EC7415 Term Paper
Financial stress effects on Swedish economy
SVAR and VECM model

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December 2021

Abstract

This term paper focuses on the impact of financial stress shocks on the Swedish economy by employing a VAR model.

1 Introduction

Numerous financial crises have occurred during the years and it's anyone's guess what the next financial crisis might be. Regulatory bodies try to develop fiscal policies trying to prevent the next financial crises and to try to increase the overall robustness of financial markets. Even thou we advance in policy and hopefully have learned a great deal of lessons from previous crisis, new challenges arise with the passing of time making no crises like the previous one alike, rendering some monetary stabilization tools useless, and putting greater pressure on co-operation between countries, central banks, and governments to resolve financial distress and to try to minimize overall damage in the economy. Looking at times of economic downturns and financial stress is important to try to understand which drivers and amplifiers that exist that can exacerbate the economic and financial outlook.

In this paper, I employ a VAR model and analyse the shocks using orthogonal impulse response functions.

The rest of the paper is structured in the following way: Section 2 describes the data and identification scheme, in section 3 an empirical analysis, section 4 present results and lastly conclusions in section 5.

2 Data & Identification

Financial stress can be measured in many different ways, where there are readily available indexes that that aggregate or model across different financial stress indicators to provide a time series capturing levels of financial stress over time. The CLIFS index is such a index developed by at the ECB which includes six, mainly market-based, financial stress measures that capture three financial market segments: equity markets, bond markets and foreign exchange markets. In addition, when aggregating the sub-indices, the CLIFS takes the co-movement across market segments into account (Dupleys et.al., 2015). Since this series is monthly it is aggregated to a quarterly series to match the frequency of the other data series.

To analyse the economic impact a number of economic variables are chosen for Sweden, such as GDP, inflation and 3-month interest rates, quarterly series from 1993Q1 to 2021Q2, all seasonally adjusted.

Since all variables are endogenous in a VAR-framework, identification through cholesky decomposition or sign restrictions are required to be able to derive how shocks move through the endogenous variables in the model. To fully identify the model using we need to have $\frac{n(n-1)}{2}$ assumptions, in this case since we have four variables, we need six identifying assumptions.

To do this we rely on economic theory to recursively specify the model, where the first variable has an effect on all other variables and not the other way around. A common way to order the variables is fast-to-slow meaning that we order the variable that reacts the fastest first and the most rigid variable last.

The variables are orderd in the following way

$$x = (CLIFS,\, BNP,\, CPI,\, INT) \tag{1}$$

The reasoning is that since the CLIFS index is market based it reacts quickly to a shock and affect all other variables, while the other variables do not affect the CLIFS index in the same period. GDP has zero contemporaneous effect on the CLIF index. GDP affects inflation in the short run but we assume prices are rigid and thereby it's not affected by changes in GDP in the same period and since monetary policy do not affect output in the long run and takes time to react due to the time inconsistency of monetary policy. Monetary policy can on the other hand affect inflation in the long run by determining interest rates.

3 Stationarity

VAR-models are estimated using OLS, and one assumption of OLS is that data is stationary. A stationary time series is defined as having a mean of zero and constant variance over time. The problem with non-stationary series is that we can encounter spurious regression where we find significant correlation due to stochastic trends. Another problem is that shocks to the model explode over time, while it gradually disappear over time in a stationary series. This concludes that time series has to be stationary before they can be included in a VAR-model (Stock & Watson, 2015, s.600).

Non-stationary series can either have a stochastic trend or a deterministic trend, in that case they have a unit-root. To test for unit-roots we use the Augmented Dicker Fuller (ADF) test. The null hypothesis in an ADF-test is that the series has a unit-root.

$$\Delta Y = \alpha_0 + \beta_t + \theta Y_{t-} + \delta_1 \Delta Y_{t-1} + ... + \delta_p \Delta Y_{t-p} + u_t \tag{2}$$

$$H_0 : \theta = 0 \, vs. \, H_1 \theta < 0 \tag{3}$$

In below table results from the ADF test is presented

Variables	**Levels**		**Difference**		
	Trend	**Drift**	**Trend**	**Drift**	*I(d)*
CLIF	-3.70***	-3.69***			*I(0)*
GDP	-4.24***	-3.69***			*I(0)*
CPI	-5.19***	-5.18***			*I(0)*
INT	-4.23***	-2.33	-5.93***	-5.83***	*I(1)*

Table 1: Statistical significance at 10%, 5%, 1% är marked as *, **, ***. A stationary variable is integrated of order I(0), and integrated of order I(1) if stationary at first difference.

4 VAR model

VAR models were proposed by Sims (2980), as a way to estimate dynamic relationships after criticizing the previous complex economic models of the time. In a VAR setting all variables are treated endogenously, where in it's structural form can be rewritten in it's reduced form as,

$$y_{t-1} \tag{4}$$

$$By_t = \Gamma y_{t-1} + \epsilon_t \tag{5}$$

where B is the structural impact multiplier matrix, containing the interdependency of the variables at time t and ϵ_t is uncorrelated shocks. This can not be estimated with OLS since the B matrix can not be estimated.

One of the challenges in specifying a VAR-model is to choose how many lags to include, since macro time-series often are short with a few observations. Too many lags will lead to having to use many degrees of freedom to estimate all parameters leading to inconsitent estimates, while too few might lead to that information about the dynamics are excluded from the model. One way to determine lag length is to use akaike information criterion (AIC), which consist of choosing a model that minimizes the criteria.

$$AIC = -2(likelihood) + 2K \tag{6}$$

Where K is the number of parameters in the model. I find that a VAR(4) is the optimal choice according to AIC. Another important aspect is to see if there is any auto-correlation in the error terms, and to test that one can use a

VAR(p)	AIC	Portmanteau
1	-6.906	0.8898
2	-6.940	0.9294
3	-6.930	0.6945
4	**-7.204**	**0.5789**
5	-7.179	0.7888
6	-7.147	0.8402
7	-7.006	0.5711

Table 2: p-values are reported for the portmanteau-test.

Portmanteau-test. Where the null hypothesis of no auto-correlation in the error terms is not rejected.

Having the identification of the model, chosen lag-length and checked for both unit-roots and and auto-correlation in the error terms. We can rewrite our reduced VAR-model in vector moving average (VMA) representation,

$$y_t = \sum_{i=0}^{\infty} A^i u_{t-1} = \sum_{i=0}^{\infty} \gamma_i u_{t-1} \tag{7}$$

where γ_i represents the effect of unit-shocks in the variable after i periods. But as earlier mentioned shocks in the reduced VAR-models are correlated, but given that identifying assumptions and choeletsky decomposition, we get the structural VAR-model that in VMA-representation is given by,

$$y_t = \sum_{i=0}^{\infty} \Theta_i \epsilon_{t-1}, \tag{8}$$

where $\Theta_i = \gamma_i B$. We can now use impulse response functions (IRF) to examine how a variable is affected over time by shocks to the system, since the error terms are no longer correlated. IRFs are given by,

$$\frac{\partial y_{i,t+h}}{\partial \epsilon_j, t} = \theta_{i,j}^{(h)}, \tag{9}$$

whre θ is the response of variable i, h periods forward in time for a shock in variable j at time t.

5 Results

From the IRFs we see the response of BNP, CPI and DINT. All the variables have an initial negative response, and we find significant negative response from all variables. The result is excepted as higher financial stress may indicate worse times ahead or lead to a downturn in the economy lowering both GDP and inflation as a result of lower economic activity, while central banks may respond with expansionary monetary policy, lowering interest rates.

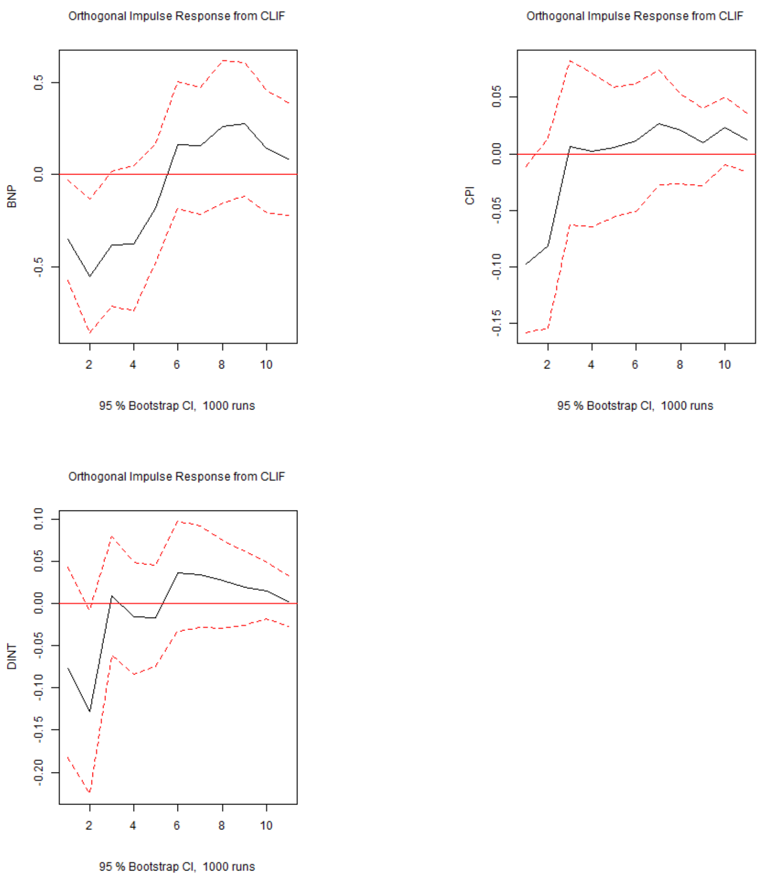

Figure 1: Response of BNP, CPI, DINT from a shock in CLIF

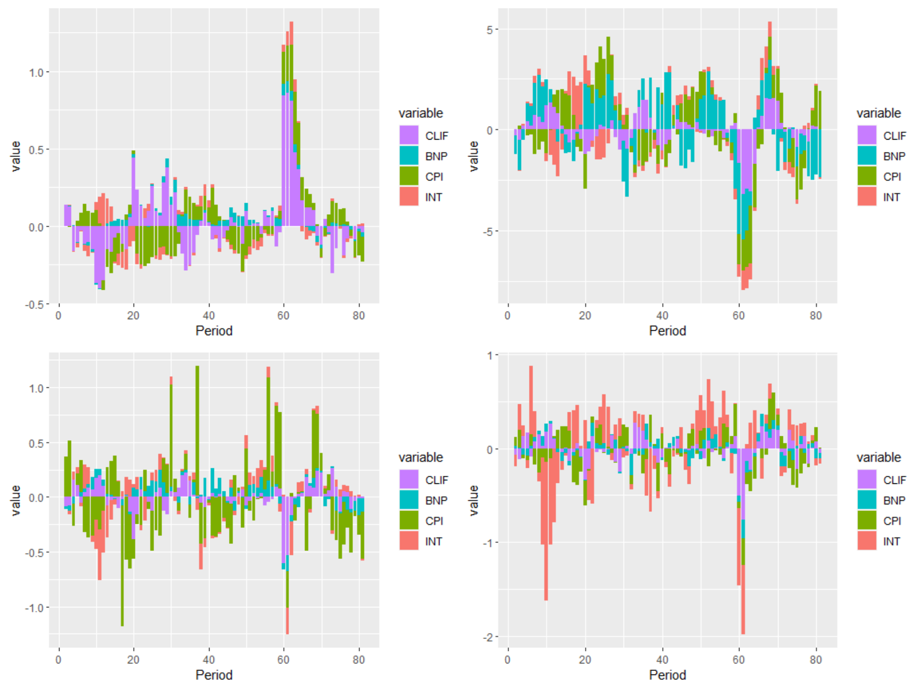

Figure 2: Historical variance decomposition of CLIF, BNP, CPI and DINT.

From the historical variance decomposition, we see that a major part of each variables variance is explained by it's own lagged variance.

6 Conclusion

We find that a unit shock in CLIF leads to significant negative responses in all other variables that diminishes after three to five periods. This after estimating a VAR(4) model where we identify the model recursively, meaning the order of the variables plays a role in how a shock to the a variables moves through the system. We use ADF-tests to check for unit-roots and, AIC to determine lag-length and Portmanteau-test to check for auto-correlation in the error terms.

7 References

Sims, C. A. (1980). Macroeconomics and reality. Econometrica: journal of the Econometric Society, 1-48.

Stock, J., Watson, M. (2001). Vector Autoregressions. Journal Of Economic Perspectives, 15(4), 101-115.