Combining zero and sign restrictions in VAR models: identifying credit supply shocks in the Netherlands

Fabio Duchi

May 17, 2015

Abstract

I use the algorithm of Arias et al. (2014), combining sign and zero restrictions in a SVAR framework, in order to disentangle the role of credit supply shocks in the Netherlands. Unlike previous methods of combining sign and zero restrictions, this algorithm has been proven to draw from the correct posterior of the structural parameters. I find that after a one standard deviation credit supply shock, M3 growth decreases immediately by about 1.50 percentage points while GDP growth slows down by approximately 0.60 percentage points over a period of more than two years. Whereas credit supply shocks impaired economic and lending activity around 2007/08 and 2010, those disturbances were not significantly depressing GDP growth after the second half of 2011.

JEL Classification: c32; E51; G01
Keywords: Credit Supply; Great recession; Sign restrictions; Zero restrictions

1 Introduction

Structural Vector Autoregressive (SVAR) models have become important tools to answer questions relevant for policy analyses. In simple terms, these models start from a time-series structure — where every variable is regressed on its lags and on the lags of the other variables analysed (VAR part) — and then disentangle the underlying macroeconomic forces using economic theory (the Structural part). Looking only at the relationship between our variables over time (VAR part), it is hard to make inferences on which macroeconomic shocks have driven movements in those variables. Therefore, we need to use economic intuition to explain macroeconomic changes.

Economic theory is incorporated in the initial VAR model using the so-called *identifying restrictions*, which can be divided into two main groups: zero and sign restrictions. Zero restrictions are set on variables that are not affected by the shock of interest for a certain period of time. For instance, financial shocks are usually assumed to have a lagged effect on aggregate macroeconomic indicators (e.g. GDP), so that on impact the researcher can impose a zero restriction on these variables. On the other hand, sign restrictions incorporate the expected co-movements of some variables following a shock. As an example, aggregate supply shocks are expected to move prices and output in opposite direction, whereas aggregate demand disturbances move them in the same direction. Given this information on how the structural shocks are expected to affect our variables, the Structural VAR model disentangles the underlying macroeconomic shocks from one another, enabling the researcher to explain the observed time-series movements. After the seminal work of Sims (1980), Structural VAR have been used to study technology shocks (Peersman & Straub, 2009) and monetary policy shocks (Uhlig, 2005), among other things.

Zero and sign restrictions do not impose the same type of information on the model. While zero restrictions specify that some variables are not affected by a shock, the sign restrictions incorporate information on how some macroeconomic indicators are expected to react to a structural disturbance. Ideally, one would like to have the freedom to use both sets of restrictions, depending on the type of economic shock of interest. The standard methodologies used for imposing those restrictions were, however, difficult to implement simultaneously. The first important contribution to this conundrum came from Mountford & Uhlig (2009), who devised a penalty function approach to draw the structural parameters. Baumeister & Benati (2010), Benati (2013) and Binning (2013) later advanced alternative ways to implement both sign and zero restrictions. To the best of my knowledge, Arias, Rubio-Ramirez & Waggoner (2014) are nevertheless the only ones that theoretically prove their algorithm correctly draws from the posterior distribution of structural parameters conditional on the sign and zero restrictions. Using their methodology, the practitioner is confident that his results will not be biased by additional and unwanted sign restrictions.

Arias et al. (2014) proposed both the econometric theory and an efficient algorithm that can correctly impose sign and zero restrictions in SVAR models. My aim is to apply this new algorithm to capture the role of credit (or loan) supply shocks in the Netherlands. The identification scheme used follows Barnett & Thomas (2013). When dealing with financial innovations, zero restrictions can be used to set that those shocks impact the real economy with a lag. Via sign restrictions, I can then distinguish credit supply shocks from other financial forces. This objective has become much more relevant after the financial crisis started in 2008, which emphasized how credit intermediation problems are important *per se* and do not only represent endogenous responses to disturbances originated in other sectors of the economy (Peersman, 2011). Financial institutions can, in other words, engender shocks driving economic fluctuations.[1]

I find that the Dutch economy experienced adverse credit supply shocks in 2007 and 2008, when the first signs of global financial distress were followed by the bankruptcy of Lehman Brothers (Trichet, 2010), and between 2010 and 2011, when Europe was hit by the sovereign debt crisis (European Central Bank, 2011). In the Netherlands, after a typical and adverse credit supply shock, M3 growth decreases by about 1.50 percentage points in the same quarter, while GDP growth slows down for more than two years and cumulatively diminishes by approximately 0.60 percentage points. Since 2011, GDP growth has not been significantly depressed by adverse bank lending shocks. The results are robust when using partial identification. That shows how a good identification of credit supply shocks does not require a full set of additional innovations, and that the extra shocks do not influence my main conclusions.

The rest of the paper is structured as follows. Section 2 reviews the identification problem and briefly introduces the algorithm used in this paper.

[1]Previous studies denoted these credit supply disturbances under the name of loan supply shocks or bank lending shocks. These definitions will be used interchangeably in the rest of the paper.

Section 3 starts by putting my research on the effect of credit supply shocks in the Netherlands in context. The following sub-sections outline data, methodology and the identifying scheme used. All the results on the Dutch case are provided in section 3.4. Finally, there is room for discussing some methodological issues, e.g. partial identification, and robustness checks.

2 Sign and zero restrictions - an overview

Typically, econometric analysis with VAR models starts with the reduced form[2], where each dependent variable is regressed on its own lags and on the lags of the other variables. In matrix notation, this can be expressed by:

$$\mathbf{y_t} = \mathbf{c} + A_1\mathbf{y_{t-1}} + A_2\mathbf{y_{t-2}} + \cdots + A_p\mathbf{y_{t-p}} + \mathbf{u_t} \tag{1}$$

where $\mathbf{y_t}$ represents an $n \times 1$ vector containing the endogenous variables at quarter t, $\mathbf{c}$ is a vector of constant terms, A_p are $n \times n$ matrices of coefficients, $\mathbf{u_t}$ are the reduced-form error terms with zero mean and covariance matrix Σ. System (1) can also be rewritten in this form:

$$\mathbf{y_t} = B\mathbf{x_t} + \mathbf{u_t} \tag{2}$$

where $B = [\mathbf{c} \ A_1 \ A_2 \ \cdots \ A_p]$ while $\mathbf{x} = [1 \ \mathbf{y}'_{\mathbf{t-1}} \ \mathbf{y}'_{\mathbf{t-2}} \ \cdots \ \mathbf{y}'_{\mathbf{t-p}}]'$. The reduced form cannot serve as a basis for structural analyses because of cross-correlation between the reduced-form errors. To give an economic meaning to the equations in the model, one needs to isolate some exogenous shocks. This is done by imposing restrictions on a decomposition of Σ, and then by computing the structural form:

$$A_0\mathbf{y_t} = \mathbf{k} + A_1^\star\mathbf{y_{t-1}} + A_2^\star\mathbf{y_{t-2}} + \cdots + A_p^\star\mathbf{y_{t-p}} + \epsilon_\mathbf{t} \tag{3}$$

where A_0 is an $n \times n$ matrix containing the contemporaneous reactions of the variables to the structural shocks, $A_p^\star$ are $n \times n$ matrices of structural coefficients for system (3) and $\epsilon_\mathbf{t}$ is an $n \times 1$ vector of structural innovations (or shocks) with $E[\epsilon\epsilon'] = I$, i.e. the identity matrix. By itself, system (3) is unidentified, i.e. it cannot be solved. The practitioner must then use economic theory to apply some restrictions on the model and hence distinguish structural shocks from one another — the *identification problem*. There are

[2]For a more detailed introduction to the SVAR (and also VAR) model, I recommend the working papers by Gottschalk (2001) and Lütkepohl (2011). More advanced material can be found in Lütkepohl & Krätzig (2004) and Hamilton (1994).

two main sets of restrictions that the practitioner can use: zero and sign restrictions. I am going to briefly discuss them in turn.

To start with, Sims' (1980) solution to the identification problem was to apply zero constraints on the matrix A_0, using a recursive structure that determines which variables are unaffected by some structural innovations on impact.[3] In other words, using zero restrictions, the practitioner specifies the variables that, according to economic theory, respond with a lag of one period to the structural shocks we are interested in. Financial shocks, as an example, can be assumed to have a lagged effect on the real economy, and placing some zero restrictions on aggregate macroeconomic variables (e.g. GDP) we can incorporate this information in the model. Using zero restrictions system (3) becomes identified, its parameters can be estimated and finally the impact of the structural shocks (the ones that have been included via the zero restrictions) on macroeconomic movements can be understood. Nevertheless, a lot of zero restrictions are required for large SVAR models, which casts doubts on how agnostic and theory-driven the subsequent identification schemes are. For instance, in order to identify a 6-variable model, the practitioner has to impose 15 zero restrictions. It might be hard to theoretically justify the imposition of such a large number of zero restrictions.

Sign-based restrictions provide an alternative way to do structural inference.[4] These restrictions are based on the expected co-movement of economic variables following a shock — information that could not be implemented with the zero restrictions alone. For instance, after a favourable aggregate demand shock, prices and output should both increase whereas supply shocks should move them in opposite directions. The SVAR model can then disentangle aggregate demand and supply disturbances using this information. In more technical terms, the researcher draws a matrix A_0, repeatedly rotates that and then keeps the draws that meet all the sign restrictions to make structural inference. As opposed to the exact identification achieved using the zero restrictions, the rotation process needs an unidentified system (3). That is what makes the two standard methodologies for zero and sign restrictions incompatible. In principle, some rotations of A_0 can yield zero responses. The set of structural parameters conditional on the zero restrictions is notwithstanding *negligible*: the impulse response of a variable could be any number, making the zero-case impossible to achieve by rotation only.

[3] There also exist other ways to set the zero restrictions. For a recent example, see Elbourne and de Haan (2009).

[4] Good examples are Canova & Nicolo (2002) and Uhlig (2005).

The information carried by zero and sign restrictions is however different. With zero restrictions, one can include in the model information about whether a shock has a lagged effect or not on some variables. In contrast, sign restrictions define the structural shocks based on the expected movement of some indicators following the disturbance (e.g. price and quantity both increase/decrease *vs.* price and quantity move in the opposite direction). Both types of restrictions provide the information needed by SVAR models to distinguish the role of different macroeconomic shocks in explaining the observed movements in the data. Using both tools would enable the practitioner to better single out the shock and/or to include additional innovations in the SVAR without imposing incredible restrictions, as in the case mentioned above concerning only zero restrictions. To include other structural shocks in the model is to ensure that the shocks of interest truly capture their exogenous component, and not an endogenous response to other disturbances (Uhlig, 2005).

In an attempt to use both identifying tools, Mountford & Uhlig (2009) devised a penalty function approach that imposes restrictions on the model using numerical optimisation methods. Others use the Cholesky decomposition and impose the sign restrictions on blocks of A_0.[5] This last methodology is nonetheless limited, as the researcher cannot impose the zero restrictions freely. Benati & Lubik (2012) is one example of a series of papers that implement both sets of restrictions using special rotation matrices, i.e. the Householder transformation matrix and the Givens rotation matrix. Finally, the algorithm used in this paper resembles the one by Binning (2013), which imposes a small number of zero restrictions, leaves the model unidentified and thus allows for the implementation of sign restrictions.

The problem with all these solutions[6] is that they do not provide "any theoretical justification that their algorithms, in fact, draw from the posterior distribution of structural parameters conditional on the sign and zero restriction" (Arias et al., 2014). This shortfall can lead to biased results by imposing unwanted sign restrictions on the data (see Arias et al. (2014)). Based on solid econometric theory, the algorithm advanced by Arias et al. (2014) combines sign and zero restrictions in a valid manner. This paper uses their algorithm, which can be summarised as follows:

[5]Barnett & Thomas (2013), whose identification scheme is used in this paper, apply this methodology. See Liu et al. (2011) for a good explanation of the method.

[6]The exception is the block identification approach. Its limitations are however likely to leave the way to the more general algorithm of Arias et al. (2014).

Step 1 Draw B and Σ from the posterior distribution of the reduced-form parameters. I follow the approach adopted by Uhlig (2005), with the prior and posterior of B and Σ belonging to the Normal-Wishart family. The prior imposed is weak;

Step 2 Draw an orthogonal (rotation) matrix Q such that the structural parameters satisfy the zero restrictions;

Step 3 Keep the draw if the sign restrictions are also met. Otherwise go back to Step 1 and take a new draw of the reduced-form parameters and of Q;

Step 4 Return to Step 1 until you have collected sufficient draws from the posterior distribution conditional on the sign and zero restrictions.

Next, I turn to the application of the SVAR model on Dutch data.

3 Credit supply shocks in the Netherlands

I examine the role of credit supply shocks in the Netherlands using the identifying restrictions proposed by Barnett and Thomas (2013). There is considerable research on the role of credit supply shocks in the rest of the world, but very few studies focussing on the Netherlands.

As stated in the introduction, the literature has become increasingly interested in the role of credit supply shocks *per se*. Some time ago banks were only considered to be part of a propagation mechanism that amplifies shocks originating elsewhere, notably monetary policy innovations. Yet, the financial crisis has called for a more careful assessment of disturbances arising *within* financial institutions — the so-called credit supply shocks. To have a better idea of what these shocks can reflect, think of the following: an unexpected contraction in bank capital (Gerali et al., 2009), a decline in the value of banks' assets (Adrian & Shin, 2010) or a change in the pricing of default risk by financial institutions (Gilchrist & Zakrajsek, 2011). Adrin and Shin (2010) illustrates how during the financial crisis a worsening of banks' assets engendered a negative spiral where deleveraging was followed by further falls in asset prices, which restricted credit supply substantially. These are all examples of exogenous shocks, originated within the financial sector, that had a negative effect on lending and economic activity. Measuring the size of these effects is the scope of this paper.

Methodologically, it is quite challenging to distinguish these exogenous credit supply shocks from the endogenous responses of financial institutions to changes in the macroeconomic environment. It is also crucial to disentangle the role of supply and demand for credit in driving the fluctuations of aggregate lending. Otherwise, there is the risk that changes in credit volume are attributed only to financial conditions, neglecting possible shifts in the demand for loans. To solve this twofold problem, researchers have mainly relied on Structural VAR models and bank lending survey data.

Bijsterbosch & Falagiarda (2014) document the growing literature that has used Structural VAR models, with different identification methods, in order to study credit supply shocks. For this paper, it is relevant to only look at the researches discussing results for the Netherlands (or at least for the Euro Area) and using an identification strategy close to the one presented here. Hristov et al. (2011), Peersman (2011), Gambetti & Musso (2012) and Bijsterbosch & Falagiarda (2014) are the papers that meet these criteria[7]. Table 1 summarizes their methods, data and main conclusions. This paper distinguishes itself by using the algorithm by Arias et al. (2014) to impose sign and zero restrictions on Structural VAR models. Doing so, I can identify a larger number of shocks (6 instead of 3/4) and hence better single out the exogenous effect of credit supply shocks. Moreover, the flexibility of that algorithm allows me to perform partial identification, i.e. the identification of only credit supply shocks — our central case. In that way, I can evaluate to what extent the inclusion of additional shocks makes my estimates more precise, as well as whether possible misspecifications of the other shocks would significantly bias my conclusions.

The second methodology that has been employed in order to disentangle the role of credit supply shocks looks at surveys. For the Netherlands, Van der Veer & Hoeberichts (2013) use bank level responses from the ECB's Bank Lending Survey on Dutch financial institutions to look at the effect of tightening lending standards on loan growth. Their research showed that tight non-price, lending standards are behind a large portion of the fall in the growth rate of business lending since 2008, although they find a significant role for contractions in credit demand. This paper adds a macroeconomic perspective to the debate.

[7]The papers using Financing Condition Indexes (FICs) are excluded from this list, because that type of proxy is not addressed in this paper.

Table 1: References for the identification of Credit Supply Shocks in the Netherlands

Paper	Methodology	Data	Variables	Identification scheme[a]	Main results
Gambetti and Musso (2012)	VAR with time-varying parameters and stochastic volatility	Euro Area, 1980-2010, quarterly data.	Real GDP CPI Inflation Loan volume Lending rate Policy rate	Aggregate Supply: +, -, +, +, ? Aggregate Demand: +, +, +, +, ? Loan Supply: +, ?, +, -, ?	Credit supply shocks have a significant effect on economic activity and credit markets (GDP growth and loan growth go up by 0.7 and 0.4 percentage points on impact, respectively). The impact of credit supply shocks seems to have changed in the last 30 years. Credit supply shocks are really important in explaining the reduction in real GDP and loan growth occurred around 2009. (Less than) half of the fall in real GDP growth (loan growth) is due to credit restrictions.
Hristov et al. (2011)	Panel VAR	Euro Area countries, 2003-2010, quarterly data.	Real GDP GDP deflator Policy rate Lending rate Loan volume	Aggregate Supply: -, +, +, ?, ? Monetary Policy: -, -, +, ?, ? Aggregate Demand: -, -, -, -, ? Loan Supply: -, ?, -, +, -	Looking at the entire Euro Area, after a typical and adverse loan supply shock both real GDP and the loan volume drop significantly. The Netherlands has experienced favourable credit supply shocks up until 2009Q1, probably due to the large equity injections given by the Dutch government in 2008. Starting from 2009, credit restrictions have started affecting real GDP and loan growth negatively.
Peersman (2011)	VAR model	Euro Area, 1999-2012, monthly data.	Ind. production HICP Loan volume Lending rate Policy rate Loans - M0	Loan Demand: 0, 0, +, +, ?, ? Monetary Policy: 0, 0, +, -, -, ? Loan Supply: 0, 0, +, -, +, +	After a typical and favourable loan supply shock, output and loan volume increase significantly. Loan supply shocks explain about one-third of the drop in economic activity during the Great Recession, and most of the pre-crisis boom. Loan supply shocks are related to changes in the risk-taking appetite of banks, triggered by low government bond yields.
Bijsterbosch and Falagiarda (2014)	VAR with time-varying parameters and stochastic volatility	Euro Area countries, 1980-2013, quarterly data.	Real GDP GDP deflator Policy rate Lending rate Credit volume	Aggregate Supply: +, -, ?, ?, ? Aggregate Demand: +, +, +, +, ? Monetary policy: +, +, -, ?, ? Loan supply: +, +, +, -, +	In the Euro Area, there is a high degree of heterogeneity with respect to the post-crisis effect of loan supply restrictions In the Netherlands, loan and GDP growth respond immediately and positively (+1.3 and +0.5, respectively) to a favourable credit supply shock. Credit restrictions have significantly impaired GDP growth during the Great Recession, and partially sustained growth in the immediate post-crisis period. As for loan growth, the bottlenecks in the supply of lending have spurred the pre-crisis boom, inhibited loan growth in the crisis, and affected negatively credit growth even around 2011.

[a] For each shock, the restrictions follow the ordering of the variables shown in the column 'variables'.

Given their micro-approach, Van der Veer & Hoeberichts do not provide information on how credit supply shocks affect macroeconomic variables, and how important they have been in the Dutch economy with respect to other structural innovations, such as loan demand disturbances. The SVAR methodology introduced in the previous section allows me to better evaluate the importance of credit supply shocks that are independent of demand shifts. By comparing my results with Van der Veer & Hoeberichts (2013) I can bridge the gap between the SVAR analysis and micro-evidence.

The rest of the paper revolves around the following two questions, with respect to the Dutch economy:

What are the reactions of important macroeconomic indicators to a credit supply shock?

How important have credit supply shocks been before, and after, the onset of the recent financial crisis, when compared to other structural innovations?

With the first question I intend to address the beliefs that practitioners have on how credit supply shocks interact with macroeconomic variables. For instance, although it is widely accepted that adverse credit supply shocks have detrimental consequences for GDP growth, there are still questions on how long and significant this effect is. Moreover, there is heated debate on whether banks have been pivotal or not for the sluggish GDP and lending growth of the past few years. The data shows that in 2013 the volumes of business lending and M3 are actually decreasing in real (as well as absolute) terms. There is little empirical evidence on what is causing that and this paper tries to bridge this gap.

3.1 Data

I use Dutch quarterly data[8] running from the third quarter of 1998 up to the first quarter of 2014. The model includes macroeconomic variables, namely CPI, real GDP and a measure of monetary policy. The zero lower bound complicates the measurement of monetary policy interventions. I follow Barnett & Thomas (2013), who used the 10-yr government bond yield as their policy rate. Theory suggests that lowering the short-term rate should also

[8]Figure 10 in Appendix A plots all the variables used in my baseline scenario.

lower the yields of long-term securities further along the yield curve. In addition, unconventional monetary policies targeted movements in the yields of bonds in order to spur economic growth. The 10-yr government bond yield should be able to capture both of these effects. These indicators are used to identity aggregate innovations.

As for the identification of credit and financial market shocks explained in the following sections, I take M3 (measure of aggregate lending), equity prices, and the corporate bond spread. According to the corporate finance literature, changes in the corporate bond spread can only be partly attributed to actual risk of default (or credit risk). The changes in the spread that are most informative of economic activity can be explained by deviations in the *price* put on risk — the so-called *excess bond premium* (Gilchrist & Zakrajsek, 2011). These deviations denote the degree of risk aversion by the marginal investors, i.e. their risk-bearing capacity. Large banks are key players in supplying credit to the private sector and in their role of market-makers for corporate bonds, which makes the price of risk in the economy really sensitive to deviations in banks' risk-taking appetite (see, for instance, Adrian and Shin (2009)). In turn, banks' risk taking appetite is linked to the tightness of their balance sheet constraints, which determines their willingness to lend more. In fact, shocks to the profitability of large banks and expansions/contractions in their balance sheet (or changes in lending standards) are the best predictors for the excess bond premium present in the market (see e.g. Adrian et al. (2010)).

Therefore, the corporate bond spread can be used as a measure of credit conditions. A survey of the literature indicates that lending rates are often used to distinguish credit supply shocks. However, Van der Veer & Hoeberichts (2013) show that credit rationing works in large part through non-price, bank lending standards (e.g. collateral requirements, non-interest rate charges, etc.). In other words, Dutch financial institutions often do not restrict the supply of credit via higher interest rates on new loans. Using the spread allows this non-price rationing to be captured as a knock-on effect on the price of risk in the economy.

Except for the policy rate and the spread, I take the quarterly growth rates of the rest of the variables. The data used are:

Consumer Price Index: standard, seasonally adjusted CPI.

Real GDP: the model uses quarterly real GDP growth, seasonally adjusted.

10-yr government bond yield: as mentioned before, this variable is used as an indicator of monetary policy. In the robustness section I use the EONIA — the overnight reference rate in the Euro Area — as the monetary policy rate, as suggested by Ciccarelli et al. (2010).

Corporate Bond Spread: as a measure of yield paid by corporations I use the Barclays Capital Euro-Aggregate Index for Dutch Corporate Issuers (Datastream: LHANCIE). The series represents the yield paid on financial, industrial and utility bonds that are investment-grade rated and of remaining maturity of more than one year. Taking the difference between this series and 10-yr government bond yield gives the corporate bond spread[9].

M3: for a measure of credit quantity, I take the monetary aggregate M3, excluding currency in circulation. That variable can be used as a proxy for total lending activity. Before computing the growth rate of M3, the variable was adjusted for breaks and deflated with the CPI.[10] In the robustness section, I also use a series on loans to the private non-financial sector as in Bijsterbosch and Falagiarda (2014).

AEX index: the growth in real equity prices was computed using the AEX (Amsterdam Exchange) index, deflated using the CPI.

3.2 Methodology

This paper relies on a Structural Vector Autoregressive model (SVAR) of the Dutch economy, using quarterly data of the six variables listed above. The model has two lags[11] and includes a constant term for all six equations in the system. The reduced-form is estimated using Bayesian methods, following Uhlig (2005). The prior and the posterior belong to the Normal-Wishart

[9]The series from Barclays Capital contains bonds which can be of maturity shorter than 10 years. Therefore, when taking the difference with the 10-yr government bond yield, the spread can be negative. That is not a problem for my analysis, because what matters is to have an indicator of financial health and hence of willingness of banks to issue loans.

[10]In order to adjust the breaks that are in M3 due to accounting changes and reclassifications, I first computed the quarter-on-quarter growth rates between the values of the series that were calculated with the same methodology. Then, starting from the last value of M3 available, I worked backward and computed all the previous data points using those growth rates.

[11]That is what the Schwarz Information Criterion (SIC) suggested.

family, and I impose a weak prior on the model. Given a draw from the posterior distribution of the reduced-form parameters, I follow the algorithm of Arias et al. (2014), detailed in section 2, in order to collect sufficient draws from the posterior distribution of the structural parameters conditional on the sign and zero restrictions.

3.3 Identification scheme

The identifying restrictions are taken from Barnett & Thomas (2013). They are set on impact - i.e. I impose theoretical information about the structural innovations only in the quarter when the shocks occur. Then I let the data *speak*.

Although this paper centres on credit supply shocks, other structural innovations are included in the model. Instead of looking at draws that meet only the restrictions of the lending disturbances, the model records a subset of draws that respect the full set of shocks and thus are better grounded in economic theory (Peersman, 2005). Moreover, using a larger identification scheme preserves the exogenous nature of the loan supply shocks. Linear combinations of other structural shocks can indeed resemble credit supply shocks. Incorporating these external factors differentiates exogenous disturbances engendered by the financial sector from movements in lending rates/volumes in response to other structural innovations. This is a way to tackle the problem mentioned at the beginning of section 3, i.e. to distinguish between shocks originating in the financial sector – my target – and endogenous responses to changes in the macroeconomic environment.

Most of the studies in the credit supply shock literature use only sign restrictions. These impose *weak* information on the SVARs, and alone do not allow for larger and theoretically sound models (Fry & Pagan, 2007). That is because the identification scheme has to distinguish shocks *ex ante*. Hence, in the case of a large SVAR model, the researcher would be compelled to add a lot of sign restrictions just to achieve this technical requirement, instead of focusing solely on theoretical intuition. As I have shown in section 2, a similar issue occurs when one can use only zero restrictions. Of course, that is not to say that my identification scheme is impervious to critiques. Zero restrictions are stronger identifying assumptions, which impose more theoretical information on the model.

Table 2: Identification Scheme

Shocks/Variables	CPI Inflation	GDP Growth	Policy Rate	Corp. Bond Spread	M3 Growth	Equity Prices Growth
Aggregate Supply	+	-	?	?	?	?
Aggregate Demand	+	+	+	?	?	?
Monetary Policy	+	+	-	?	?	?
Credit (Loan) Supply	0	0	0	+	-	?
Loan Demand	0	0	0	+	+	?
Equity Price	0	0	0	0	0	1

Table 2 shows the identifying restrictions[12]. The first three aggregate shocks are considered to be the most important factors in driving economic fluctuations. Hence, they are included in the model to ensure that credit supply shocks are truly exogenous. The remaining structural innovations depict credit and financial market disturbances. These will be discussed in turn:

Aggregate shocks[13]

The restrictions used to identify aggregate shocks are well-established in the literature (see papers in table 1 and references therein), on the basis of standard theoretical models presented in all economic textbooks as well as of more recent DSGE evidence (see Peersman and Straub (2006) for a good summary). After an aggregate supply shock (e.g. technology shock allowing for lower production costs), inflation and output move in opposite directions, while they move in the same direction after an aggregated demand shock (e.g. changes in government spending).[14] Aggregate demand shocks are split into monetary policy shocks and all other aggregate demand shocks. Through

[12]In order to have some more examples and references for the sign restrictions relevant for my case, one can check Hristov et al. (2011) and Peersman (2011)

[13]Barnett & Thomas (2013) assert that the aggregate shocks typically shift the demand for credit by "affecting the level of activity and the general level of interest rates". I will not take a precise stance on this issue. One should see the inclusion of aggregate shocks in the model as a way to better single out the role of credit supply innovations.

[14]What matters are the *relative* sign restrictions imposed on the variables. For instance, an aggregate demand shock can be denoted by all pluses or all minuses. Those identifications do not change the meaning incorporated in the structural shock, and hence are interchangeable.

various transmission channels of monetary interventions, such as the traditional interest rate channel and balance sheet effects (see Antony & Broer (2010) for an extensive review of all the channels), a lower policy rate boosts aggregate demand and thus raises both inflation and output growth — the monetary policy shock. Other aggregate demand shocks create inflationary pressures, and thus the Central Bank reacts by rising the policy rate.

Credit and financial market shocks

Credit supply and loan demand shocks are distinguished from aggregate shocks with a timing restriction. Innovations in the credit market can be reasonably assumed to take time to impact the real economy. For instance, when there is a contraction in credit supply, firms are not likely to immediately change current production, as that is determined by the previous accumulation of capital. It is in later periods that investment possibilities will be restricted by a lower availability of funding. This lagged impact is included in the model via the zero restrictions in Table 2, denoting that on impact loan supply and demand shocks do not affect CPI, GDP and the policy rate. I do not impose any more restrictions in the successive quarters, to keep the model as agnostic as possible.

As for the central case of this paper, credit supply shocks move the corporate bond spread and M3 in opposite directions. It is the co-movement of these two variables that distinguish disturbances to the supply of credit from other innovations. In the context of the financial accelerator literature emphasised, among others, by Bernanke et al. (1996), a reduction in credit supply causes asset prices to decrease, firms' net worth to diminish, incentive to default to rise and finally corporate bond spreads to increase as lenders demand compensation for the higher risk contained in privately issued debt instruments. In addition, spreads incorporate information about credit supply conditions (see section 3.1). When matched with a decrease in aggregate lending, higher corporate bond spreads depict a reduction in the "effective risk-bearing capacity of the financial sector and, as a result, a contraction in the supply of credit" (Gilchrist & Zakrajsek, 2011).

Loan demand shocks (or capital market substitution shocks) indicate a shift in the preference that firms have, *given a certain level of economic activity*, for bank lending as opposed to capital market finance. These are specified by an increase/decrease of *both* the corporate bond spread and M3. As such, a higher corporate bond spread is expected to induce firms to move away from privately issued debt securities and to look for loans at financial institutions, thus boosting M3 growth. Therefore, a loan demand shock represents a *preference* shock to the demand for credit, not an aggregate level of credit demand. That distinction will be crucial in interpreting the results.

Finally, the equity price shock reflects noise in equity prices. The zero restrictions in the identification scheme incorporate our assumption that this volatility will not affect any other variable, at least on impact. By including shocks in the stock market, we control for possible movements in the values of security that might induce corporates to change their capital structure. Thus, credit supply shocks will reflect only bottlenecks originated in the financial sector and not possible shift in the funding mix of businesses.

3.4 Results

3.4.1 Loan (credit) supply and loan demand shocks

Figure 1: Impulse responses to an adverse credit supply shock

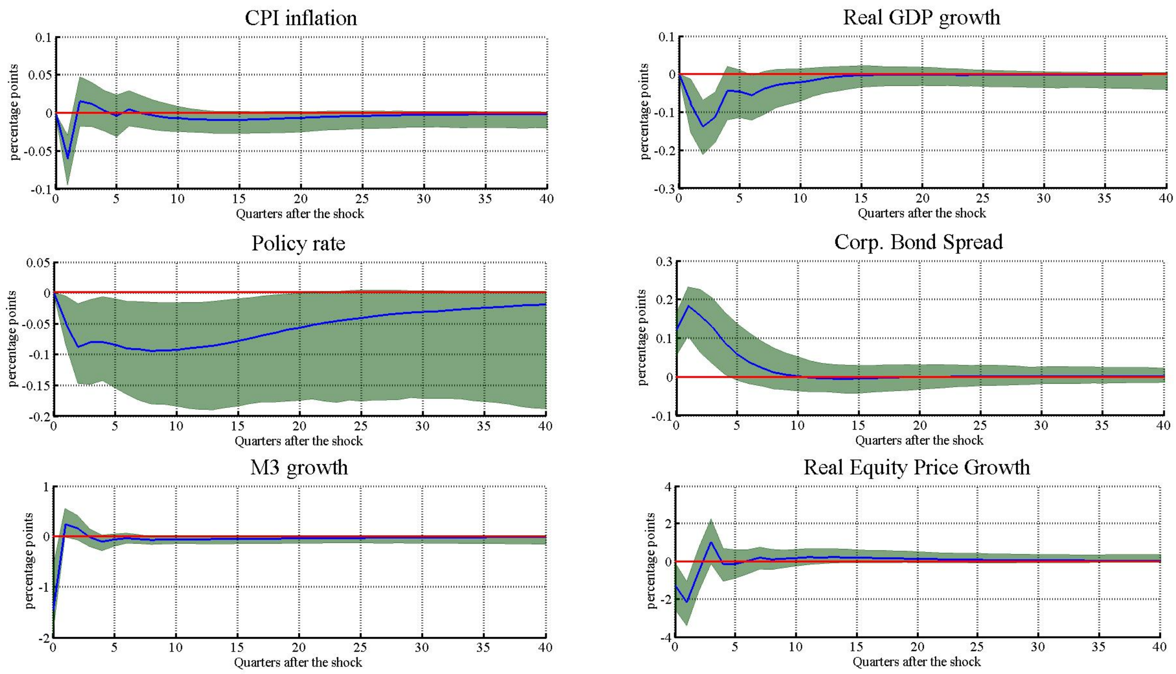
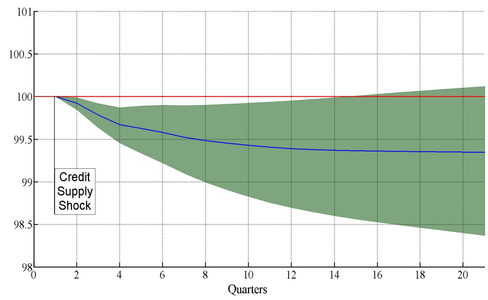


Figure 1 presents the impulse response functions (IRFs) of the variables in the model to a one standard deviation credit supply shock[15]. Again, a credit supply shock denotes a credit contraction (expansion) that causes M3 to decrease (increase) and the corporate bond spread to rise (decrease), with a lagged effect on the real economy. Here we show the effect of a typical (i.e. one standard deviation) and contractionary credit supply shock. I postpone the discussion about the economic significance of credit supply shocks in the next sub-sections.

Looking at the IRFs, Real GDP growth decreases significantly for about one year after the shock, before slowly going back to its previous trend. Cumulatively, the negative effect on real GDP growth lasts for more than two years and adds up to approximately -0.60 percentage points. That can be seen even better when looking at the impulse response on the level of Real GDP (Figure 2). Starting from an index of 100, a one standard deviation credit supply shock hits significantly the volume of GDP and has a permanent effect. Such a permanent impact has been confirmed in other studies looking at the effects of banking crises, such as Cerra & Saxena (2008) and Teulings & Zubanov (2013). Because the impact on GDP growth is long-lasting, if some adverse credit supply shocks follow one another, their impact accumulates and will then inhibit economic growth.

Figure 2: Response of real GDP to a one standard deviation credit supply shock



Going back to Figure 1, the fact that both price and GDP growth decrease suggests that credit supply shocks feed into the real economy via a decrease in aggregate demand rather than supply. We can attribute this spillover effect due to the lack of investment that follows a credit contraction. With regards to the other macroeconomic indicators, M3 growth decreases by about 1.5

[15]The blue line depicts the median response of all the draws from the posterior distribution of the structural parameters, while the shaded area represents the 68% confidence interval.

percentage points in the same quarter when the credit supply shock occurs. Albeit short, it is a permanent and significant effect on the level of M3. The policy rate also falls, denoting the expansionary response of monetary policy to a decrease in CPI and GDP growth. The corporate bond spread's response is positive and lasts for more than two years. The confluence of these results is consistent with the idea that a lower supply of funding inhibits investment, which in turn hampers economic growth and prompts central banks to react by loosening monetary policy.

Figure 3: Impulse responses to a loan demand shock

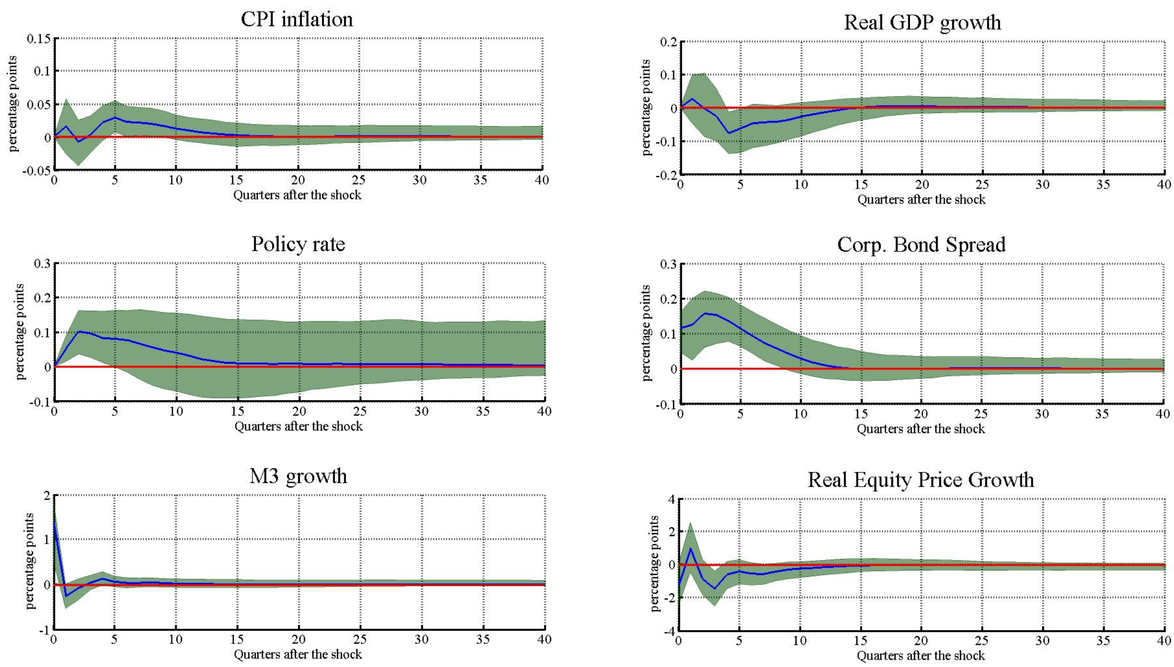


Figure 3 shows the IRFs to a one standard deviation loan demand shock. With respect to our identification scheme, the shock denotes a movement of firms towards bank finance and away from the capital market at quarter zero. The positive response of M3 growth is significant but short. The increase in spread lasts for more than two years, and it is approximately equivalent to the number of quarters in which GDP growth is subdued. The effect on GDP growth is not highly significant, but might suggest that the financial strains caused by higher risk premia (higher spread) are causing a slowdown in economic activity. Note that the corporate bond yield (and thus the spread) would decrease if there was a simple fall in the supply of bonds after the loan demand shock. However, the IRFs show how the corporate bond spread remains high for a long period of time. This signals how the larger risk premium present in the market (and hence higher refinancing costs) is likely to be behind the subdued GDP growth and triggers the substitution of capital market finance for bank lending. The response of monetary policy is contractionary, probably due to the expansion in bank credit. This intervention might have also contributed to the slowdown in GDP growth.

Although the IRFs in Figure 1 depict the responses of macroeconomic indicators to a typical credit supply shock, they are not sufficient to assess the role played by those disturbances around the financial crisis. Indeed, we also need data on the size of the credit supply shocks that hit the Dutch economy. In the next section, I put together those two pieces of information by analysing the historical decompositions of M3 and GDP growth. Historical decompositions will better illustrate the importance of credit supply shocks in driving GDP and lending growth — their economic significance.

3.4.2 Credit supply shocks and their impact on the real economy

Figure 4: Series of credit supply shocks

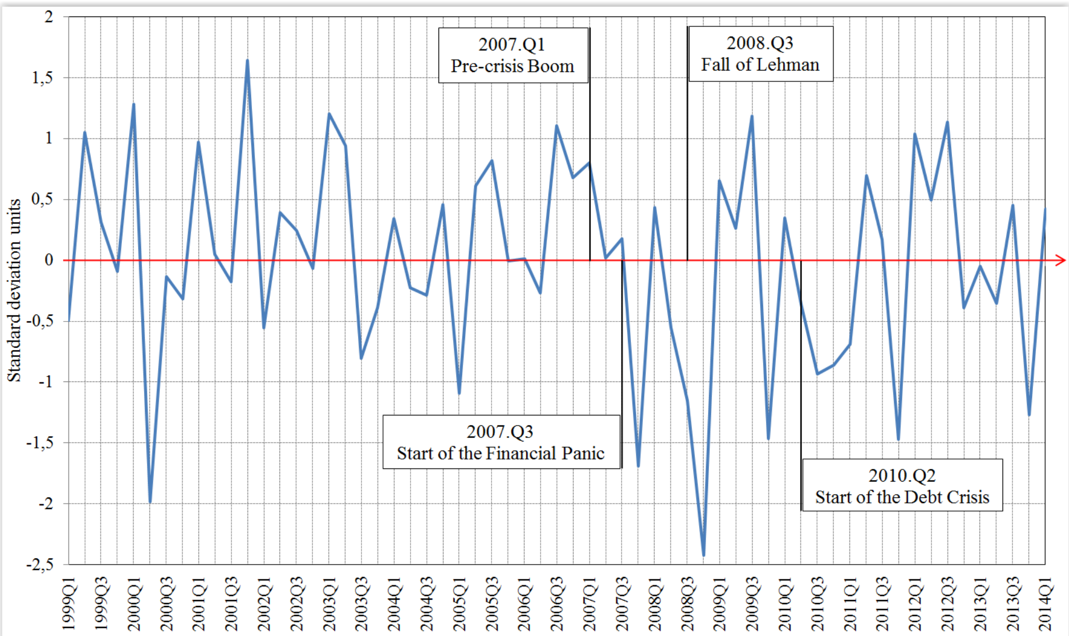
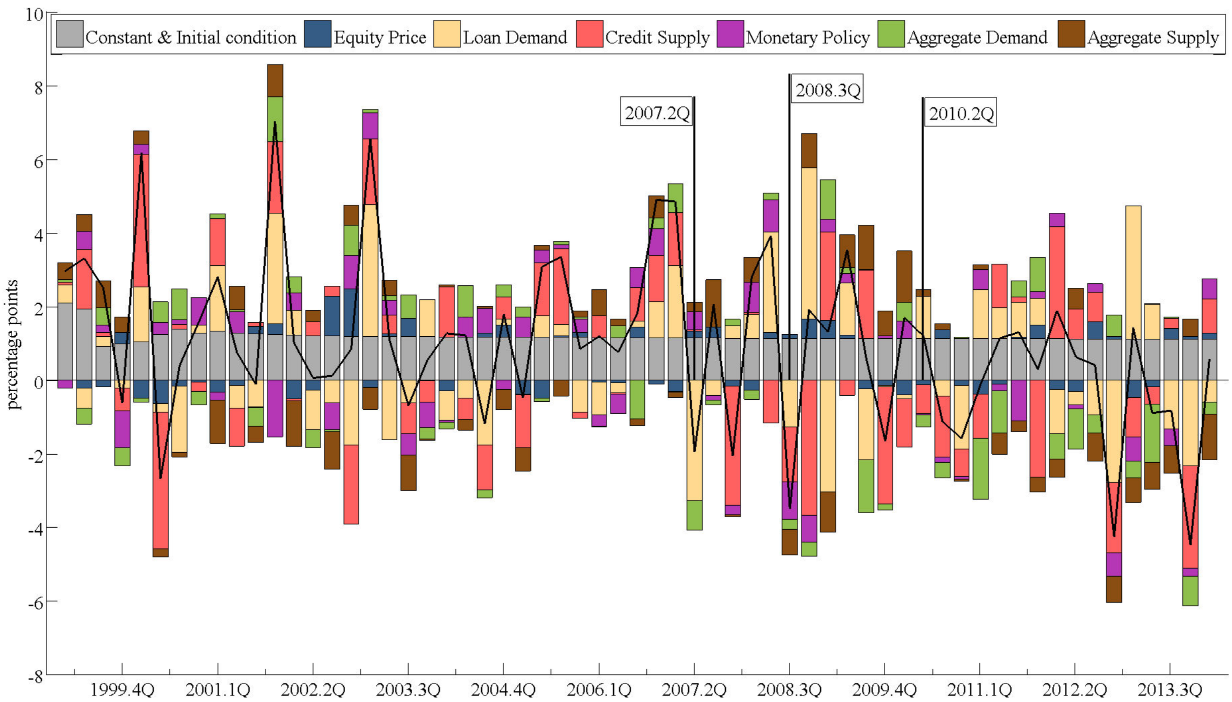


Figure 4 presents the series of credit supply shocks obtained from our model. Before 2007 one can distinguish about two years of favourable credit supply shocks, which is in line with the frequently heard stories of easy credit supply in that period. Data from The World Bank illustrates how domestic credit to the private sector went from 156.7% (as a percentage of GDP) in 2005 to 198.8% in 2009 — an increase of about 27 percentage points. That was mainly driven by the recent developments in the shadow banking market. The Dutch securitization issuance (relative to GDP) was one of the highest in Europe, moving in the pre-crisis years (2005-08) from 7.5% of GDP to 11.4% (data from the European Securitization Forum). Paired with banks' access to international capital markets, financial innovation favoured a lending boom to the private sector mainly in the form of mortgages to households (OECD, 2014).

Figure 5: Historical decomposition of M3 growth[16]



This result is more evident when looking at Figure 5, which decomposes movements in M3 growth by using the set of structural shocks identified

[16]The black line depicts the actual data points. The grey bars represent the constant term and the initial condition. The latter denotes the effect that the first two data points have on future quarters. That is due to the two lags adopted for the initial reduced-form VAR. One can see that slowly this effect fades out, and the grey bars tend towards the constant of the Moving Average representation - something that should be expected with a stationary variable. All the historical decompositions are computed using the median target (MT) method (see Fry & Pagan (2010)).

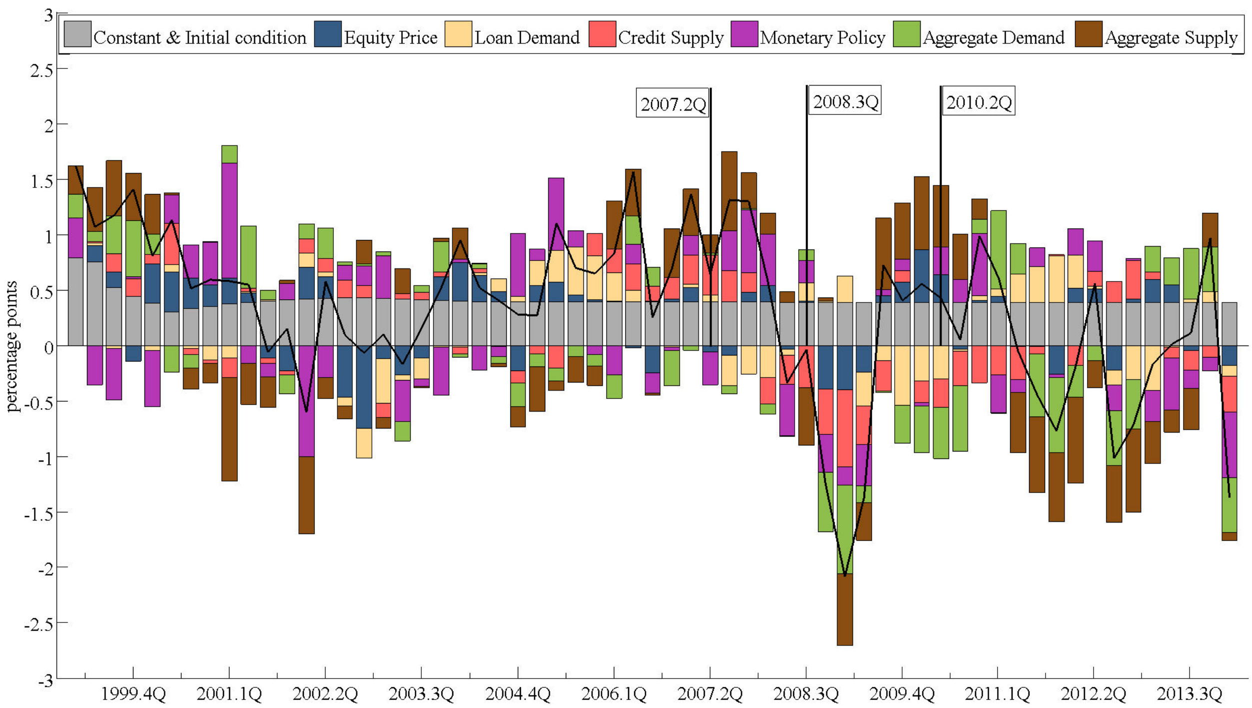
above. The red bars denote the cumulative effect of credit supply shocks on M3 growth. These shocks had a positive effect on M3 growth from 2005 up until the first quarter of 2007, again reflecting loose lending standards. However, the Dutch financial sector was vulnerable to the financial crisis (Masselink & Van den Noord, 2009). First, Dutch financial institutions were heavily dependent on external credit, with foreign claims of Dutch banks amounting to more than 300% of GDP. Second, the large share of stock holdings by occupational pension funds made people's retirement benefits and premiums sensitive to stock market movements. Finally, Dutch households and corporations relied heavily on bank financing. It was through these channels that stress in the US subprime mortgage market had spillover effects in the Netherlands (as well as in Europe more broadly). The financial panic started in August 2007, when the money market spread jumped, confidence evaporated and the ECB stepped in by providing liquidity (Trichet, 2010). In the following quarter, an adverse credit supply shock marked the beginning of a period of severe tightening of lending standards that impaired M3 growth (Figure 5). Although the fall of Lehman Brothers provoked a significant credit supply shock (2008, fourth quarter), M3 growth was partially sustained by a positive demand for bank credit in that period.

In 2010, the Eurosystem underwent the sovereign debt crisis (European Central Bank, 2010). Starting in May 2010, fears about rising government debt in some European countries called for additional interventions by the ECB. Higher uncertainty and the consequent shortages of liquidity can be seen between the second quarter of 2010 and the first quarter of 2011 (Figure 5). I register a sizeable credit supply shock already in the fourth quarter of 2009 (Figure 4), which coincides with the onset of Greece's difficulties.

More recently, the Netherlands experienced two large falls in M3 growth in the last quarter of 2012 and 2013, driven not only by adverse loan supply shocks but also by noteworthy preference shocks to the demand for credit (loan demand shocks). Figure 11 in Appendix A shows the volume of long-term securities issued by Dutch non-financial corporations, notably bonds — a variable external to my model. The negative loan demand shocks occurred in the last quarter of 2012 and 2013 denoted a shift away from bank lending towards the capital market, reflected in an higher issuance of bonds in those quarters (see Figure 11). The drop in demand for bank finance recorded in the first quarter of 2009 was also mirrored by a large volume of privately issued debt securities. These results give validity to the identification and meaning attributed to the loan demand shock.

Before moving to the impact that credit supply shocks had on GDP growth, I would like to compare Figure 4 with Figure 3 from Van der Veer & Hoeberichts (2013), reporting changes in bank lending standards on business lending in the Netherlands. Overall, both studies record looser lending standards in 2005 and 2006. The end of 2007 and the entire 2008 were marked by adverse credit supply shocks according to Figure 4 as well as to Van der Veer & Hoeberichts (2013). Whereas my model captures some credit restrictions due to the debt crisis, the bank lending surveys analysed by DNB do not. Bank lending surveys might have been biased by the impossibility of the recipients to distinguish between truly exogenous restrictions and endogenous reactions of banks to changes in the macroeconomic environment. Starting from 2012, both Figure 4 and Van der Veer & Hoeberichts see favourable credit supply shocks followed by adverse, but still less important, bank lending restrictions in 2013. Overall, both studies can*not* find significant evidence that the banks were still restricting lending growth significantly from 2012 onwards.

Figure 6: Historical decomposition of GDP growth



The IRFs in Figure 1 showed that the effect of a credit supply shock on GDP growth is long-lasting. Therefore, when adverse (or favourable) credit supply shocks follow one another, their impact on GDP growth accumulates.

Figure 6 helps me to address that potential problem by plotting the historical decomposition of GDP growth.

Loose lending standards, fostered by a low-interest-rate environment, channelled large credit volumes to the private sector and thus supported economic growth before 2007. In 2007, the above-average positive GDP growth experienced by the Netherlands reinforced the idea that its favourable fiscal and labour market conditions would have curbed the problems arising in the financial sector. However, in 2008 the Dutch economy saw a fall in world trade and consumer confidence that inhibited economic growth. On top of that, the vulnerabilities of the financial sector (see above) became more prominent, the credit boom slowly lost momentum and the contractions in bank lending registered after 2008 (see Figure 4) contributed to the downward trend in GDP. The adverse credit supply shocks that occurred in 2008 piled up and decreased real GDP growth by about 0.70 percentage points in the first quarter of 2009.[17]

At the end of 2008/beginning of 2009, the Dutch government implemented several reforms to stimulate growth while injecting liquidity in the financial sector (OECD, 2010). The latter measures attenuated the negative credit contractions experienced at the beginning of 2009 (Figure 6 illustrates that the credit supply shock in the last quarter of 2009 is actually positive). The rebound in world trade and accommodating monetary policies were also favouring a positive GDP growth at the end of 2009.

In 2010, whilst GDP growth peaked up, the sovereign debt crisis started unfolding. The following uncertainty in the interbank market (reflected in still high Credit Default Swap spreads in the banking sector — see OECD, 2014) likely caused the credit contractions shown in Figure 6. Notwithstanding, loan supply frictions became gradually less important in the subsequent periods. Behind the double-dip recession commenced at the end of 2011, there was an increase in unemployment, a sluggish response of world trade and, more importantly, declining consumer confidence that translated into low domestic demand (OECD, 2012). Credit supply shocks were actually favouring GDP growth during the economic downturn experienced at the end of 2012[18]. Overall, although adverse bank lending shocks can still be found in the first quarter of 2014, other macroeconomic innovations (e.g. aggregate supply and demand) have been driving the period of low growth that started in the second half of 2011.

[17]These are quarter-on-quarter growth rates

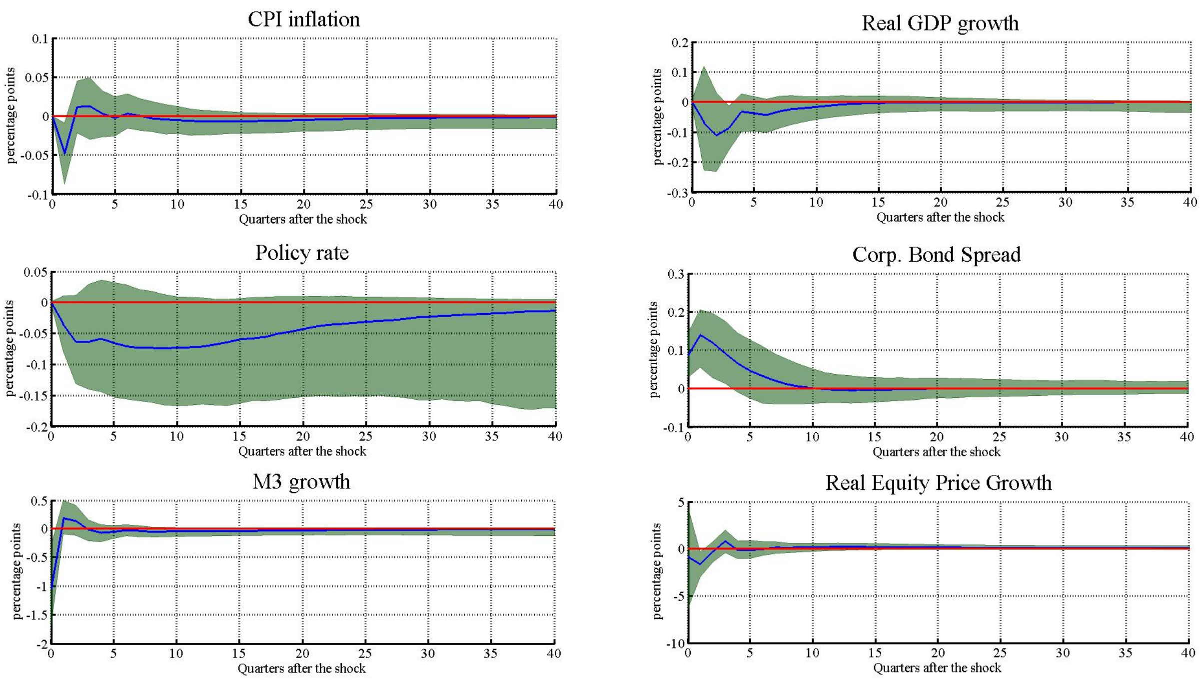
[18]This is circumstantial evidence that the low growth in 2012 was driven mainly by

4 Robustness checks

This section details results from alternative specifications.

4.1 Partial identification

Figure 7: Impulse Responses to an adverse credit supply shock under partial identification



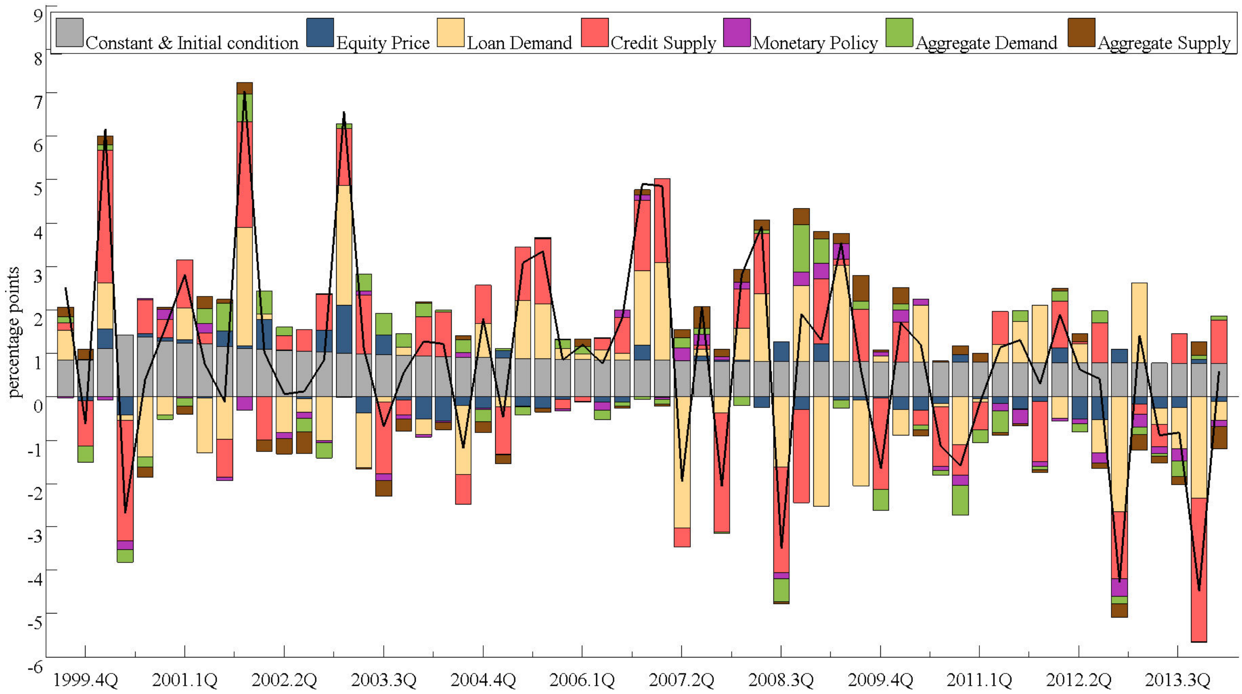
Partial identification means that instead of identifying a full set of shocks, I identify only credit supply shocks — my central case. In other words, none of the other structural innovations presented in table 2 is incorporated in the model. As mentioned in the Introduction and in section 3, partial identification allows me to check whether possible misspecifications in the identification of additional shocks modify my results. If misspecification is a problem, I expect the IRFs to a credit supply shock to change significantly when performing partial identification. Figure 7 presents the responses to the partially identified credit supply shock. Firstly, the shape and timing

contractionary fiscal policy, not by weaknesses in banks.

of the responses are very similar to Figure 1, where all the shocks in table 2 are imposed on the SVAR. The confidence intervals for GDP and equity prices registered in Figure 1 are smaller, which implies that the identification of additional innovations does make my estimate more precise. However, generally speaking, the impulse responses do not vary significantly enough to necessitate a full set of shocks in the identification scheme. The historical decompositions of the effect of credit supply shocks on the variables in the model (not shown) are also very similar. Therefore, regardless of the other innovations that are imposed on the data, my main conclusions stay the same.

4.2 EONIA

Figure 8: Historical decomposition of M3 growth — EONIA



In the data section I discussed how 10-yr government bond yields reflect monetary policy interventions better than the usual ECB refinancing rate, i.e. the interest rate at which the central bank lends money to commercial financial institutions. However, it is still not clear what is the best measure of monetary policy when the refinancing rate has reached the zero lower bound. That is because central banks started using non-conventional monetary policies when they could not intervene in the money market via the usual interest rate channel. Therefore, an interest rate close to zero does not reflect all the policies adopted by the ECB. Ciccarelli et al. (2010) proposed as a valid policy rate during the financial crisis the EONIA, the overnight reference rate in the Euro Area. It is interesting to see whether the results of my model are robust when using the EONIA as a measure of monetary policy.

Figure 8[19] illustrates that my conclusions do not change significantly. As in Figure 5, Figure 8 shows that the financial panic started around the third quarter of 2007 was preceded by a credit boom. Sizeable credit intermediation problems are recorded around the bankruptcy of Lehman Brothers as well. Lastly, credit supply shocks, paired with low demand for bank finance, are still found to have caused the decrease in M3 growth in the last quarter of 2012 and 2013.

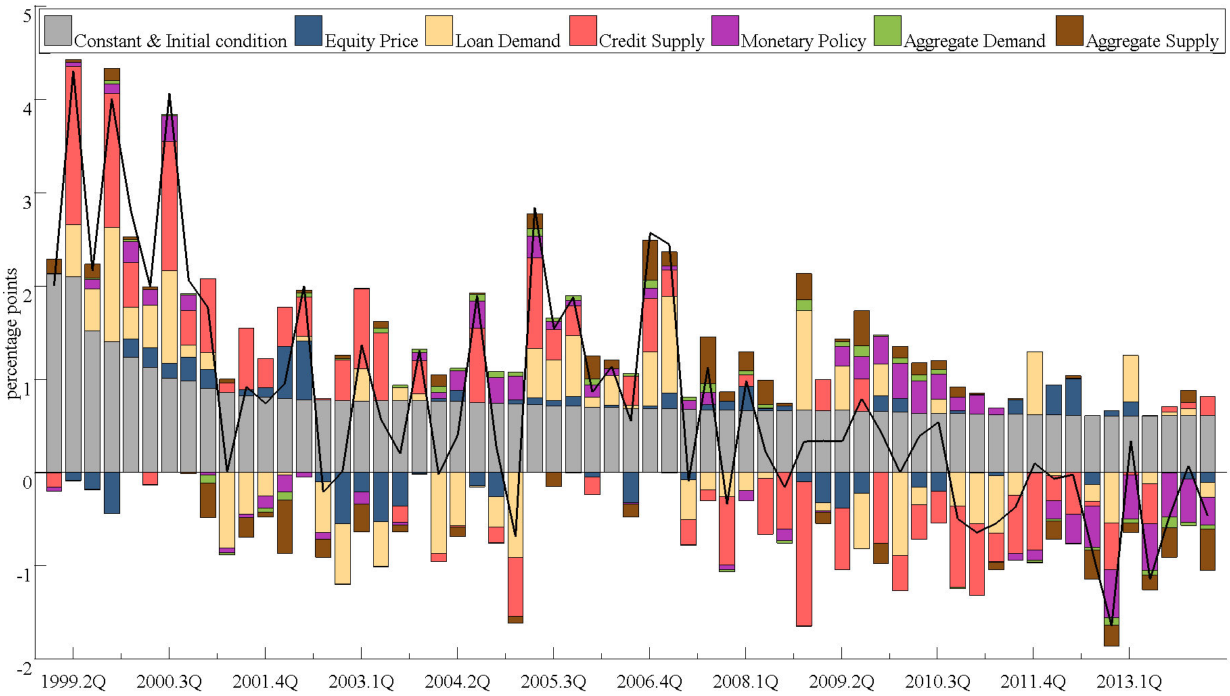
4.3 Credit by the financial sector to the Dutch non-financial private sector

In the baseline scenario, I use M3 to identify loan demand and loan supply shocks. Bijsterbosch & Falagiarda (2014), instead, take a measure of credit to the Dutch non-financial private sector (including households and businesses) computed by the Bank for International Settlements. It is interesting to see whether using the latter changes my main conclusions. Figure 9 illustrates the historical decomposition of credit to the Dutch non-financial private sector, which replaces M3 in the model.

As in Figure 5, the second quarter of 2007 marks the start of the financial turmoil. Moreover, the fall of Lehman Brothers is recorded in both graphs by a large and adverse credit supply shock. Thereafter, M3 and Loans growth have not been able to go back to their previous trends, with credit supply disturbances leading to a slowdown in Figure 5 and Figure 9. When looking at credit to the Dutch non-financial private sector, it is more evident that

[19]For this and the following historical decomposition I plotted the median values, without using the MT method. That is because the two methodologies lead to different results in these cases. I chose the median values because they incorporate information about the entire distribution of the structural parameters. The MT method takes only one draw out of that distribution, and doing so we might lose information.

Figure 9: Historical decomposition of loans to Dutch non-financial corporations



credit supply frictions have not inhibited lending growth after 2013. The historical decomposition of GDP (not shown) illustrates that from 2012 onwards other structural disturbances have driven the recent period of low economic growth. To summarize, my main conclusions remain unchanged.

5 Conclusion

This paper has used the algorithm by Arias et al. (2014) in order to disentangle the role of credit supply shocks in the Dutch economy. The SVAR methodology has so far allowed researchers to single out the effect of credit supply shocks, and using both sign and zero restrictions is a good addition to the work done in the literature on this topic. Those two identification tools impose two sets of information on the model, increasing the options that one can use to define meaningful innovations and make structural inferences. That flexibility is even more relevant for financial shocks, which can reasonably be assumed to have a lagged effect on real variables (zero restriction) and cause a well-established contemporaneous response on other credit and financial market indicators (sign restrictions). Using sign and zero restrictions I can identify a large model, in order to better define the effect of credit supply shocks. However, I show that partial identification can provide estimates which are precise enough while not changing my conclusions significantly.

Moving to the Dutch case, my series of exogenous credit supply shocks is consistent with the financial turmoil caused by the financial crisis and by the debt crisis. A typical, adverse credit supply shock has a short-lasting but significant effect on M3 growth, while the sluggish response of GDP growth lasts more than two years. The effects of bank lending contractions have been economically significant in lowering M3 and GDP growth around the fall of Lehman Brothers. Nevertheless, after the second half of 2011, low GDP growth cannot be ascribed to those credit intermediary problems.

The research by Bijsterbosch & Falagiarda (2014), among others, shows the importance of including time-varying parameters when using SVAR models. The severity of the crisis might have created significant differences in the effect of credit supply shocks on the real economy. Combining time-varying parameters with zero and sign restrictions might be fruitful for further research.

6 Appendix A

Figure 10: Variables in the baseline scenario

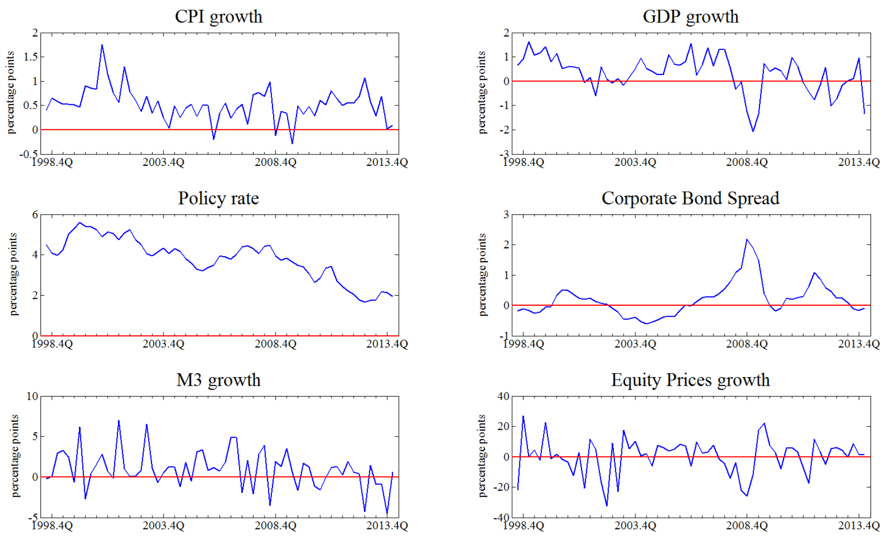
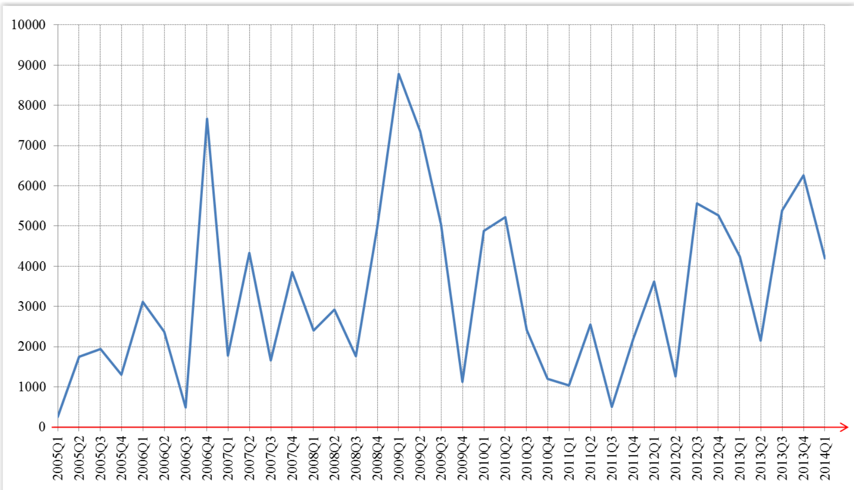


Figure 11: Gross issues of long-term securities, other than shares, by Dutch non-financial corporations

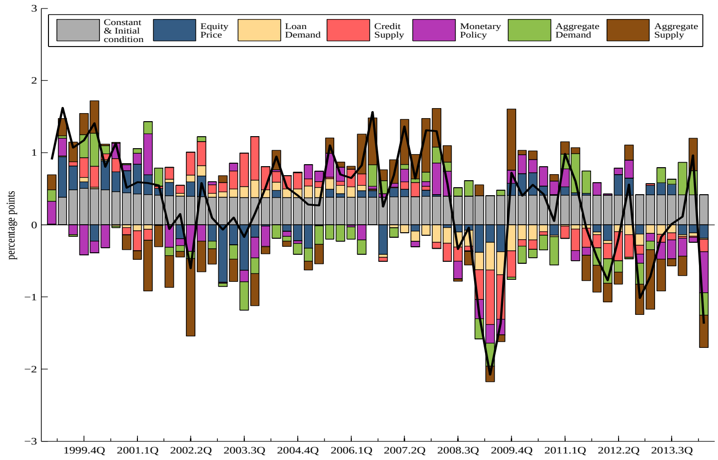


7 Appendix B

In this appendix, I illustrate some additional model specifications[20]. First of all, I am going to show the historical decompositions of GDP when different lag structures are used.

In figure 12 and 13, one and three lags are employed, respectively, to estimate the reduced-form VAR. With one lag, the pre-crisis credit boom is less evident, and the credit supply shocks were found to be more important in the first dip of the 2011-13 recession. By adopting three lags, the conclusions that can be drawn are closer to the ones presented in the main body of the paper. Nevertheless, while with one lag we might not specify the model well enough, using three lags in such a large VAR system can over-fit the data. The model with two lags, consistent with a large body of literature and determined by the usual information criteria, is to be preferred.

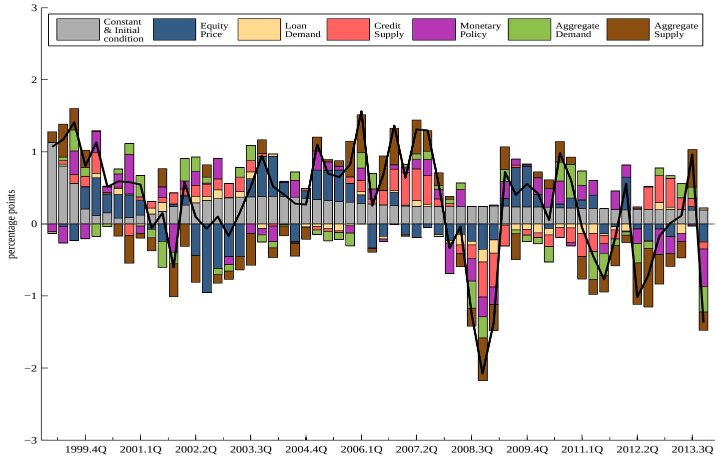
Figure 12: Historical decomposition of GDP growth - 1 lag



From the figures illustrated in the results section, one can easily notice that the quarter-on-quarter growth of M3 is a really erratic variable. That makes the results harder to interpret. Although econometrically quarter-on-quarter growth rates are more appropriate in VAR models, it is interesting to look at the results with year-on-year growth of M3 as the proxy for credit (see Figure 14). The signs of easy credit supply preceding the financial crisis are

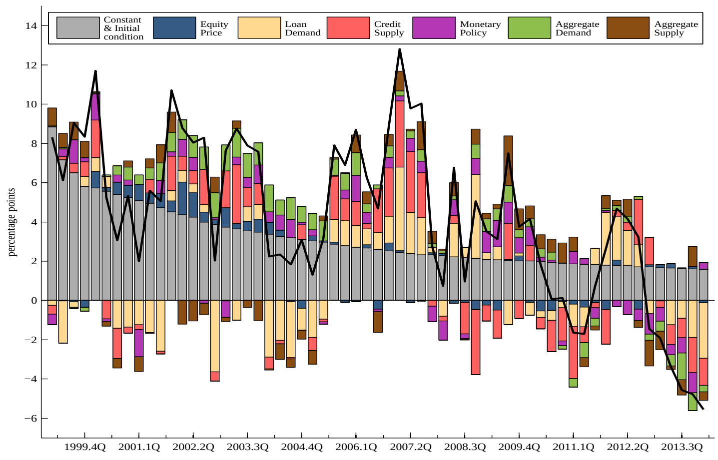
[20]In the following graphs, I am always going to use the median values as summary measures for the historical decompositions

Figure 13: Historical decomposition of GDP growth - 3 lags



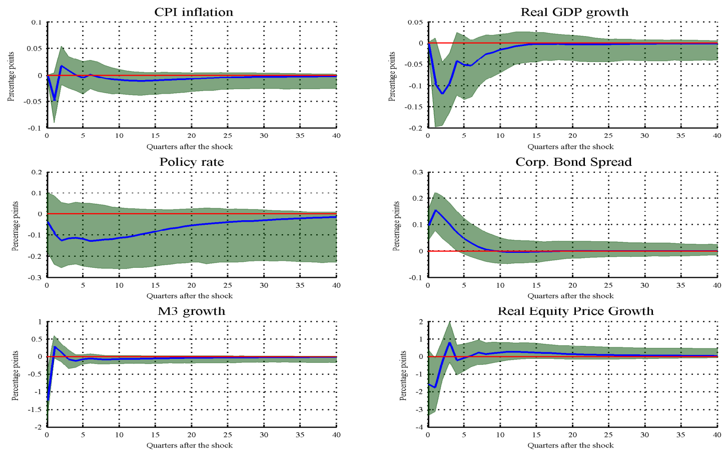
now much more evident. Moreover, the negative loan supply shocks following the third quarter of 2008 (fall of Lehman Brothers) clearly indicate the subsequent credit restrictions. The model hints at possible loan supply contractions that occurred in 2013, although those are not reflected in sluggish GDP growth (not shown). This last point reiterates the notion that credit supply shocks were not significantly impairing GDP growth in the last two years of our sample.

Figure 14: Historical decomposition of M3 growth - year-on-year growth rate



The partial identification performed in the robustness section essentially

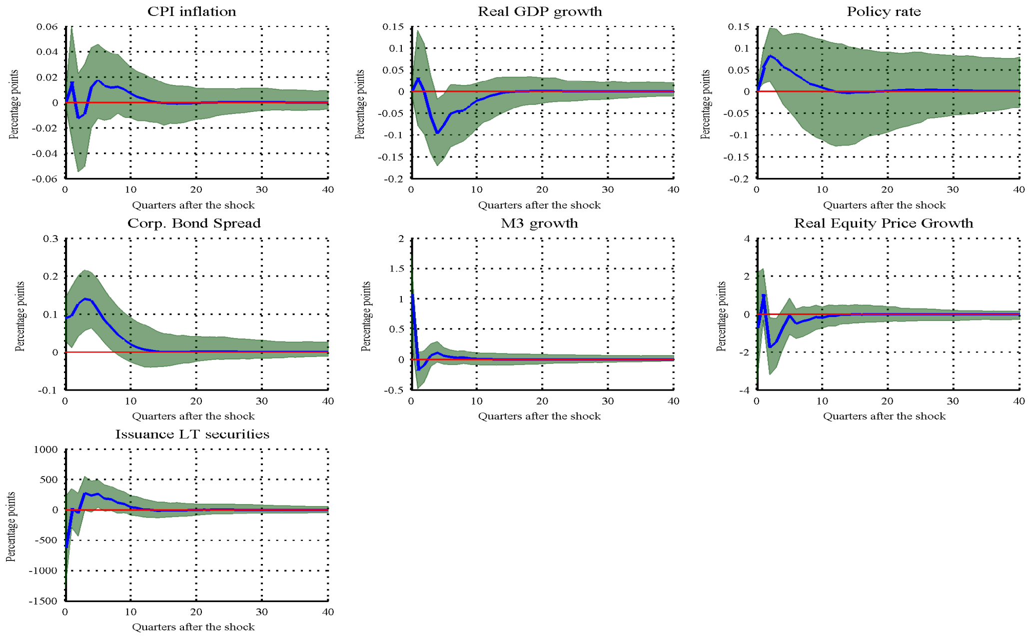
Figure 15: IRFs to a credit supply shock — no zero restrictions on policy rate



obviates the need for testing alternative sign and zero restrictions for all the shocks in the model, except for the central case of this paper — the credit supply shock. One might argue that the immediate availability of data on market liquidity makes central banks really responsive to credit supply contractions. In our identification scheme, we can allow for this possibility by removing the zero restrictions placed on the policy rate with regards to the credit supply and loan demand shocks. Hence, the data will determine the response of the policy rate on impact. The following IRFs for a typical credit supply shock are illustrated in Figure 15. The results are really similar to the ones presented in the main body of the paper. There are signs of an immediate and accommodating response of the central bank to a lending contraction, which could not be captured when the zero restrictions were used.

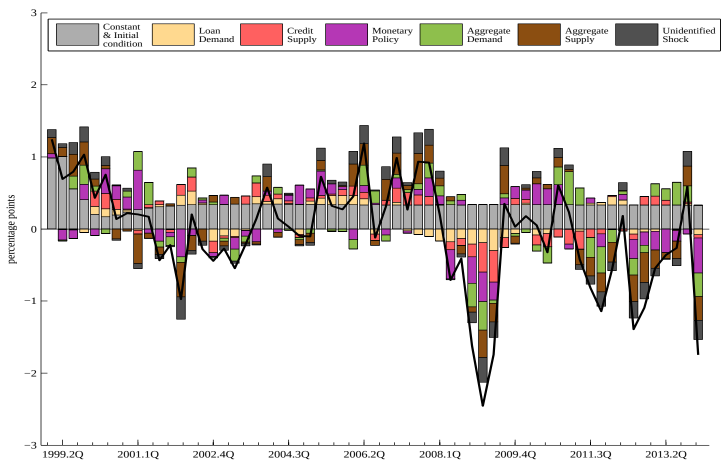
To address the link between loan demand shocks and the issuance of long-term (LT) securities by non-financial corporations, I have also added the variable illustrated in Figure 11 to the SVAR model. In more technical terms, I included the variable in the reduced-form VAR, left the resulting 7th shock unidentified and re-estimated the IRFs of all the variables to a load demand shock. According to the story outlined above, we expect that when a loan demand shock occurs, i.e. when both the spread and M3 growth increase, there is a lower issuance of long-term securities, notably bonds. Figure 16 shows that this is exactly what happens. The high corporate bond spread drives firms away from the corporate bond market towards lending

Figure 16: IRFs to a loan demand shock - issues of LT securities



from financial institutions. Although the effect might seem short-lasting, both M3 growth and issuance of long-term securities have an influence on the capital structure of a firm even in the long-run.

Figure 17: Historical Decomposition GDP growth - unidentified shock



Lastly, it is worth noting that a large body of literature does not identify the Equity Price shock used in this paper. To see whether the identification of the Equity Price disturbance modifies our results, I remove that shock from the model and leave the sixth shock unidentified. The following historical decomposition of GDP is illustrated in Figure 17. As one can see, the credit supply shocks follow the pattern outlined in the results section.

References

[1] Adrian, Tobias and Hyun Song Shin (2009a). 'Money, liquidity and monetary policy'. American Economic Review, papers and proceedings, volume 99, issue 2.

[2] Adrian, Tobias & Shin, Hyun Song (2010). 'Liquidity and leverage'. Journal of Financial Intermediation, Elsevier, vol. 19(3), pages 418-437, July.

[3] Adrian, Tobias; Moench, Emanuel & Shin, Hyun Song (2010). 'Macro risk premium and intermediary balance sheet quantities'. IMF Economic Review 58(1): 179-207.

[4] Antony, J.; Broer, P. (2010). 'Linkages between the financial and the real sector of the economy — A literature survey'. CPB Document No. 216. CPB Netherlands Bureau for Economic Policy Analysis.

[5] Arias, Jonas E.; Rubio-Ramírez, Juan F. & Waggoner, Daniel F., (2014). 'Inference based on SVARs identified with sign and zero restrictions: theory and applications'. Dynare Working Papers 30, CEPREMAP.

[6] Barnett, Alina & Thomas, Ryland (2013). 'Has weak lending and activity in the United Kingdom been driven by credit supply shocks?'. Bank of England working papers 482.

[7] Baumeister, C. & Benati L. (2010). 'Unconventional monetary policy and the great recession'. European Central Bank Working Papers (1258).

[8] Benati, L. (2013). 'Why are recessions associated with financial crises different?'. Working Paper.

[9] Benati, L. & Lubik, T. A. (2012). 'Sales, inventories, and real interest rates: A century of stylized facts'. CAMA Working Papers 2012–19, Australian National University, Centre for Applied Macroeconomic Analysis.

[10] Bernanke, B.S.; M. Gertler & Gilchrist S. (1996). 'The financial accelerator and the flight to quality'. The Review of Economics and Statistics, vol. 78, no. 1, pp. 1–15.

[11] Bijsterbosch, M. & Falagiarda, M. (forthcoming). 'Credit supply dynamics and economic activity in Euro area countries. A time-varying parameter VAR analysis'. Journal of International Money and Finance.

[12] Binning, A. (2013). 'Underidentified SVAR models: a framework for combining short and long-run restrictions with sign-restrictions'. Norges Bank Working Papers.

[13] Canova, F. & De Nicoló, G. (2002). 'Monetary disturbances matter for business fluctuations in the G-7'. Journal of Monetary Economics, Vol. 49, Issue 6, September, pages 1131–1159.

[14] Cerra, V. & Saxena, S.C. (2008). 'Growth dynamics: the myth of economic recovery'. American Economic Review, vol. 98[1]: 439-57.

[15] Ciccarelli, M.; Maddaloni, A. & Peydró (2010). 'Trusting the Bankers: a new look at the credit channel of monetary policy'. Working paper series 1228, European Central Bank.

[16] Elbourne, Adam & de Hann, Jakob (2009). 'Modeling monetary policy transmission in acceding countries: vector autoregression versus structural vector autoregression'. Emerging Markets Finance and Trade, vol. 45(2), pages 4–20, March.

[17] European Central Bank (2011). 'Annual Report 2010'. Published in March 2011.

[18] Fry, R. & Pagan, A. (2007). 'Some issues in using sign restrictions for identifying Structural VARs'. NCER Working Paper Series, No. 14.

[19] Fry, R. & Pagan, A. (2010). 'Sign restrictions in structural vector autoregressions: a critical review.' NCER Working Paper Series, No. 57.

[20] Gambetti, L. & Musso, A. (2012). 'Loan supply shocks and the business cycle'. ECB Working Paper Series No.1469.

[21] Gerali, A., Neri, S., Sessa, L. and Signoretti, F. (2010). 'Credit and Banking in a DSGE Model of the Euro Area'. Journal of Money, Credit and Banking, Vol. 42, Issue 6, pages 107-141.

[22] Gilchrist, S. & Zakrajšek E. (2011). 'Credit spreads and business cycle fluctuations'. Working paper 17021, National Bureau of Economic Research, Cambridge.

[23] Gottschalk, Jan (2001). 'An introduction to the SVAR methodology: identification, interpretation and limitations of SVAR models'. Kiel Working Paper (Preliminary version of August 2001). No. 1072, Kiel Institute of World Economics.

[24] Hamilton, James D. (1994). 'Time Series Analysis'. Princeton University Press.

[25] Hristov, N.; Hulsewig, O. & Wollmershauser, T. (2011). 'Loan supply shocks during the financial crisis: evidence for the Euro Area'. CESifo Working Paper Series. No. 3395, CESifo Group Munich.

[26] Liu, P., Mumtaz, H., & Theophilopoulou, A. (2011). 'International transmission of shocks: a time-varying factor-augmented var approach to the open economy'. Bank of England working papers 425, Bank of England.

[27] Lütkepohl (2011). 'Vector Autoregressive Models'. EUI Working Paper. European University Institute, Department of Economics.

[28] Lütkepohl & Krätzig (2004). 'Applied Time Series Econometrics'. New York: Cambridge University Press.

[29] Masselink, M. & Van den Noord, P. (2009). 'The global financial crisis and its effects on the Netherlands'. ECFIN Country Focus, Volume 6, Issue 10. European Commission's Directorate-General for Economic and Financial Affairs.

[30] Mountford, A. & Uhlig, H. (2009). 'What are the effects of fiscal policy shocks?'. Journal of Applied Econometrics, 24 (6), 960–992.

[31] OECD (2010). 'OECD Economic Surveys: Netherlands, April 2010'.

[32] OECD (2012). 'OECD Economic Surveys: Netherlands, April 2012'.

[33] OECD (2014). 'OECD Economic Surveys: Netherlands, April 2014'.

[34] Peersman, G. (2005). 'What caused the early millenium slowdown? Evidence based on vector autoregressions.' Journal of Applied Econometrics 20: 185–207 (2005).

[35] Peersman, G. (2011). 'Bank lending shocks and the Euro Area business cycle'. Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium.

[36] Peersman, G. & Straub, R. (2006). 'Putting the New Keynesian Model to a test'. IMF Working Paper.

[37] Peersman, G. & Straub, R. (2009). 'Technology shocks and robust sign restrictions in a Euro area SVAR'. International Economic Review, Vol.50 (3) 727–750.

[38] Sims, Christopher A. (1980). 'Macroeconomics and Reality'. Econometrica, Econometric Society, vol. 48(1), pages 1–48, January.

[39] Teulings, C.N. & Zubanov, N. (2013). 'Is economic recovery a myth? Robust estimation of impulse responses'. Journal of Applied Econometrics, vol.29[3]:497-514.

[40] Trichet, Jean-Claude (2010). 'State of the Union: the financial crisis and the ECB's response between 2007 and 2009'. Journal of Common Market Studies 2010, Vol. 48 Annual Review pp. 7–19.

[41] 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.

[42] Van der Veer, Koen & Hoeberichts, Marco (2013). 'The level effect of bank lending standards on business lending'. De Nederlandsche Bank Working Paper No. 396.