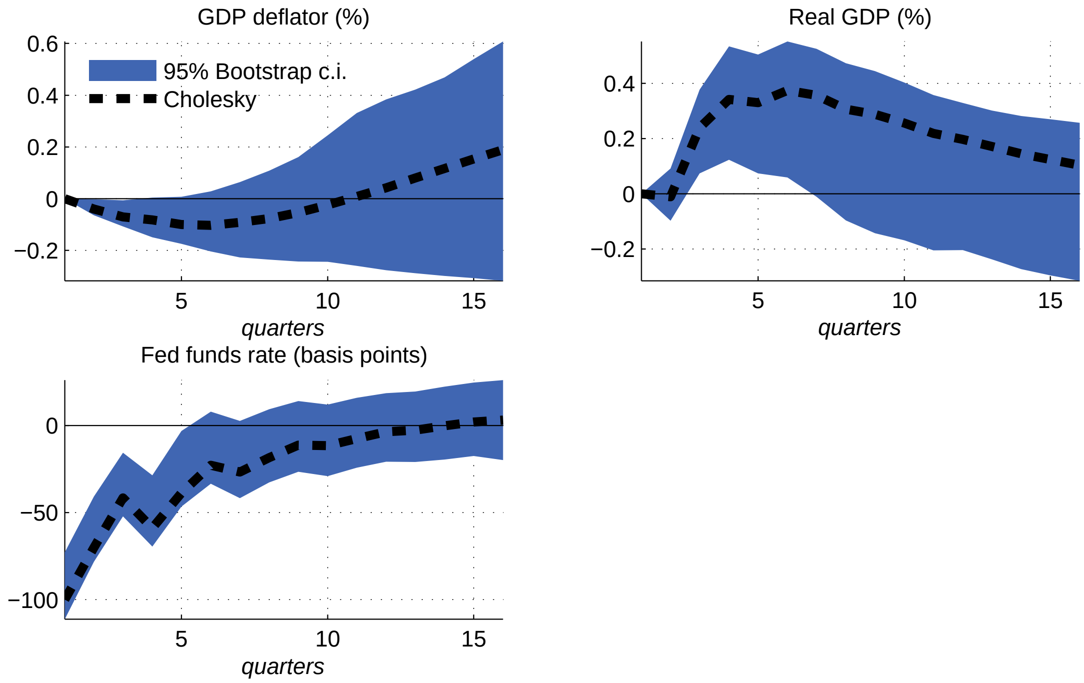
Figure 27: Robustne ... ber of ... d-step ... Sign-r



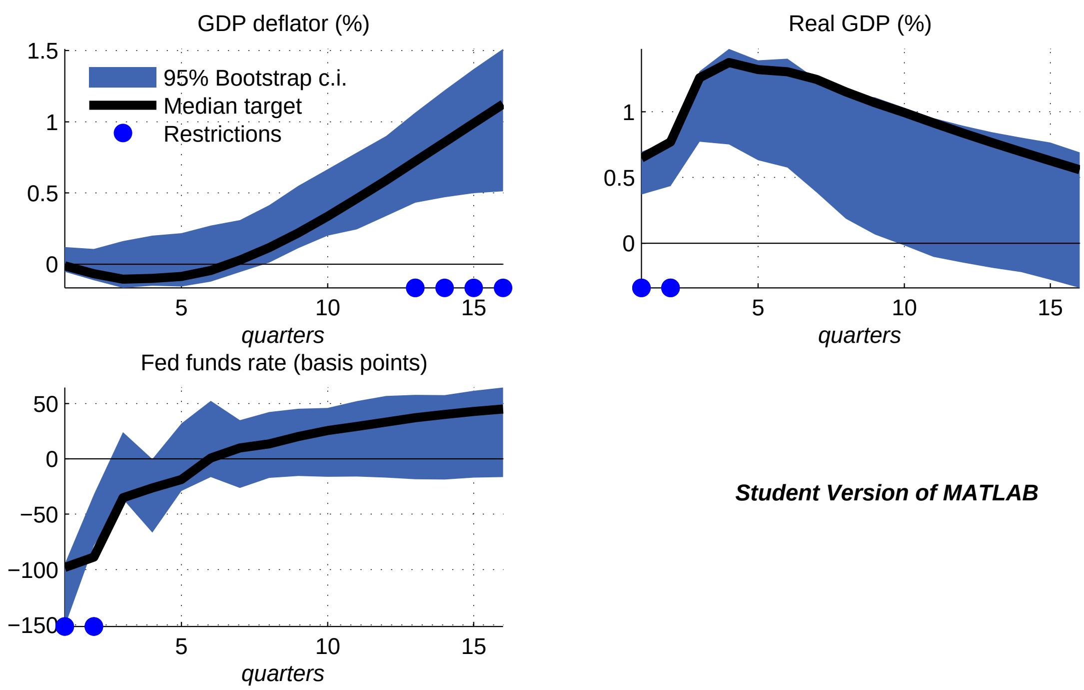
Notes: This figure shows that the results from the second-step estimations of figure 5, Sign-restricted decomposition, are robust along the number of lags included of the shocks.

Figure 28: Bootstrap confidence interval on first step estimation

Panel A: Cholesky decomposition



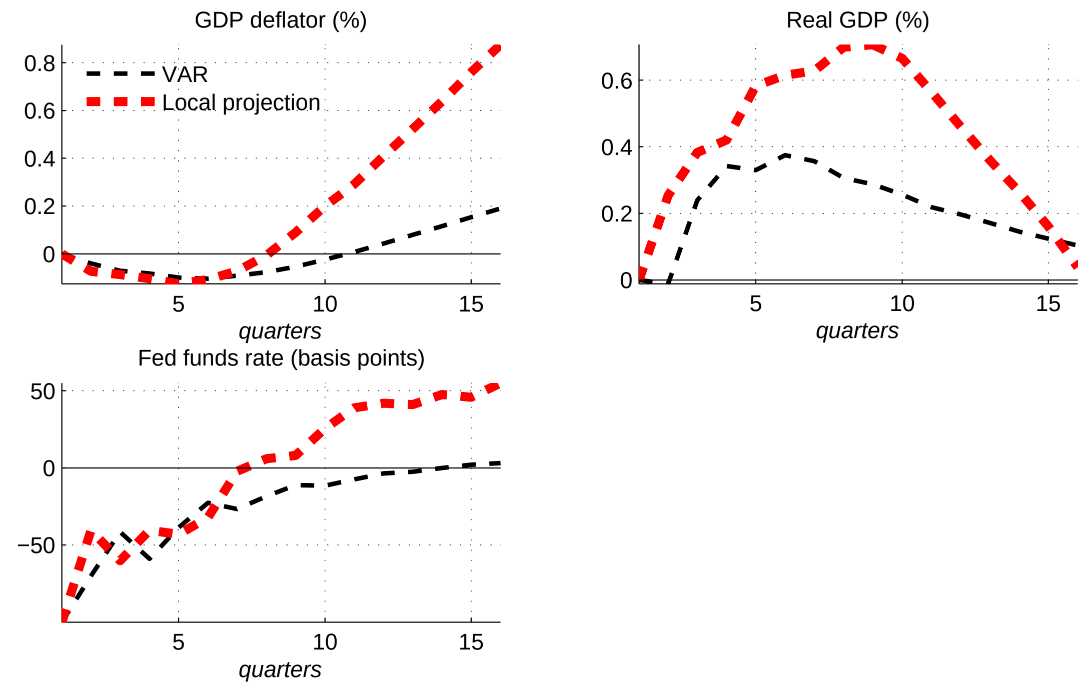
Panel B: Sign restriction (median target)



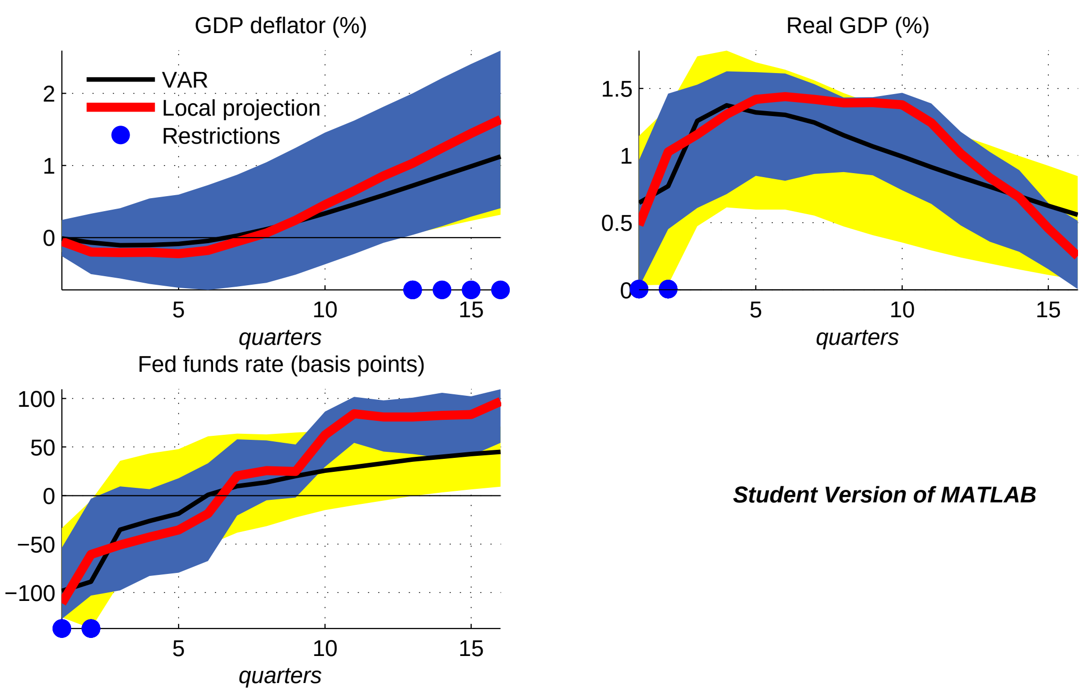
Notes: This figure the bootstrap confidence interval for the first-step estimation computed by bootstraping the reduced-form shocks along 1000 iterations.

Figure 29: Local projection á la Jorda (2005) in first step estimation

Panel A: Cholesky decomposition



Panel B: Sign restriction (median target)



Notes: This figure suggests that the results from the first-step estimations of figure 2 are robust to non linearities in the data generating process of Y_t. The light-yellow and dark-blue areas show the 95% of the sign-restricted models estimated respectively for the VAR and for the local projection.