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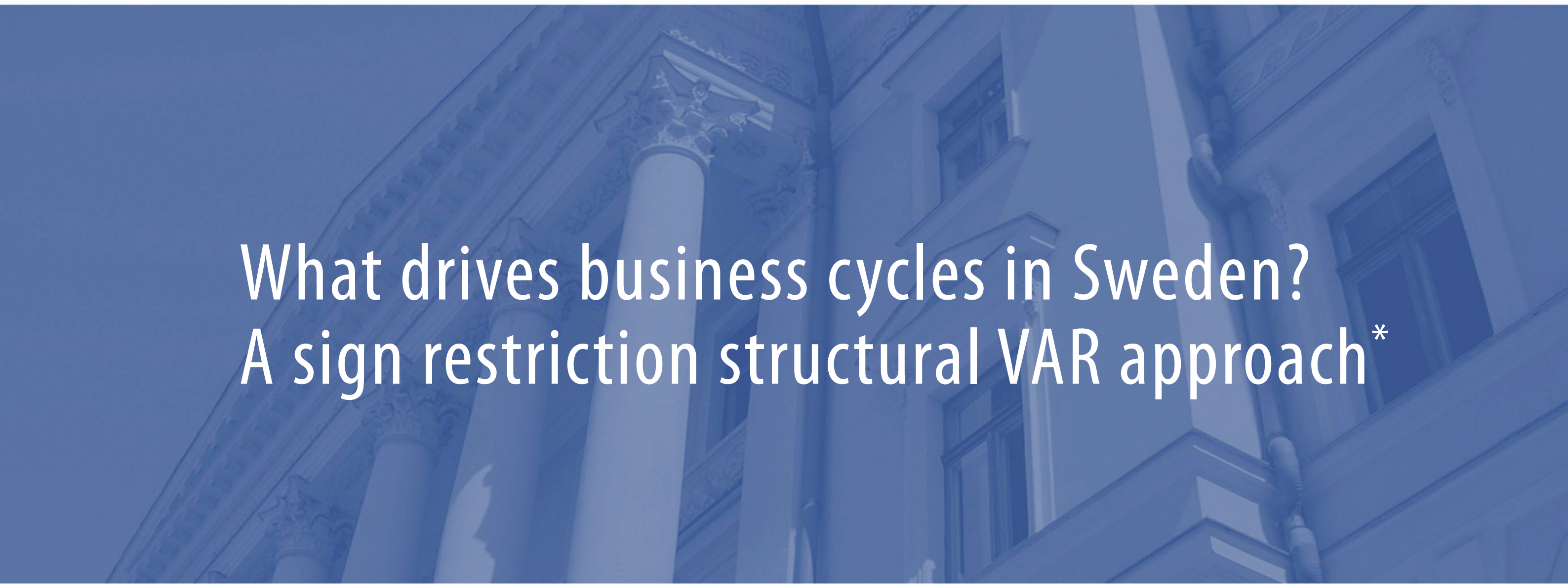

What drives business cycles in Sweden? A sign restriction structural VAR approach*

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Abstract

What are the structural shocks that drive the business cycle in Sweden? In this paper we have identified a structural VAR model for Sweden using the sign restriction method. The model includes two demand and two supply shocks. With the help of the model we provide an interpretation of the Swedish business cycle and explain what are the shocks that have been driving the output in the last two decades. The model's forecasting properties are also discussed. Results suggest that a technology shock was contributing strongly to the GDP growth in several long periods. A positive technology shock was present during the dot-com boom and as the IT bubble bursted the positive technology wave continued. Sweden was benefiting from several positive shocks before the outburst of the global financial crisis in 2008 and the contribution from an external demand shock was even greater than the productivity shock. In turn, as the financial crisis began, the external demand shock was weighing heavily on GDP growth. The domestic demand shock does not seem to have contributed neither in the build up of the boom nor in the bust. Moreover, the forecast error variance analysis suggests that almost half of the forecast error in the GDP growth is due to external demand shocks and productivity shocks. This sounds plausible for a small open, knowledge- based economy like Sweden.

1 Introduction

Since Sims (1980) introduced vector autoregressive (VAR) models in his seminal paper *Macroeconomics and Reality*, VARs have established their place in the macroeconometricians toolbox. They are used in reporting properties of time series variables and in forecasting them. Although, as powerful tool as VAR is, it has its limitations.

What is driving output growth in the economy - is it a productivity shock or something else? Why is Sweden close to deflation? Sometimes mere description of data is not enough to understand the outcome. If we want to give an interpretation to the data through a model, we need to take a step further and move from a VAR to a structural VAR (SVAR), as an example.

In this paper we seek to provide an interpretation of Swedish business cycle through a sign restriction identified structural VAR model and quantify what are the shocks that have been driving the economy in the last two decades. In the analysis we concentrate mainly on output growth and inflation.

In empirical macroeconomics structural vector autoregressive models have been used in (i) the analysis of impulse response functions that measure the effect of a structural shock on the model variables. (ii) Decomposing time series into cumulative structural shocks. The shock contributions quantify the cumulative effect of a given structural shock on the model variable's historical path. (iii) Providing forecast error variance decompositions (FEVD). Forecast error variance decomposition is the percentage of the variance of the error made in forecasting a variable due to a specific shock at a specific time horizon. (iv) Forecasting. With these models we are able not only to run unconditional forecasts, as with simple VAR models, but we may plan forecasting exercises where the forecast is conditional on a given path of structural shocks. (Kilian, 2011)

The sign restriction approach differs from the rest of the structural VARs. In the sign identified structural VAR the number of shocks need not be equal to the number of variables. Neither is there a need to impose linear restrictions between the reduced form and structural errors. In the sign restiction method the restrictions are set directly on the shape of the impulse responses. Often the applied restrictions are based on impulse responses of some relevant DSGE model, on theoretical results or some other economic reasoning.

The sign restriction literature started first with monetary policy applications (Faust 1998, Canova and De Nicolo 2002, Uhlig 2005) and after that the research has expanded to cover various themes. Faust (1998) concentrated on how much of the GDP forecast errors in the US can be contributed to monetary policy shocks. Canova and De Nicolo (2000) focused in their research on how monetary shocks affect business cycles in G7 countries. Uhlig (2005) examined what is the monetary policy shock's effect on output. Since then the sign restiction approach has been applied to various topics, for example, to study the effects of fiscal policy shocks (Mountford and Uhlig, 2009), or stock price movements (Berg, 2010). Several researchers have focused on technology shocks. Peersman and Straub (2004) examined the impact of technology shocks on hours worked in the euro area and found a positive effect. They also identified monetary policy, labour supply and demand shocks. Dedola and DeNeri (2006) apply the sign restriction method to US data and find that a technology shock leads to persistent positive effects on output and real wages and it likely has a positive impact on hours. Table 1 in the appendix presents some of the existing research. A more comprehensive overview to the sign restriction literature can be found in Fry and Pagan (2011) for example. Kilian (2011) is an excellent general review on structural VAR methods.

The sign restriction identified structural VAR model used in this paper has six variables and four identified shocks. We have included traditional key macro variables in the model: real GDP, total hours worked in the economy, inflation, real wage per hour, central bank repo rate and real exports of goods and services. The model has two demand shocks and two supply shocks - an external demand shock, a domestic demand shock, a technology shock and a labour supply shock. In defining the sign restrictions we have taken guidance both from a relevant DSGE model and from the theory. To our knowledge there are no previous publications on which structural shocks, and productivity shock in particular, have contributed to Swedish business cycle by decomposing the growth rate of GDP into structural shocks. The data period used throughout this paper extends back to the 1993 and not further because of the structural break in the time series due to the Swedish Riksbank's shift from the fixed exchange rate regime to a floating one in November 1992.

Our results suggest that a technology shock was contributing strongly to GDP growth during the IT boom. As the IT bubble bursted the positive technology shock carried on still. Before the outburst of the global financial crisis in 2008 Sweden was benefiting from several positive shocks. A positive technology shock was present but the contribution from an external demand shock, was however even greater. In turn, as the financial crisis began, the external demand shock was weighing heavily on GDP growth being the largest negative contributor. It is worth noting that the domestic demand shock does not seem to have contributed either in the build up of the boom or in the bust.

The relative forecast error variance analysis suggests that almost half of the forecast error in the GDP forecast 12 quarters ahead is due to external demand shocks and productivity shocks in the SVAR. This can be broadly interpreted as the sources of the business cycle given the model. The finding sounds plausible for a small open knowledge based economy like Sweden. Around 25 % of the error in the GDP forecast is generated by the external demand shocks. Moreover, we find that almost 20 % of the error in the GDP forecast is due to technology shocks. The share of errors due to technology shocks aligns very close to those of the Riksbank's DSGE model, Ramses II[1].

Recently, in 2013 and onwards, inflation has been very low and even approaching zero. How is the close-to-deflation experience perceived by the model?

[1] In the Ramses II, the stationary technology shocks explain 23 per cent of the forecasting error in the GDP in the 8th quarter (Adolfson et al., 2013).

The identified structural shocks are weighing heavily on inflation and the unidentified shocks are supporting inflation: a positive labour supply and negative domestic demand shocks have slowed down inflation markedly. Even if the reader might be easily tempted to believe that monetary policy is influencing inflation positively through the pooled unidentified shocks, such conlusion is beyond the model and can not be drawn.

The paper is organized as follows. In chapter 2, the method and the data is introduced. In the third chapter we use the model as a tool to give an intrerpretation of the past and discuss the forecasting properties of the model. The last chapter concludes.

2 The method and data

2.1 From VAR to sign restriction SVAR

The sign restriction approch differs from rest of the structural VARs. In the sign identified structural VAR the number of shocks need not to be equal to the number of variables. Neither is there a need to impose linear restrictions between reduced form and structural errors, for example by setting some parameters to zero. In the sign restiction method the restrictions are set on the shape of impulse responses. We will discuss these restrictions more in detail in the following chapter. Before that, we take one step back and establish the connection between a simple reduced form vector autoregressive model and a structural one. One way to present it is to start with a reduced form VAR. To keep the example as simple as possible we assume a model with one lag.

A reduced form VAR1 in a matrix form is following

$$\mathbf{y}_t = \mathbf{A}\mathbf{Y}_{t-1} + \varepsilon_t \tag{1}$$

where $\boldsymbol{\varepsilon}$ is a vector of the reduced form errors, $\mathbf{y}$ is a vector of model variables and A is a coeffient matrix. Ordinary least squares (OLS) method can be applied to estimate the equation, because only lagged values of endogenous variables appear on the right hand side. Hence, OLS estimates are consistent. Multiply by the inverse of the impact matrix $\mathbf{B}^{-1}$ from the left hand side (LHS)

$$\mathbf{B}^{-1}\mathbf{y}_t = \mathbf{B}^{-1}\mathbf{A}\mathbf{Y}_{t-1} + \mathbf{B}^{-1}\boldsymbol{\varepsilon}_t \tag{2}$$

But in the SVAR we have structural shocks i.e. innovations u instead $\mathbf{B}^{-1}\boldsymbol{\varepsilon}_t$. The SVAR1 presentation is

$$\mathbf{B}^{-1}\mathbf{y}_t = \mathbf{B}^{-1}\mathbf{A}\mathbf{Y}_{t-1} + \mathbf{u}_t \tag{3}$$

From above it is clear that the structural shocks u are linear combinations of the reduced form shocks ε.

$$\mathbf{B}^{-1}\boldsymbol{\varepsilon}_t = \mathbf{u}_t \Leftrightarrow \boldsymbol{\varepsilon}_t = \mathbf{B}\mathbf{u}_t \tag{4}$$

Multiplying the SVAR presentation by the impact matrix (LHS) $\mathbf{B}$, we arrive to a slightly different SVAR1 presentation that is very similar to VAR

$$\mathbf{y}_t = \mathbf{A}\mathbf{Y}_{t-1} + \mathbf{B}\mathbf{u}_t \tag{5}$$

Then, for example in a two variable model is, the contemporaneous effect of the first structural shock size 1

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \tag{6}$$

$$\begin{bmatrix} y_{1t} = b_{11} * u_{1t} + & b_{12} * u_{2t} \\ y_{2t} = b_{21} * u_{1t} + & b_{22} * u_{2t} \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} y_{1t} = b_{11} \\ y_{2t} = b_{21} \end{bmatrix}. \tag{8}$$

But how do we extract B from the consistent OLS estimates of the reduced form parameters? We have to assume that stuctural shocks are uncorrelated

$$E(\mathbf{u}_t \mathbf{u}_t^T) = \mathbf{\Omega}_u = \mathbf{I} \tag{9}$$

Then we can show that by using the definition $\boldsymbol{\varepsilon}_t = \mathbf{B}\mathbf{u}_t$, the reduced form error covariance matrix is

$$E(\varepsilon_t \varepsilon_t^T) = \mathbf{B}E(\mathbf{u}_t \mathbf{u}_t^T)\mathbf{B}^T \tag{10}$$

$$\mathbf{\Omega}_{\boldsymbol{\varepsilon}} = \mathbf{B}\mathbf{\Omega}_u \mathbf{B}^T \tag{11}$$

$$\mathbf{\Omega}_{\boldsymbol{\varepsilon}} = \mathbf{B}\mathbf{I}\mathbf{B}^T \tag{12}$$

$$\mathbf{\Omega}_{\boldsymbol{\varepsilon}} = \mathbf{B}\mathbf{B}^T \tag{13}$$

In the case of the usual Cholesky decomposition $\mathbf{B}$ would be a lower triangural matrix. In the sign restriction approach $\mathbf{B}$ is not a lower triangular, though we will make use of Cholesky decomposition as an intermediate step to extract $\mathbf{B}$. Here $\mathbf{P}$ is a Cholesky lower triangular matrix that satisfies $\mathbf{\Omega}_{\boldsymbol{\varepsilon}} = \mathbf{P}\mathbf{P}^T$. Any such matrix that meets the criteria will do and is used only for computational purposes. Then any orthogonal matrix [2] $\mathbf{D}$ yields $\mathbf{B} = \mathbf{P}\mathbf{D}$ and satisfies

$$\mathbf{\Omega}_{\boldsymbol{\varepsilon}} = \mathbf{B}\mathbf{B}^T \tag{14}$$

$$\mathbf{B}\mathbf{B}^T = \mathbf{P}\mathbf{D}\mathbf{D}^T\mathbf{P}^T \tag{15}$$

$$\mathbf{P}\mathbf{D}\mathbf{D}^T\mathbf{P}^T = \mathbf{P}\mathbf{I}\mathbf{P}^T \tag{16}$$

$$\mathbf{P}\mathbf{I}\mathbf{P}^T = \mathbf{P}\mathbf{P}^T. \tag{17}$$

[2] Orthogonal matrix is a square matrix with following properties $\mathbf{D}^T\mathbf{D} = \mathbf{D}\mathbf{D}^T = \mathbf{I}$. That is, columns and rows are orthogonal unit vectors, whrere the vector and row product is zero and every row and vector length is unity.

The procedure continues in the following way. Draw **D** randomly by using QR decomposition[3]. Then calculate **B** and compute the impulse responses. Check if the impulse responses satisfy the restrictions that are given directly to the shape of the impulse responses. If the impulse responses satisfy the given restrictions, then save the impact matrix **B**. Continue random drawing until you have achieved N accepted draws. Then sort the models by impulse response distance to the median according to the given sign restrictions. Finally, choose the model which represents the median impulse responses.

The particular impulse matrix B that produces the median impulse responses could be interpreted as one that creates typical responses to the identified structurals shocks. It should be noted that there does not exist a unique B. Regarding our model, we have drawn randomly until we have identified 500 impact matrixes and hence 500 different SVAR models in the structural VAR identification procedure. The sign restrictions that were used in sorting the model and choosing the median one are discussed in the following section.

More on the technical background of the sign restriction approach can be found for example in the publications by Berg (2010), Kilian (2011), Fry and Pagan (2011, 2007).

2.2 Sign restrictions and the data

The model has six variables and four identified shocks. Traditional key macro variables are included in the model: real GDP (#1), total hours worked in the economy (#2), inflation (#3)[4], real wage per hour (#4)[5], central bank repo rate (#5) and real exports of goods and services (#6). Variables are seasonally adjusted year on year per cent changes excluding the central bank repo rate. The properties of the variables are reported in table 2 and the time series evolution in figure 1. The model has the following four shocks: external demand (#1), domestic demand (#2), technology (#3) and labour supply (#4). The first two shocks are demand shocks and the latter are supply shocks.

The four shocks were chosen for a reason. Additional shocks were tried with an aim to broaden the structural analysis. However, increasing the number of shocks comes in practice at the expense of difficulties in the identification process and drives down the ratio of accepted impact matrixes to total number of draws considerably. If more general and flexible sign restrictions are applied then the identificiation process may be smoother but we did not want to compromise our sign restrictions that we deemed robust.

[3] Draw randomly values from $NID(0,1)$ to get matrix **L**. **L** is $V \times V$ size, where V is the number variables in the VAR. Derive QR decomposition of **L** that $\mathbf{L} = \mathbf{QR}$ and $\mathbf{QQ}^T = \mathbf{I}$. **Q** is an orthogonal matrix and R is an upper diagonal matrix. QR decomposition can be done to any real square matrix. Finally set $\mathbf{D} = \mathbf{Q}^T$.

[4] Consumer price measure is the Swedish KPIF, which is the national consumer price index with a fixed interest rate. This measure is neither directly affected by changes in the mortgage rates nor immediate effects of changes in monetary policy.

[5] Hourly wage in the whole economy according short-term earnings statistics deflated by private consumption deflator.

In our model, the sign restrictions on impulse responses are designed according to table 1. The table should be read in a way that a positive sign restriction, for example, of the labour supply shock indicates it has a positive effect on GDP. What is a positive effect on GDP? In our case, we have defined that a positive effect means that the sum of the GDP impulse responses is positive in the following four quarters after the labour supply shock. This four quarter sum rule applies for all restrictions.

Table 1. Sign restrictions on impulse responses

	Variables					
Shocks	Output	Hours	Prices	Wages	Interest rate	Exports
External demand	+		+			+
Domestic demand	+		+			0, -
Technology	+		-	+		
Labour supply	+		-	-		

How to choose the identification strategy and plausible restrictions. In the literature it is common to apply sign restrictions according to a DSGE model or imitate the restrictions implied by theory. For example, Peersman and Straub (2004) apply sign restrictions that are valid for both a theoretical small size sticky price model and a RBC model. Our identification strategy is based on imposing sign restrictions from a relevant DSGE model. In this case the relevant DSGE model is the Riksbank's new macromodel Ramses II by Adolfson et al. (2013). Moreover, we apply the minimum set of restrictions that are needed to uniquely identify the shocks. The advantage of using only the required minimum set of restrictions is that it allows us increased theoretical flexilbility. More specifically, we combine Ramses II sign restrictions with the restrictions laid out by Peersman and Straub (2004) that suit for both sticky price and RBC model whenever possible.

A key issue in the sign restrictions models is to be able to uniquely identify different shocks. All of the structural shocks in the model have a positive effect on output. In order to separate the demand shocks from the supply shocks we need to introduce sign restriction on inflation. The demand shocks will have an increasing effect on inflation whereas both supply shocks will slow down inflation. How can we disentangle a positive technology shock from a labour supply shock? We need to impose a new restriction on real wages. We assume that a positive technology shock will speed up real wage growth and a labour supply shock will slow it down. This holds for the Ramses II model as well as for the sticky price and RBC models by Peersman and Straub (2004). A positive technology shock lowers the marginal costs of production which in turn results in slower inflation. After a labour supply shock prices fall which implicitly means that the effect on nominal wages has to be larger.

Now we have laid out a minimum number of restrictions to separate between the supply shocks and hence we do not need to introduce a restriction on hours worked. This way we may remain agnostic on productivity shock's effect on hours worked and we are not forced to choose between a real business cycle model (a positive effect) and a NK DSGE model (a negative effect), see discussion for example in Peersman and Straub (2004, 2006).

To discriminate uniquely between external and domestic demand shocks we need to lay out an additional restriction on impulse responses. In the case of a domestic demand shock we assume that the effect on real export growth is non-positive. This sign restriction is similar to Ramses II. It can be argued, for example, that the immediate positive effect on inflation affects adversely the relative price of the export product, which leads to a substitution effect and lower exports. In contrast, in the case of an external demand shock, that is higher exogenous world demand for Swedish products, the relative price channel argument is still valid but the positive income effect prevails.

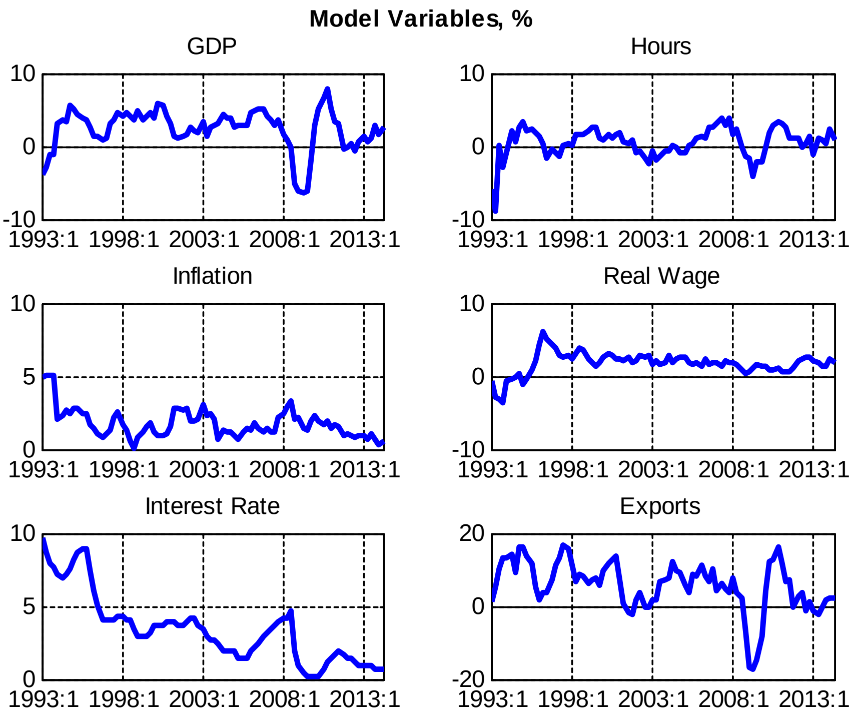

Figure 1. Model variables.
Variables are defined as year-on-year per cent changes excluding the interest rate, which is in levels.

Table 2. Properties of the variables 1993Q1-2013Q3

	Output	Hours	Prices	Wages	Interest rate	Exports
Mean	2.4	0.5	1.8	1.8	3.6	5.9
Maximum	7.9	3.8	5.1	6.2	9.75	15.7
Minimum	-6.4	-6.4	0.1	-3	0.25	-15.0
Autocorrelation	0.83	0.77	0.76	0.81	0.94	0.88
Std. Dev.	2.9	2.0	1.0	1.5	2.4	6.4
Observations	83	83	83	83	83	83

3 Results

3.1 Structural analysis

The main advantage of using a structural VAR instead a reduced form VAR is that it enables us to analyze and interpret the observed data through a model. The model can be used to decompose the observed data into structural shock contributions, that is, to show how the model interprets the historical path of a variable. This type of decomposition analysis on GDP growth has been done for the US and the euro area by Christiano et al. (2008) and for Finland by Newby et al. (2011)[6]. A structural VAR model is also used in calculating forecast error variance decompositions (FEVD). The forecast error variance decomposition is the size of the variance of the error made in forecasting a variable due to the model's structural shock. In this section we focus on the structural shock contributions and FEVD results. The response functions to a unit structural shock are presented in the appendix (figure 2).

The figures 2 and 3 show the cumulative contribution of each structural shock to the evolution of GDP growth and inflation over time. The black line is the sum of all structural shocks and it corresponds to the difference between observed data and the model's constant and the initial conditions.[7] For example in figure 2, the black line is above zero around the turn of the millenium indicating that the Swedish economy was experiencing more positive shocks than negative. According to the model, a strong technology shock was contributing to GDP growth during the IT boom. As the IT bubble bursted the positive technology shock continued. Also before the outburst of the global financial crisis in 2008 Sweden was benefiting from a positive technology shock. However at the same time the contribution from an external demand shock was even greater. In turn, as the financial crisis began, the external demand shock was weighing heavily on GDP growth and being the largest negative contributor. It is noteworthy that the domestic demand shocks do not seem to have contributed either in the build up of the boom or in the bust. Regarding labour supply shocks, they have had more positive effect on the balance in 2010s.[8]

[6] Both Christiano et al. (2008) and Newby et al. (2011) use a DSGE model.

[7] In other words, the trend and the shocks sum up to the observed data.

[8] We have experimented with two alternative models to check the robustness of the labour supply shock's effect. First, we ran our model in levels specification. In the second case, we removed the changes in the working age (15-64 years) population from the total hours worked in the economy variable and ran the model in differences. In both cases labour supply shock plays a considerable role in the economy still. These are not reported in this paper. The figures are delivered by request.

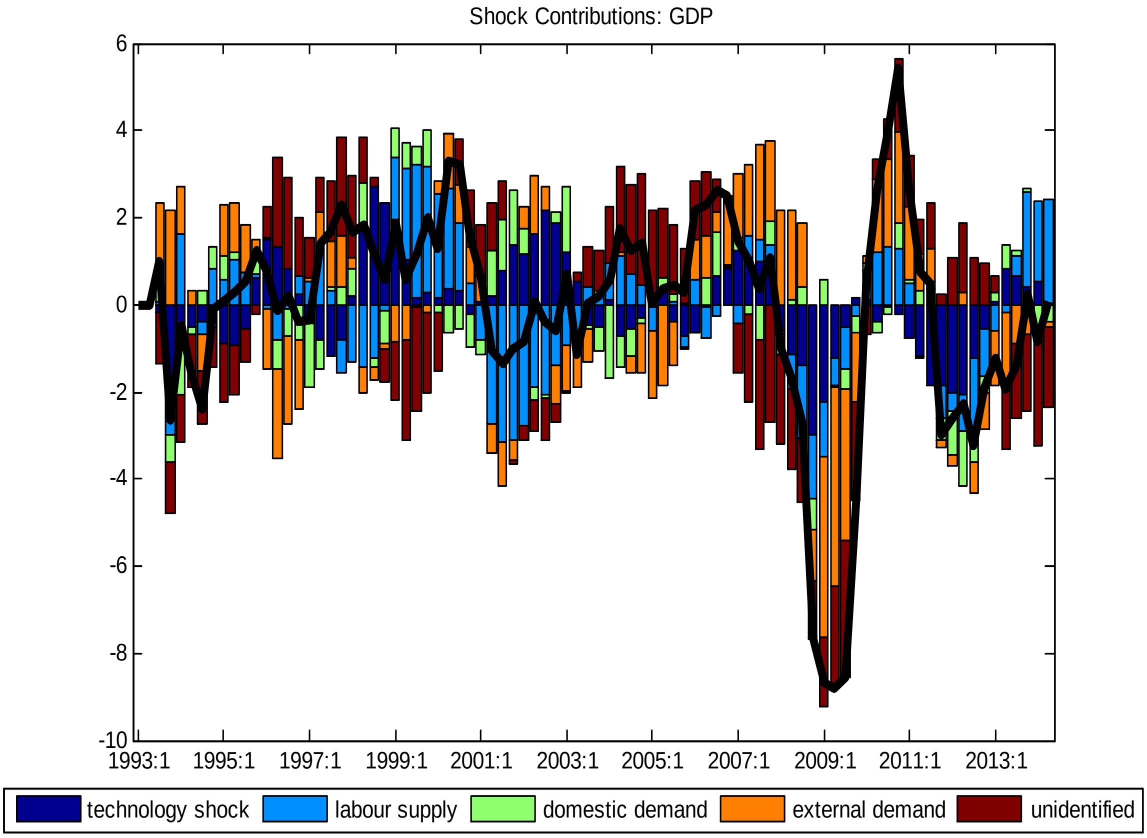

Figure 2. Historical decomposition of GDP, yoy, per cent.
Figure shows how the SVAR model interprets GDP's deviation from the model trend.
The black line is the sum of the different shocks.

How does the structural model interpret the evolution of inflation (figure 3)? As we already discussed, a positive technology shock was present during and after the IT boom and was supporting the high GDP growth. It appears that the same shock wave was keeping the prices in check which is seen as a negative contribution to inflation. More recently inflation has been very low and even approaching zero. How is this close to deflation experience perceived by the model; the identified structural shocks are weighing heavily on inflation and the unidentified shocks are supporting inflation. It seems that a positive labour supply and negative domestic demand shocks have slowed inflation down markedly.

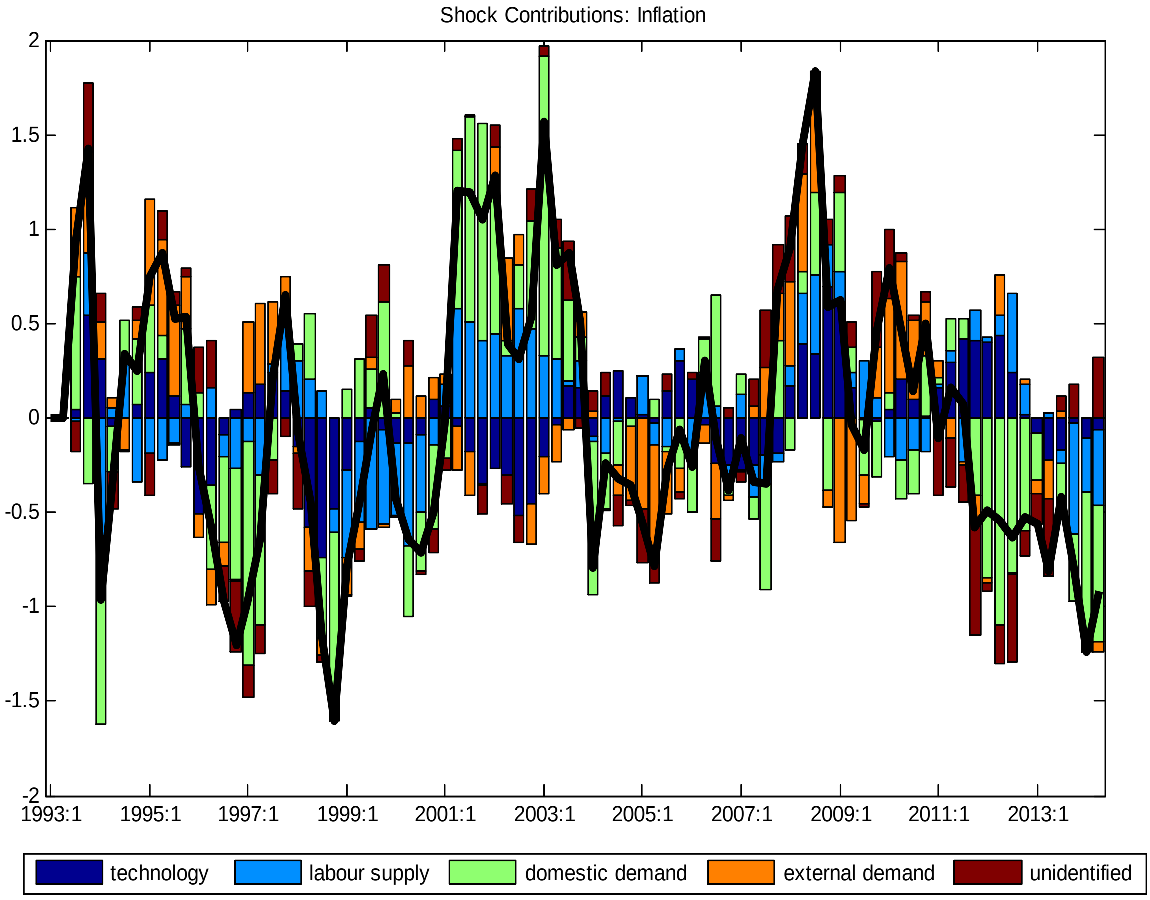

Figure 3. Historical decomposition of inflation, yoy, per cent.
Figure shows how the SVAR model interprets inflation's deviation from the model trend. The black line is the sum of the different shocks.

Figure 4 presents the relative forecast error variance decompositions for the GDP growth. It sums up to unity and shows the share of the variance of the error made in forecasting GDP due to a specific shock at a specific quarter. In case of GDP, we might broadly interpret it as what are the causes for a business cycle in the economy given the model. Our findings indicate that almost half of the variation is generated by external demand and productivity shocks. More than 20 % of the error in the GDP forecast 8 quarters out is due to external demand shocks. According to the model, around 20 % of the error in the GDP forecast 8 quarters ahead is due to technology shocks, a contrast to RBC economic thought that say output fluctuations are caused by TFP shocks mainly. The share of errors due to technology shocks align very close to the

Riksbank's Ramses II model where stationary technology shocks explain 23% in the 8th quarter. This result is in line also with the sign restriction identified SVAR for the euro area by Peersman and Straub (2004) where a TFP shock explains a significant amount, around 20 to 30 per cent, of the variation[9].

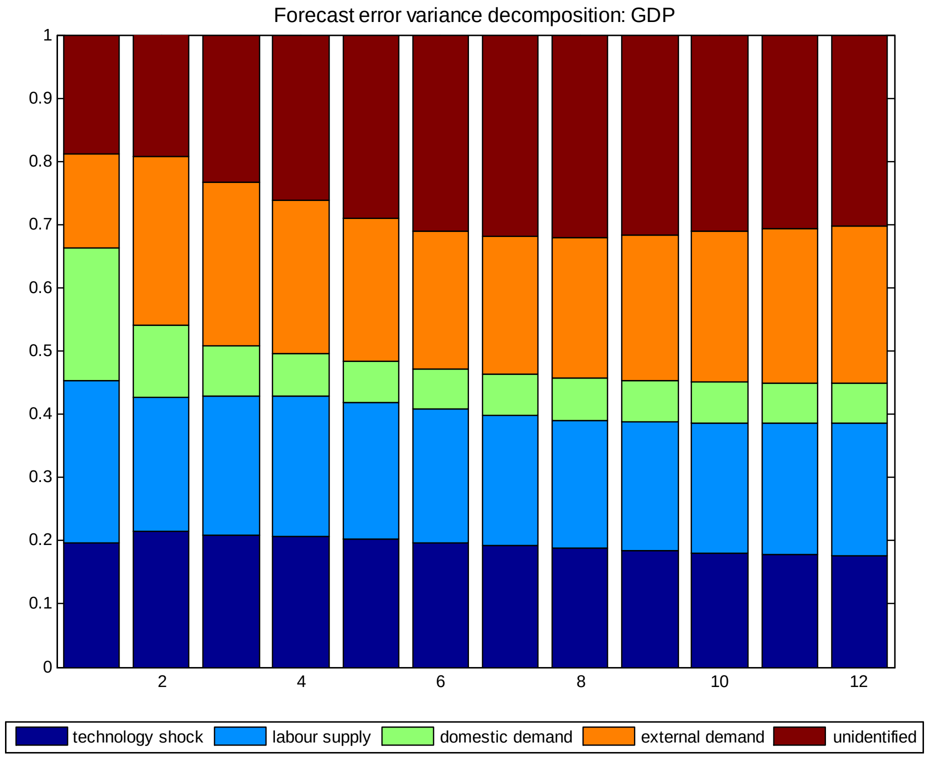

Figure 4. Relative forerecast error variance decomposition.
Figure shows the percentage of the variance of the error made in forecasting a variable due to a specific shock at a specific a time horizon (quarters).

3.2 Forecasting properties

The model can be used as a forecasting tool as any VAR model. To assess the foreast accuracy we have run unconditional 8 step ahead within sample predictions for the whole period. Figure 5 presents the GDP growth predictions made in every quarter since 1993Q1. By using eyeball econometrics it seems

[9] Peersman and Straub (2004) identify both level and difference models for the euro area. In 12 quarters out forecast the FEVD accounted by a TFP shock is around 20 per cent in the levels specification and around 30 per cent in the difference specification.

the model performs quite well in the short term forecasting. For example the forecasts made since 2007, well ahead of the collapse of Lehman Brothers, are able to predict the slowdown in growth. It should not come as a surprice that the unforeseen size of the fall in the GDP at the end of 2008 and the following rebound in the economy are underestimated in the forecasts.

To assess the forecast performance of the model in a more rigorous way, we have run competing one variable one lag autoregressive models for all the SVAR variables (figure 6). The comparison of the root mean squared forecasting errors (RMSE) between the SVAR and AR reveals that our model outperforms the single equation model for all the variables in question at all considered forecasting lengths from 1 to 8 quarters. There is only one exception. Regarding inflation forecasts further out (6 to 8 quarters), the forecasting errors are practically the same for both the AR and SVAR model. We have tested the robustness of these results and we have cut the sample period to leave out the post financial crisis period. The qualitative results still hold and the SVAR model has greater forecasting power than the single eguation forecasts[10].

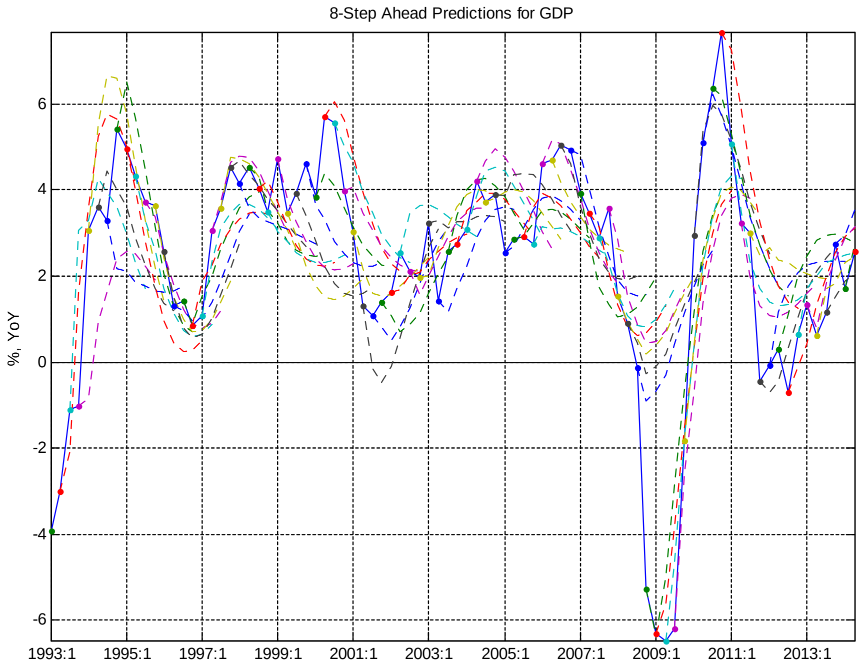

Figure 5. 8-step ahead with-in-sample predictions for GDP. The blue dotted line shows the actual GDP.

[10]Not reported in this paper. The RMSE results are delivered by request.

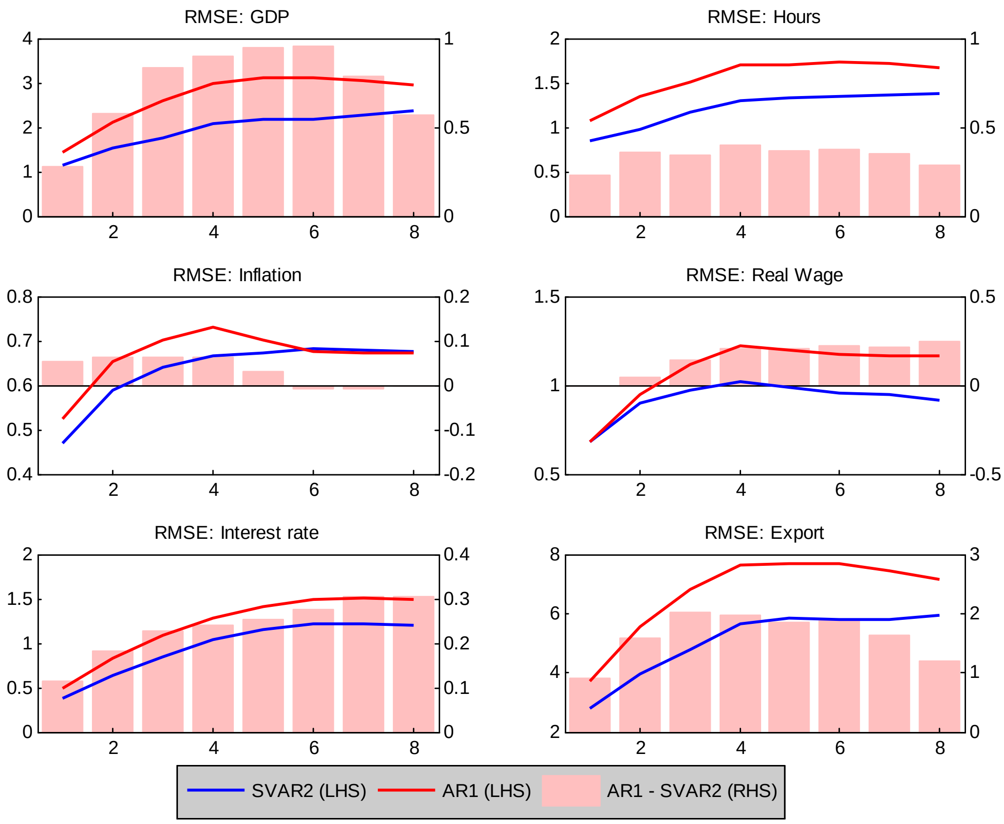

Figure 6. Forecasting properties of the SVAR(2) model compared to the AR(1) models. Root mean square errors (RMSE) are calculated 8 quarters ahead for the period 1994Q1 - 2013Q3.

We run another within sample unconditional forecast but now for a shorter period from 2013Q1 to 2014Q2 along with the forecast uncertainty (figure 7). The red line shows the actual GDP published by the statistical office of Sweden. In the fanchart we have applied the RMSEs[11] to illustrate the uncertainty involved in forecasting. Note that here we do not incorporate any parameter uncertainty, only the historical forecast errors of the model. The unconditional GDP forecast generated by the model seems reasonable and aligns close to the actual GDP: the actual GDP lies close or within the 70 per cent uncertainty interval during the whole forecast period. To demonstrate how the model fares a conditional forecast, the figure 3 in the appendix presents a GDP forecast for the same period but conditional on actual export growth[12].

[11]The RMSEs in the figure are calculated using a sample period before the financial crisis 1994Q1 - 2008Q2.

[12]The same RMSE of the unconditonal forecast is used in the conditional forecast to illustrate the uncertainty.

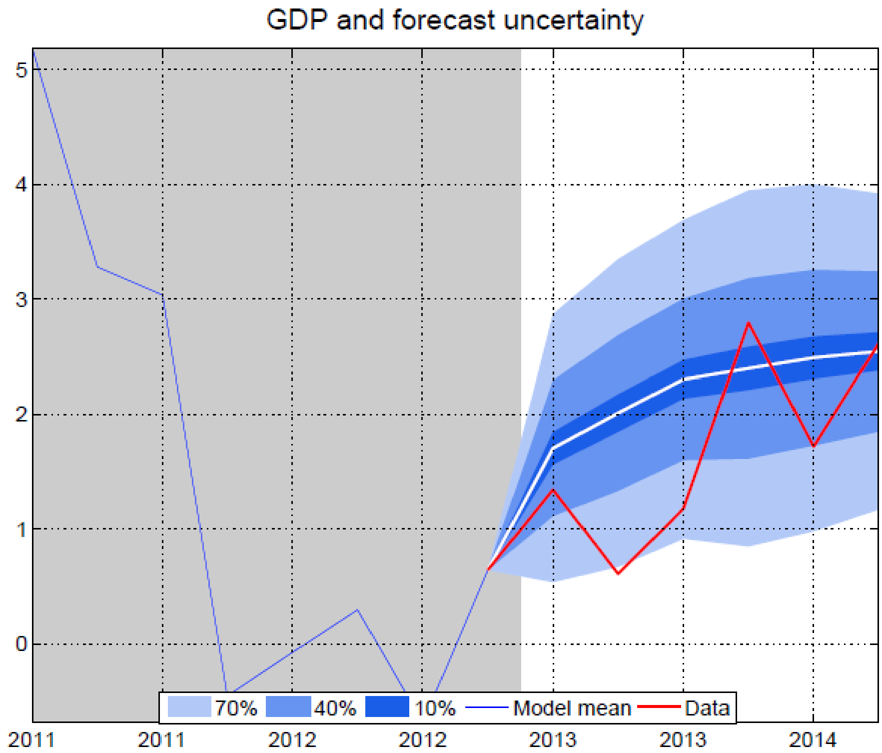

Figure 7. Unconditional GDP forecast, YoY, per cent.
The red line shows the actual GDP in the within sample forecasting period.

4 Conclusions

In this paper we have identified a structural VAR model for Sweden using the sign restriction method. The model includes six key macro variables and it has two demand shocks and two supply shocks. In defining the sign restrictions we have taken guidance both from a relevant DSGE model and from theory. With the help of the model we provide an interpretation of the Swedish business cycle and explain which shocks have been driving output in the last two decades. To our knowledge there are no previous publications on which structural shocks, and productivity shock in particular, have contributed to Swedish output growth by decomposing the GDP into structural shocks.

Our results suggest that a technology shock was contributing strongly to the GDP growth in several long periods. A positive technology shock was present during the IT boom and as the IT bubble bursted the positive technology shock continued. A positive technology shock is present also in the high output growth period that ended to the collapse of Lehman Brothers. Moreover, Sweden was benefiting from several positive shocks before the outburst of the global financial crisis in 2008 and the contribution from an external demand shock was even greater than that from the productivity shock. In turn, as the financial crisis began, the external demand shock was weighing heavily on GDP growth and being the largest negative contributor. The domestic demand shock does not seem to have contributed neither in the build up of the boom nor in the bust. The relative forecast error variance analysis suggests that almost half of the forecast error in the GDP forecast 12 quarters out is due to external demand shocks and productivity shocks. This sounds plausible for a small open, knowledge based economy like Sweden. The share of the error due to the technology shock compares well with the stationary technology shocks of the DSGE model by the Swedish Riksbank.

This line of work focusing on Sweden could be continued in several ways. As always when using growth data some information is lost. As a next step this shortcoming could be circumvented by applying the sign restriction method to identify shocks in a vector error correction model. Another way forward could be to introduce more shocks to the model. Though, it should be acknowledged that this comes at the expense of difficulties in the identification process and drives down the ratio of accepted impact matrixes to total number of draws unless more general and flexible sign restrictions are applied. However, if this path is followed, an interesting question beyond the current model would be to quantify the effect of monetary policy shocks on inflation, especially in the current cycle, as Sweden has been sliding closer to deflation since 2013.

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A Appendix

Table 1. Sign restriction VAR literature, non-exhaustive

Theme	**Author**	**Year**
Monetary policy	Faust	1998
	Canova and De Nicolo	2002
	Uhlig	2005
	Castelnuovo	2012
Fiscal Policy	Mountford and Uhlig	2009
	Caldara and Kamps	2008
Fluctuations	Sanchez	2007
Technology	Peersman and Straub	2004
	Dedola and Neri	2006
Stock price	Berg	2010
Other	Peersman and Straub	2006

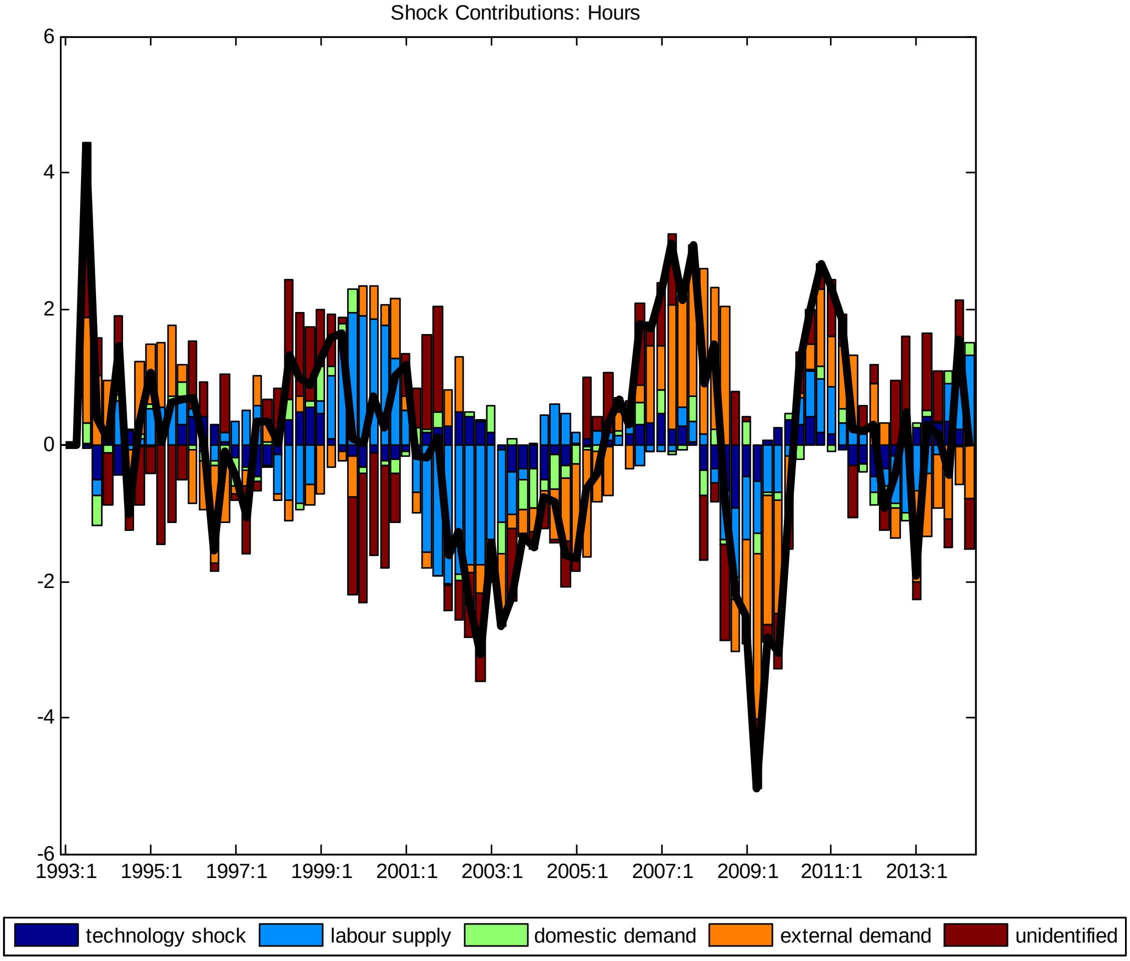

Figure 1. Historical decomposition of hours, YoY, per cent.
Figure shows how the SVAR model interprets hours' deviation from the model trend.
The black line is the sum of the different shocks.

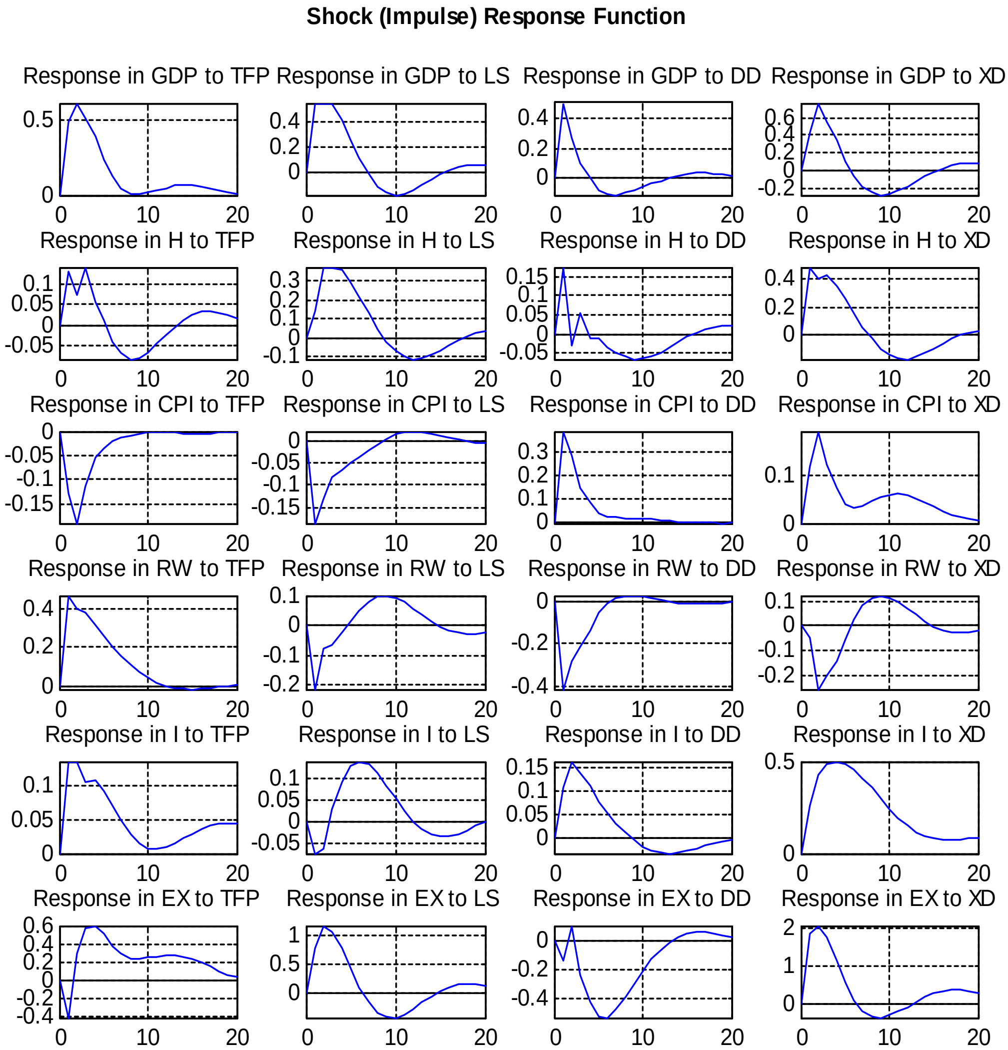

Figure 2. Response functions to a unit structural shock.
The identified structural shocks are technology (TFP), labour supply (LS), domestic demand (DD), external demand (XD). The variables are output (GDP), hours (H), inflation (CPI), real hourly wage (RW), interest rate (I) and export (EX).

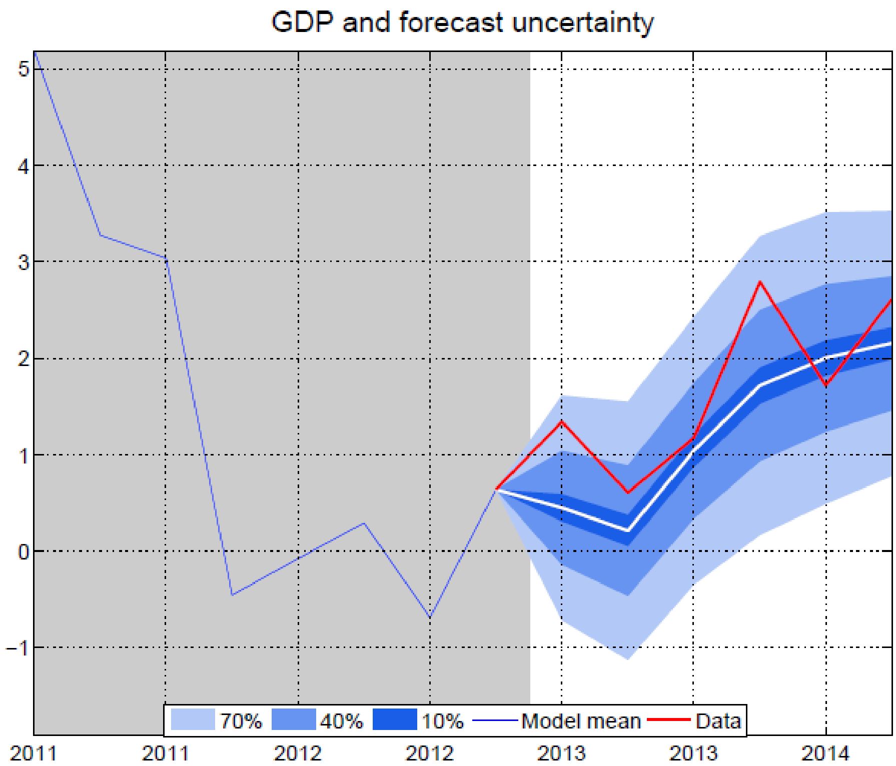

Figure 3. Conditional GDP forecast given the exports, YoY, per cent.
The red line shows the actual GDP in the within sample forecasting period.

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