Monetary Policy and Defaults in the US

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Abstract

I document empirically that an unexpected monetary expansion increases the probability that non-financial firms default on loans. I use a three-step approach that applies local projections on several time series of monetary shocks selected with Granger-causality restrictions. I find that the default probability on US business loans, measured with the delinquency rate and the charge-off rate, increases between two and three years after a monetary expansion. A leverage effect on the side of firms could contribute to explain this result. When the policy rate decreases, the cost of borrowing falls and firms react 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 find evidence consistent with this effect, because the aggregate leverage ratio of US firms does increase in response to a monetary expansion.

JEL Classification: E44, E52

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1 Introduction

In this paper I study the effect of a monetary expansion on the probability that firms default on loans. It is 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. In contrast, I study US aggregate data and find empirically that this default probability increases. In particular, I measure this probability using the delinquency rate and the charge-off rate on business loans. These rates are defined as the value of business loans whose repayments are overdue for more that one month and six months, respectively, relative to the value of all outstanding business loans. I consider a monetary shock that decreases the federal funds rate by 1%. I find that the delinquency rate and the charge-off do not respond for the first three years and two years respectively, and then increase for approximately one year by around 50 basis points. This increase equals as much as 25% of the typical variation of the delinquency and the charge-off rates over the business cycle, which is approximately 200 basis points.

There are several forces that could explain the increase in defaults following a monetary expansion. One of them centers around a leverage effect from the side of firms. When the cost of borrowing decreases, firms have a higher incentive to take on debt. Under certain conditions, this leads to a higher leverage ratio, which pushes up the default rate on loans because equity is now providing a lower buffer to the risky loan. I take this prediction to the data and find that the leverage ratio of firms does increase in response to a monetary expansion around two years and a half after the shock. In particular, I consider again an expansionary monetary shock that generates a 1% decrease in the federal funds rate. When measuring leverage as the ratio of assets over equity, hence a measure between 1 and infinity, I find that leverage increases by up to 3.5%. On average this implies an increase from 1.77 to 1.83. When measuring leverage as the ratio of liabilities over assets, hence a measure between 0% and 100%, I find that leverage increases by 2 percentage points. On average this implies an increase from 44% to 46%. The increase in leverage accounts for as much as 25% of the difference between the minimum and the maximum value of the aggregate leverage ratio of firms in the period considered.

As known in the literature, the endogeneity problem of the federal funds rate makes it challenging to identify the effects associated with a monetary policy intervention. Since the policy rate is set in response to the state of the economy, it is essential to isolate the effect that the policy rate exerts on the economy from the economic conditions that justified the variation of the policy rate in the first place. This issue is particularly relevant to the study of defaults. In fact, a negative correlation between the policy rate and the default rate on loans might still reflect the fact that the Federal Reserve Bank decreases the interest rate during a recession and hence in a period typically associated with higher default rates. To tackle this identification issue I use a variety of methods to obtain measures of monetary shocks, i.e. fluctuations in the federal funds rate that are not the feedback response to the economy, nor the effect of other structural shocks. The use of these shocks is in line with the extensive empirical literature on monetary policy based on Vector Autoregressive (VAR) models following Bernanke and Blinder (1992) and Christiano, Eichenbaum and Evans (1999), as well as with the methodology developed by Romer and Romer (2004).[1]

I use a three-step empirical strategy based on Granger-causality restrictions. First, I identify several candidate time series of monetary shocks using a combination of Romer and Romer (2004) shocks, small VAR models identified following Canova and De Nicoló (2002) and a Factor Model by Forni and Gambetti (2010). Second, I use Granger-causality tests to rule out shocks that might still be capturing the feedback response of the federal funds rate to the ability of firms to repay their loans. Third, I compute impulse responses with local projections by Jorda (2005). There are three main advantages associated with this approach. The first one relates to the data availability. The delinquency rate and the charge-off rate are available only after 1987Q1 and 1985Q1, respectively. The three-step approach allows to exploit information before 1987Q1 on several macroeconomic variables in order to generate a more accurate estimate of monetary shocks. The second advantage relates to the fact that the delinquency rate, the charge-off rate and the leverage ratio of firms display several breaks in the trend. Including these variables in a single VAR model would require compromising on the number of trend breaks included in the estimation in order to retain degrees of freedom. In contrast, the approach used in this paper allows to select deterministic variables that are specific to each variable studied. The third advantage of this approach is that it is very transparent in using a statistical criterion to select, out of potentially very different candidate models, the most appropriate one given the research question at hand.[2]

This paper relates to the extensive theoretical and empirical literature on monetary policy. The economic literature typically identifies inflation as the main cost associated to a monetary expansion. Central banks are known to face a trade-off between output and inflation, and inflation is considered costly from a welfare perspective for instance because of the relative price adjustments implied by nominal price rigidities (see Galí (2008) and Christiano, Trabandt and Walentin (2011)). In principle, the result that a monetary expansion increases the default rate of firms suggests that central banks could also face a trade-off between output and defaults. This hypothesis opens the door for research on whether an increase in defaults is

[1] One way of rationalizing the existence of monetary shocks is to view them as the effect of the decision process within monetary policy committees, where the prevalence of one view or another one is marginally affected by exogenous factors that make one member of the committee more convincing than another in a particular meeting. See for instance Bernanke and Mihov (1998) and Primiceri (2005) for a discussion of monetary shocks.

[2] For completeness, I report in Appendix A a preliminary analysis carried out by including the delinquency rate and the charge-off rate in a small VAR model. This preliminary analysis does not deliver conclusive results, potentially due to the small sample size of a VAR when including delinquency and charge-off rates directly.

detrimental from a welfare perspective. The goal of this paper is less ambitious and limits itself to document an aggregate effect for the US.

The paper relates to the literature on the risk-taking channel of monetary policy that follows Rajan (2006) and Borio and Zhu (2008). Jimenez, Ongena, Peydró and Saurina (2010), Ioannidou, Ongena and Peydró (2009) and Lopez, Tenjo and Zarate (2011) analyze the relationship between monetary policy and firms' default on loans using microeconomic data. In particular, they use a rich credit registry dataset on loans for Spain, Bolivia and Colombia and find that a monetary expansion initially reduces the default probability of existing loans. This effect is short-lived because the default probability on new loans increases and pushes up the aggregate default rate once the existing loans come to maturity. The results of my paper are consistent with their finding on new loans, although a direct comparison is not possible because of the absence of a credit registry dataset for the US. The results of the paper are also in line with the analysis developed for the US by Maddaloni and Peydró (2011), Altunbas, Gambacorta and Marquez-Ibanez (2010), Paligorova and Santos (2012) and De Nicoló, Dell'Ariccia, Laeven and Valencia (2010). These authors find that a monetary expansion leads banks to loosen credit standards, run a higher default probability, charge lower interest rate spreads to risky borrowers relative to safe borrowers and have a higher ratio of risk-weighted assets to total assets.

The existing theoretical literature tends to interpret the results on new loans by Jimenez *et al.* (2010), Ioannidou *et al.* (2009) and Lopez *et al.* (2011) in terms of a risk-shifting behaviour by banks. Several proposed models feature borrowers characterized by different risk profiles, and study if a monetary expansion affects whether it is, say, subprime borrowers that receive credit, relative to triple-A borrowers (see for example Challe, Mojon and Ragot (2013), Dubecq, Mojon and Ragot (2009), Agur and Demertzis (2012) and Fahri and Tirole (2009)).[3] The leverage effect commented in this paper does not rely on the ex-ante differences in the risk profiles of borrowers, but on the possibility that monetary policy affects their leverage ratio. In a related paper (Piffer (2013)) I show that the prediction of a leverage effect triggered by a monetary expansion is consistent with a New Keynesian model featuring the "costly state verification" debt contract by Townsend (1979). In that model the firm chooses the leverage ratio optimally and the lender demands a leverage premium that covers the opportunity cost of lending. In this paper I have shown empirically that the leverage effect commented in Piffer (2013) is consistent with US aggregate data.

Section 2 explains the key variables used in the analysis. Section 3 outlines the empirical strategy used and reports the main results. Some of the technical details are reported in the Appendix. Section 4 discusses the most interesting robustness checks that have been done. Section 5 concludes.

[3]See also Drees, Eckwert and Vardy (2012), Acharya and Naqvi (2012), Dell'Ariccia, Laeven and Marquez (2010), Stein (2012), Valencia (2011), Bruno and Shin (2012), Angeloni and Faia (2013) and Cociuba, Shukayev and Ueberfeldt (2012) for related works.

2 Dataset

The key variables of the analysis are the ones that capture the probability that firms default on loans. This probability is of course not directly observable, but it can be proxied for the US using the delinquency rate and the charge-off rate on business loans available from the Federal Reserve Bank.

A borrower is defined "delinquent" on a loan if the payments are overdue for longer than 30 days. The delinquent status holds independently on whether the lender has started the foreclosure process of repossessing the borrower's collateral. When the borrower becomes severely delinquent (traditionally after six months from the first omitted payment) the lender charges off from his balance sheet the amount of the loan that is considered noncollectable. This allows the lender to book the corresponding loss in the income statement and benefit from a tax exemption on the loss. The delinquency and charge-off rates are defined as the ratio of the value of the delinquent/charged-off loans over the value of outstanding loans. The two time series are only available from 1987Q1 and 1985Q1, respectively.[4]

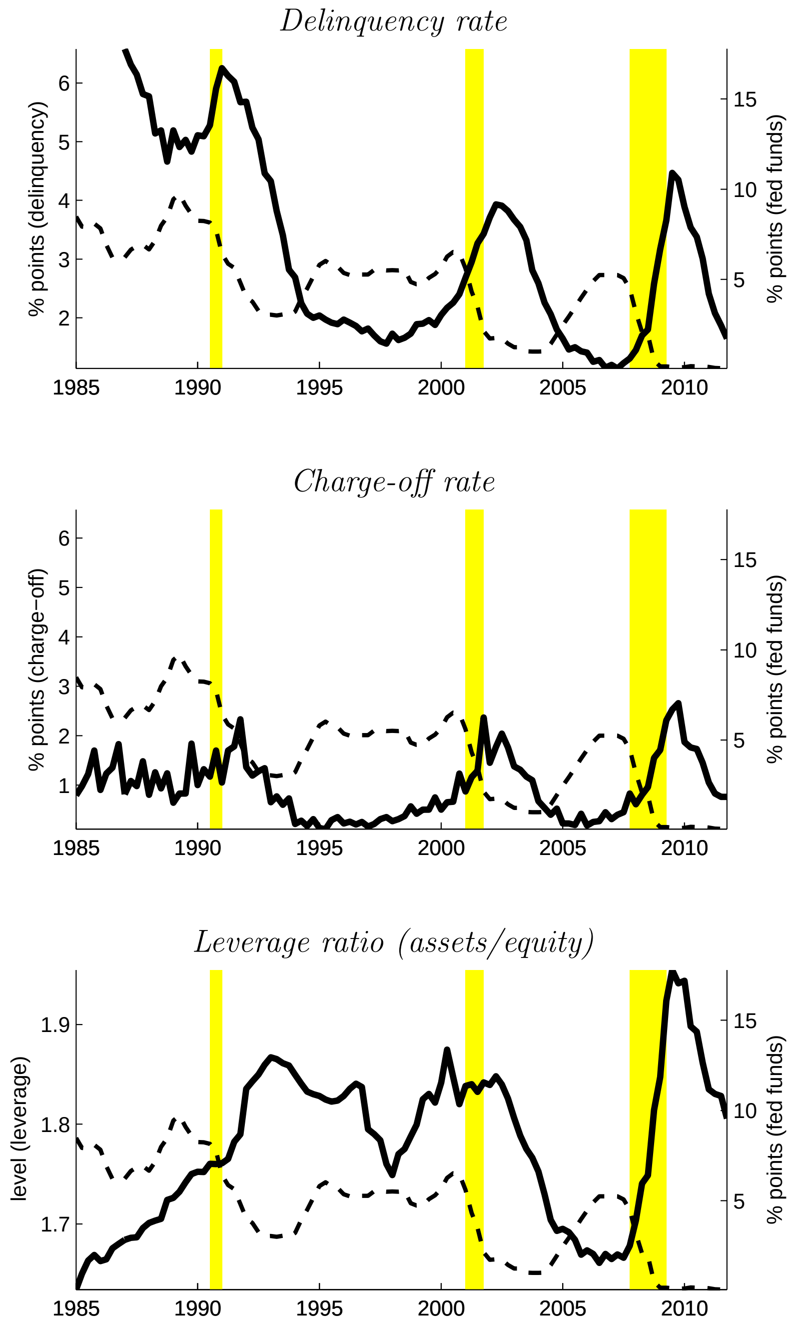
The other key variable of interest for the analysis of the paper is the leverage ratio of firms. Leverage is defined as the ratio of assets over equity, as for instance in Adrian and Shin (2008). Balance sheet data are available at the aggregate level from the Flow of Funds, which provide data separately for the corporate and for the non-corporate sectors. I aggregate the corresponding balance sheet items into a unique non-financial sector.[5] Balance sheet items are reported at book value. Equity is computed residually as the difference between total assets and total liabilities.

Figure 1 shows the evolution of the delinquency rate, the charge-off rate and the leverage ratio of firms, compared to the evolution of the federal funds rate. The leverage ratio can be computed from the Flow of Funds starting from 1955Q1. For comparability, the analysis is carried out only for the same period used for the

[4]The delinquency and charge-off rates are available from the Federal Reserve Board, Data Download Program, and are computed from the "Report of Condition and Income" (Call Report) filed by all US-chartered commercial banks on a quarterly basis. Further technical details on delinquency and charge-off rates are available on http://www.federalreserve.gov/releases/chargeoff/about.htm. An additional measure of the probability that firms default on loans is the rate of non-performing loans by commercial banks, which nevertheless includes both business and non-business loans. A default on loans does not mechanically imply the default of the firm. While comprehensive data on the default rate of firms is not available from the Federal Reserve Bank, the data on Expected Default Frequencies of firms by Moody's KMV allow a heuristic comparison of the two probabilities. This dataset is not publicly available. Levin, Natalucci and Zakrajseky (2004) report an average Expected Default Frequency of firms during the dotcom bubble (1997Q1-2003Q3) of 0.55%. The mean of the time series of the delinquency rate and the charge-off rate in the corresponding period equal 2.52% and 0.90%, respectively. The Survey on the Terms of Business Lending from the Federal Reserve Bank reports that approximately only 40% of business loans are secured by collateral and that the average maturity of business loans equals 5 quarters. These statistics are available only for the sample period after 1997.

[5]The corporate sector is approximately twice as large as the non-corporate sector. The results are robust to the use of data on only one sector, as shown in figure 15 of Appendix C.

Figure 1: Firms' default on loans and leverage ratio (solid, lhs) vs. federal funds rate (dashed, rhs axis)



Notes: the shaded bands indicate NBER recessions, the dashed lines show the federal funds rate, the solid lines show the delinquency rate (top graph), the charge-off rate (middle graph) and the leverage ratio of firms (bottom graph). The period considered is 1985Q1-2011Q4.

Table 1: Summary statistics

	Mean %	percentile(2.5) %	percentile(97.5) %	Correlation with real GDP
Delinquency rate	3.10	1.2	6.25	-0.76
Charge-off rate	0.93	0.16	2.36	-0.59
Leverage ratio	1.77	1.66	1.97	-0.55

Notes: The mean and percentiles are computed on the level of the corresponding variable. The correlation with real GDP is computed after filtering out seasonal and low frequencies using an X-12 ARIMA filter and an HP filter, respectively. The smoothing parameter used in the HP filter equals 1600. The period considered is 1985Q1-2011Q4.

charge-off rate.[6] The vertical shaded bands indicate the NBER recessions, which in the time period covered correspond to the aftermath of the Gulf war, to the end of the dotcom bubble and to the beginning of the subprime crisis. Table 1 complements the analysis of figure 1 by reporting summary statistics on the mean, the 2.5th and 97.5th percentiles and the correlation with real GDP. This correlation is computed after filtering out low and seasonal frequencies using an X-12 ARIMA algorithm from the US Census Bureau and the HP filter, respectively. The smoothing parameter used in the HP filter equals 1600, which is standard for quarterly data.

Overall, figure 1 and table 1 suggest that:

1. The delinquency rate averages around 3.10% and displays a downward trend over the sample. The charge-off rate averages around 0.93% and displays no trend over the sample;

2. Both the delinquency rate and the charge-off rate are strongly counter-cyclical. Some of their peaks lag the NBER recessions by as much as a year. On average, the trough-to-peak variations of the delinquency rate equals 1 percentage point after the Gulf war, 2 percentage points after the dotcom bubble and 3 percentage points after the subprime crisis. The trough-to-peak variations of the charge-off rate equal approximately 2 percentage points over the entire sample period covered;

3. The leverage ratio of firms averages around 1.77 and moves counter-cyclically.

[6] Figure 11 in Appendix C shows the evolution of the leverage ratio since 1955Q1 of all firms, of corporate firms and of non-corporate firms.

3 Empirical strategy

The empirical strategy used in this paper consists of three steps. In the first step I collect several candidate time series of monetary shocks. In the second step I use Granger-causality tests to restrict the candidate models to those that are more appropriate to address the research question of the paper. In the third step I use the monetary shocks that meet the Granger-causality restrictions to compute impulse responses.

3.1 First step: selecting candidate time series of monetary shocks

The first step of the analysis consists of selecting candidate times series of monetary shocks. The first set of candidate shocks that I use follows the contribution by Romer and Romer (2004). In short, Romer and Romer identify an index of the intended variations of the federal funds rate. They then regress such index on the FOMC's forecasts of real output growth, the GDP deflator and the unemployment rate. The residuals of such regressions capture the variations in the policy rate that are orthogonal to the FOMC's expectations of the state of the economy captured by the forecasts. The original Romer and Romer shocks cover the period between 1969M3 and 1996M12. I also use the series extended by Coibion, Gorodnichenko, Kueng and Silvia (2012) to 2008M12.[7]

An alternative approach to isolate random variations in the policy rate consists of using large models, i.e. models that can include more than 100 variables. It is not clear a prior if the research question of this paper is addressed more effectively with a large model or with a small VAR model with a relatively limited number of variables. On the one hand, large models can include a lot of data potentially informative of the response of the Federal Reserve Bank to the financial situation of firms and on their loan repayment possibilities. On the other hand, this additional information comes at the cost of requiring the imposition of more structure to the data. I will use the Factor Model by Forni and Gambetti (2010), which deals with the inclusion of as many as 112 variables by assuming that a 16 unobservable factors are responsible for the dynamics of all the variables in the dataset, and by assuming that 4 underlying structural shocks determine the dynamics of the unobservable factors. The period covered by the paper is 1973M4-2007M12, and the identification is recursive. The included financial variables that are potentially informative of the state of the repayment possibilities by firms are several indexes of industrial production, the tightness of unemployment in different sectors, several stock price indexes and a range of interest rates.[8]

The remaining candidate time series of monetary shocks are generated with small

[7] I am grateful to the authors for having shared their estimates.

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Table 2: Small VAR models

		Models							
		1	2	3	4	5	6	7	8
real GDP	(log)	✓	✓	✓	✓	✓	✓	✓	✓
GDP deflator	(log)	✓	✓	✓	✓	✓	✓	✓	✓
fed funds rate	(basis points)	✓	✓	✓	✓	✓	✓	✓	✓
Assets	(log)	✓	✓	✓	✓	✓	✓	✓	✓
Equity	(log)	✓	✓	✓	✓	✓	✓	✓	✓
Avg. borrowing rate of firms	(basis points)		✓			✓	✓		✓
1 year Treasury bill	(basis points)			✓		✓		✓	✓
10 year Treasury bill	(basis points)				✓		✓	✓	✓

Notes: The table shows which variables are included in the 8 small VAR models generated.

VAR models. The baseline model includes five variables, which are the log of real GDP, the log of the GDP deflator, the federal funds rate, the log of firms' assets and the log of firms' equity. The order in which they enter the model does not matter, since I identify the models using sign restrictions (more on this later). I then generate other models by adding to the baseline model all possible selections of three additional variables, which are the average borrowing rate of firms, the yield on the 1-year Treasury bill and the yield on the 10-year treasury bill. The exact variables included in each model is shown in table 2. The inclusion of real GDP, the GDP deflator and the federal funds rate is standard in the empirical literature on monetary policy.[9] The remaining variables capture information on the financial situation of firms regarding their balance sheet and their cost of borrowing. Note that the variables included are implicitly informative also of other variables, like the leverage ratio, the ratio of total liability over GDP and the interest rate spreads against the federal funds rate or against the risk-free rate on short-term and long-term borrowing. The levels of the eight variables included in the analysis are shown in figure 2.

For each of the small VAR considered, I estimate the following model:

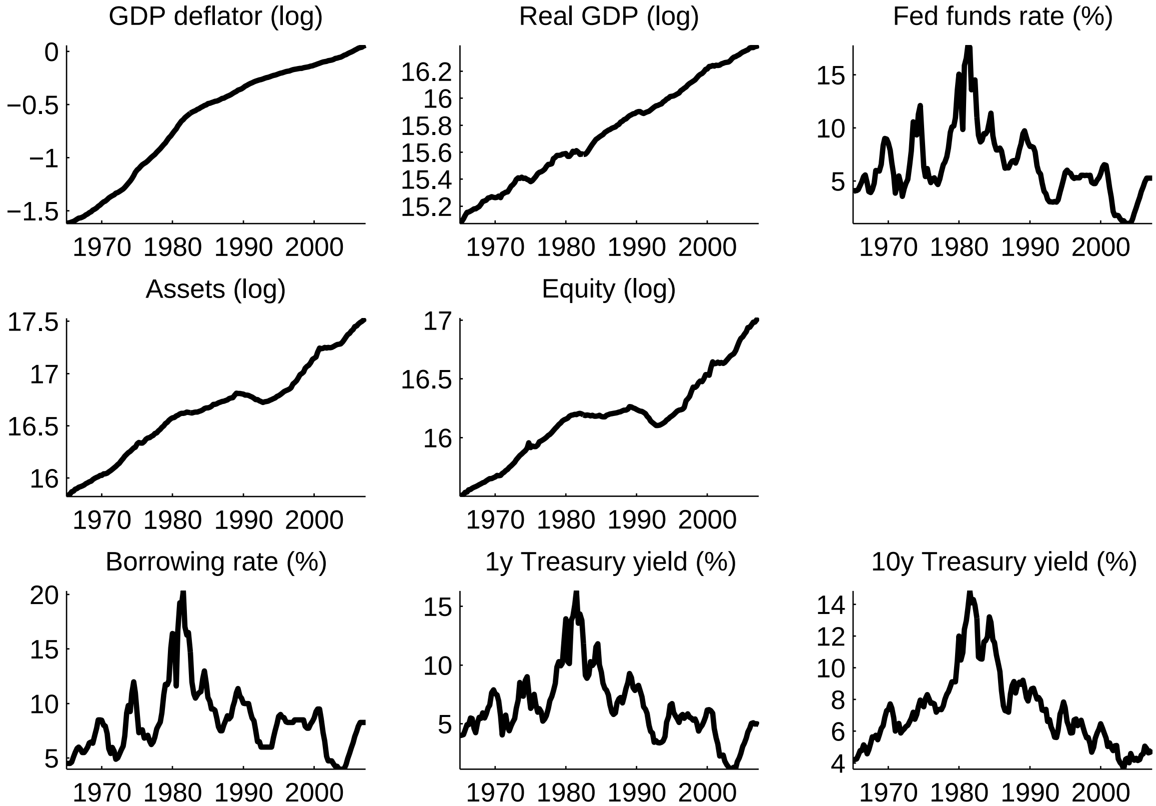
$$Y_t = \alpha_t + A(L)Y_{t-1} + R_t. \tag{1}$$

The 6x1 vector α_t includes a constant, a linear trend with no time breaks and seasonal dummies. The 6x6 matrix $A(L)$ includes four lags.[10] The variance-covariance matrix of R_t is Σ. I estimate the model using least square estimation with data

[9] One exception is Canova and De Nicoló (2002), who use the slope of term structure instead of the interbank overnight interest rate.

[10] The results are robust to using de-seasonalized variables instead of controlling for such frequencies using dummy variables. The inclusion of four lags in the right-hand side is 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 six, three and three lags. The results remain unchanged.

Figure 2: Variables included in the small VAR models



Notes: All variables are shown as they enter the small VAR model, i.e. interest rates in levels and the remaining variables in logs. The sample period is 1965Q1-2007Q2

in the period between 1965Q1 and 2007Q2. The choice of 1965Q1 as the first observation of the sample is relatively standard in the literature and is taken from Christiano, Eichenbaum and Evans (1999) and Uhlig (2005).[11] The period after 2007Q2 is excluded from the analysis because it corresponds to a largely exceptional period, compared to the rest of the sample.

The contemporaneous relationships among the variables included in Y_t are captured by the residuals. This implies that a shock to $R_{t,i}$ does not bear any structural interpretation. I follow the literature and assume that the reduced-form shocks are a linear combination of as many structural shocks S_t:[12]

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

Since the model is partially identified, the assumption that S_t has dimensions 6x1

[11] The sample period included in Olivei and Tenreyro (2007), Coibion (2012) and Canova and De Nicoló (2002) starts in 1966Q1 1970M1 and 1973M1, respectively.

[12] See Cooley and Roy (1985) for a discussion on this point.

is without loss of generality, as the 5 non-monetary shocks in S_t can be viewed as a combination of all non-monetary shocks driving Y_t.

The only condition imposed by the data on the estimation of P is

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

There are infinite candidate matrices P that satisfy this condition. The literature solves this problem by introducing a limited set of theoretically-motivated assumptions. I follow Canova and De Nicoló (2002) and identify each model using sign restrictions. This approach allows for contemporaneous effects among the variables included in the analysis, which is consistent with Bernanke and Mihov (1998), Canova and De Nicoló (2002) and Canova and Pina (1999).[13] In particular, generate several orthogonal representations of the data using the following algorithm:

1. generate $L = 1000$ candidate matrices P_{cand} defined as $P_{cand} = P_{ee} \cdot Q$; P_e stands for the eigenvalue-eigenvector decomposition of Σ; Q is one of the L 6x6 orthogonal matrices generated through a combination of reflection and rotation methods and through QR decomposition (see Appendix B for the details);

2. use $\{P_{cand,l}\}_{l=1}^{L}$ to compute $6 \cdot L$ sets of impulse responses, i.e. L responses to a structural shock to the $i-th$ element of Y_t, with $i = 1, 2, ..., 6$;[14]

[13] Bernanke and Mihov (1998) claim that one cannot rule out contemporaneous effects with quarterly data (as in this paper), 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. While part of the literature still considers it plausible to assume that a monetary shock affects real GDP only after one quarter (see for instance Olivei and Tenreyro (2007)), it is not clear whether a recursive ordering of the specific variables used in this paper would be appropriate. Including firms' balance sheet variables after the federal funds rate would realistically allow the monetary shock to affect firms' financing decisions within the same quarter of the shock, but it would unrealistically impose that the Federal Reserve Bank responds to shocks to the financing condition of firms with at least a lag of 3 months. Including, instead, balance sheet variables before the federal funds rate would realistically allow the Federal Reserve Bank to respond contemporaneously to shocks to the financial situation of firms, but would unrealistically impose that the monetary shock has no effect on firms' balance sheet variables within the first 3 months after the shock. In unreported robustness checks I found that the results do not change when considering a partially recursive structure in which the federal funds rate does not affect real GDP and the GDP deflator contemporaneously, but affects and responds to the other variables included. This partially recursive structure is used for instance by Eickmeier and Hofmann (2012).

[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 policy rate, but that it generates responses consistent with what economic theory associates to a monetary shock. This distinction is relevant because, in this application, generating models by only giving a shock to the third element of S_t would significantly reduce the set of impulse responses, despite the wide range of orthogonal matrices Q considered. I will explain that the exercise restricts the analysis to three sign-restricted representations. While the median target representation of model 6 corresponds to a shock to the third element of Y_t (the

3. identify an expansionary monetary shock by ruling out models associated with either an increase in the interest rate(s) during the first two quarters, a decrease in output during 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]

The above algorithm generates 6001 candidate structural representations for each of the eight small VARs considered. These are reduced to an average of 230 sign-restricted representations. For simplicity, I will only use the median target sign-restricted representation á la Fry and Pagan (2011).[16] This implies that each of the 8 models reduces to one median target sign-restricted representation.

3.2 Second step: restricting candidate monetary shocks

The procedure outlined in the previous section delivers eleven candidate time series of monetary shocks, i.e.:

- one series of the original Romer and Romer shocks;
- one series of the Romer and Romer shocks extended by Coibion *et al.* (2012);
- one series of shocks from the Factor Model by Forni and Gambetti (2010);
- eight series of median target representations of the small VARs.

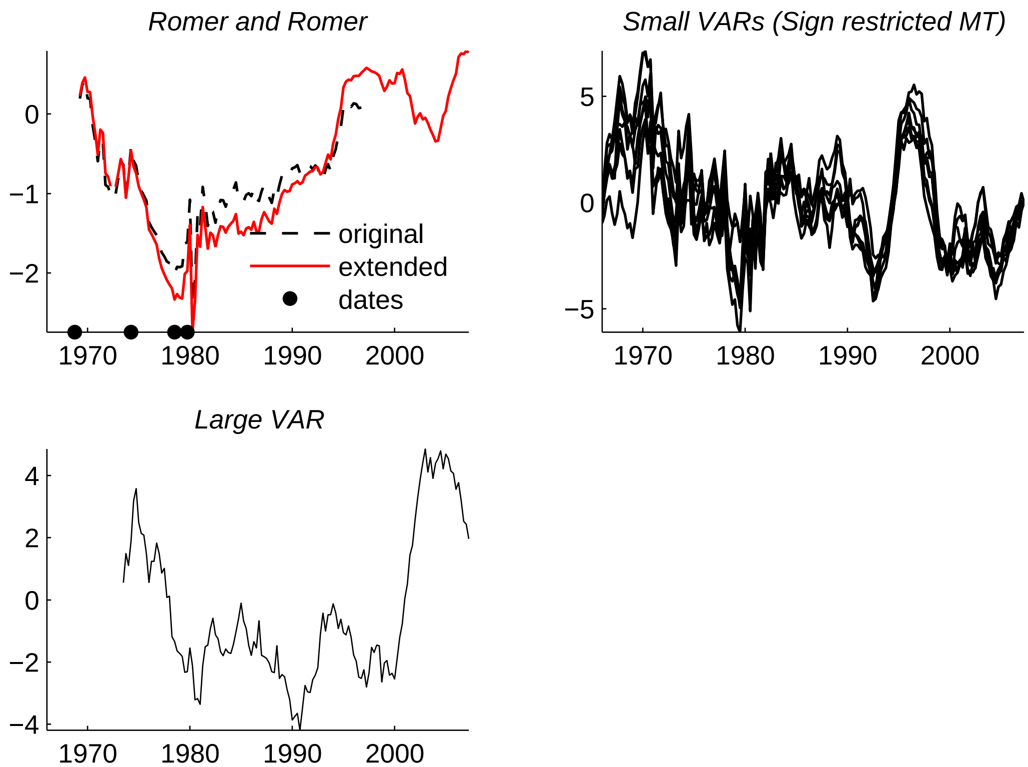
equation of the interest rate), the median target representations of model 2 and 6 correspond to a shock to the sixth element of both models, which in those models correspond to the borrowing rate of firms and to the 10-year Treasury bill, respectively.

[15]The restrictions on real GDP and the GDP deflator reduce the risk of mistakenly capturing aggregate 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. Unreported robustness checks found that the results hold when including the monetary aggregate M1, restricted to decrease for the first two quarters. 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) 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 main difference between the median model and the median target model is that the former potentially switches from one representation to another. To avoid this, the median target is defined as the single representation that is closest to the median, after accounting for the appropriate normalization. See Fry and Pagan (2011) for a discussion.

I follow Coibion (2012) and report in figure 3 the cumulated monetary shocks. These are computed for each series of shocks as the sum of all monetary shocks up to time t. An increase in the cumulative monetary shocks indicates a tightening of monetary policy. Monthly series are transformed to quarterly time series using the average within quarter.

Figure 3: Candidate time series of cumulative monetary shocks



Notes: The figure shows cumulative monetary shocks, i.e. the sum of all shocks until time t for each candidate time series of monetary shocks. For the Romer and Romer (2004) shocks I also report the Romer and Romer (1989) dates.

While there are differences among the cumulative shocks in figure 3, a general pattern emerges, especially for the Romer and Romer shocks and for the shocks from the small VARs. In particular, the monetary shocks are largely suggestive of 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, 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. The evidence from the monetary shocks from the large VAR is less explicit about this pattern, but there are some similarities, especially in the early 80s and in the 90s.

It was explained that the identified candidate monetary shocks are appropriate for the analysis of this paper only if they do not detect the systematic response of the policy rate to the probability that firms default on loans. It is hard to say a priori which of the candidate shocks is doing a better job at addressing this endogeneity problem. To tackle this issue, I impose the restrictions that the candidate monetary shocks are not Granger-caused by variables that are realistically informative of how likely it is that firms default on loans. I use the following 5 variables to run the test:

1. the delinquency rate;
2. the charge-off rate;
3. the spread of the average borrowing rate of firms over the federal funds rate;
4. the leverage ratio of firms;
5. the debt-to-GDP ratio of firms.

In principle, the true time series of monetary shocks should not be Granger-caused by *any* variable. In practice I will show that this is not in general the case, neither for the shocks estimated in this paper nor for the shocks taken from the literature.

In particular, I run Granger-causality tests using the following regression:

$$s_t = \gamma_0 + \gamma_1 v_{t-1} + \gamma_2 v_{t-2} + ... + \gamma_m v_{t-m} + \epsilon_{t+s}. \tag{4}$$

The scalar s_t indicates the candidate time series of monetary shocks while the scalar v_t indicates the variable used in the test. The five variables considered in the analysis are included in equation (4) one at the time in order to avoid loosing too many degrees of freedom. I use an F-statistic to test the hypothesis that the parameters on all regressors, excluding the constant, are *jointly* equal to zero, i.e. $\gamma_1 = \gamma_2 = ... = \gamma_m = 0$. I consider values of $m = 1$ and $m = 12$. I restrict candidate series of shocks by ruling out those for which any of the tests on any of the above five variables is found to Granger-cause the time series of the shocks at a Type-I error of 5%.

The results of the tests are reported in table 3. This table lists the "problematic" lag(s), i.e. the number of lags m in equation 4 including which the Granger-causality is not rejected at 10% Type-I error. To guide the reading of the table, consider the case of the original Romer and Romer shocks reported in the first line. The test finds that these shocks are Granger-caused when including four lags of the delinquency rate, six,eight,nine and eleven lags of the charge-off rate and eleven lags of the leverage ratio of firms. Remember that the Romer and Romer shocks are computed from the regression of the intended variation of the policy rate on the forecasts of output growth, GDP deflator and the unemployment rate. Indeed, unreported tests find that output, the GDP deflator and the unemployment rate do not Granger-cause the Romer and Romer shocks. What table 3 suggests is that controlling for these

Table 3: Granger-causality restrictions on candidate time series of monetary shocks

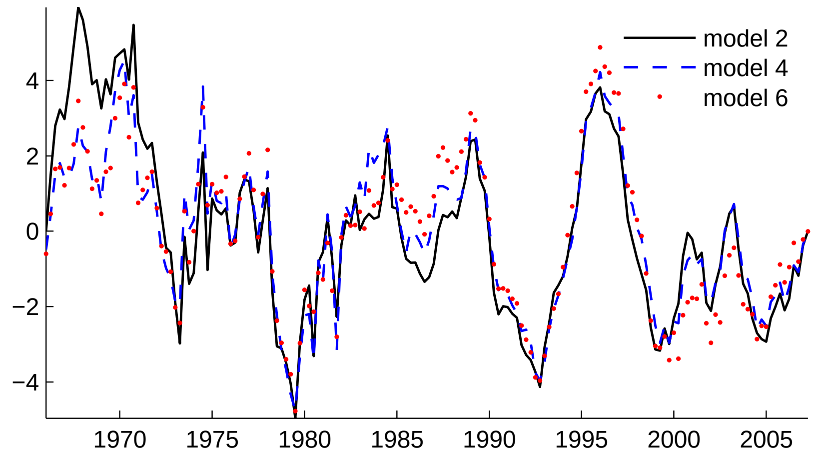
Candidate shocks	Delinquency rate	Charge-off rate	Spread	Leverage ratio	Debt/GDP ratio	Satisfies restrictions?
ROMER and ROMER						
original	4	6,8-11		11		
extended	3-12	1-12			10-12	
SMALL VARs						
1	7					
2						✓
3	7,8,10	10-12				
4						✓
5	7	11-12				
6						✓
7	7-12	8-12				
8	7-9	10-12				
LARGE MODEL						
Factors	9-12	1-4		1-4		

Notes: The table shows the results of Granger-causality tests on the candidate time series of monetary shocks from Section 3.1. The table reports the number of lags m in equation (4) *including which the hypothesis of no Granger causality is rejected at 5% Type-I error. The restrictions imposed are that none of the variables considered (delinquency and charge of rates, spread, leverage and dept-to-GDP ratios) Granger cause the candidate shocks. Only three candidate shocks satisfy these restrictions, as shown in the last column of the table. The corresponding cumulative monetary shocks are shown in figure 4.*

forecasts is not enough to fully detect the response of the policy rate to the probability that firms will default on loans. This implies that, while the Romer and Romer shocks are likely to be appropriate for the study of certain macroeconomic variables, they are not suitable for the study of firms' delinquency and charge-off rates. I will return to the endogeneity of the Romer and Romer shocks in Section 3.3.

Overall, table 3 shows that there are three candidate monetary shocks that meet the Granger-causality restrictions. These are the shocks corresponding to models 2,4 and 6 of the small VAR models. The cumulative monetary shocks of these models are shown in figure 4. The correlations between the series equal around 0.90. Figure 5 shows the impulse responses corresponding to the three models. Figures 6 reports the results of an exercise developed to assess the relative contribution of monetary shocks to the dynamics of the variables in model 2 (the analysis for the other 2 models is very similar and is not reported). The left graph compares the level of each variable with the counter-factual level computed by feeding to the model all structural shocks

Figure 4: Restricted cumulative monetary shocks



Notes: this figure shows the cumulative monetary shocks that satisfy the Granger-causality restrictions from table 3 and that are therefore used to compute the impulse responses in Section 3.3. The period considered is 1966Q1-2007Q2.

except the monetary shocks.[17] The right graph reports the differences between the two series. Overall, figure 6 shows that monetary shocks have a significant role for the the dynamics of all variables, since the counter-factual variables differ from the true variables by as much as 150 basis points for interest rates and as much as 2 percentage points for the other variables. This suggests that, while the effects associated to a single monetary shock are relatively small as documented in figure 5, the contribution of *all* monetary shocks considered together can be quite significant.

3.3 Third step: compute impulse responses

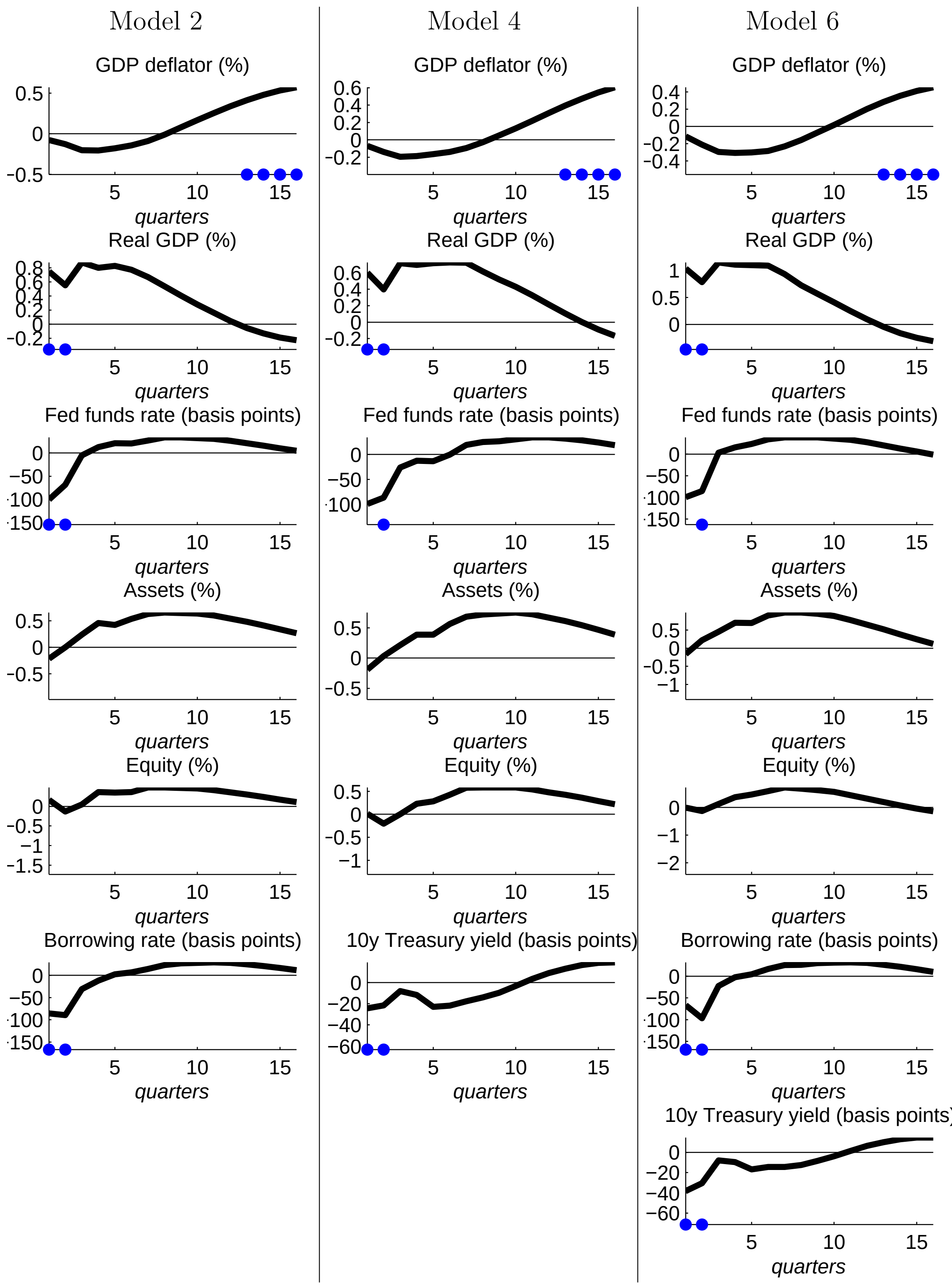
Given the 3 restricted candidate series of monetary shocks from Section 3.2, I follow Tenreyro and Thwaites (2013) and use local projection methods by Jorda (2005) to compute impulse responses. More precisely, I use the following regression:

$$d_{t+l} = \alpha_l \cdot s_t + \beta + f(\gamma, t) + u_{t+l}. \tag{5}$$

Equation (5) allows to compute the impulse response of variable d to a shock to variable s at lag l. The impulse response is computed as $\hat{\alpha}_l \cdot \gamma$, where $\hat{\alpha}_l$ is the estimate of the coefficient α_l and γ is a parameter controlling for the sign and magnitude of the shock considered. β is the parameter on a constant and $f(\gamma, t)$ controls for a

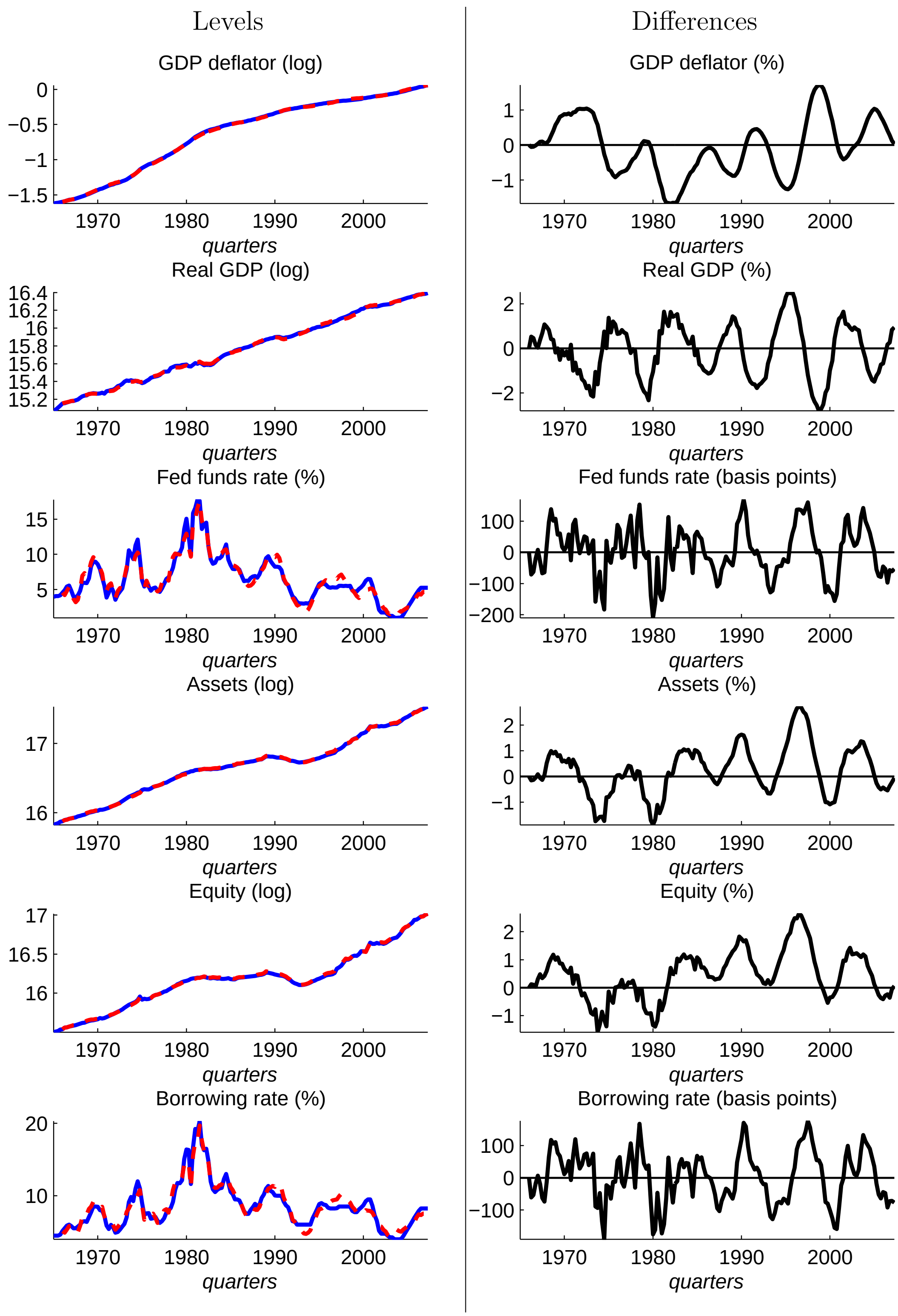
[17] By construction, the counter-factual variables coincide with the data when feeding to the model all structural shocks.

Figure 5: Impulse responses of the restricted models



Notes: This figure shows the impulse responses of the three sign-restricted models that satisfy the Granger-causality restrictions from table 3.

Figure 6: Assessing the role of monetary shocks. Small VAR - model 2



Notes: The left column compares the data (solid blue line) to the counter-factual time series (dashed red line). The counter-factual is computed by generating pseudo data using the estimated model from equation (1) *and feeding into the model only non-monetary shocks. The first 4 observations are set equal to the dataset, while the rest of the computation is set recursively. The right column reports the difference between the true and the counter-factual time series. The period considered is 1966Q1-2007Q2.*

linear time trend and for the trend breaks shown in figure 12 of Appendix C. The results are not affected by the inclusion of these breaks.[18]

The impulse responses from equations (5) are computed for three variables, which are the delinquency rate, the charge-off rate and the leverage ratio of firms. The delinquency rate and the charge-off rate are only available after 1987Q1 and 1985Q1, respectively. This implies that, for the period of interest for this paper, i.e. until 2007Q2 as explained in Section 3.1, I only have 82 and 90 observations, respectively. To address the concern that the sample size is relatively small, I estimate equations (5) using Bayesian methods. Figure 13 in Appendix C documents that the results are robust to using OLS estimation with a 95% bootstrap confidence interval constructed on 500 extractions from the residuals. The leverage ratio of firms is available from 1955Q1, but I use only the data after 1987Q1 in order to ensure comparability with the results for the delinquency and the charge-off rates. The results are robust to the use of a longer time period for the leverage ratio.

For the Bayesian estimation of equation (5), I assume that the error term is normally distributed. I then use the prior belief that the parameters estimated and the inverse of the variance of the error term follow a conjugate Normal-Gamma distribution:

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

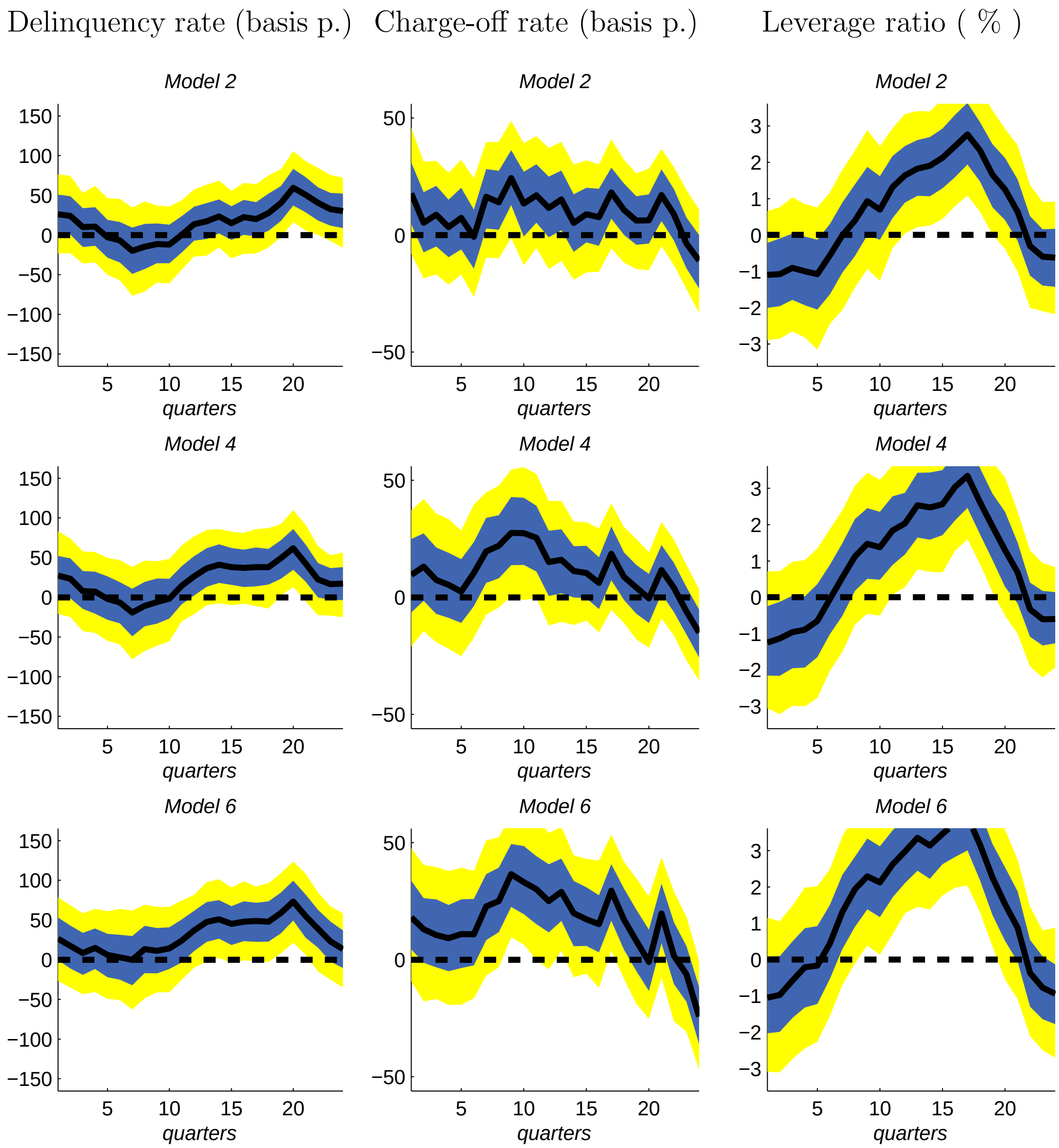
The vector δ equals $(\alpha_l, \beta, \gamma_0, \gamma_1, ..., \gamma_n)$. I calibrate the hyper-parameters $\underline{\delta}, \underline{V}, \underline{s}^{-2}, \underline{\nu}$ to impose a non-informative prior on the deterministic variables and on h. I then impose the prior belief on the parameter α_l such that the prior mean of the impulse response to a monetary shock is zero, i.e. that the monetary shock has no impact on the dependent variable. The variance of α_l is chosen such that the variance of the prior distribution equals the sample variance of the dependent variable. The derivation of how the prior distribution and the data combine into the posterior distribution is available in Koop (2003) and Koop and Korobilis (2009).

Figure 4 shows the impulse responses of the delinquency rate, the charge-off rate and the leverage ratio of firms to an expansionary monetary shock that decreases the federal funds rate by 1%. The figure is divided into three rows, depending on which of the three restricted time series of monetary shocks from Section 3.2 is used. The vertical axis of each graph reports one standard deviation of the dependent variable above zero and one below zero. This is also the standard deviation imposed to the variance of the prior distribution of the impulse response, as explained above. The dashed and solid lines show the prior mean and the posterior mean of the impulse response, respectively. The shaded areas report the 68% and 95% coverage intervals, corresponding approximately to one and two standard deviations from the mean, respectively.

Consider first the impulse responses of the delinquency rate and the charge-off

[18]Formally, $f(\gamma, t)$ equals $\gamma_0 \cdot t + \gamma_1 \cdot tI\{t > \bar{t}_1\} + \gamma_2 \cdot tI\{t > \bar{t}_2\} + ... + \gamma_n \cdot tI\{t > \bar{t}_n\}$, with $\{\bar{t}_0, \bar{t}_1, ..., \bar{t}_n\}$ the points at which trend breaks are included and $I\{.\}$ the indicator function.

Figure 7: Impulse responses for defaults



Notes: The figure shows the effect of a monetary policy shock that generates a 1% decrease in the federal funds rate. The impulse responses are computed using Bayesian estimation of equation (5)*. The dashed line shows the prior mean of the impulse response. The solid line shows the posterior mean of the impulse response. The shaded areas show the 95% and 68% posterior coverage intervals. The prior variance of the impulse response in the Bayesian estimation equals the sample variance of the dependent variable. The vertical axis ranges over one standard deviation from both sides of the prior mean.*

Table 4: Magnitude of the responses to a monetary shock

	Mean	Avg. business cycle variation	Standard deviation	Avg. max response to monetary shock	Avg. response of output
Delinquency rate	3.10%	200 bps	165 bps	65 bps (12Q-20Q)	91 bps
Charge-off rate	0.93%	200 bps	56 bps	30 bps (8Q-12Q)	91 bps
Leverage ratio	1.77	14%	0.05	3.5% (10Q-20Q)	91 bps

Notes: The table summarizes the magnitude of the effects from figure 4 and compares it to some key summary statistics. The monetary shock is set to generate a 1% decrease in the federal funds rate. For the leverage ratio, the average business cycle variation is computed as the percentage difference between the minimum and the maximum value of the variable in the sample period considered. The period considered is 1985Q1-2007Q2.

rate. Overall, figure 4 suggests that the default probability on loans by firms does not respond significantly at the beginning, and then increases significantly above zero for approximately one year. The exact timing and magnitude of the effect depends on whether one measures the default probability using the delinquency rate or the charge-off rate. The delinquency rate tends to increase by 65 basis points three years after the shock. This effect is statistically significant only for the 20th quarter. The increase in the charge-off rate, instead, occurs after two years from the monetary shock, it equals 30 basis points and it is statistically significant for 1 to 4 quarters.

Table 4 helps to assess the economic relevance of the effects shown in figure 4. It reports the average maximum increase across models implied by figure 4, together with the average number of quarters for which the effect is statistically significant. It compares this effect to the mean, the average business cycle variation and the standard deviation of the variable, as well as against the average effect that the same shock generates on output. The monetary shock delivers a variation in the delinquency rate and in the charge-off rate that equals around 1/3 and 1/6 of their business cycle variation, respectively, and that equals 1/3 and 1/2 of their standard deviation, respectively. This effect is surprisingly big given the relative small effect of monetary policy shocks on output. As shown in figure 5 from Section 3.2, the three restricted small VAR models predict an increase in real GDP of 87, and 72 and 114 basis points, respectively. The increases in the delinquency rate and the charge-off rate equal as much as more than half of the increase in real GDP.

The last result of this section relates to the effect of monetary policy shocks on the leverage ratio of firms. It was anticipated in the introduction that one possible reason why the default rate on loans by firms increases in response to a monetary expansion is that firms increase their level of indebtedness. Under certain conditions this increase in firms' debt pushes up their leverage ratio, which implies a higher risk of default. The last column of figure 4 reports the impulse response of the leverage ratio of firms. Overall, the monetary shock generates a statistically significant increase in the leverage ratio starting from one year and a half after the shock, which peaks to of around 3.5% three years after the shock. I find this effect economically significant, since it equals one forth of the percentage variation of the leverage ratio between the minimum and the maximum value observed in the period considered. This variation equals 14% which is computed as the percentage difference between 1.63 (in 1985Q1) and 1.87 (in 2000Q2).[19] Applied to the mean level of leverage, this effect implies an increase in leverage from 1.77 to 1.83. Equivalently, it implies that the share of assets financed with debt increases from 43% to 45%.

4 Robustness of the results

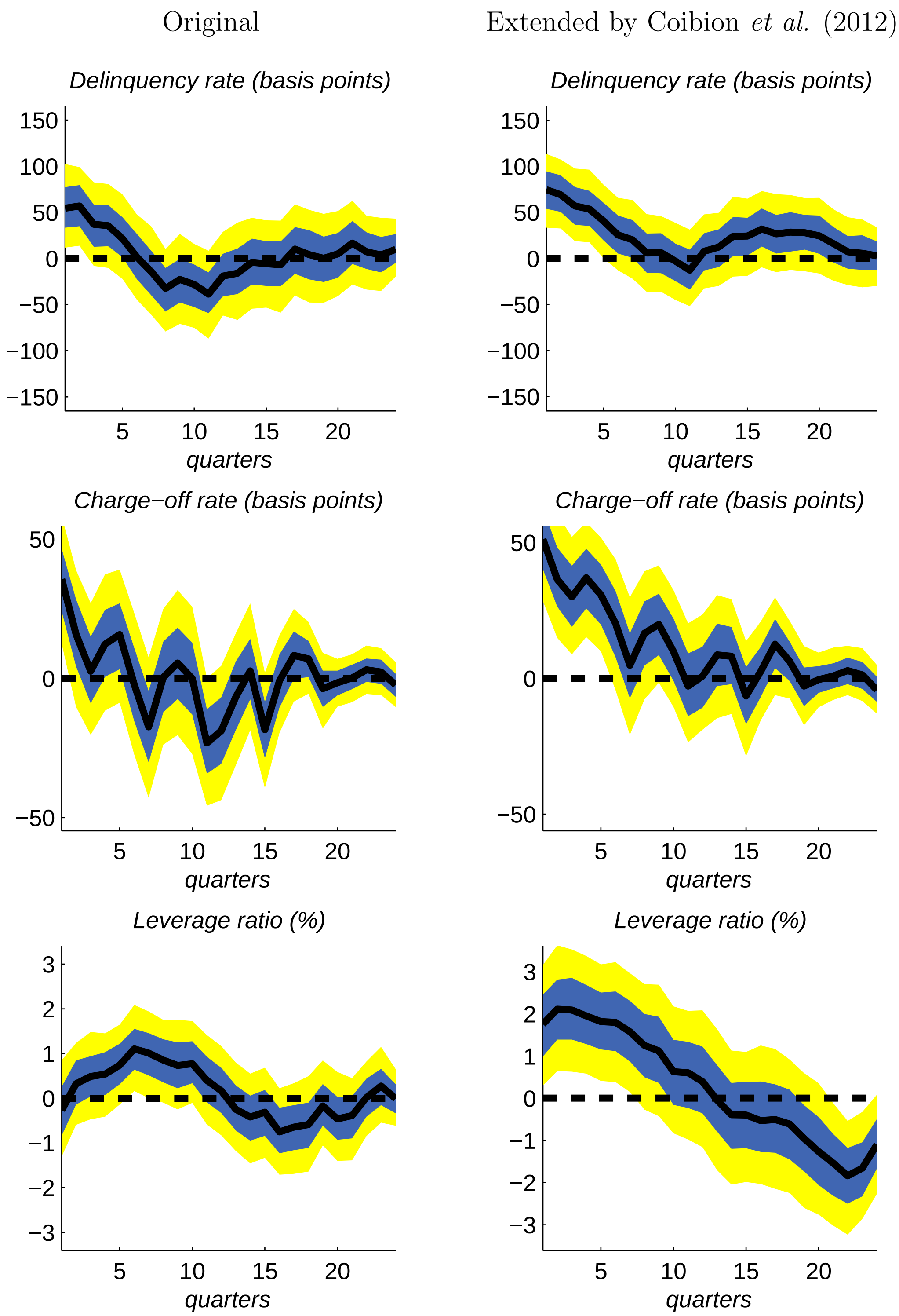
The use of Bayesian estimation allows to address the robustness of the results of figure 4 by using alternative prior beliefs. In particular, it is informative to go against the result of the previous section and impose the prior belief that the loan default rate and the leverage ratio of firms *decrease* in response of a monetary expansion. It is then left to the exercise to see if such a prior is consistent with the data.

Figure 14 in Appendix C replicates the analysis of figure 4 by imposing that the prior mean of the impulse response of the delinquency rate and the charge-off rate decreases by 100 basis points. This decrease equals half of the average variation of the two rates along the business cycle, as commented in Section 2. It is interesting to see that such a strong prior is not enough to revert the result of an increase in the default rate on loans. The increase in the delinquency rate after twenty quarters is still in place, and its statistical significance is unchanged. The charge-off rate still increases two years after the shock, but now insignificantly. The increase in the charge-off rate after six quarters remains significant. The same analysis is reported for the leverage ratio. The prior belief imposed is that the leverage ratio decreases by 6%, which is half of the maximum percentage variation of the leverage ratio in the relevant sample period. The figure shows that the leverage ratio still increases, and that this increase is statistically significant.

Another robustness check of the results from figure can be done using the time series of monetary shocks that had been ruled out using Granger-causality tests. For simplicity I only report the exercise from the Romer and Romer shocks (figure 8), although a similar results holds for other restricted models. The results of an increase in the loan default rates and in the leverage ratio of firms hold also for monetary shocks that had been ruled out in Section 3.2. What is interesting to notice is that the

[19] I use this measure instead of a typical variation over the business cycle, as for defaults, because the leverage ratio does not display a clear cyclicality but more a trending behaviour with several breaks.

Figure 8: Impulse responses using Romer and Romer shocks



Notes: The figure shows the effect of a monetary policy shock that generates a 1% decrease in the federal funds rate. The impulse responses are computed using Bayesian estimation of equation (5). The dashed line shows the prior mean of the impulse response. The solid line shows the posterior mean of the impulse response. The shaded areas show the 95% and 68% posterior coverage intervals. The prior variance of the impulse response in the Bayesian estimation equals the sample variance of the dependent variable. The vertical axis ranges over one standard deviation from both sides of the prior mean.

Granger-causality tests help to nest down the *timing* of these effects. In fact, some of the models that had been ruled out predict that the increase in defaults and in leverage occur on impact. While this result could be plausible for the leverage ratio, it is hard to believe that a monetary expansion can possibly generate an increase in the default rate on loans on impact. Such an effect is more likely to be due to some endogeneity still captured in the candidate monetary shock which reflects that it is the federal funds rate that decreases in response to a high delinquency and charge-off rate. The Granger-causality tests of Section 3.2 suggest that this is indeed the case, and that such representations of the data should be dismissed.

5 Conclusions

This paper studies the effect of an unexpected monetary shock on the the probability that firms default on loans. Jimenez *et al.* (2010), Ioannidou *et al.* (2009) and Lopez *et al.* (2011) have found that a monetary expansion decreases the probability of default on existing loans and increases the probability of default on new loans. Their analyses focus on Spain, Bolivia and Colombia, respectively. I report evidence on the US that suggests that the aggregate default probability on business loan does not respond during the first two to three years, and then increases for a year. The increase is both statistically and economically significant.

The literature tends to interpret the results by Jimenez *et al.* (2010), Ioannidou *et al.* (2009) and Lopez *et al.* (2011) in terms of a risk-shifting effect by banks, according to which banks react to the lower cost of borrowing by shifting towards relatively more risky loans. Indeed, several contributions support this interpretation, including Maddaloni and Peydró (2011) and Paligorova and Santos (2012). In a related paper (Piffer (2013)) I argued that part of the increase in defaults could also come from the fact that a monetary expansion potentially leads firms to take on more leverage because it decreases the cost of debt. I have shown that empirical evidence is consistent with this interpretation, as the leverage ratio of US non-financial firms does increase after a monetary expansion.

References

[1] ACHARYA V. and N. HASSAN (2012): "The seeds of a crisis: a theory of bank liquidity and risk-taking over the business cycle", *Journal of Financial Economics*, vol. 106(2)

[2] ADRIAN T. and H. S. SHIN (2007): "Liquidity and Leverage"

[3] ADRIAN T. and H. S. SHIN (2008): "Financial Intermediaries, Financial Stability, and Monetary Policy", FRB of New York Staff Report No. 346

[4] AGUR I. and M. DEMERTZIS (2012): "Excessive Bank Risk Taking and Monetary Policy", ECB Working Paper 1457

[5] ALTUNBAS Y., L. GAMBACORTA and D. MARQUEZ-IBANEZ (2010): "Does Monetary Policy affect Bank Risk-Taking?", BIS Working Paper 298

[6] ANGELONI I. and E. FAIA (2013): "Capital Regulation and Monetary Policy with Fragile Banks", *Journal of Monetary Economics*, vol. 60(3), 3111 - 3182

[7] BANBURA M., D. GIANNONE and L. REICHLIN (2009): "Large Bayesian Vector Auto Regressions", *Journal of Applied Econometrics*, vol. 25(1), 71 - 92

[8] BARTH III M. and V. RAMEY (2002): "The Cost Channel of Monetary Transmission", NBER Macroeconomics Annual, vol. 16

[9] BERNANKE B. and A. BLINDER (1992): "The Federal Funds Rate and the Channels of Monetary Transmission", *American Economic Review*, vol. 82(4), 901 - 921

[10] BERNANKE B., J. BOIVIN and P. ELIASZ (2005): "Measuring the Effects of Monetary Policy: Factor-Augmented Vector Autoregressive (FAVAR) Approach", *Quarterly Journal of Economics*, vol. 120(1), 387 - 422

[11] BERNANKE B., and MIHOV I. (1998): "Measuring Monetary Policy", *Quarterly Journal of Economics*, vol. 113(3), 879 - 902

[12] BOIVIN J., M. T. KILEY and F. S. MISHKIN (2011): "How has the Monetary Transmission Mechanism Evolved Over Time?", in *Handbook of Monetary Economics*, vol. 3A, 369 - 422

[13] BORIO C. and H. ZHU (2008): "Capital Regulation, Risk Taking and Monetary Policy: a Missing Link in the Transmission Mechanism", BIS Working Paper

[14] BRUNO V. and H. S. SHIN (2012): "Capital Flows and the Risk-Taking Channel of Monetary Policy", BIS Working Paper No. 400

[15] CANOVA F. and G. DE NICOLÓ (2002): “Monetary disturbances matter for business fluctuations in the G-7”, *Journal of Monetary Economics*, vol. 49, 1131 - 1159

[16] CANOVA F. and J. P. PINA (1999): “Monetary Policy Misspecification in VAR Models”

[17] CASTELNUOVO E. (2012): “Monetary Policy Neutrality? Sign Restrictions go to Monte Carlo”

[18] CHALLE E., B. MOJON AND X. RAGOT (2013): “Equilibrium Risk Shifting and Interest Rate in an Opaque Financial System”, *European Economic Review*, vol. 63, 117 - 133

[19] CHRISTIANO L. M. EICHENBAUM and C. EVANS (1999): “Monetary Policy Shocks: What have we learned and to what end”, in *Handbook of Macroeconomics*, vol. 1, part A, 65 - 148

[20] CHRISTIANO L. M. TRABANDT and K. WALENTIN (2011): “DSGE Models for Monetary Policy Analysis”, in *Handbook of Monetary Economics*, vol. 3A

[21] CICCARELLI M. and A. REBUCCI (2003): “Bayesian VARs: A Survey of the Recent Literature with an Application to the European monetary System”, IMF working paper WP/03/102

[22] COCIUBA S., M. SHUKAYEV and A. UEBERFELDT (2012): “Collateralized Borrowing and Risk Taking at Low Interest Rates?” University of Western Ontario, Economic Policy Research Institute Working Papers 20121, University of Western Ontario, Economic Policy Research Institute

[23] COIBION O. (2012): “Are the effects of monetary policy shocks big or small?”, *American Economic Journal: Macroeconomics*, vol. 4(2), 1 - 32

[24] COIBION O., GORODNICHENKO Y., KUENG L. and SILVIA J. (2012): “Innocent Bystanders? Monetary Policy and Inequality in the U.S.”

[25] COOLEY T. F and S. F. LeROY (1985): “Atheoretical Macroeconometrics”, *Journal of Monetary Economics*, vol. 16, 283 - 308

[26] DE NICOLÓ G., G. DELL’ARICCIA, L. LAEVEN and F. VALENCIA (2010): “Monetary Policy and Bank Risk Taking”, IMF working paper

[27] DELL’ARICCIA G., L. LAEVEN and R. MARQUEZ (2010): “Monetary Policy, Leverage, and Bank Risk-Taking”, IMF working paper

[28] DEN HAAN W. J. and V. STERK (2011): "The Myth of Financial Innovation and the Great Moderation", *The Economic Journal*, vol. 121(553), 707 - 739

[29] DREES B., B. ECKWERT and F. VARDY (2012): "Cheap money and Risk Taking: Opacity versus Fundamental Risk"

[30] DUBECQ S., B. MOJON and X. RAGOT (2009): "Fuzzy Capital Requirements, Risk-Shifting and the Risk Taking Channel of Monetary Policy", Working papers 254, Banque de France

[31] EICKMEIER S. and B. HOFMANN (2012): "Monetary policy, housing booms and financial (im)balances", *Macroeconomic Dynamics*, vol. 17(4), 830 - 860

[32] FAHRI E. and J. TIROLE (2009): "Leverage and the Central Banker's Put", *American Economic Review: P & P*, vol. 99(2), 589 - 593

[33] FORNI M.. and L. GAMBETTI (2010): "The dynamic effects of monetary policy: A structural factor model approach", *Journal of Monetary Economics*, vol. 57, 203 - 216

[34] FRY R. and A. PAGAN (2011): "Sign Restrictions in Structural Vector Autoregressions: A Critical Review", *Journal of Economic Literature*, vol. 49(4), 938 - 960

[35] GALÍ J. (2008): "Monetary Policy, Inflation, and the Business Cycle", Princeton University Press

[36] IOANNIDOU V., S. ONGENA and J. PEYDRÓ (2009): "Monetary Policy, Risk-Taking and Pricing: Evidence from a Quasi-Natural Experiment"

[37] JIMENEZ G, S. ONGENA, J. PEYDRÓ and J. SAURINA (2010): "Hazardous Times for Monetary Policy: What do Twenty-Three Million Bank Loans Say about the Effects of Monetary Policy on Credit Risk-Taking?", Bank of Spain, Documentos de Trabajo, n. 0833

[38] JIMENEZ G, S. ONGENA, J. PEYDRÓ and J. SAURINA (2013): "Hazardous Times for Monetary Policy: What do Twenty-Three Million Bank Loans Say about the Effects of Monetary Policy on Credit Risk-Taking?", *Econometrica* (forthcoming)

[39] JORDA O. (2005): "Estimation and Inference of Impulse Responses by Local Projections", *American Economic Review*, vol. 95(1)

[40] KADIYALA K. R. and S. KARLSSON (1997): "Numerical Methods for Estimation and Inference in Bayesian VAR-Models", *Journal of Applied Econometrics*, vol. 12, 99 - 132

[41] KILIAN L. (2012): “Structural Vector Autoregressions”,

[42] KOOP G. (2003): “Bayesian Econometrics”, John Wiley & Sons.

[43] KOOP G. and D. KOROBILIS (2009): “Bayesian Multivariate Time Series Methods for Empirical Macroeconomics”

[44] LEVIN A., NATALUCC F. M. and E. ZAKRAJSEK (2004): “The Magnitude and Cyclical behaviour of Financial Market Frictions”

[45] LOPEZ M., F. TENIJOU and H. ZARATE (2011): “The risk-taking channel and monetary transmission mechanism in Colombia”

[46] MADDALONI A. and J. PEYDRÓ (2011): “Bank Risk-Taking, Securitization, Supervision and Low Interest Rates; Evidence From the Euro Area and the US Lending Standards”, *Review of Financial Studies*, vol. 24, 2121 - 2165

[47] MILES D. (2010): “Leverage and Monetary Policy”, speech delivered at the ESRI/FFS Conference, Dublin, 12 October

[48] PALIGOROVA T. and J. SANTOS (2012): “Monetary policy and bank risk-taking: evidence from the corporate loan market”

[49] PAUSTIAN M. (2007): “Assessing Sign Restrictions”, *The B.E. Journal of Macroeconomics*, vol. 7(1)

[50] PIFFER M. (2013): “Monetary Policy, Leverage, and Default”

[51] PRIMICERI G. (2005): “Time Varying Structural Vector Autoregressions and Monetary Policy”, *The Review of Economic Studies*, vol. 72, 821 - 852

[52] OLIVEI G. and S. TENREYRO (2007): “The Timing of Monetary Policy Shocks”, *American Economic Review*, vol. 97 (3), 636 - 663

[53] RAJAN R. (2006): “Has Finance Made the World Riskier”, *European Financial Management*, vol. 12(4), 499 533

[54] ROMER C. and ROMER D. H. (1989): “Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz”, in *NBER Macroeconomics Annual*, vol. 4, 121 - 184

[55] ROMER C. and ROMER D. H. (2004): “A New Measure of Monetary Shocks: Derivation and Implications”, *American Economic Review*, vol. 94(4), 1055 - 1084

[56] RUBIO-RAMIREZ J.F., D.F. WAGGONER and T. ZHA (2005), “Markov-Switching Structural Vector Autoregressions: Theory and Application”, Working Paper 2005-27, Federal Reserve Bank of Atlanta

[57] STEIN J. (2012): "Monetary Policy as Financial-Stability Regulation", *Quarterly Journal of Economics*, vol. 127(1), 57 - 95

[58] TENREYRO S. and G. THWAITES. (2013): ""Pushing On a String: US Monetary Policy is Less Powerful in Recessions", CEP Discussion Papers dp1218, Centre for Economic Performance, LSE.

[59] TOWNSEND R. (1979): "Optimal Contracts and Competitive Markets with Costly State Verification", *Journal of Economic Theory*, vol. 21, 265 - 293

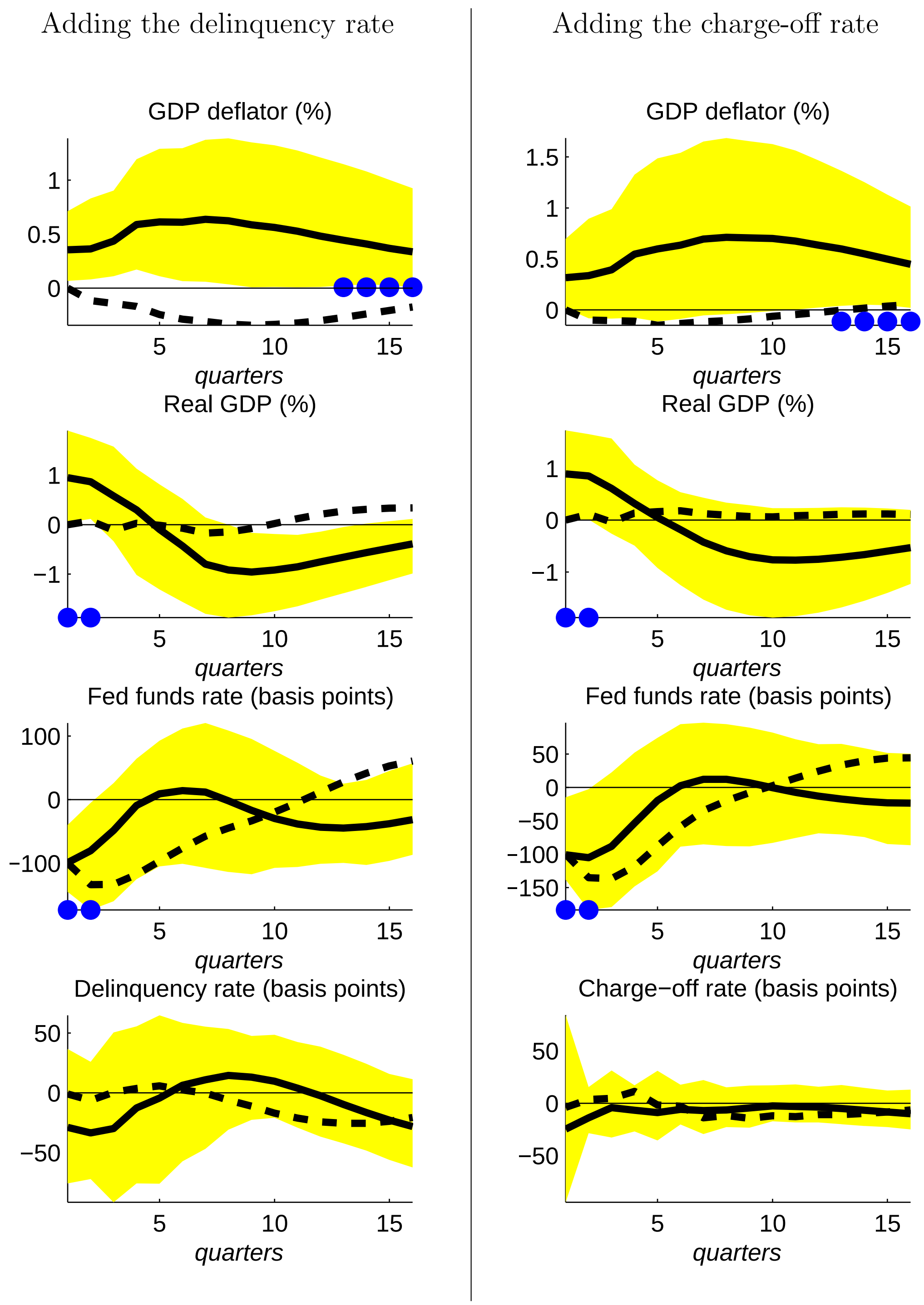
[60] UHLIG H. (2005): "What are the effects of monetary policy on output? Results from an agnostic identification procedure", *Journal of Monetary Economics*, vol.52, 381 - 419

[61] VALENCIA F. (2011): "Monetary policy, bank leverage and financial stability", IMF working paper, WP/11/244

6 Appendix A: Preliminary analysis

This Appendix shows the impulse responses from two small VAR models. Both models include log of real GDP, log of the GDP deflator and the federal funds rate. They then include either the delinquency rate or the charge-off rate. The estimation and identification is identical to the analysis in Section 3.1, except that it also reports the impulse response from the Cholesky identification. The sample period is 1987Q1-2007Q2 for the model with the delinquency rate and 1985Q1-2007Q2 for the model with the charge-off rate. Figure 9 shows that the results are in general inconclusive. The Cholesky identification does not capture something that economic theory would associate to a monetary expansion. The sign-restricted models do by construction, but the effect on the default probability on loans is not clear. This could be due to the relatively short sample period considered.

Figure 9: Preliminary analysis: small VARs with delinquency and charge-off rates



Notes: The dashed and solid lines show the response from the Cholesky identification and from the sign-restricted median target identification. The shaded area shows the 95% sign-restricted models. The blue dots where sign restrictions are imposed.

7 Appendix B: algorithm to generate orthogonal matrices

The matrix P_{ee} is computed by first decomposing the matrix Σ into a matrix A of its eigenvectors and a matrix B listing its eigenvalues along the diagonal. The matrix P_{ee} is then defined as $A * B^0.5$ and it satisfies the condition $P_{ee}P'_{ee} = \Sigma$ by construction. Given P_{ee}, the computation of L candidate matrices P_{cand} that satisfy condition 3 from Section 3.1 requires the generation of L kxk matrices Q satisfying condition $QQ' = I$, where k is the number of variables included in Y_t of equation (1). Since there are infinite possible representations of the data, the richer the set of Qs considered, the more likely it is that the true matrix P^* that has generated the data is actually replicated in the model.

I start by generating $3 \cdot M$ 2x2 orthogonal matrices. Rubio-Ramirez, Waggoner and Zha (2005) generate orthogonal matrices using the QR decomposition, while Canova and De Nicoló (2002) use Givens rotation.[20] In this paper I use both approaches. QR orthogonal matrices R_{qr} are generated using the orthogonal-triangular decomposition of a matrix. This operation decomposes a 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 instead defined as

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

with $\theta \in [0, 2\pi]$.[21] The orthogonality of R_{rot} 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

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

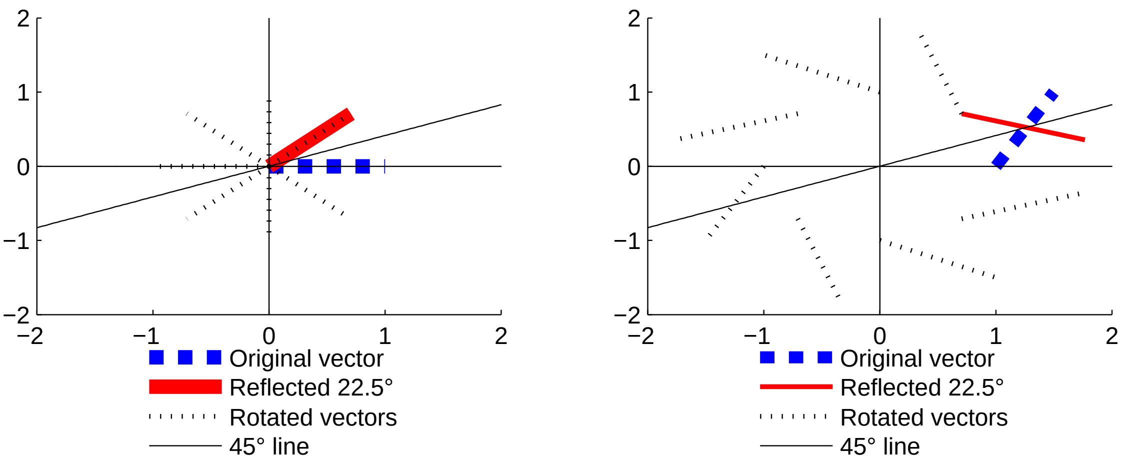
Rotation matrices generate a vector $y = x \cdot R_{rot}$ such that the vector x is rotated clockwise (or a vector $y = R_{rot} \cdot x$ such that the vector x is rotated counter-clockwise) by an angle of θ about the origin of the Cartesian coordinate system. Reflection matrices, instead, generate a 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 vectors coincide, the set of vectors

[20] 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.

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

generated through rotations does not fully overlap with the set of vectors generated by reflection matrices, as illustrated intuitively with the exercise in figure 10. 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 10: Rotation vs. reflection matrices

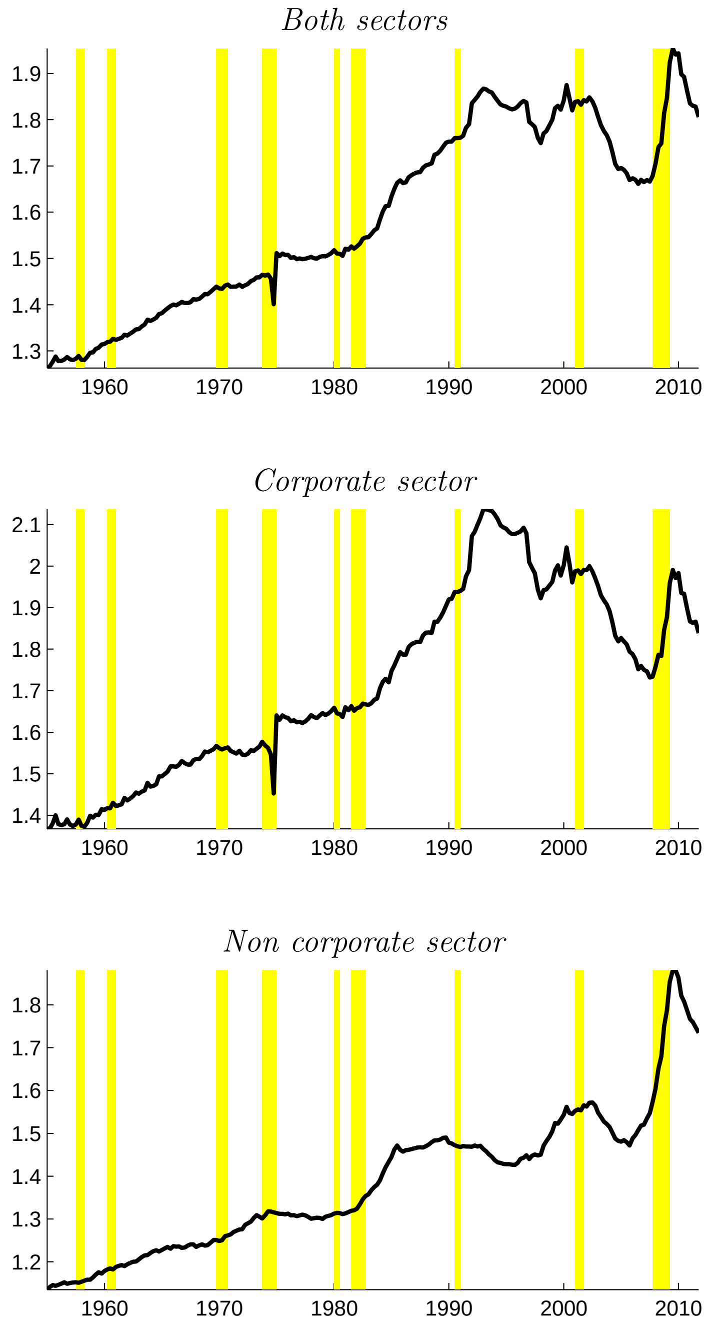


Notes: The left graph shows that the reflection around the 22.5 degree line of the vector between point (0,0) and point (1,0) (blue dashed line) gives the vector between point (0,0) and (0.7071, 0.7071) (red solid line). The same vector, though, is generate by a counter-clockwise rotation of the original 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.

Last, the $3 \cdot M$ 2x2 $R = \{R_{qr}, R_{rot}, R_{refl}\}$ orthogonal matrices generated through rotations, reflections and QR decompositions need to be combined into 6x6 orthogonal matrices. This is achieved using a multiplication similar in spirit to Canova and De Nicoló (2002). For each of the L kxk orthogonal matrices $Q(i)$ that needs to be generated, extract k 2x2 matrices R. Generate then a kxk identity matrix E. Select two of its columns a and b randomly and rewrite 4 of the elements of E as $E(a,a) = R(1,1)$, $E(a,b) = R(1,2)$, $E(b,a) = R(2,1)$ and $E(b,b) = R(2,2)$. The matrix Q is obtained by multiplying the k matrices E obtained. By construction Q is an orthogonal matrix and can be used to generate alternative structural representations of the data. Unreported robustness checks found that the results are not affected by the exact value of M as long as it is not too small. In the paper, M is set equal to 500.

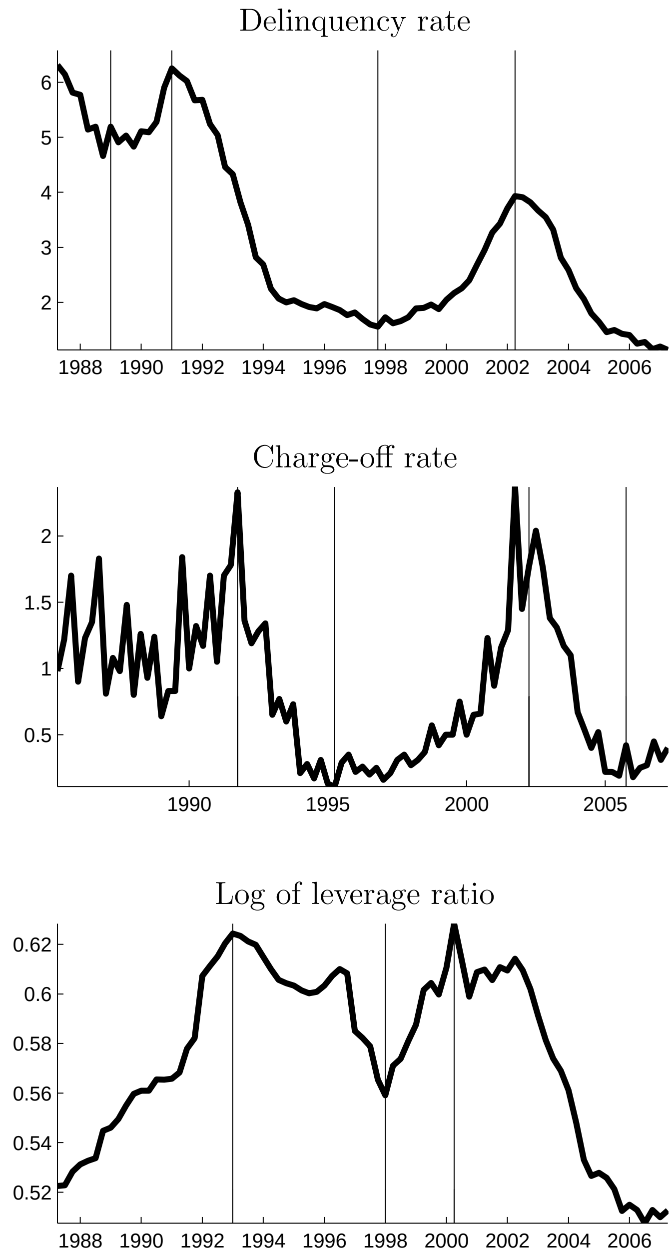
8 Appendix C: additional graphs

Figure 11: Firms' leverage ratio, full sample period



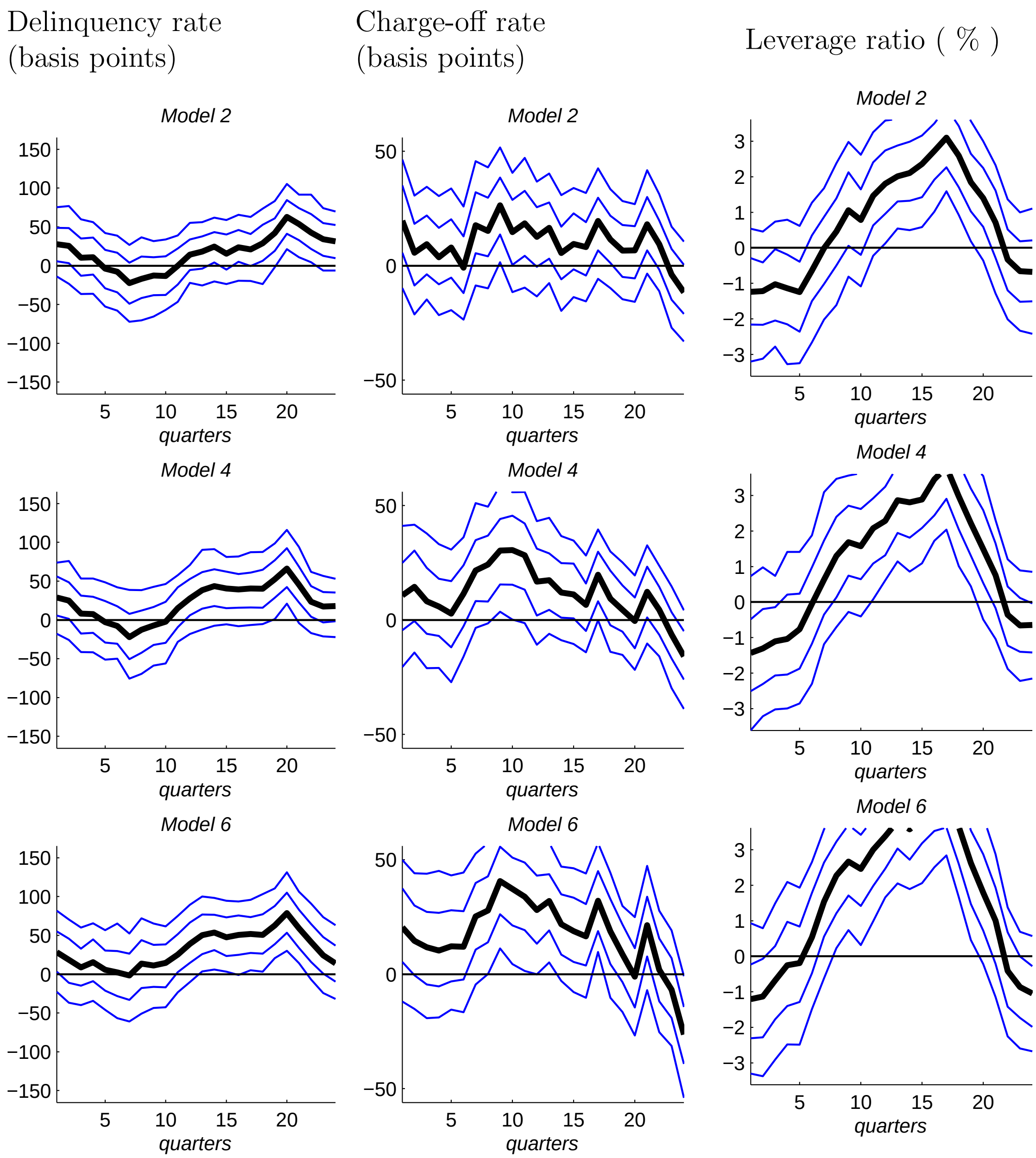
Notes: the shaded bands indicate NBER recessions. The marked fall and hike in the aggregate leverage ratio of corporate firms in 1974Q4 is due to an initial fall in trade payables and a consequent spike in tax payables.

Figure 12: Trend breaks included in equation (5)



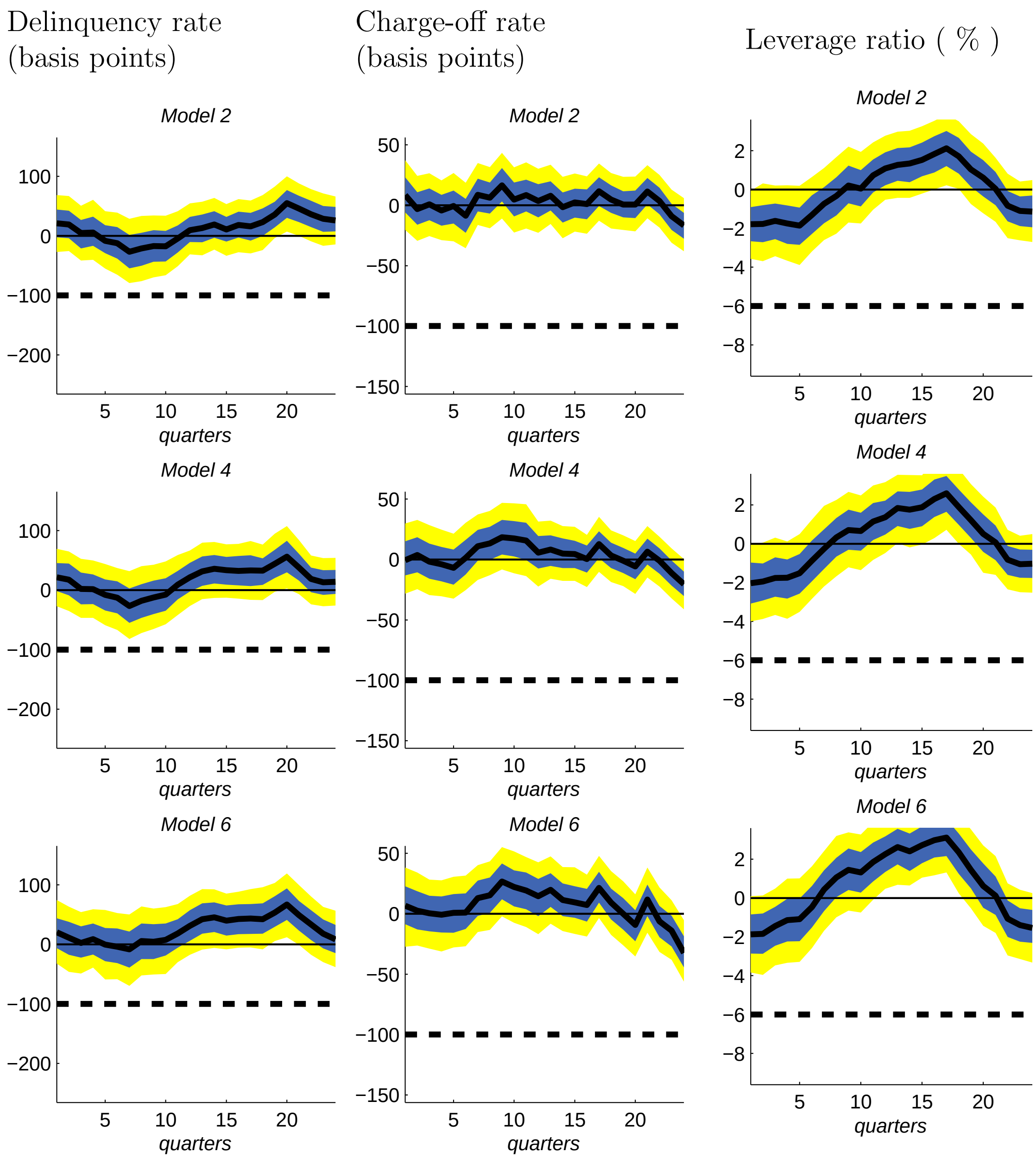
Notes: The vertical lines show where trend breaks in the linear trend are included in the estimation of equations (5).

Figure 13: Impulse responses using restricted shocks - OLS estimation



Notes: The impulse responses are computed using OLS estimation with a 95% and a 68% bootstrap confidence interval on 500 iterations. For comparability, the vertical axis range on the same values as from figure 4.

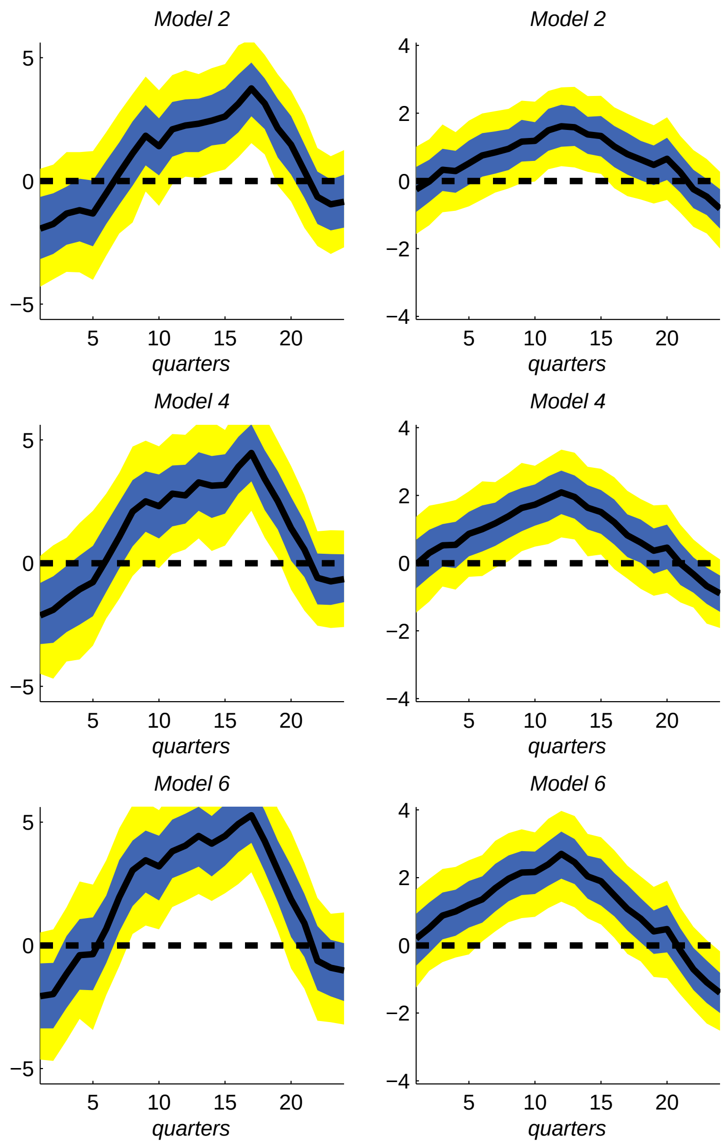
Figure 14: Impulse responses with a different prior mean



Notes: The figure shows the effect of a monetary policy shock that generates a 1% decrease in the federal funds rate. The impulse responses are computed using Bayesian estimation of equation (5)*. The dashed line shows the prior mean of the impulse response. The solid line shows the posterior mean of the impulse response. The shaded areas show the 95% and 68% posterior coverage intervals. The prior variance of the impulse response in the Bayesian estimation equals the sample variance of the dependent variable. The vertical axis ranges over one standard deviation from both sides of the prior mean.*

Figure 15: Impulse responses for leverage, corporate vs. non corporate

Corporate sector Non-corporate sector



Notes: The figure shows the effect of a monetary policy shock that generates a 1% decrease in the federal funds rate. The impulse responses are computed using Bayesian estimation of equation (5)*. The dashed line shows the prior mean of the impulse response. The solid line shows the posterior mean of the impulse response. The shaded areas show the 95% and 68% posterior coverage intervals. The prior variance of the impulse response in the Bayesian estimation equals the sample variance of the dependent variable. The vertical axis ranges over one standard deviation from both sides of the prior mean.*