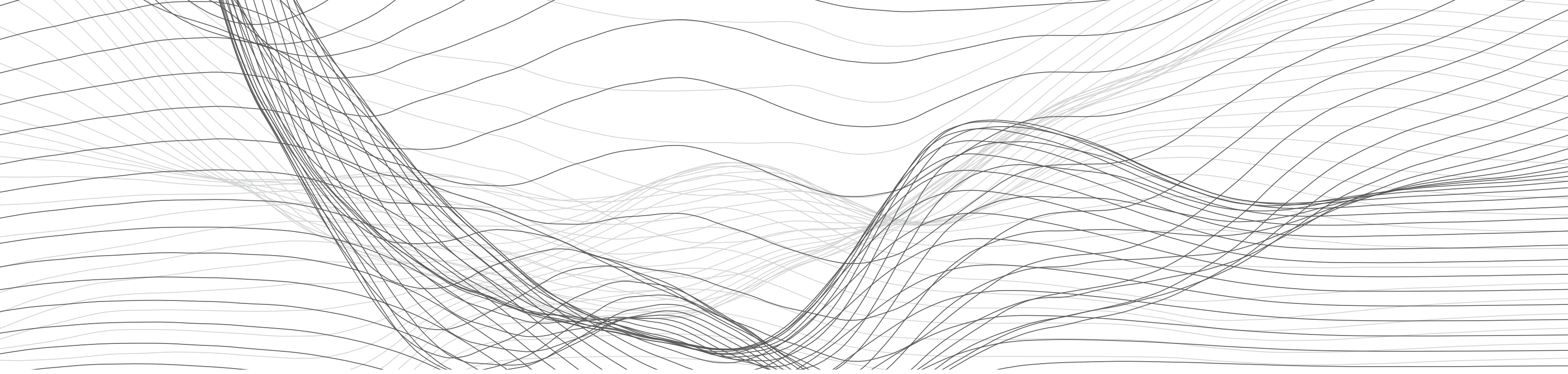

Credit cycles and real activity – the Swiss case

Gregor Bäurle and Rolf Scheufele

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Credit cycles and real activity - the Swiss case[*]

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22 August, 2016

Abstract

The global Great Recession has sparked renewed interest in the relationships between financial conditions and real activity. This paper considers the Swiss experience, studying the impact of credit market conditions and housing prices on real activity over the last three decades through the lens of a medium-scale structural Bayesian vector autoregressive model (BVAR). From a methodological point of view, the analysis is challenging for two reasons. First, we must cope with a large number of variables which leads to a high-dimensional parameter space in our model. Second, the identification of economically interpretable shocks is complicated by the interaction among many different relevant factors. As to the first challenge, we use Bayesian shrinkage techniques to make the estimation of a large number of parameters tractable. Specifically, we combine a Minnesota prior with information from training observations to form an informative prior for our parameter space. The second challenge, the identification of shocks, is overcome by combining zero and sign restrictions to narrow the plausible range of responses of observed variables to the shocks. Our empirical analysis indicates that while credit demand and, in particular, credit supply shocks explain a large fraction of housing price and credit fluctuation, they have a limited impact on real activity.

JEL classification: C11, C32, E30, E44, E51, E52

Keywords: Credit supply and demand, housing prices, SVARs, Bayesian shrinkage

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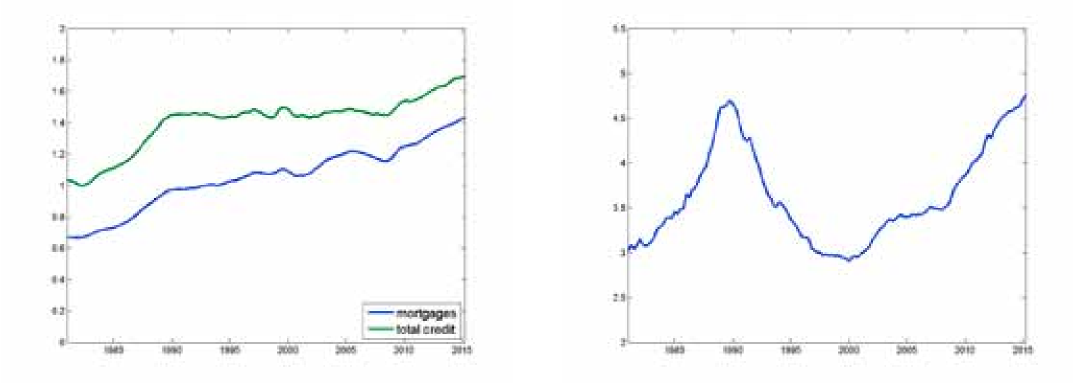
1 Introduction

The recent financial crisis has sparked renewed interest in the interactions between the financial sector and the real economy. In particular, housing and housing finance are seen as crucial factors in the origin of the financial crisis. Therefore, understanding the relation among housing prices, credit conditions and real activity has become a key topic in macroeconomics. This paper considers the Swiss experience, studying the impact of credit market conditions and housing prices on real activity over the last three decades through the lens of a structural Bayesian vector autoregressive model (BVAR).

Switzerland is a particularly interesting case in this regard because the housing market has played a central role in the Swiss business cycle in recent decades. In contrast to many other industrialized countries, which experienced a lengthy period of housing price increases followed by a rapid decline during the financial crisis, Switzerland has seen nearly 15 years of continuous housing price increases and strong credit growth. Before this boom, however, Switzerland experienced a sustained slump in the housing market beginning in the early 1990s, followed by a period of abnormally low GDP growth with low internal demand (see Figure 1). This scenario is currently threatening many industrialized countries. Not surprisingly, the slump in the 1990s was preceded by a period of overly strong housing prices and credit growth in the 1980s, accompanied by a significant growth of overall economic activity.

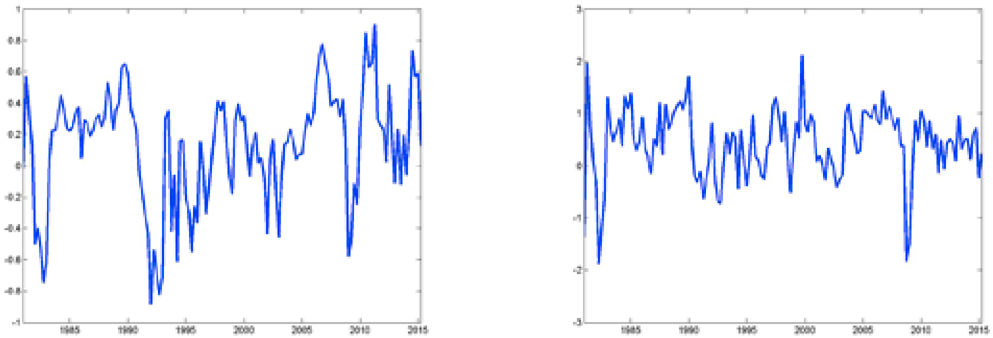
There are a number of anecdotal explanations for these fluctuations. First, the expansionary conduct of monetary policy in the 1980s and the subsequent substantial tightening that commenced at the end of 1988 are often described as primary determinants of the boom and subsequent slump in the Swiss housing market (see Meyer 1998, Müller 2012). A second, complementary view is that changes in lending standards in the 1980s – which are also related to overly optimistic expectations held by households and especially by banks – contributed to an unsustainable increase in credit. When the market turned, this untenable increase in credit created stress in the banking sector that amplified the negative dynamics of housing prices in the 1990s (Thalmann 2010, Meyer 1998). Other factors cited in descriptions of the Swiss housing and business cycles include demand fluctuations (mainly through changes in income and population growth) and the sluggish

Figure 1 — Housing prices, credit and real activity



(a) Credit to GDP

(b) Real housing prices



(c) Hours worked (quarterly changes)

(d) GDP (quarterly changes)

adjustment of housing supply to housing demand (Meyer 1998).

However, no study to date has systematically analyzed the importance of these different factors using econometric methods. We attempt to fill this gap by disentangling five different sources of economic fluctuations within our BVAR framework and assessing their relative importance to housing prices and real activity. The first two sources of economic fluctuations, monetary policy shocks and bank lending shocks, alter the supply of credit. The remaining shocks influence the demand for housing. We focus on population shocks, shocks to income caused by changes in foreign demand and housing preference shocks (i.e., shocks that cause housing prices to rise but are unrelated to other fundamental variables).

From a methodological point of view, the analysis is challenging for two reasons. First, we must cope with the *large dimension* of the parameter space in our model. Second, the *identification* of economically interpretable shocks is complicated by the interaction among many different factors in our model.

As to the first challenge, we use Bayesian shrinkage techniques to make the estimation of a large number of parameters tractable. Specifically, we combine a Minnesota prior, i.e., the idea that a priori, the series follows a simple statistical model (see, e.g., Doan et al. 1984, Litterman 1986, Banbura et al. 2010, Giannone et al. 2015) with information from training observations to form an informative prior for our parameter space. The weights of the different sources of prior information are taken as unknown parameters and determined within our numerical posterior analysis. This implementation follows Giannone et al. (2015), who use the same idea to determine the weights of different components of a Minnesota prior. This Bayesian shrinkage technique enables us to expand the data set to include several interest rate measures and subcomponents of GDP (e.g., construction investment) in addition to the more standard macroeconomic variables, such as consumer prices, credit and stock prices. Because Switzerland is a small open economy, we also take into account exchange rate developments and an export-weighted measure of foreign GDP.[1]

The second challenge, the identification of shocks, is overcome by using the method proposed by Arias et al. (2014) to implement zero and sign restrictions to limit the response of observed variables to the shocks. The zero restrictions are established mainly to distinguish three different sets of shocks, namely, a block of foreign shocks influencing all variables on impact; a block of domestic macroeconomic shocks not influencing foreign variables on impact but influencing all domestic variables in the model; and a block of financial shocks influencing only fast-moving financial variables. The sign restrictions are included to disentangle the shocks within these blocks. The sign restrictions are chosen carefully to ensure that they match the responses we would expect based on theoretical considerations. Accordingly, a key assumption is that contractionary monetary policy and credit supply shocks lead to lower housing prices but higher mortgage interest rates, whereas negative housing demand shocks cause both lower housing prices and lower interest rates. This disentangles credit supply shocks, i.e., monetary policy and lending shocks, from housing demand shocks.

Our work relates to a quite new but rapidly growing body of theoretical and empirical

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[1] In this regard, we also abstract from the international transmission of credit market shocks and concentrate on domestic shocks.

work on the relationship between the financial sector and the macroeconomy. Prior to the financial crisis, many theoretical and empirical macroeconomic models typically ignored the direct impact of credit aggregates, interest rate spreads and housing on real economic activity (e.g., Christiano et al. 2005, Smets and Wouters 2007). The few prominent exceptions in the theoretical literature emphasize the role of the financial system as an accelerator of shocks (e.g., Kiyotaki and Moore 1997, Bernanke et al. 1999) or underscore the importance of housing to the business cycle (Goodhart and Hofmann 2008, Iacoviello 2010, Iacoviello and Neri 2010). Since the emergence of the global financial crisis, a new consensus has been established, namely, that in addition to standard macroeconomic (supply and demand) and monetary policy shocks, financial shocks should be regarded as an important source of fluctuations. Therefore, many studies have included certain financial aspects in DSGE policy models and have empirically investigated the role of financial frictions. Examples of theoretical work on the role of credit include Atta-Mensah and Dib (2008), Christiano et al. (2009), Curdia and Woodford (2010) and Gerali et al. (2010).[2]

In the empirical literature, interesting contributions on the role of credit supply shocks have come from Busch et al. (2010), Eickmeier and Ng (2015), Helbling et al. (2011), Meeks (2012), Gambetti and Musso (2012), Hristov et al. (2012) Fornari and Stracca (2012) and Peersman and Wagner (2014). A key issue is the role and relative importance of the credit supply shocks and standard monetary policy shocks identified by Musso et al. (2011) in the US and the EU. Studies that consider specific housing issues include Jarocinski and Smets (2008), Goodhart and Hofmann (2008), Musso et al. (2011) and Hirata et al. (2012).

Three main results emerge from our analysis. A first and very robust finding is that the effects of credit supply and demand shocks on real activity are limited, playing a substantive role only in specific episodes. The only source that has a robust impact on GDP is credit supply shocks related to monetary policy. However, the contribution of monetary policy shocks to real economic fluctuation is much lower than the contribution of foreign demand shocks. Second, our set of credit supply shocks (i.e., bank lending shocks and monetary policy shocks) explains a large fraction of housing price and credit fluctuations.

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[2] Beck et al. (2014) provide an excellent overview of recent advances in the incorporation of financial frictions into DSGE models.

Indeed, these shocks tend to be more important for housing prices than our identified housing demand shocks, i.e., housing preference shocks and population shocks. Third, we obtain tentative evidence that among the shocks related to credit supply, monetary policy shocks dominate bank lending shocks. Generally, our results are consistent with a credit channel of monetary policy.

The paper is structured as follows. First, we present the empirical methodology. Then, we describe our data set and our identifying assumptions about economic shocks. Finally, the results are presented and conclusions are drawn.

2 Econometric framework

We assume that the observations are generated by a vector autoregressive process:

$$\begin{aligned} y_t &= B_0 + B_1 y_{t-1} + \ldots + B_p y_{t-p} + Q\varepsilon_t && (1) \\ \varepsilon_t &\sim N(0, I_n) \ , && (2) \end{aligned}$$

where y_t is a $n \times 1$ vector of observed endogenous variables and ε_t is a $n \times 1$ vector of unobserved exogenous shocks. $B_0, \ldots, B_p$ and Q are matrices containing the unknown parameters. The likelihood of the model is invariant to orthonormal transformations of Q, the contemporaneous impact of shocks on observed variables. We therefore parameterize the likelihood function in terms of $\Sigma = Q'Q$ and estimate this reduced form model. In a second step, we identify Q based on further restrictions derived from economic theory.

We prefer to use a Bayesian estimation approach rather than a classical OLS-based estimator. In our model, a large number of series interact at different lags, such that the number of parameters relative to the number of available observations is quite large. A Bayesian approach that implements some shrinkage on the parameter space is particularly useful in these circumstances.

2.1 Prior and posterior distributions of the reduced form model

We rewrite the system for each sample as follows (see, e.g., Giannone et al. 2015). First, we define the matrices $y = [y_{p+1}, \ldots, y_T]'$, $Y = vec(y)$, $x_t = [1, y'_{t-1}, \ldots, y'_{t-p}]'$, $x =$

$[x_{p+1}, \ldots, x_T]'$, $X = I_n \otimes x$, and $e = vec([\varepsilon_{p+1}, \ldots, \varepsilon_T]')$. Then, we write the system as

$$\begin{aligned} Y &= X\beta + e & (3) \\ e &\sim N(0, \Sigma \otimes I_{T-p}) \ , & (4) \end{aligned}$$

where $\beta = vec(B)$ with $B = [B_0, \ldots, B_p]'$. Hence, the system can be written as a linear regression model and standard Bayesian methods for such models can be applied. The number of regressors is $k = np + 1$ in each sample, and the number of available time periods is denoted by T.

We follow the bulk of the literature by selecting a natural conjugate prior distribution for the model parameters, setting

$$\begin{aligned} \Sigma &\sim IW(\underline{\Psi}, \underline{d}) & (5) \\ \beta|\Sigma_i &\sim N(\underline{\beta}, \Sigma \otimes \underline{\Omega}) \ . & (6) \end{aligned}$$

The resulting posterior distribution can be shown to be

$$\begin{aligned} \Sigma|\beta, y, X &\sim IW(\underline{\Psi} + \hat{\varepsilon}'\hat{\varepsilon} + (\hat{B} - \hat{\underline{\beta}})'\underline{\Omega}^{-1}(\hat{B} - \hat{\underline{\beta}}), T - k + \underline{d}) & (7) \\ \beta|\Sigma, y, X &\sim N(\hat{\beta}, \Sigma \otimes (x'x + \underline{\Omega}^{-1})^{-1}) \ , & (8) \end{aligned}$$

with $\hat{B} = (x'x + \underline{\Omega}^{-1})^{-1}(x'y + \underline{\Omega}^{-1}\underline{\beta})$, $\hat{\beta} = vec(\hat{B})$, $\hat{\varepsilon} = y - x\hat{B}$ and $\hat{\underline{\beta}}$ being a $k \times n$ matrix obtained from suitably reshaping $\underline{\beta}$.

2.2 Parameterizing the prior distribution

A standard idea for the parametrization of the prior distribution is to implement an uncertain a priori believe that the data are generated by a simple statistical model, such as a univariate random walk. An alternative idea is to use a so-called training sample to determine the prior parameters. Our strategy is to use a combination of these ideas and to treat the respective tightness of the two parts as a hyperparameter to be determined in a formal posterior analysis.

We implement this idea by adding two sets of *dummy observations* to the actual sample. The first set $(\sqrt{\gamma}y^{Minn}, \sqrt{\gamma}X^{Minn})$ implements the Minnesota prior. We choose the procedure outlined by Banbura et al. (2010) and define the dummy observations accordingly. The second set $(\sqrt{\lambda}y^{Train}, \sqrt{\lambda}X^{Train})$ stems from the idea that data prior to the actual sample contain certain information on the true process, but for various reasons, we belief this information to be less accurate than the observations in the actual sample. The observations in the first and second sets are multiplied by factors λ and γ, respectively, parameterizing the tightness of the prior. If we multiply the likelihood of these observations by the initial improper prior $p(\Phi, \Sigma) \propto |\Sigma|^{-(n+1)/2}$, we obtain the prior distribution implied by adding the observations to the data set:

$$
\begin{aligned}
\underline{\beta} &= (\gamma X'_{Minn}X_{Minn} + \lambda X'_{Train}X_{Train})^{-1}(\gamma X'_{Minn}y_{Minn} + \lambda X'_{Train}y_{Train}) \\
\underline{\Omega} &= (\gamma X'_{Minn}X_{Minn} + \lambda X'_{Train}X_{Train})^{-1} \\
\underline{\Psi} &= \gamma(Y_{Minn} - X_{Minn}\underline{\beta})'(Y_{Minn} - X_{Minn}\underline{\beta}) + \lambda(Y_{Train} - X_{Train}\underline{\beta})'(Y_{Train} - X_{Train}\underline{\beta}) \\
\underline{d} &= T_{Minn} + T_{Train}
\end{aligned}
$$

We determine the prior weights λ and γ by conducting a formal posterior analysis. Specifically, we add a gamma prior for these parameters and simulate from its posterior distribution by introducing a random walk Metropolis-Hastings step into the otherwise standard posterior sampling procedure for the VAR coefficients (see, e.g., Giannone et al. 2015, for an application of the same idea to a Bayesian VAR with different sets of dummy observations). Thus, we produce draws from the posterior distribution of the reduced form coefficients using the following algorithm. Starting with initial parameters β_0, Σ_0, λ_0 and γ_0, we iterate $j = 1, \ldots, J$ times over the following steps:

Step 1: Draw β_j and Σ_j sequentially from (7) and (8).

Step 2: Draw a candidate value λ^* from

$$
\begin{pmatrix} \lambda^* \\ \gamma^* \end{pmatrix} = \begin{pmatrix} \lambda_{j-1} \\ \gamma_{j-1} \end{pmatrix} + \zeta
$$

with $\zeta \sim N(0, V)$, V being the scaled inverse hessian of the posterior density

> evaluated at the posterior mode of $p(\lambda, \gamma | y, X) \propto p(\lambda, \gamma) p(y | \lambda, \gamma)$.[3] Accept the candidate values with probability
>
> $$\alpha = \min \left\{ 1, \frac{p(\lambda^*, \gamma^* | y, X)}{p(\lambda_{j-1}, \gamma_{j-1} | y, X)} \right\},$$
>
> i.e., set $\gamma_j = \gamma^*$ and $\lambda_j = \lambda^*$ if the candidate value is accepted and keep the previous draw otherwise ($\gamma_j = \gamma_{j-1}$ and $\lambda_j = \lambda_{j-1}$). The scale of V is set such that the acceptance rate is between 0.2 and 0.3.

We exclude the first 10 % of these draws to ensure that the chain has convergence to the ergodic distribution. This produces $0.9J$ draws from the joint posterior distribution of the reduced form parameters $B_0, \ldots, B_p$ and Σ.

2.3 Identification of structural form

As described above, the restriction $QQ' = \Sigma$ implied by the reduced form model is not sufficient to identify the mapping from reduced form residuals to the structural shocks Q. Indeed, we will not attempt to *exactly* identify Q but rather rely on an idea put forward by Uhlig (2005), among others, and restrict Q to a plausible *range* by imposing a priori restrictions on the response of certain variables to the shocks. We implement this idea using the method described in Arias et al. (2014), which allows us to combine zero restrictions, i.e., the assumption that a shock does not influence an observed variable at a certain horizon, and sign restrictions, which implement beliefs on the direction of the response of observed variables to shocks. The procedure involves taking K random draws from the distribution of Q conditional on the restriction $QQ = \Sigma$ and the zero restrictions for each draw of the reduced form parameters, and keeping the draws that satisfy the sign restrictions.[4] We present the specific restrictions in our application following the description of our data set. In the Appendix 6.2, we discuss the properties of the full prior

---

[3] The marginal likelihood $p(y|\lambda)$ can be derived analytically, see, e.g., Giannone et al. (2015). The parameters of gamma distribution are chosen such that the mean is 0.5 and the standard deviation is 1. Additionally, we normalize γ with the sample size of the training sample relative to the actual sample.

[4] More precisely, we randomly rotate an arbitrary initial Q_0 by multiplying an orthonormal rotation matrix Ω drawn from the uniform distribution with respect to the (normalized) Haar measure on $O(n)$ conditional on the zero restrictions, see Arias et al. (2014). Restrictions on combinations of variables can be implemented by calculating the responses of these combinations and checking whether they satisfy the restrictions.

distribution, including the sign-restrictions, and show that the prior is sufficiently loose in the sense that the prior intervals are quite wide, particularly if only information from the Minnesota prior is combined with the sign restrictions.

2.4 Data and specification

Table 1 describes the data and their sources. We estimate the model on a quarterly frequency, i.e., we aggregate monthly data and interpolate annual data using related indicators before estimating the model. All variables except the interest rates are transformed with the natural logarithm. We consider data from Q1 1981 to Q2 2015. The first five-year period of the sample, i.e., 1981-1986, serves as our training sample. We opt for the training sample approach because certain data are not measured consistently throughout the sample (credit, mortgage rates, housing prices). In addition, with the training sample, we can take the full data set into account, but with a lower weight. We set the lag length p equal to four but also experiment with smaller and larger numbers of lags to assess the robustness of the results (see section 4). The number of draws from the posterior distribution is set to 220,000, such that by discarding the first 10%, we obtain 200,000 draws from the posterior distribution of the reduced form parameters. We set $K = 10$ and obtain a total of 1600 accepted draws from the distribution of the structural parameters. Note that the dramatic reduction in the number of draws is due to the numerous restrictions that must be implemented to identify the five shocks in our large BVAR. These restrictions are described in the following section.

Table 1 — Description of variables used

Series	Frequency (original)	Description
Real variables		
GDP	quarterly	Seco estimates, real (seasonally and calender adjusted)
Working hours	quarterly	internal estimates based on SFSO employment figures
Construction investment	quarterly	Seco estimates, real (seasonally and calender adjusted)
Foreign working age population (number of persons without Swiss nationality)	annual	SFSO estimates, interpolated to quarterly frequency by use of Chow-Lin
Interest rates		
Short-term interest rate	Monthly	3-Months Libor, linked to 'Frankensatz' 3 Months in Q1 1998
Mortgage rate	quarterly	2-years, linked 1996 (Cantonal Banks) and 2007 (VZ Banks)
Long-term interest rate	Monthly	10-Y Eidgenossen
Foreign long-term interest rate	working days	10-Y German gov. bonds
Assets		
Credit volume	Annual/monthly	Credit to households and firms, monthly only from 1988
Mortgages to households	Annual/monthly	Mortgages to households, monthly only from 1988
Prices		
Housing prices	quarterly	Wüest & Partner, offer prices
Consumer prices excl. rents	monthly	SFSO estimates
Consumer prices rents component	monthly	SFSO estimates
Foreign variables and exchange rates		
Exchange rate	quarterly	nominal, export-weighted
Foreign GDP	quarterly	real, export weighted

2.5 Identifying restrictions

With respect to GDP, our major variable of interest, we follow the principle put forward by Uhlig (2005) and set only a minimum number of restrictions to remain agnostic toward the sign of its response (see table 2).[5] Specifically, the effect of credit supply and demand shocks on GDP are not directly restricted (with the sole exception of population shocks). Our identifying restrictions can be broadly grouped in two types.

The first type partitions the shocks into different blocks according to their short-term influence on *groups of variables*. The block of foreign shocks potentially influences all variables in the model on impact. The block of domestic 'macroeconomic' shocks influences all domestic variables on impact but not the foreign variables. Finally, the block of domestic 'financial' shocks influences *fast-moving* domestic financial variables (e.g., interest rates, exchange rates, housing prices) on impact but not foreign variables or *slow-moving* domestic variables such as GDP, working hours and inflation. Note that the blocks are separated using only zero restrictions on elements of Q.

The second type of restriction extracts the shocks of interest within these blocks. Particularly for the identification of shocks within the financial block, we cannot rely exclusively on zero restrictions but instead must add plausible sign restrictions on both single variables and combinations of variables (e.g., interest rate spreads and ratios). Generally, these restrictions are in line with theoretical models of the credit and housing markets following Iacoviello and Neri (2010), Curdia and Woodford (2010) and Gerali et al. (2010). We now discuss in detail the specific restrictions for each shock of interest.

---

[5] In principle, as shown by Baumeister and Hamilton (2015), the mere application of the uniform prior on the rotation matrix implemented in the procedure by Arias et al. (2014) leads to an informative prior on the responses, even if no actual sign restriction is imposed. However, for many responses, the posterior distributions are quite wide (or distinctly positive, as with the response of GDP to foreign demand shocks), which gives us some confidence that our results are not spurious due to unintended consequences of the uniform prior on the rotation matrix.

Table 2 — Identified shocks

		Monetary policy	Bank lending	Housing preference	Population	other domestic	Foreign demand	Other foreign
Foreign block	Foreign GDP	0	0	0	0	0	+	0
	Foreign interest rates	0	0	0	0	0		
Non-financial block (slow moving)	Population	0	0	0	+			
	GDP	0			+			
	Construction	0	0	+				
	Working hours	0	0	0				
	CPI without rents	0	0	0				
	CPI rents	0	0					
Financial block (fast moving)	Short rate	-	0	0				
	Long rate							
	Exchange rate	+						
	Mortgage rate							
	Housing prices	+	+	+				
	Credit	+	+	+				
Combinations	Mortgage rate - Long rate		-	+				
	Price - rents			+				
	GDP - working hours				-			
	Credit - GDP		+					

Monetary policy shocks

We assume that an expansionary monetary policy shock moves short-term rates down and drives credit up. Furthermore, we exploit the uncovered interest rate parity and assume that it leads to a depreciation of the Swiss franc. Note that monetary policy shocks are considered to be ’financial’ shocks that do not influence ’slow-moving’ variables on impact. That is, we implement a set of zero restrictions typically used in the identification of monetary shocks, implying that real variables and inflation do not contemporaneously react to monetary policy shocks. Although quite restrictive, this is a standard assumption in the literature (e.g., Christiano et al. 1999). Additionally, we assume that an expansionary monetary policy leads to housing price increases.

The assumption that credit volume increases following an expansionary monetary policy is consistent with the existence of a credit channel of monetary transmission, as described by Bernanke and Gertler (1995). In their model, monetary policy influences the external finance premium faced by firms that do not have internal resources to finance new investment projects. Typically, two major mechanisms are suggested to explain the link between monetary policy actions and the external finance premium: the balance sheet channel (a borrower’s external finance premium is inversely related to her net worth, which in turn is influenced by monetary policy) and the bank lending channel (the supply of credit is influenced by monetary policy). Both channels are expected to have a sizable effect on the housing market (Bernanke and Gertler 1995). The bank lending channel is particularly relevant because mortgages are provided almost exclusively by banks.

Bank lending shocks

Bank lending shocks include financial innovations (e.g., through securitization), increases in the risk appetite of banks, modifications in the capital requirements for financial intermediaries and changes in the liquidity provided by the central bank. As argued by Bernanke (1993), the government or central bank can interfere with the normal process of bank lending in a number of ways. Credit controls, restrictions on loan growth and marginal reserve requirements are historical examples of credit supply shocks that are not caused directly by monetary policy actions. Another example is variations in bank capital.

In particular, real estate losses exacerbated by tougher capital regulations may constrain bank lending (other examples can be found in Bernanke 1993).

Accordingly, our definition of a bank lending shock captures movements in credit that are unrelated to monetary policy (and therefore orthogonal to short term interest rates) and lead to declining mortgage risk premiums (defined as the difference between mortgage rates and long-term bond yields). Additionally, this shock is set to increase the credit-to-GDP ratio (the restrictions are similar to Eickmeier and Ng 2015). The assumed decline in the mortgage risk premium is intended to separate credit supply from housing demand factors (which are assumed to widen the mortgage premium). The increase in the credit-to-GDP ratio is critical to separate it from real shocks (aggregate demand), which may also impact credit volumes, but only proportionally. Note that although bank lending shocks are grouped into the financial block, we allow them to have an immediate impact on GDP. Furthermore, it is assumed that positive bank lending shocks lead to housing price increases.

Housing demand shocks

To identify housing demand shocks, we broadly follow Jarocinski and Smets (2008) and Musso et al. (2011). However, we decompose the housing demand shock into two types of separate shocks: a housing preference shock and a population shock. The housing preference shock can be interpreted as in the DSGE model of Iacoviello and Neri (2010), which exogenously increases households' willingness to spend on housing. More broadly, this shock can be interpreted as sentiment. Thus, there might be times when households are overly optimistic (or overly pessimistic) concerning future rental revenues. Obviously, the housing preference shock also includes speculation motives. The assumed restrictions imply positive reactions by housing prices, credit and construction investment (which corresponds to Jarocinski and Smets 2008, Musso et al. 2011).

Additional drivers of housing prices and credit can be found in population expansion. This factor is particularly important in Switzerland, where population growth is driven mainly by migration, which varies depending on institutional settings and the state of the business cycle. Therefore, it is desirable to distinguish a housing demand shock caused by additional population from housing demand shocks caused by other factors. The population shock is defined as increases in GDP and the size of the foreign population and decreases in productivity. Biany and Gete (2014) follow a similar approach to disentangle population shocks from other sources of housing demand (although population is not a separate variable in their analysis).

Foreign shocks

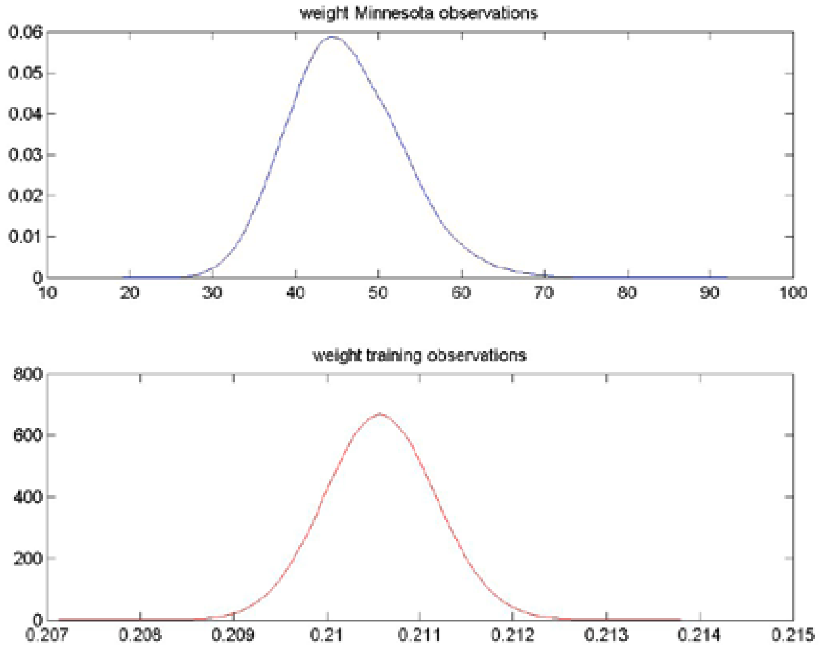
To improve the interpretability of our results, we also identify a foreign demand shock. Due to high external dependence (export-to-GDP ratio), it is expected that this type of shock is a major driver of Swiss GDP and may also be responsible for moving other domestic variables. As described above, all domestic shocks are assumed to have no effect on foreign demand, reflecting the fact that Switzerland is a small open economy. Among foreign shocks, we disentangle foreign demand shock using zero restrictions. Specifically, our foreign demand shock is the only shock influencing both foreign GDP and foreign interest rates on impact. Because we are not primarily interested in the exact source of foreign fluctuations but rather attempt only to capture the effect of a 'typical' change in foreign GDP, this operational assumption appears to be reasonable.

3 Results

3.1 Prior weights

As described in Section 2.4, our BVAR is estimated over the sample period Q1 1987 to Q2 2015, with observations from 1981-1986 serving as a training sample. We opt for the training sample approach because certain series are not measured consistently throughout the sample (credit, mortgage rates, housing prices). Moreover, with the training sample, we can take the full data set into account, but with a lower weight. According to our estimates, the training sample observations enter with a weight of approximately 22% (see figure 2). The posterior distribution of the Minnesota prior is given in the same figure and corresponds closely to that reported by Giannone et al. (2015) for their medium scale

Figure 2 — Posterior distribution of hyperparameters



Note: γ is normalized with the sample size of the training sample relative to the actual sample.

BVAR.[6]

3.2 Impulse response analysis

Response to monetary policy shocks

We start by looking at a conventional monetary policy shock. By construction, an expansionary monetary policy shock leads to a short-term decrease in the policy rate, an increase in credit and housing prices, and depreciation. Based on these identifying assumptions, we find that a monetary policy shock leads to a sluggish increase in GDP (see figure 3). The maximum effect is reached after approximately 1 1/2 to 2 years. This finding is fully consistent with both international experience (Bernanke and Gertler 1995, Christiano et al. 1999) and Swiss studies (e.g., Kugler and Jordan (2004), see also overview

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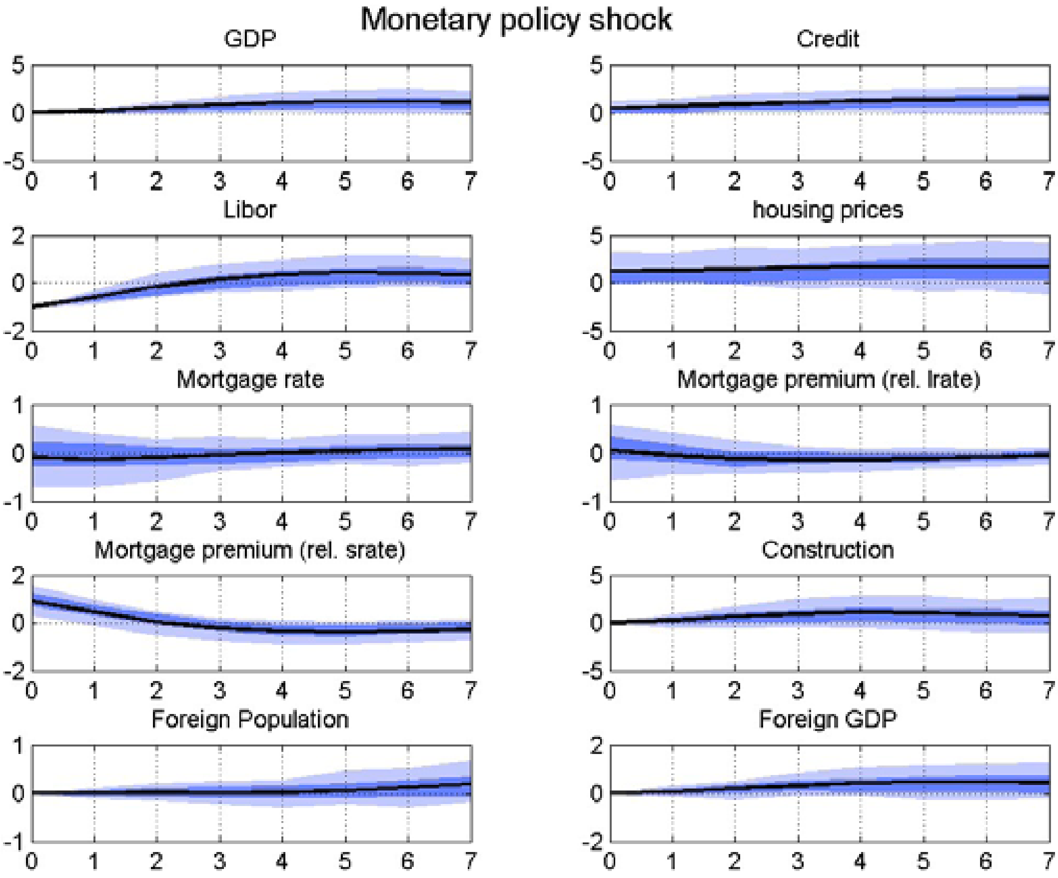
[6] Note that Giannone et al. (2015) define the Minnesota prior in a slightly different way: $\mu = 1/\sqrt{\lambda}$. This approach implies that our posterior mean of approximately 46 corresponds to a value of 0.15, which is between the modes of their large- and medium-scale BVAR model estimates. Our estimates for the Minnesota weight are quite large compared to our prior assumptions. However, reparameterizing the weight such that the prior refers to the square root of λ does not shift the posterior distribution to a relevant extent, suggesting that the prior is sufficiently loose.

in Bäurle and Steiner (2015)).

Furthermore, there is evidence that monetary policy has some effect on construction investment, with a lag of approximately one year. This confirms the finding of Bernanke and Gertler (1995) that residential investment (which is a major component of construction investment) typically reacts notably to a monetary policy shock. Bernanke and Gertler (1995) interpret this as an indication of the existence of a credit channel of monetary policy. Additionally, there is a temporary positive effect on productivity and a persistent positive effect on credit. Note that the uncertainty regarding the reaction of housing prices remains substantial, implying that the data are not informative in this respect.

Figure 3 — IRFs to a monetary policy

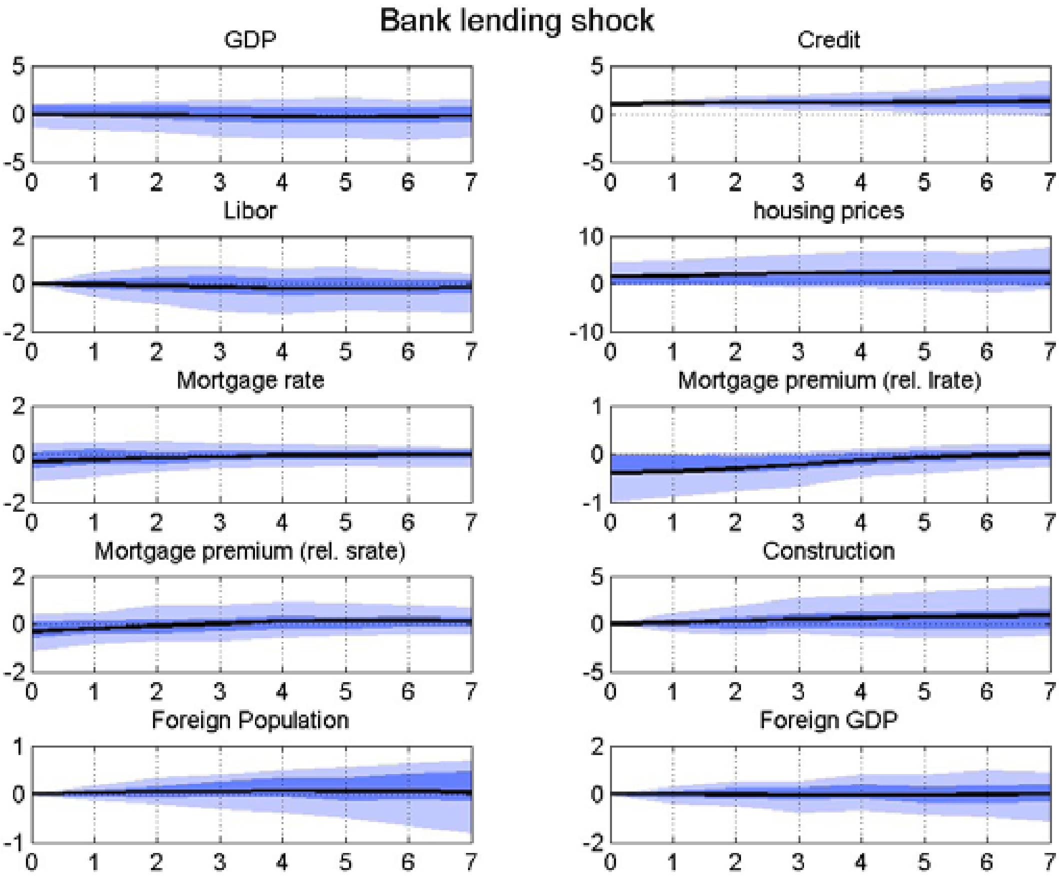


Note: Figures show the median along with the 50% and 80% highest posterior density (HPD) intervals.

Response to bank lending shocks

The average effect of bank lending shocks on major variables in the system remains very limited with the pre-specified restrictions (see figure 4). Overall, the impact on the real economy seems to be small. This confirms earlier studies (e.g., Cochrane 1994), which suggest that credit shocks do not explain a significant portion of output fluctuations. However, this result does not mean that these shocks never have a significant impact on the real economy (see the historical decompositions below). Furthermore, one must acknowledge that the uncertainty of the IRFs is rather high, which may be because the main identifying assumption relies on the reaction of the mortgage premium, which does not have a large variation in our sample.

Figure 4 — IRFs to a bank lending shock



Response to housing demand shocks

A housing preference shock is assumed to have a positive short-term impact on credit, housing prices, construction investment, mortgage spread and to the price-to-rent ratio. The resulting estimate of the impact on GDP remains limited (see figure 5). This finding may not be surprising against the backdrop of Schmid (2013) and Galli (2015), neither of whom found strong wealth effects due to higher housing prices in Switzerland. One explanation for this limited effect may be that households must save more to invest in housing (which ceteris paribus has a negative impact on GDP). Thus, positive effects on construction investment might be compensated by a negative effect on private consumption due to a higher savings rate, which is consistent with reactions to housing preference shocks in DSGE models (Iacoviello and Neri 2010). Indeed, our results imply that the construction-to-GDP ratio increases after a housing preference shock.

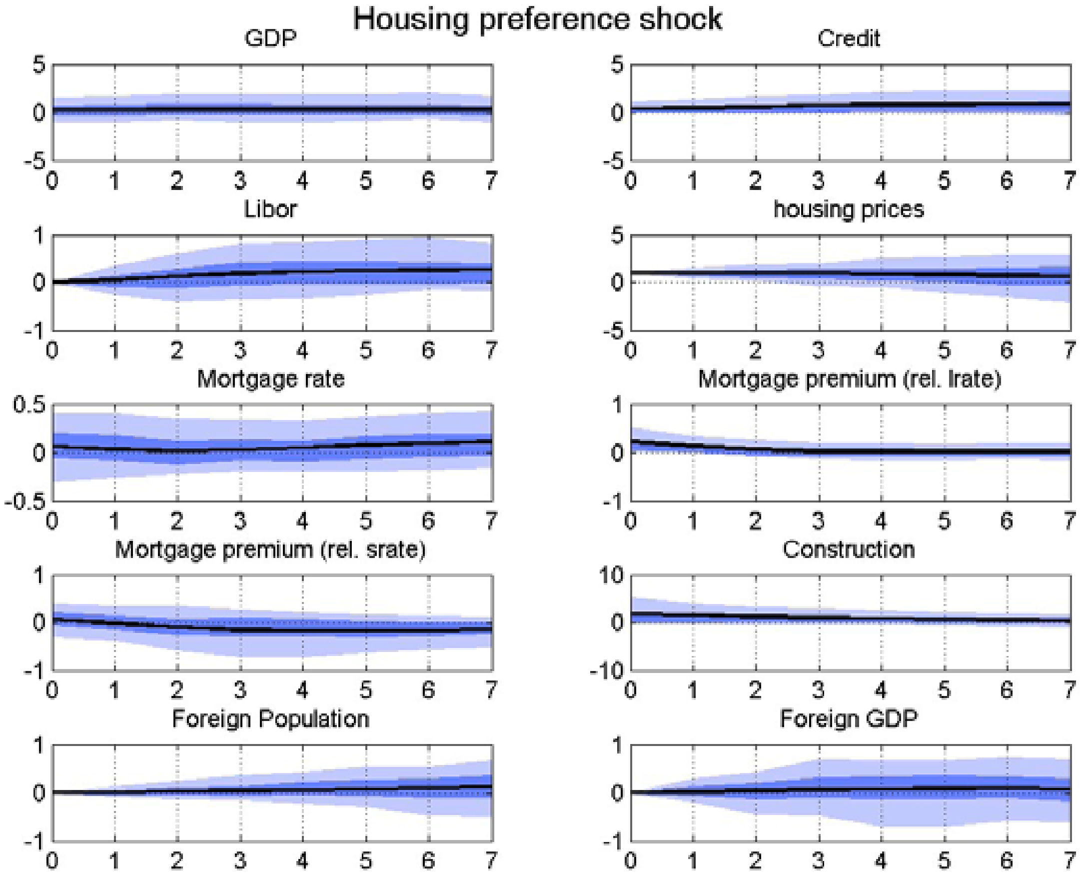
Interestingly, we find that monetary policy seems to react to housing demand shocks by increasing interest rates. This might explain the temporary effects of housing demand shocks on housing prices, construction investment and the price-to-rent ratio.

Population shocks generally have a very low impact on macroeconomic variables (see figure 6). In particular, they do not have substantial effects on housing prices or credit. The only exception to the general rule is working hours, where a positive response is observed.

Response to foreign demand shocks

The foreign demand shock has a large and significant impact on many variables of the system (see figure 7). A positive shock increases GDP, interest rates, working hours and inflation. Interestingly, it has a negative impact on credit, construction investment and housing prices. These results imply that the response of monetary policy to a foreign demand shock more than offsets the potential positive income effects (which could boost housing demand). Additionally, we find that a foreign demand shock increases the demand for workers and therefore leads to an increase in foreign population following certain quarters, suggesting that the size of the foreign population responds to demand conditions in Switzerland.

Figure 5 — IRFs to a housing preference shock

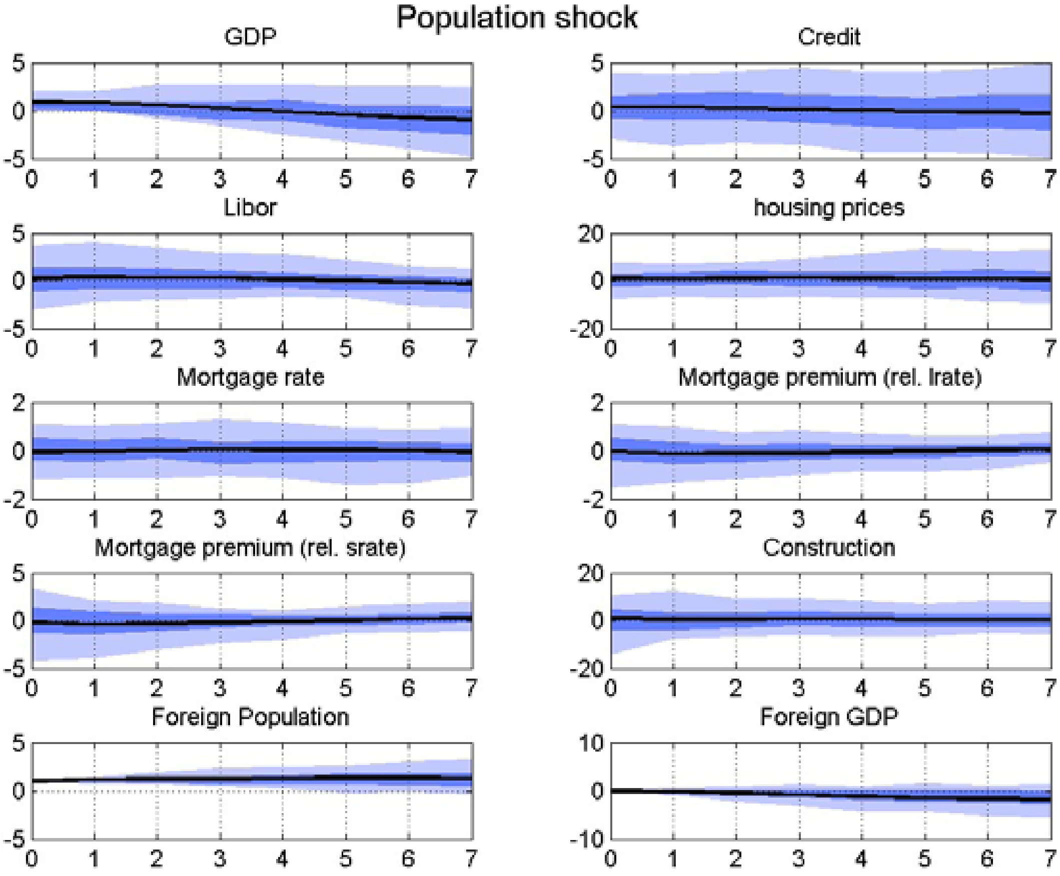


Overall, our findings for the foreign demand shock can be viewed as a robustness check for our model. We find little evidence that credit supply and demand shocks have pronounced effects on our set of macro and financial variables. This lack of evidence could be due to a poorly specified model and a large degree of estimation uncertainty. However, the distinct results found for the foreign demand shock suggest the opposite. In this case, IRFs are characterized by very little uncertainty, which can be taken as evidence that our model is able to extract information once this information is actually contained in the data.

3.3 Shock contributions

To assess the relative importance of our identified shocks, we study the forecast error variance decomposition (FEVD) at different horizons (see table 3). The FEVD yields

Figure 6 — IRFs to a population shock



estimates of the *average* contribution of the respective shocks over the business cycle. Additionally, we decompose the observed series into contributions of historical shocks.[7] This process gives an indication of which types of shocks matter in different episodes. Certain shocks may matter only slightly for certain variables on average but may matter substantially in particular events. We investigate the relative importance of shocks to credit, housing prices, GDP and working hours (see figures 8, 9, 10 and 11). Because we consider a medium-scale VAR with 14 variables, it is important to note that there will be a large fraction of unexplained variance (because approximately 2/3 of shocks are not explicitly identified).

Generally, we find housing prices are affected by combination of credit shocks. The

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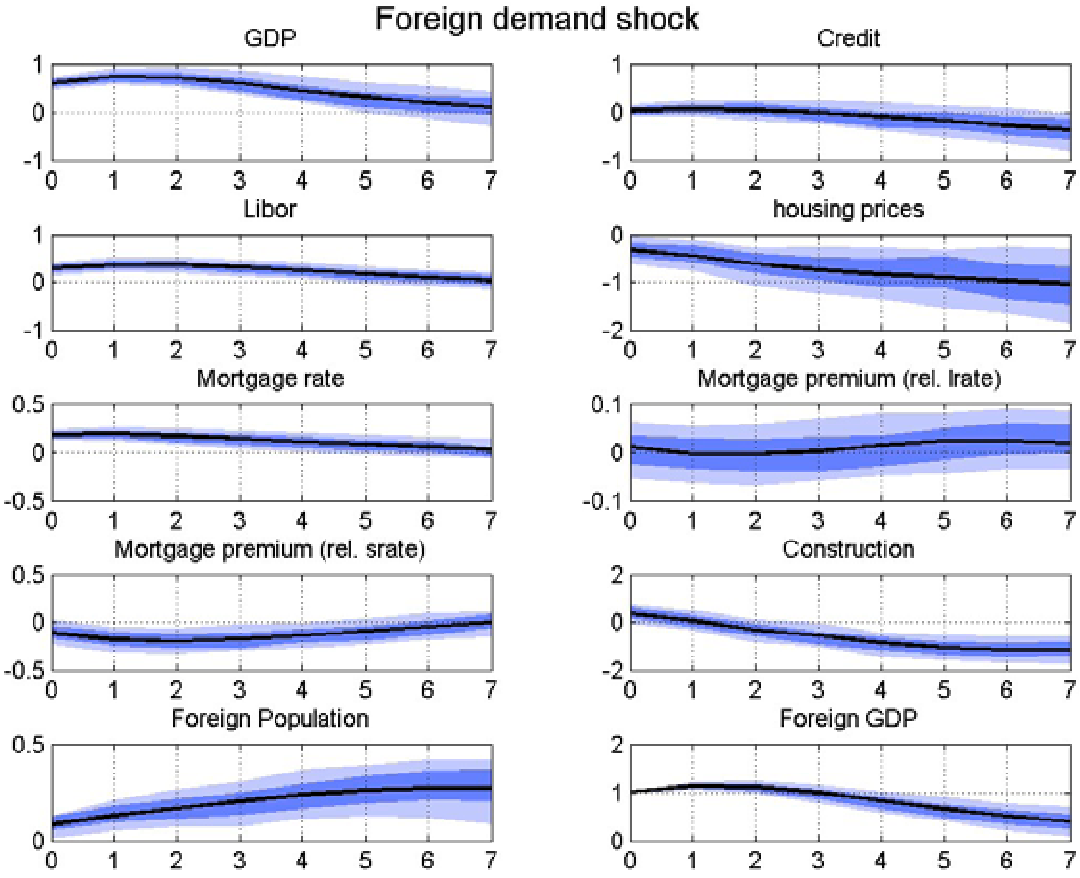
[7] The shares in Table 3 are calculated based on the median contributions for each shock relative to the median contributions of all shocks evaluated for each draw. This approach guarantees that the contributions sum up to one. The historical contributions are calculated as the median historical contributions evaluated for each draw. Note that the calculated contributions do not necessarily exactly sum up to the actual data.

Table 3 — Forecast variance decomposition for different variables

	on impact	after 1 year	after 4 years
I. Credit			
- Foreign demand shock	0.7	4.7	7.4
- Bank lending shock	21.7	13.4	9.6
- Monetary policy shock	6.9	14.4	9.4
- Housing preference shock	7.1	11.1	6.9
- Population shock	5.2	5.1	4.9
II. Housing prices			
- Foreign demand shock	3.4	9.7	8.6
- Bank lending shock	9.9	9.1	7.6
- Monetary policy shock	11.3	7.0	6.2
- Housing preference shock	11.5	5.9	6.8
- Population shock	5.7	4.4	5.3
III. GDP			
- Foreign demand shock	37.5	19.4	14.6
- Bank lending shock	6.0	5.4	5.7
- Monetary policy shock	0.0	7.7	6.5
- Housing preference shock	10.3	7.2	7.4
- Population shock	2.1	4.1	5.9
IV. Working hours			
- Foreign demand shock	11.0	12.9	9.7
- Bank lending shock	0.0	4.4	5.9
- Monetary policy shock	0.0	6.1	6.2
- Housing preference shock	0.0	7.8	7.7
- Population shock	34.0	9.5	6.6

Note: Share of the total in percentage points

Figure 7 — IRFs to a foreign demand shock



most recent housing price boom can be traced back to bank lending, housing preference and monetary policy shocks, whereas population shocks play a minor role in this area. However, the average effects of credit supply and housing demand shocks on real activity are relatively small, particularly when compared to findings in related studies (e.g., in the US). Nonetheless, there are certain episodes in which those shocks matter. In particular, monetary policy shocks had a measurable impact on GDP in the aftermath of the crisis.

Decomposition of credit

Table 3 shows the FEVD for credit, revealing that three sources have a substantial impact on credit: bank lending, monetary policy and housing preference shocks. In the short term, bank lending shocks contribute the most; more than 20% of the variation in credit volumes is explained by this shock. Foreign demand and population shocks do not have a

Figure 8 — Historical decomposition for credit

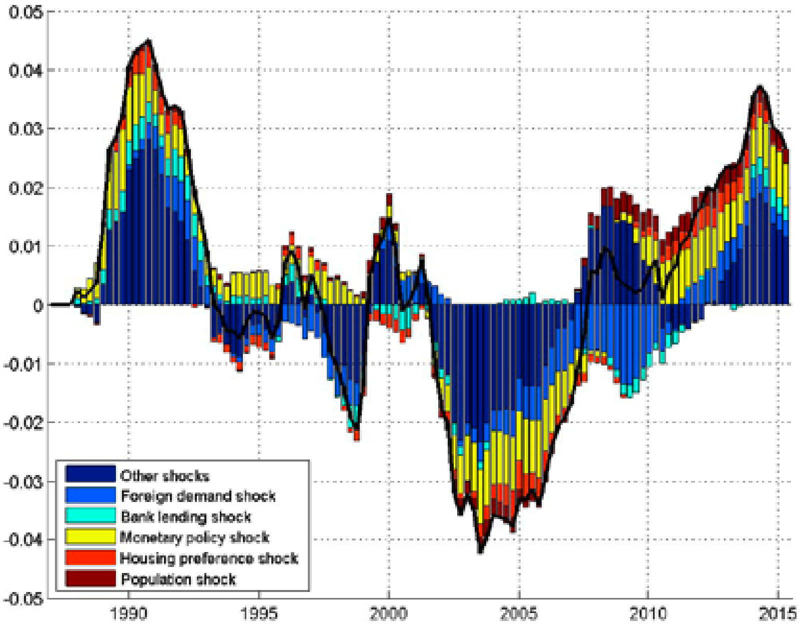
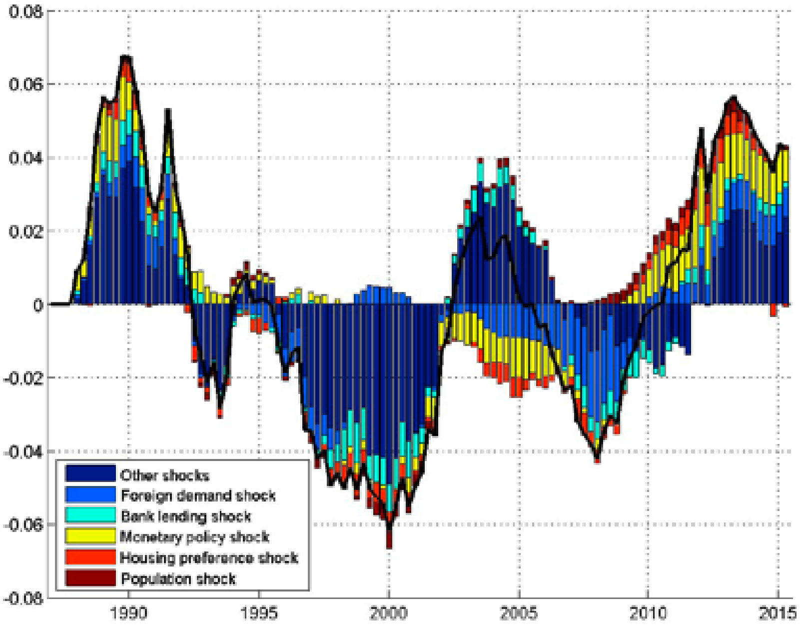


Figure 9 — Historical decomposition for housing prices



significant impact on credit.

By investigating the effect of shocks on credit over time (figure 8), we find the following. During the early 1990s, when Switzerland experienced a large housing upturn, most shocks contributed positively to credit development, with housing preference shocks, monetary policy shocks and bank lending shocks showing similar contributions. During the downturn in the mid-1990s, housing preference shocks contributed negatively, whereas bank lending and monetary policy shocks had slightly positive impacts. After 2000, weak credit development was mainly a result of contractionary housing preferences, monetary policy shocks and slow population growth. The same set of shocks contributed to strong credit growth following the financial crisis.

Generally, these findings suggest that the provision of credit is important for the transmission of monetary policy and emphasize the credit channel of monetary policy (as discussed in Bernanke and Gertler 1995). Our results confirm that monetary policy can substantially affect the supply of credit. Bank lending shocks that are unrelated to monetary policy (e.g., shocks caused by capital regulation or capital crunches) are less important and seem to have mattered more in the early 1990s.

Decomposition of housing prices

Regarding housing prices, we again find that bank lending, housing preference and monetary policy shocks contribute almost equally to the forecast error variance on average (table 3). Together, these types of shocks account for more than 30% on impact. Foreign demand contributes primarily at longer horizons. The contribution of population shocks is quite small, which is consistent with the result mentioned in the previous section: housing prices do not show a substantial reaction to population shocks.

Historically, housing price swings have been driven by a combination of shocks (Figure 9). However, the relative contributions of our identified shocks differ across episodes. In particular, bank lending shocks dominated other identified shocks in the early and late 1990s, whereas monetary policy shocks dampened housing price growth substantially in the mid-2000s. The most recent upturn in prices is driven mostly by monetary policy shocks in combination with supporting housing preference shocks. Additionally, population shocks and bank lending shocks provide further support for housing prices, although their contributions are quite small.

Figure 10 — Historical decomposition for GDP

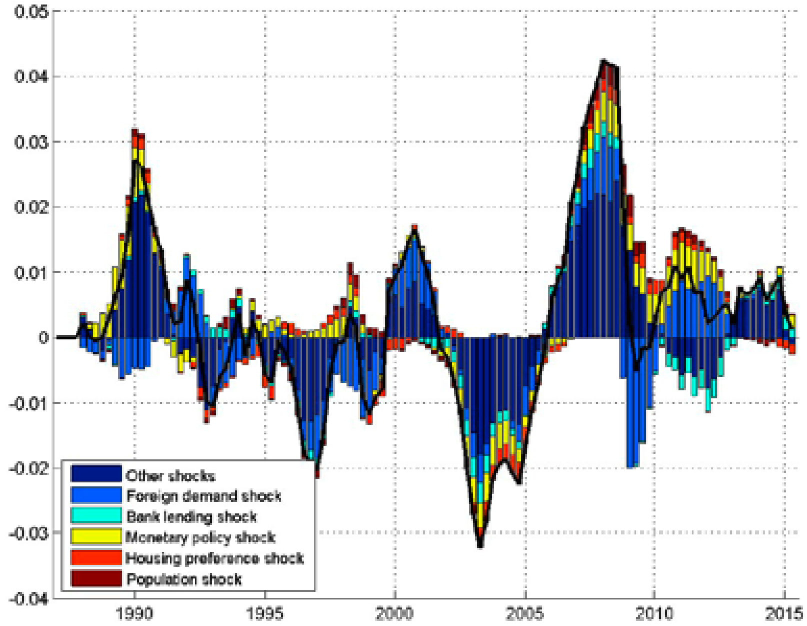
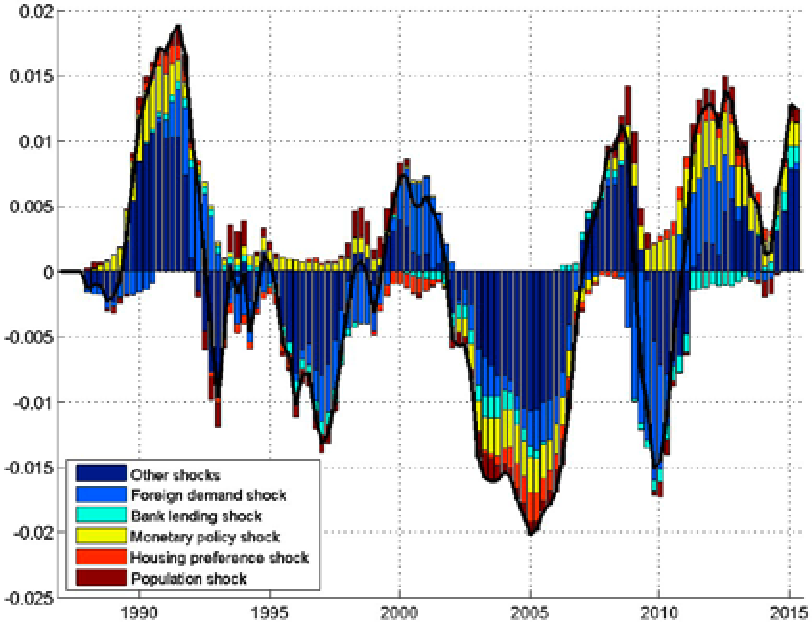


Figure 11 — Historical decomposition for working hours



Decomposition of GDP

We find that foreign demand explains a very large fraction of variation in GDP (table 3), contributing to more than 35% of the variation in the short-term. Foreign demand shocks contribute substantially even in the long term. Housing preference and monetary policy shocks also matter. Whereas housing preference shocks are more important in the short-term, monetary policy shocks contribute mainly in the medium term. However, taken together, credit supply and demand shocks cannot explain more than 25% of GDP fluctuations.

Investigating the historical contributions, we see that there is no specific episode in which bank lending shocks contributed substantially to fluctuations in GDP. However, monetary policy shocks mattered during the financial crisis and thereafter. In particular, monetary policy shocks helped to stabilize the economy, which was suffering from the slump in foreign demand in the aftermath of the crisis. Additionally, housing preference shocks contributed positively to real activity during that episode. However, the quantitative importance of these shocks remains relatively small.

Decomposition of working hours

Similar findings are found for working hours. As is the case for GDP, foreign demand shocks are a major driver of working hours. However, population growth shocks also seem to be an important factor. On impact, 30% of the variation is explained by population growth shocks, implying that new foreigners directly attain jobs and firms can instantaneously eliminate labor shortages with foreign workers. After some lag, working hours also react to foreign demand shocks. Housing preference shocks were important around 2005 and 2011 (Figure 11), suggesting that the construction sector, with its high labor intensity, has some impact on aggregate employment dynamics.

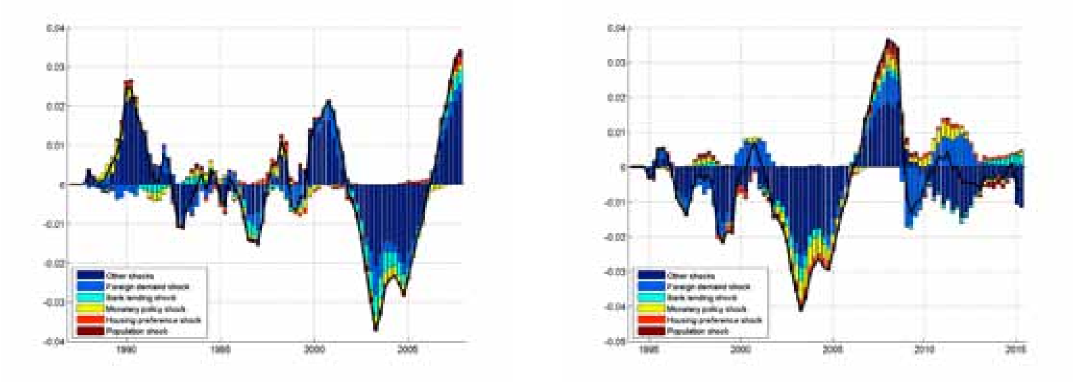
4 Robustness

We experimented with a number of alternative specifications (see figure 12). First, we used different settings in our VAR models. Both the number of lags and the tightness of the Minnesota prior are investigated. The number of lags has a minor impact on the results. As an alternative to our baseline specification, wherein 4 lags are considered, lag lengths of 2 and 6 were used. All of our findings remain valid with the alternative specifications, reflecting the fact that a lag length of two is already a good approximation and that the

Minnesota prior shrinks longer lags towards zero.

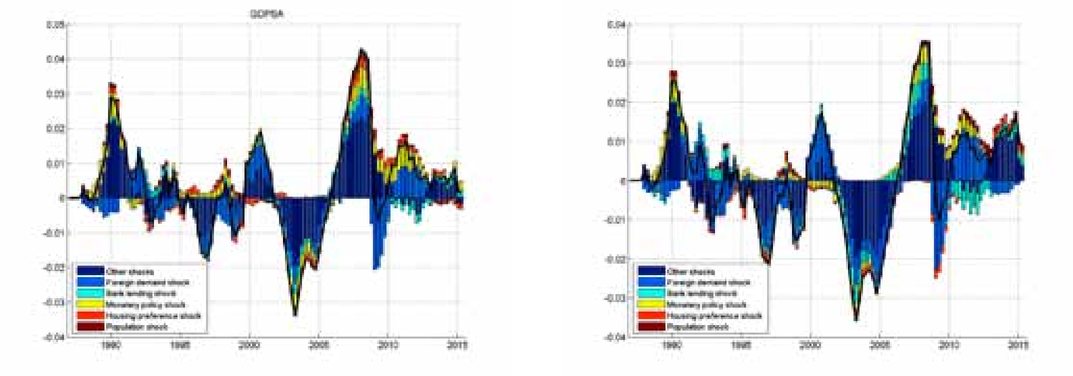
To check the sensitivity of our result to the Minnesota prior, we used a smaller degree of shrinkage in the estimation (choosing the 5% quantile of the posterior distribution for this Minnesota shrinkage parameter). The impact on the historical decomposition remains very limited; only the uncertainty surrounding the estimates notably increases. These results suggest that there is no substantial bias in our impulse response analysis and structural decompositions.

Figure 12 — Robustness checks



(a) Sample 1987 to 2007

(b) Sample 1994 to 2015



(c) Lower weight Minnesota Prior

(d) Mortgages to households

Note: Historical decompositions based on alternative BVAR specifications.

Second, we experimented with different samples and data. First, we excluded the period following the financial crisis from our sample; then, we omitted the first housing boom from our sample. Neither experiment produced significant differences compared to our baseline specification. If anything, we see a slightly more pronounced contribution by bank lending shocks at the very end of the sample period. Additionally, we varied the data set slightly by replacing total credit with household mortgages. Using household mortgages, we find even smaller differences compared with our baseline results. Again, bank lending may be somewhat more important than it is in the baseline specification.

Finally, we changed several of our identification restrictions. Specifically, certain sign restrictions are altered. Minor changes to the identification restrictions do not change any of our qualitative results.[8]

5 Conclusions

This paper analyzed credit supply and demand shocks in the Swiss economy. Using a medium-scale BVAR model, we were able to take into account various interactions among housing prices, credit, interest rates and real activity measures. To identify meaningful economic shocks, we used a combination of zero and sign restrictions.

Our empirical analysis shows that the effects of credit supply and demand shocks on real activity are limited, playing a substantive role only in specific episodes. After the financial crisis, both monetary policy shocks and housing preference shocks contributed positively to real activity. Furthermore, foreign demand can explain a substantial portion of the variation in real variables and thus must be taken into account.

We find that credit supply shocks (i.e., bank lending shocks and monetary policy shocks) explain a large fraction of housing price and credit fluctuations. Indeed, credit supply shocks tend to be more important for housing prices than our identified housing demand shocks, i.e., housing preference shocks and population shocks. Furthermore, there is evidence that monetary policy shocks dominate bank lending shocks.

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[8] For instance, we relaxed the assumption that housing preference shocks increase construction on impact. In another specification, we omitted the restrictions of monetary policy shocks and bank lending shocks on housing prices.

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6 Appendix

6.1 Additional figures and tables

Table 4 provides an overview of identification assumptions in the literature and figure 13 displays the structural shocks.

Figure 13 — Historical shocks

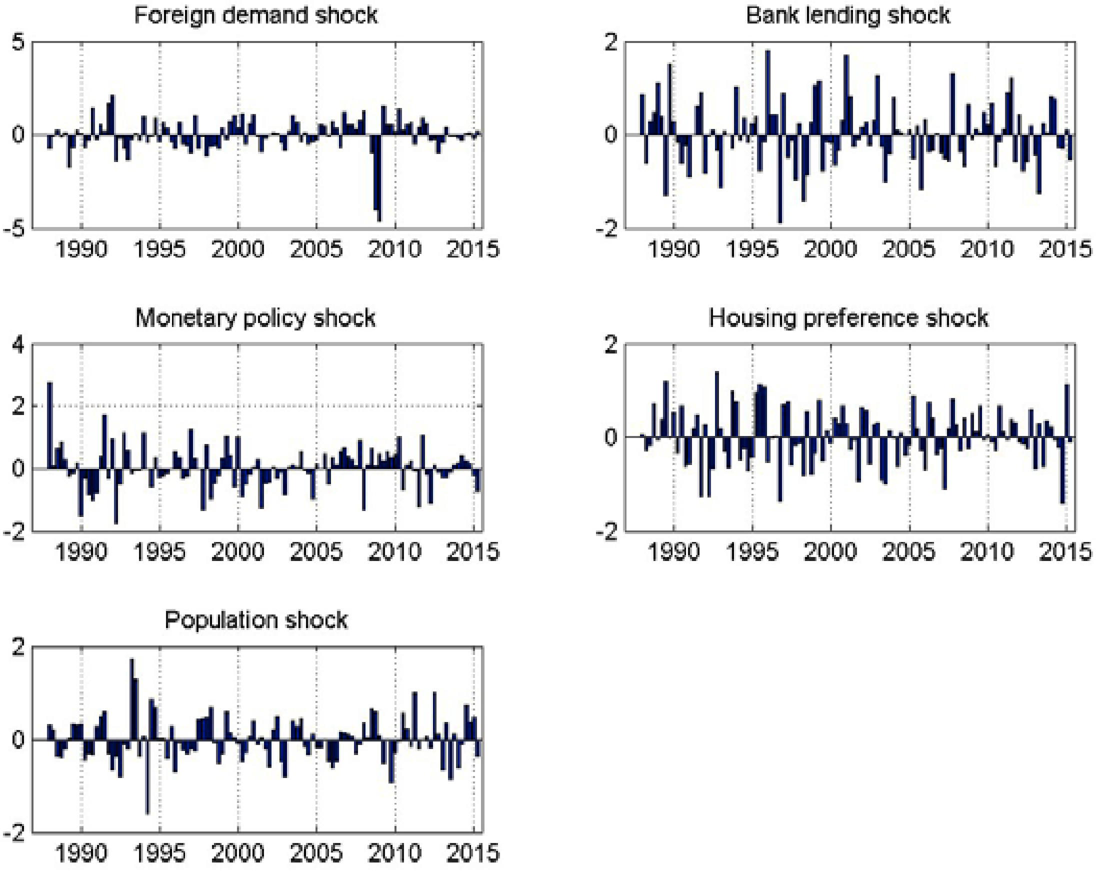

TABLE 4 — OVERVIEW SHOCK DEFINITIONS

	credit supply / lending shock			monetary policy shock			housing demand			productivity			demand			population			housing preference		
	+	-	0	+	-	0	+	-	0	+	-	0	+	-	0	+	-	0	+	-	0
Credit		1,3,6,7,10, 12		1,9						7											
GDP		1,3,8,9	9,10	1,4,8,11		9,10,13				7,12			4			12				12	
Prices			8,9,10	1,4, 7,11		8,9,10,13			13				4								
Lending rate (or Mortgage rate)	1,9				1,9														14		
Short-term interest rate		1,8,9	10		1,4,7,8,9,10,11								4								
Corporate bond rate	3																				
Default rate		6	7																		
Credit - GDP		3																			
Corporate bond - Government bond	3																				
Corporate bond - Short term interest	3																				
non-default component of bond spread	2																				
Non-financial firms stock prices				4									4								
Financial - non financial stock prices														4							
Private investment				4																	
Housing investment							13												14		
Housing investment - GDP									13												
CA - GDP																				12	
Credit mix		8		8																	
Credit spread	6,7					11															
Productivity	6	12								12							12				
Reserves				7																	
Exchange rate (appreciation)		8			8,11																
House prices		8, 12		8			13			12						12			12,14		
Credit - Monetary base		9																			

Notes: 1: Busch et al. (2010), 2: Meeks (2012), 3: Eickmeier and Ng (2015), 4: Fornari and Stracca (2012), 5: Abildgren (2012), 6: Helbling et al. (2011), 7: Hirata et al. (2012), 8: Halvorsen and Jacobsen (2014), 9: Peersman (2011), 10: Peersman and Wagner (2014), 11: Tamasi and Vilagi (2011), 12: Biany and Gete (2014), 13: Jarocinski and Smets (2008), 14: Iacoviello and Neri (2010)

6.2 Analyzing the a priori impact of identifying restrictions

In any Bayesian analysis, it is important to thoroughly discuss the properties of the prior distribution. In our case, the formal presentation of the prior is complicated for several reasons. First, the weights of the different elements in the prior are unknown, which makes the marginal density of the parameters non-standard even though the conditional distribution of the parameters is available in closed form. Second, the sign restrictions must be interpreted as part of the prior distribution (see, e.g., Baumeister and Hamilton 2015). Third, the statistics of interest, i.e., variance decompositions and impulse response functions, are a non-linear transformation of the parameters. We mitigate this complication by numerically drawing from the prior distribution, including the sign restrictions, and graphically analyze its properties. Figure 14 shows the 50% and 80% highest posterior density (HPD) intervals of the impulse response function implied by the full set of prior information.[9] The response of the policy interest rate is normalized to a one-percentage-point decrease. We see that the prior is informative with respect to the short-term reaction of credit to monetary policy shocks but relatively uninformative with respect to the reaction of housing prices: a monetary policy shock leading to a one-percentage-point decrease in the interest rate leads to increases in credit volumes that are mostly below 1%, whereas the interval for housing prices goes up to 5%. Furthermore, the prior is informative regarding the short-term reaction of GDP because it incorporates a zero reaction on impact.

The fact that the prior is informative with respect to the credit reaction may be the result of two channels. First, it could be that the sign restriction for the credit variable is informative. Second, it is possible that the training observations are informative. Baumeister and Hamilton (2015) show that for a given covariance matrix Σ, the uniform prior on the rotation matrix implemented in the procedure proposed by Arias et al. (2014) is already informative regarding the impulse responses. Thus, if the training observations are informative with respect to Σ, we may obtain an informative prior through this channel. Figure 15 shows the implied prior by setting the weight of the training sample to zero.[10] Based on this analysis, we can deduce that both channels are at work. The HPD intervals

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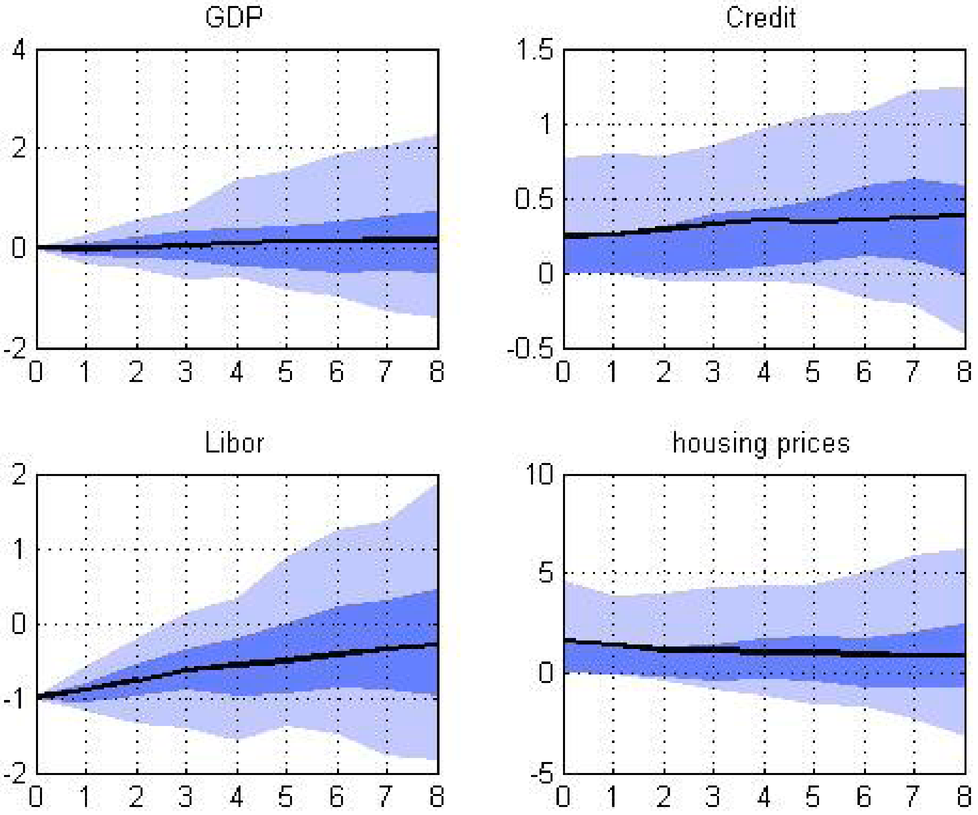
[9] The weight of the prior is set to the posterior mean.

[10] The weight of the Minnesota prior is again set to its posterior mean.

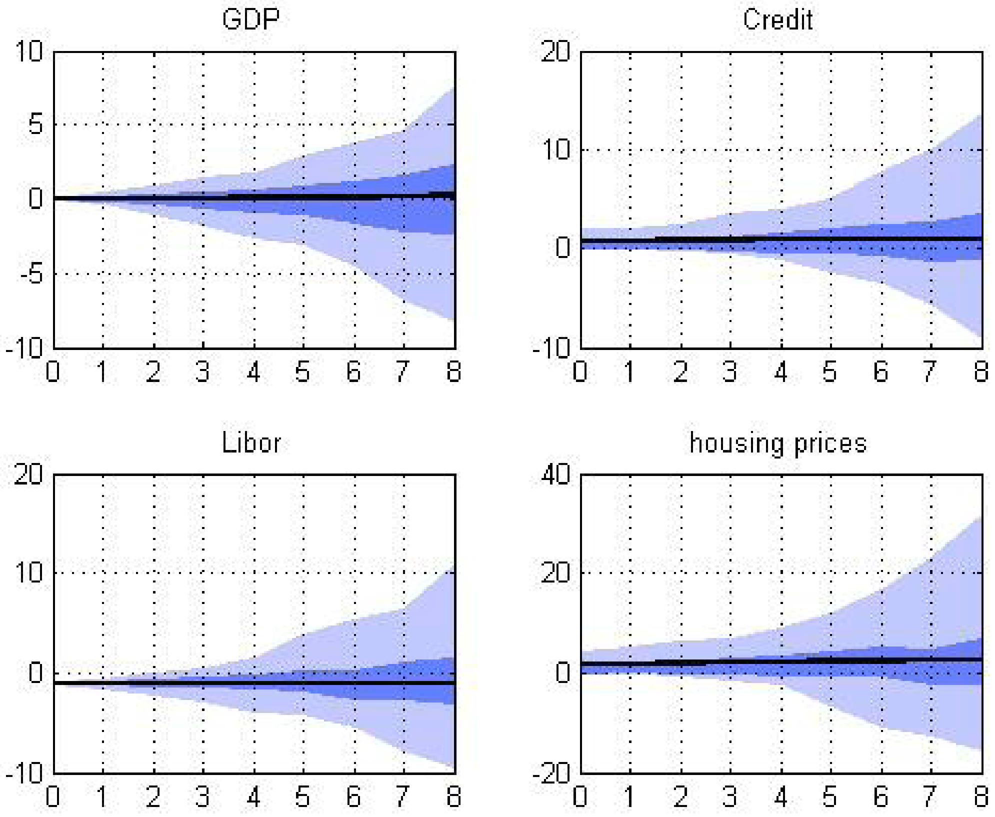
Figure 14 — Response to monetary policy shock according to training sample and Minnesota prior



Note: Figures show the median and the 50% and 80% highest prior density (HPD) intervals.

for the reaction of credit are much wider than those based on the full prior information, suggesting that training sample is informative. However, the intervals for the reaction of housing prices are still somewhat wide compared to those for the reaction of credit. Because the Minnesota prior per se treats credit and housing prices symmetrically, the sign restrictions lead to tighter intervals. Indeed, an inspection of the sign restrictions shows that credit has one more restriction than housing prices. For GDP, we see that the training sample observations are also somewhat informative at a medium-term horizon. The intervals at a horizon of one year are in the range of -0.5 to 1 based on the full prior, whereas the Minnesota prior only shrinks the response to an interval ranging from -2 to 2. Overall, it is apparent that the exact specifications of the sign restrictions influence the prior distribution. However, it is also evident that the prior is sufficiently loose, in the sense that the prior intervals are quite wide, particularly if only information from

Figure 15 — Response to monetary policy shock according to the Minnesota prior



the Minnesota prior is combined with the sign restrictions. In this case, the intervals rapidly become very wide. In the case of GDP, the 80 % interval easily covers the range of GDP responses found in previous studies of Switzerland, most of which find that a 1-percentage-point reduction in the policy interest rate leads to an increase in GDP of between 0 and approximately 2% after two years. See the overview in Bäurle and Steiner (2015).

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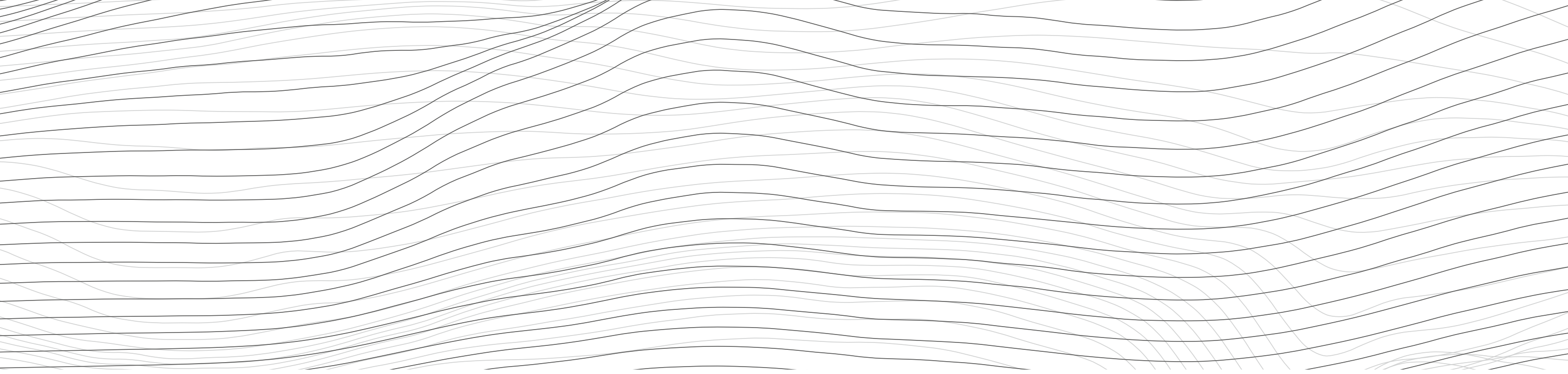

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