Exploring the Link Between Financial Stress and Fiscal Policy in Sweden: A Bayesian Approach

Erik Carle

January 2023

1 Introduction

In recent years, the relationship between financial market fluctuations and fiscal policy has become a topic of interest in the field of economics. The financial market plays a crucial role in determining the overall economic stability of a country, and thus, understanding the relationship between the market and government policies is important (Afonso, Slavík, and Baxa 2011). This study aims to investigate this relationship in the context of Sweden by analyzing quarterly data from 1996:2 to 2022:2 using Bayesian methods.

2 Data

The data consist of four variables; the Country Level Index of Financial Stress (CLIFS) index, general government debt as share of GDP, short-term interests rates and government expenditures as share of GDP that is adjusted for seasonality.

Table 2.1: Descriptive statistics of the data material

Index	Source	Transformation	Min.	Mean	Max.	SD
General government debt (as share of GDP)	OECD	Log differences	-7.354	-0.259	5.590	2.780
General government expenditures (as share of GDP)	OECD	Log differences	-5.642	-0.345	5.951	1.327
Interbank rate	OECD	Differences	-2.017	-0.071	.613	0.388
CLIFS	ECB	Differences	-1.345	0.020	3.590	0.593

The general government debt, final government expenditures and the interbank rates are measured on a quarterly level and collected from OECD's database. The CLIFS index comprises six financial stress indicators, primarily derived from market data, that capture fluctuations within three distinct financial market segments: equities, bonds, and foreign exchange markets. The index is retrieved from ECB's database and is measured on a monthly basis and is therefore transformed into a quarterly series before estimation. The government expenditure ratio is calculated by dividing the government expenditures with the GDP. The sample of series are transformed into quarterly differences.

3 Econometric framework

This section introduces the prior specification, the posterior draws and lastly the model framework.

3.1 Prior selections

To obtain more more precise estimates of the coefficients one can "shrink" information based on some prior knowledge about the data which ultimately will lead to more precise inference and impulse responses. In this study I will utilize the Wishart distribution as the prior distribution for the covariance matrix parameter Σ. In order get the posterior distribution of Σ, we first have to specify a prior distribution $P(\Sigma)$. After that we have specified a prior distribution, we can use Bayes' Theorem to obtain the posterior distribution, the theorem is defined as

$$P(\Sigma|D) = \frac{P(D|\Sigma)P(\Sigma)}{P(D)},$$

given our sample D. Since our variables are measured in differences we follow the approach by (Koop and Korobilis 2009) and define the prior (KMx1) mean vector as zero. Where K is the vector of endogenous variables and M is a vector of explanatory variables. Define the prior mean vector as

$$\mu_0 = \begin{bmatrix} 0_1 & 0_2 & \cdots & 0_{39} \end{bmatrix}^T. \tag{3.1}$$

It is common in the literature, e.g. in (Woźniak 2016), to assume that the precision matrix Ω to be diagonal - as it can be challenging to make reliable a prior statements about dependencies between variables. Consequently, these are often assumed to be zero and we set the inverse covariance matrix as a diagonal. The (KMxKM) precision matrix is defined as the inverse of the covariance matrix, $\Omega := V_0^{-1}$. Define

$$\Omega = \begin{bmatrix} 1_{1,1} & 0_{1,2} & \dots & 0_{1,39} \\ 0_{2,1} & 1_{2,2} & \dots & 0_{2,39} \\ \vdots & \vdots & \vdots & \vdots \\ 0_{39,1} & 0_{39,2} & \dots & 1_{39,39} \end{bmatrix} \tag{3.2}$$

For an Wishart prior, prior degrees of freedom and a prior error variance of the endogenous must be specified. We fix the degrees of freedom prior to the number of estimated coefficients, $m_0 = 39$ and specify a prior (KxK) identity covariance "scale" matrix $S_0 = I$. With mean vector $\mu_0 = 0$ and scale matrix S_0, we assume the distribution of the sample covariance matrix $Z = X'X$ to be Wishart distributed with a scale matrix and degrees of freedom parameter, $Z \sim W_p(S, v)$, see e.g. (Zhang 2021). As a result, random matrices following the Wishart distribution can be generated in, e.g. a Gibbs sampler. Note that when using the Wishart distribution for precision matrix Ω, the degree of freedom parameter acts as a tuning parameter, where a larger m_0 leads to more information is supplied through the prior (Zhang 2021).

3.2 Posterior draws

By estimating the posterior distribution of the covariance matrix and the coefficients, we are able to make predictions about the response of financial stress to changes in fiscal policy, and vice versa. After the priors are specified, we run a Gibbs sampling algorithm - a method that belongs to the category of Markov-Chain-Monte-Carlo (MCMC) techniques, for an simulation of Wishart-distributed random matrices. We first add a posterior draw of the normal distribution from the function $post\_normal()$ to the Gibbs sampler that that produces a vector of posterior draws μ of the A coefficient from Equation 3.3. We then make use of the function $rWishart()$ to generate a random matrix that has a Wishart distribution with updated posterior covariance matrices and the the prior degrees-of-freedom parameter is updated by the sample size, so that $m_1 = m_0 + T$.

We then invert the generated matrix to obtain Σ. We run the algorithm with 3 000 iterations and 1 500 burn-in draws, where 1 500 outputs are stored for impulse response functions. Upon completion of the Gibbs sampler, point estimates for the coefficient matrix can be obtained through calculation of the mean and standard deviations of the posterior draws. A presentation of the point estimates from the posterior draws is presented below.

Table 3.1: Posterior inference of the coefficient matrix parameter

	f_1	i_1	s_1	f_2	i_2	s_2	f_3	i_3	s_3	f_4	i_4	s_4	γ
f	0.11	−0.96	−0.83	0.03	−0.72	0.50	−0.17	0.65	0.34	0.30	0.61	0.83	−0.93
	(0.08)	(0.66)	(0.38)	(0.08)	(0.67)	(0.42)	(0.08)	(0.68)	(0.40)	(0.08)	(0.57)	(0.39)	(0.22)
i	−0.02	0.58	−0.18	−0.02	−0.35	0.05	−0.00	0.07	−0.14	−0.01	−0.10	−0.01	−0.04
	(0.01)	(0.11)	(0.05)	(0.01)	(0.12)	(0.06)	(0.01)	(0.12)	(0.05)	(0.01)	(0.09)	(0.05)	(0.03)
s	−0.01	−0.20	−0.01	−0.03	−0.07	−0.20	−0.05	0.20	−0.03	0.00	0.27	−0.11	0.02
	(0.02)	(0.22)	(0.10)	(0.02)	(0.23)	(0.12)	(0.02)	(0.24)	(0.11)	(0.02)	(0.18)	(0.11)	(0.05)

where the standard deviations is in parenthesis and γ is the constant. Point estimates for Σ (the covariance matrix) can also be obtained by calculating the means of the posterior draws by the sampler, we obtain

When comparing the mean of posterior coefficients to the frequentists approach, one can see that the two approaches produces fairly similar estimates (see line 129 in R file for reference). It is worth noting that if we would have

Table 3.2: Posterior inference of the covariance matrix parameter

Σ_{ff}	Σ_{fi}	Σ_{fs}	Σ_{ii}	Σ_{is}	Σ_{ss}
4.32	-0.03	0.13	0.06	-0.04	0.24
(0.55)	(0.04)	(0.09)	(0.01)	(0.01)	(0.03)

used priors with more information the results may have differed in magnitude. A deeper analysis on various prior selection would however been outside the scope for this paper.

3.3 Bayesian Vector Autoregression

The Bayesian vector autoregressive model have the same formal representation as the frequentist of order p=4, VAR(4) model, i.e.

$$Y_t = c + \sum_{i=1}^{p=4} A_i y_{t-i} + \varepsilon_t \tag{3.3}$$

We follow the routine by (Afonso, Slavík, and Baxa 2011) and place the CLIFS (s_t) at last by the assumption that the index reacts contemporaneously to the other variables. The inter-bank rate is ordered after the fiscal variable by the assumptions that the interest rate reacts contemporaneously to fiscal policy but not vice versa. As in (Blanchard and Perotti 2002), we consider all changes in government debt (f_t), to be entirely automatic due to the delays in implementing fiscal policy measures. By the VAR specification in Equation 3.3, we let $Y_t = [f_t \quad i_t \quad s_t]^T$ denote the column vector of endogenous variables, c the vector of intercept terms, A_i is a matrix of coefficients and ε_t is a vector of the error terms. For our quarterly series we chose as recommended by (Blanchard and Perotti 2002), a lag length $p = 4$ to measure the lagged effects up to one previous year.

Results

In this section the results of the impulse response functions is presented. Lastly, a robustness test for the main results in terms of an alternative fiscal policy tool is presented.

3.4 Impulse response functions

To evaluate the dynamic behavior of the model, orthogonalised impulse responses functions (OIRFS) is used to analyze the transmission of shocks across the variables within the Bayesian VAR framework.

The OIRF is based on the decompositon of the covariance matrix, so that $\Sigma = PP'$, where P is a lower triangular matrix obtained by Choleski decomposition. Therefore, and as discussed in section 3.3, the CLIFS index (the last variable in the system) will be sensitive to shocks of the other variables while the first variable (the fiscal policy variable) is not sensitive to a contemporaneous shock of the other variables, but not vice versa. A visual representation of the impulse functions is presented in Figure 3.1-3.3 where the vertical axis of the plots represents the response of the variable of interest while the horizontal axis represents the time period in which the response occurs. The plotted line represents the mean response of the variable and the shaded area around it represents the 95 percentage credibility interval of the response as a measure of significance.

In Figure 3.1 where the responses of CLIFS is presented, one can note that the CLIFS index first reacts positive to a one standard deviation shock to the government debt. This effect diminishes up to the third quarter, where the change is approximately -0.04 units.

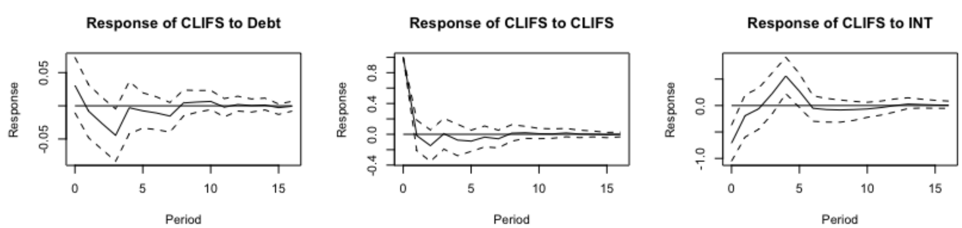

Figure 3.1: Impulse response of the CLIFS index

In Figure 3.2 the dynamic response of the government debt ratio is visualised. A one standard deviation shock on the CLIFS index change government debt ratio with approximately -0.84 units in the next quarter. Four quarters after the shock is at the highest unit change at approximately 0.96 units before the shock goes to zero.

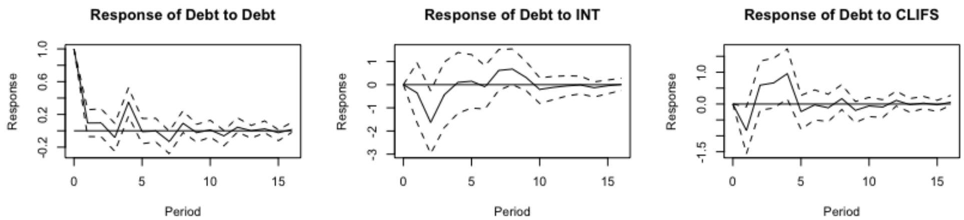

Figure 3.2: Impulse response of government debt

In Figure 3.3 the response variable is the interbank rates. The government debt ratio has a significant but weak negative effect until the third period, where the effect then converges to zero. A one standard deviation change in the CLIFS index affect the interest rate negatively, with a significant change of approximately -0.18 units after one quarter.

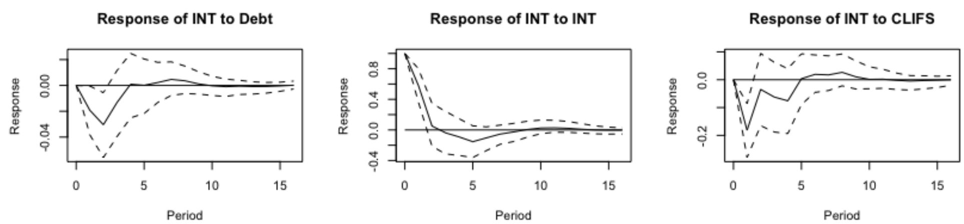

Figure 3.3: Impulse response of interbank rates

3.5 Alternative specification

To test for robustness, we replace the general government debt ratio with general government expenditure as a percentage of GDP, as an alternative specification for the fiscal policy variable.

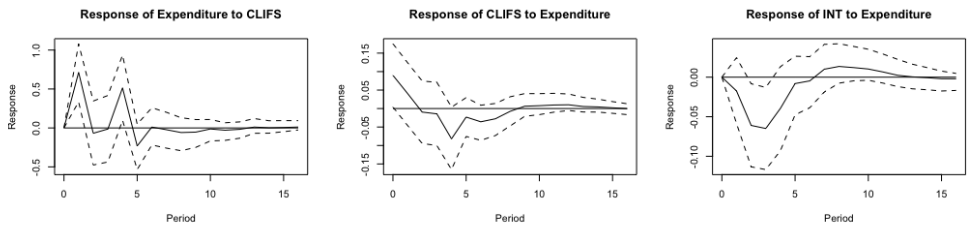

Figure 3.4: Impulse response of government expenditures

One can note that a shock to the CLIFS index has a significant effect on government expenditures in period 1, with as increase of approximately .714 units. The shock has also a significant effect on government expenditure later in period 4 with a .51 unit increase. The effect of a shock to government expenditure has a weak negative effect on financial stress up to period 4, the effect on financial stress is however not significant during this period.

By comparison on how the alternative specification differ in relation to the specification in section 3.4, one can see that the effect on fiscal policy has approximately the same negative direction and magnitude on financial market stress where the contemporaneous effect is positive but then goes to negative before it diminishes, the effect is however not significant.

Conclusion

This study used Bayesian vector autoregression and impulse response functions to analyze the relationship between fiscal policy and financial stress using quarterly data for Sweden between 1996:2-2022:2. The results of the analysis indicates that a shock on the government debt ratio as well as the government expenditure ratio decrease the CLIFS index (as in unit changes), the effect was however weak and not significant.

References

Afonso, António, Michal Slavík, and Jaromír Baxa (Apr. 2011). *Fiscal developments and financial stress: a threshold VAR analysis*. Working Paper Series 1319. European Central Bank. URL: https://ideas.repec.org/p/ecb/ecbwps/20111319.html.

Blanchard, Olivier and Roberto Perotti (2002). "An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output". In: *The Quarterly Journal of Economics* 117.4, pp. 1329–1368. ISSN: 00335533, 15314650. URL: http://www.jstor.org/stable/4132480 (visited on 01/09/2023).

Koop, Gary and Dimitris Korobilis (2009). *Bayesian Multivariate Time Series Methods for Empirical Macroeconomics*. Working Paper series. Rimini Centre for Economic Analysis. URL: https://EconPapers.repec.org/RePEc:rim:rimwps:47_09.

Woźniak, Tomasz (2016). "Bayesian Vector Autoregressions". In: *Australian Economic Review* 49.3, pp. 365–380. DOI: https://doi.org/10.1111/1467-8462.12179. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1467-8462.12179. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-8462.12179.

Zhang, Zhiyong (2021). "A Note on Wishart and Inverse Wishart Priors for Covariance Matrix". In: *Journal of Behavioral Data Science* 2, pp. 119–126. DOI: 10.35566/jbds/v1n2/p2. URL: https://jbds.isdsa.org/index.php/jbds/article/view/19.