The effects of financial stress on the Swedish economy

Andreas Timoudas

Department of Economics, Stockholm University

Spring 2022

Abstract

In this thesis I study the effects of a shock to financial stress on the Swedish economy using a mean adjusted Bayesian VAR model. To capture the effect of financial stress, the Riksbank's financial stress index used to monitor financial stability, was used as a proxy variable for financial stress. In order to explore its effect on the Swedish economy, variables such as GDP growth, inflation and short term interest rates was used, where the main results are presented as impulse response functions, historical decompositions and forecast error variance. The results suggest that the effects of financial stress shocks have negative effects on the Swedish economy but that the magnitude of the effect is sensitive to the identification of financial stress.

Keywords: *Macroeconomics, Time-series, Bayesian vector autoregressive model*

1 Introduction

Historically there have been several financial crisis affecting the Swedish economy, the most notorious in recent years being the Swedish banking crisis in the 1990s, the dotcom bubble in the 2000s and the global financial crisis 2007. These kind of events are usually unexpected and severe for the general public.

Functioning banking institutions and financial markets require financing, trust and capital to operate in normal conditions (See Berger et al., (1995), Guiso et al., (2008), Knell & Sticks (2010)). When Lehman Brothers went bankrupt in 2008, uncertainty and financial stress spread globally, as fire sales destroyed asset values when people pulled their money from the financial markets and banks, since no one knew what might collapse next. To backstop and try to restore trust the Troubled Asset Relief Program (TARP) was passed in the US while in Sweden, the crisis fortunately remained a liquidity crisis, still forcing the Swedish central bank, the Riksbank, to lower interest rates and increase its balance sheet up to three times to the following year to stabilize the situation.[1]

It is reasonable to believe that financial stress has an effect on the real economy, as uncertainty and distress creates an unpredictable environment. In this type of environment economists agree that it holds back business investments and household consumption.[2] Since there are real economic consequences of financial stress, monitoring financial stability has become increasingly more important for central banks as well as for the development of macroprudencial economic policies which are aiming at ensuring financial stability and preventing disruption.

The question this study aims to shed light on is how a small open economy as Sweden would be affected by a shock to financial stress and what connection there is between financial stress and macroeconomic variables such as GDP growth, inflation, and interest rates. This study has its base to study the dynamics between these variables.

In general financial stress is unobservable, but exhibit key features such as increased degree of perceived risk and uncertainty. Financial stress shocks can thus be interpreted as the heightening of uncertainty from a so called stress event in the financial sector that propagate to the macro-economy. Financial systems also tend to be procyclical, in that credit growth, leverage and excessive risk taking happen during good times when the economy is booming which

[1] Leung, (2020)

[2] Leland (1968), Bernanke (1983), Ferderer (1993), Bloom (2009) and Gilchrist et al. (2014).

in some cases is the foundation of what financial imbalances stand on. The imbalances and overextensions generate vulnerabilities that may in a later time materialise (Borio (2007), Cardarelli et al (2010)). The consequences of financial stress are challenging to predict, as financial institutions are interconnected, and contagion is highly dependent on several factors. Financial stress events do not always materialise in macroeconomic consequences as they can depend on several unknowns such as severity, duration and contagion. An example of a financial stress event that did not materialize in any great macroeconomic affects is the flash crash in 2010 where the Dow Jones Industrial Average dropped over a 1,000 points and recovered to previous values in fifteen minutes. What caused the said flash crash is in dispute, but there has been several similar stress events that had no known macroeconomic consequences.

I have chosen to limit this study to the Swedish economy as I noticed there are few studies about how financial stress affects the Swedish economy. This study is executed by using a Bayesian mean-adjusted VAR-model proposed by Villani (2009). The contribution of this study lies in explaining how the Swedish economy is affected by a shock to financial stress from the chosen variable over the period 1995-2021 using impulse response functions.

I found that the effects of a positive shock to financial stress depend on identification strategy. Results from recursive ordering were not robust to changes in variable ordering, while identification with sign restriction showed that a positive shock to financial stress had a negative although insignificant impact on GDP growth and inflation rate.

2 Previous literature

In this section, I briefly review previous literature on the topic of the thesis, focusing on studies examining the relationship between financial stress and uncertainty and the real economy.

Stockhammar & Österholm (2014) studied the effect of the euro area shocks on the Swedish economy by using a mean-adjusted Bayesian VAR-model. The authors found that shocks to the euro area had considerable effect on Swedish GDP growth. Stockhammar & Österholm (2014) also studied the effects of US policy uncertainty on Swedish GDP Growth, where policy uncertainty was measured as the policy uncertainty index developed by Baker et.al. (2012). Using a mean-adjusted Bayesian VAR-model showed that increased US policy uncertainty had significant negative effects on Swedish GDP growth, which according to the authors had its origin from effects on investment growth and export growth. This thesis is inspired by these studies made by Stockhammar & Österholm, and furthers the analysis by incorporating the latest data and using a different proxy variable for uncertainty, mainly the financial stress index created and used by the Swedish central bank, the Riksbank, to monitor financial stability.

Utland & Roye (2010) conducted a study of the effects of external shocks on countries in emerging Asia using a BVAR model. They showed that almost half of the forecast error variance in emerging Asia's real GDP growth could be explained by external factors. Roye (2011) constructed a financial market stress indicator (FMSI) for Germany and the euro area using a dynamic factor model to be used in a Bayesian VAR-model. Roye found that about fifteen percent of variation in real GDP growth could be accounted for variations in the FMSI, and 30 percent respectively for the euro area. He also showed that including the FMSI significantly improved out-of-sample forecasting accuracy for real GDP in Germany compared to other models.

Bjellerup & Shahanazarian (2012) developed a framework for the propagation of financial systems to the real economy. They investigated four channels of propagation, mainly interest rate, bank reserves, balance sheet, and uncertainty channel where the theory of propagation of each channel is that increased interest rates lead to higher credit costs and lower consumption and investments. Increased market, credit or financial risk depreciates banks balance sheet through lower asset prices which under bank capital reserve requirements can lead to lower credit expansion and higher interest rates for the bank to maintain profitability. Falling asset prices leading to depreciated balance sheets for firms and households which may lead to lower collateral values and tougher credit requirements which creates a feedback loop of lowering asset prices further. Lastly increased uncertainty in the form of increased volatility in asset pricing, leads to lower investments being made and lower consumption. Using a VAR model which included three propagation variables, a financial stress index for the uncertainty channel, repo rate and wealth gap to capture interest rate, banking and balance sheet propagation respectively, they found that a shock to the financial stress index reduced GDP growth significantly where a one percent increase in financial stress variable led to a negative response of 0.4 percent decrease of GDP-growth after two years.

Laséen (2020) studied the effects of monetary policy on economic activity and asset prices using an external instrument, mainly monetary policy surprises to identify monetary policy shocks and remove contemporaneous central bank information shocks. This method of external instruments in VAR models was introduced by Stock (2008) and has later been used more widely and seen as state of art. Laséen found that a tightening of monetary policy has significant effects by reducing economic activity and inflation. Further, he found that central bank information shocks do not bias the identification of monetary policy shocks in the Swedish case.

3 Financial Stress Index

Financial stress indices have been adopted by several financial organisations and central banks over the years as a tool to monitor financial conditions since financial systems play a central role in the economy. For financial markets to function well, liquidity, trust and symmetric information is required so that participants can agree on fair prices. In distressed times, trust can deteriorate quickly and asset-values can can suddenly shift leading to lower levels of liquidity. Funding can become more difficult and expensive as risk premium increases and liquidity risk premium increases.

The Riksbank's FSI-index is calculated based of four sub-markets where there are three indicators for each sub-market. Each indicator is ranked by magnitude in relation to earlier observations as to increase the index's ability to account for new information. The financial stress index is calculated as an equally-weighted mean value of the sub-market indicators, which are squared and adjusted with regards to the correlations between the sub-market indicators (Johansson & Bonthron (2013)). As seen in Table 2, stress is measured in the form of factors such as volatility, spreads and valuation losses. These factors represent uncertainty about asset prices and flight to safe assets which can be considered important features of financial stress. A selected subset of stress events are presented in Table 1.

Event	Date
Swedish banking crisis	1991Q3
ERM crisis, Black Wednesday	1992Q3
SEK exchange floated	1992Q3
Gota bank and Nordbanken nationalization	1992Q2
Russian crisis	1998Q3
Dot-com bubble	2000Q2
U.S. sub-prime mortgage crisis	2007Q1
Bear Stearns collapse	2008Q1
Latvia banking crisis	2008Q1
Lehman Brothers bankruptcy	2008Q3
Iceland banking crisis	2008Q3
Greece banking crisis	2009Q3
Euro Crisis	2011Q3
Covid-19 pandemic	2020Q1

Table 1: Selected financial stress events affecting Swedish economy.

Hakkio & Keeton (2009) describe the key features of financial stress as increased uncertainty of both fundamental value of assets, and investor behavior as well as unwillingness to hold illiquid and or risky assets. Given Hakkio & Keeton's description of financial stress, the Riksbank's financial stress index sub market indicators captures the key features by looking at volatility which can be seen as a measure of uncertainty. Increased spreads can indicated both low liquidity and increased uncertainty while differences in yield increases between covered and government bonds can indicate flight to safe assets. Given Hakkio & Keeton's (2009) descriptive features, the financial stress index calculated by the Riksbank provides a better proxy for financial stress and uncertainty shocks than just stock market volatility which is used by Österholm & Stockhammar (2016) since it captures cross sections of different markets providing greater coverage of macroeconomic risks.

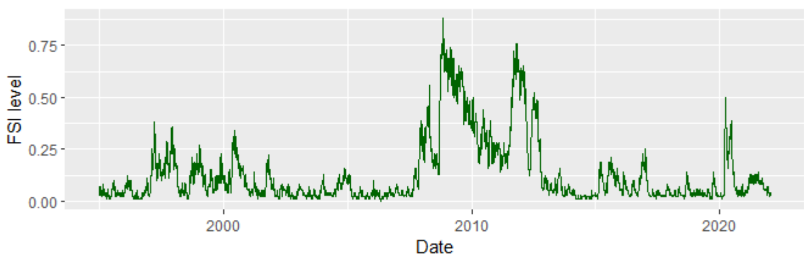

Figure 1: Financial Stress Index

Table 2: Sub-markets and indicators in the new stress index

SUB-MARKETS	INDICATORS
Stock market	Implied volatility Market value in relation to the highest in 2 years Estimated liquidity based on turnover data
Bond market	Difference between 5-year covered bond yield and 5-year swap rate Difference between 5-year covered bond yield and 5-year swap rate minus the 2-year equivalent Difference between 5-year swap rate and 5-year government bond yield
Money market	Difference between 3-month Stibor rate and 3-month treasury bill yield (TED spread) Historical volatility of TED spread Difference between 3-month Stibor rate and 3-month implied Stibor rate
Foreign exchange market	Implied volatility of USD/SEK Implied volatility of EUR/SEK 30 day change in the value of the krona against a basket of currencies (TCW index) in absolute terms

4 Analysis

In this section I will briefly present the VAR-framework proposed by Sims (1980) and later Villani (2009) the mean adjusted Bayesian VAR model.

4.1 Vector auto regression

The VAR framework was proposed by Sims (1980) as an alternative to complex macroeconomic models. In a VAR-model all variables are treated as endogenous and the model has been widely adapted in macroeconomic research since it offers great flexibility. The drawback with VAR models is that often a lot of parameters must be estimated depending on lag length.

VAR-models are estimated using OLS, where one of the assumptions is that the data is stationary. Stationary being defined as constant mean and variance over the whole series. Stationarity ensures that a shock in the system will fade away with time and if the data is not stationary a shock will persist and one can encounter spurious regression. A structural VAR model with one lag can be described as,

$$\boldsymbol{B}y_t = \boldsymbol{\Gamma}y_{t-1} + \boldsymbol{\epsilon_t} \tag{1}$$

where $\boldsymbol{B}$ is the structural impact multiplier matrix consisting of the interdependence between the variables in time t, while $\boldsymbol{\epsilon}_t$ are shocks independent of each other. The structural VAR model cannot be estimated with OLS because of the impact matrix and the VAR model has to be rewritten in it's reduced form,

$$y_t = \boldsymbol{A}y_{t-1} + u_t \tag{2}$$

where $\boldsymbol{B}^{-1}\boldsymbol{\Gamma} = \boldsymbol{A}$ and $\boldsymbol{B}^{-1}\epsilon_t = u_t$. This can be estimated using OLS given that the error terms have zero mean, constant variance and no autocorrelation.

$$E(u_t) = 0, \quad E(u_t, u_t') = \Omega, \quad E(u_t, u_{t-k}) = 0. \tag{3}$$

The problem with the reduced VAR model is that variables are often correlated with each other, meaning that they are dependent and that a shock in one variable is affected by simultaneous shocks to other variables. This creates the need for identification to be able to interpret shocks in the system as dynamic processes. In this study, two methods are used, mainly recursive ordering with the Cholesky decomposition and sign restriction. These are explained in Section 6.1.

4.2 Mean adjusted Bayesian VAR

The empirical analysis is made in a Bayesian VAR framework using the Villani (2009) mean-adjusted model, which can be described in a general form as,

$$\boldsymbol{\Pi}(L)(\boldsymbol{x}_t - \boldsymbol{\mu}) = \boldsymbol{e}_t, \tag{4}$$

where $\boldsymbol{\Pi(L)} = \boldsymbol{I} - \boldsymbol{\Pi}_1 L - ... - \boldsymbol{\Pi}_m L^m$ is a lag polynomial of order m, $\boldsymbol{x}_t$ is an $n \times 1$ vector of stationary variables, $\boldsymbol{\mu}$ is a $n \times 1$ vector of unconditional means describing the steady state of the included variables, and $\boldsymbol{e}_t$ is a $n \times 1$ vector $e_t \sim N(0, \Sigma)$ with *iid* elements. Since macroeconomic variables have relatively short sample size, we run the risk of over-parametrisation. One way to deal with this issue, as suggested by Litterman (1986), is to impose prior information on the parameters.

Villani (2009) proposed the mean-adjusted BVAR-model since he thought that all available priors for VARs focused on the dynamic coefficients, and for the most were non-informative about the deterministic component of the model. Villani's adjustment of the BVAR-model allows to model the unconditional means of the variables, by setting the prior unconditional means of each variable explicitly. This is important as it is known that stationary VARs converge to the unconditional mean, at long horizons. The model will be identified recursively using Cholesky decomposition, and later with sign restrictions.

5 Priors

All parameters, $\boldsymbol{\theta}$ in the model are treated as random variables in the Bayesian approach. Where $\boldsymbol{\theta} = (\mathbf{\Pi}, \mathbf{\Sigma}, \boldsymbol{\mu})$ is given a prior distribution $\pi(\boldsymbol{\theta})$. It is then used to derive the posterior distribution $p(\boldsymbol{\theta}|\boldsymbol{X}_t)$ which is the distribution of the parameters given the observed data. The likelihood function is given by

$$L(\boldsymbol{X}_t|\boldsymbol{\theta}) = \prod_{t=1}^{T} f(\boldsymbol{x}_t|\boldsymbol{X}_{t-1}, \boldsymbol{\theta}), \tag{5}$$

which is the distribution of the observed data given the parameters. Bayes's rule tells us that the posterior distribution equals

$$p(\boldsymbol{\theta}|\boldsymbol{X}_T) = \frac{L(\boldsymbol{X}_t|\boldsymbol{\theta})\pi(\boldsymbol{\theta})}{p(\boldsymbol{X}_T)}, \tag{6}$$

where $p(\boldsymbol{X}_T)$ is the marginal likelihood. From this we see that the posterior depended on the data as well as any prior beliefs.

Villani (2009) shows normal-diffuse priors in the steady-state VAR are,

$$p(\mathbf{\Sigma}) \propto |\mathbf{\Sigma}|^{\frac{-(n+1)}{2}} \tag{7}$$

$$\boldsymbol{\mu} \sim N_n(\boldsymbol{\theta}_{\boldsymbol{\mu}}, \mathbf{\Omega}_{\boldsymbol{\mu}}) \tag{8}$$

$$vec(\mathbf{\Pi}) \sim N_{mn^2}(\boldsymbol{\theta}_{\mathbf{\Pi}}, \mathbf{\Omega}_{\mathbf{\Pi}}) \tag{9}$$

The prior distribution of the steady state $N_n(\boldsymbol{\theta}_{\boldsymbol{\mu}}, \mathbf{\Omega}_{\boldsymbol{\mu}})$ is specified in Section 6, while the distribution of the lag coefficients $\sim N_{mn^2}(\boldsymbol{\theta}_{\mathbf{\Pi}}, \mathbf{\Omega}_{\mathbf{\Pi}})$ is specified by the Minnesota Prior beliefs (Litterman, 1986).

The Minnesota prior beliefs was introduced by Doan et al. (1984) and Litterman (1986) as a way to deal with the issue of over-parametrisation in VAR-models, by imposing tightness on the parameters and thus restricting the lag-structure. I follow Villiani's (2009) slight modification of the Minnesota prior and set the prior mean of variables in first difference to 0, and 0.9 for variables in levels. Villani argued that since Littermens usual prior mean or unity for variables in levels is inconsistent with having a prior on the steady state. For the variance-covariance matrix of the coefficients $\mathbf{\Omega_\Pi}$, shrinkage hyperparameters $\lambda_1, \lambda_2, \lambda_3$ is used to form the tightness on the lag structure. It's specified as:

$$diag(\mathbf{\Omega_\Pi}) = \begin{cases} \left(\frac{\lambda_1}{m^{\lambda_3}}\right)^2 & \text{for own lags} \\ \left(\frac{\lambda_1 \lambda_2}{m^{\lambda_3}}\right) & \text{for lags of variable } q \text{ in equation } r \end{cases} \tag{10}$$

Where the number of lags is denoted by m. The hyperparameters impose tightness according to Table 3. σ_q^2 is the variance of the residuals from as univariate AR(m) estimation of for variable q. $\frac{\sigma_q^2}{\sigma_r^2}$ controls for differences in scale and units of measurement for the variables. The hyperparameters follow the standard practice of the Minnesota prior (Litterman, 1896).

Hyperparameter	Description	Value
λ_1	Overall Shrinkage	0.2
λ_2	Cross-variable Shrinkage	0.5
λ_3	Lag-decay	1

Table 3: Minnesota hyperparameters

Villani (2009) states that the steady-state BVAR-model is untractable, but that the distribution of each set of model parameters given the other parameters is tractable, and that a Gibbs sampler can be used to draw from the joint posterior. In this study, I have used 10,000 draws using a Gibbs sampler.

6 Study Design

In this section I will cover the data used in the model, the recursive ordering which is used to identify the structural shocks and the steady state priors for all variables. The data consists of quarterly observations ranging from 1995 to 2021 with respect to four macroeconomic variables.

$$\boldsymbol{x}_t = (SMSI \quad y \quad \pi \quad \Delta i). \tag{11}$$

Table 4: Variable description and identifiers.

Variable	Description	Identifier
$SFSI$	Swedish Financial Stress Index	SFSI
y	Swedish GDP growth	BNP
π	Swedish inflation rate	CPI
Δi	3-month rate for Swedish treasury bills (first difference)	DINT

The SFSI data is originally daily observations, that have been aggregated to quarterly observations. The remaining variables are seasonally adjusted. While the SFSI index was provided by the Riksbank, the remaining data has been obtained from the FRED database. All variables are included in the model as stationary processes, where Δi is stationary in first difference while other variables are stationary in levels. Lag length is set to four, as determined by Akaike's information creterion (AIC).

The steady state priors are chosen according to Section 5 with the intervals for the steady state priors are specified in Section 6. Since there is no theory on the prior for SFSI, I have imposed a rather diffuse prior with a wide distribution around the prior mean. For the steady state prior of Swedish GDP growth, I have used Villani (2009) and for inflation rate Beechey & Österholm (2010). Beechey & Österholm (2010) provide steady state intervals for annual inflation rate. Since data used in this study is quarterly, the interval specified by the authors was adjusted to quaterly inflation rate. For the steady state prior for 3 months interest rate, I have set a prior around the zero mean since it is in first difference.

	$SMSI$	y	π	Δi
95% prior probability interval	(2, 10)	(2, 2.5)	(0.2. 0.6)	(-0.5, 0.5)

Table 5: Steady state priors

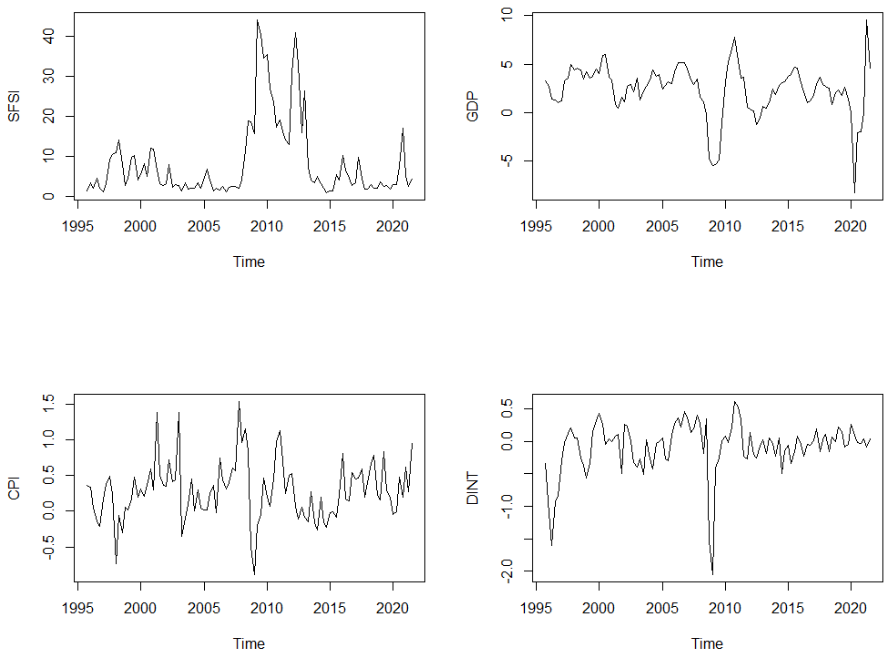

Figure 2: Plots for all variables.

6.1 Identification

In this section I will present the different types of identification used in identifying structural shocks. Since the VAR model is estimated in its reduced form, shocks are correlated meaning all variables are contemporaneously dependent.

6.2 Cholesky identification

The Cholesky decomposition is a common way used to identify shocks as structural shocks, where the ordering of the variables is of importance. To order the variables one has to use economic reasoning and theory. In this model, the financial stress index is ordered first where the identifying assumption is that it affects GDP growth, inflation and interest rates and that the other variables do not affect the financial stress index in the same period but with a lag. In other words, the index is contemporaneously independent of all shocks but its own. Given the frequency of publishment of GDP and inflation data, it is not available for the markets in real term and thus cannot be acted upon or reflected in real time market variables. The ordering is also based on the assumption that financial stress shocks contemporaneously affect the sub-market indicators that the financial stress index is constructed of. This ordering with the stress or uncertainty variable ordered first has been established in previous studies such as Bloom (2009), Baker et al. (2012).

6.3 Sign restrictions

Sign restriction is another method to identify structural shocks. Given the economic theory of the aggregate demand, aggregate supply model. We know, for example that positive demand shock increases both output and price while a positive supply shock increases output and decreases prices, this suggests that the sign or the set of values of the effect can be set given a positive shock on a variable in a VAR over a horizon. This approach of sign restrictions does not require a specific ordering of the variables as when using the Cholesky decomposition. Uhlig, (2017) covers two principles on using sign restrictions, mainly to impose those restrictions you can reasonably impose. All identified shocks are presented in Table 6.

A commonly used strategy is to impose restriction based on results from a relevant DSGE model which in the case of Sweden would be Adolfson et al. (2008), Corbo & Strid, (2020) or use base restrictions from theory. A requirement is that each shock is uniquely identified, meaning no other shock has the same set of restriction and if that is not the case, shocks cannot be distinguished. While there is considerable literature and theory on sign restrictions for demand, supply and monetary policy (Pearsman & Straub (2009)), there is little for financial stress shocks.

Since the interest is to study the effect of GDP growth and inflation to a shock of financial stress, those are left unrestricted as to not prejudge the outcome. And restrictions are instead imposed on SFSI and change in interest rates. In response to the great financial crisis 2008, the Riksbank cut the policy rate by 4.5 percentage points over the course of six month and announced to offer fixed-rate loans to lower short term interest rates and improve financial conditions. The effect of these announcements was later estimated to have led to a decline of short-term interest rates of 0.3 percentage points (Elmér et al., (2012)). This provides historical evidence albeit anecdotal of policy response aimed at stabilizing financial conditions as well as trying to affect the shorter end of the yield curve. In the event of flight to safe assets, demand for government bonds increase pushing prices of those assets up. Since yield of bonds is inversely related to to it's price, interest rates decrease consequently.

Although there is an "inflation puzzle" depending on if financial stress shocks are modeled as demand or supply shocks.[3] Hence, sign is depended on which effect that is the greatest. Abbate et al., (2020) provide evidence that a financial stress shock temporarily increases inflation because of increased borrowing cost and credit following a financial shock, suggesting financial shocks act as supply shocks. Looking at Bjellerup & Shahanazarian (2012) briefly explained in Section 2, we reasonably expect that a positive shock to financial stress reduces GDP growth through higher credit costs and lower consumption and investments.

Table 6: Sign restrictions identification

	Financial Stress	Demand	Supply	Monetary Policy
$SFSI$	+		-	
y		+	+	-
π		+	-	-
Δi	-	+	-	+

7 Results

In this section results from the impulse response functions (IRF) will be presented and the historical decomposition for the structural shocks. Since the topic of this thesis is the effect of financial stress on the Swedish economy, only IRF's regarding a shock to SFSI will be presented in this section. All IRF's can be found in the Appendix in Figure 9.

The impulse response functions from a one standard deviation unit shock to the SFSI index are given in Figure 3. We find that a shock the the SFSI has a significant effect on Swedish GDP growth, with a maximum effect of where growth is reduced with 0.41 percentage points. The effect of the shock goes to zero after five quarters. The other economic variables show no significant effect over the horizon. Inflation rate is reduced with a maximum effect of 0.12 percentage point were the effect disappears after 10 quarters. Since the 3-month interest rate is in first difference the effect is interpreted as the rate of change. All IRFs are presented in the Appendix in Figure 9.

[3]See following papers model financial shocks as demand shocks: Curdia and Woodford (2010), Gertlerand Karadi (2011) and Del Negro et al. (2015). As supply shocks: Gilchrist et al. (2017), De Fiore and Tristani (2013) and Meh and Moran (2010).

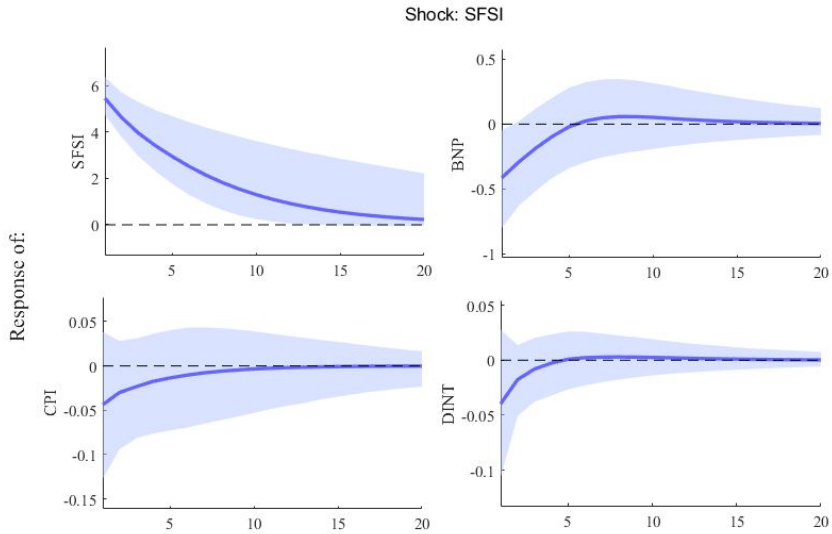

Figure 3: Impulse response functions from a shock to the SFSI index. Solid lines are the median response. Shaded area represents a 95% confidence interval.

In the historical decomposition in Figure 4, we see the contribution of each structural shock to the historical dynamics of the variables meaning the historical value is decomposed into different components. We find that most of the historical fluctuations is contributed by the variables own shocks over time. During the period of the the great financial crisis in 2007-2009 and the euro crisis in 2009-2013 we see that the increased financial stress contributes to a large extent of the reduced GDP growth. The following period of normalizing financial conditions we also see that it attributes almost all of the GDP growth the following three quarters to the decreased financial stress conditions. In the later period of 2020, when the pandemic took place, we see that financial stress played little or no role in the reduced GDP growth. For the inflation rate we find that financial stress produces similar results as to GDP growth.

Forecast error variance lets us interpret how important a shock is in explaining the fluctuations of the variables in the model, it also allows us to see how the importance of a shock changes over time. From Figure 5 we can see that financial stress can explain very little of the fluctuations in the economic variables over all periods. For GDP growth the 5-6 percent of the variance is explained by shocks to financial stress.

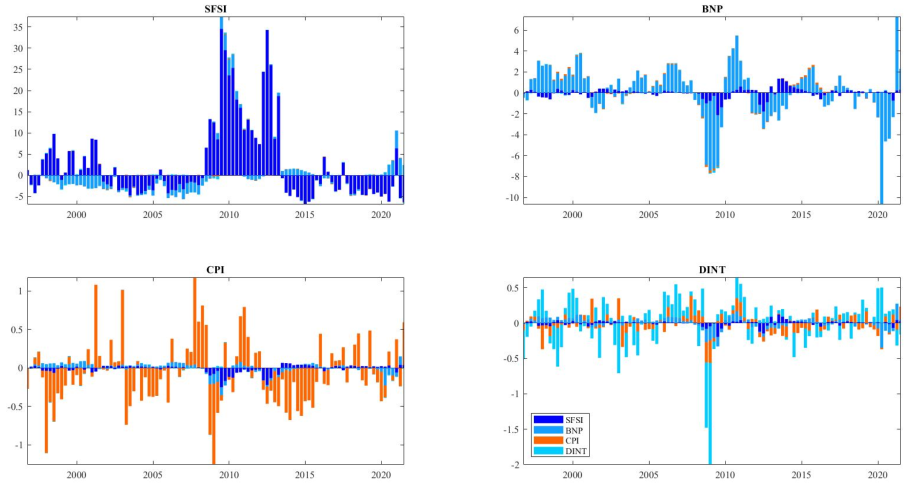

Figure 4: Historical variance decomposition of all variables, measured as the median.

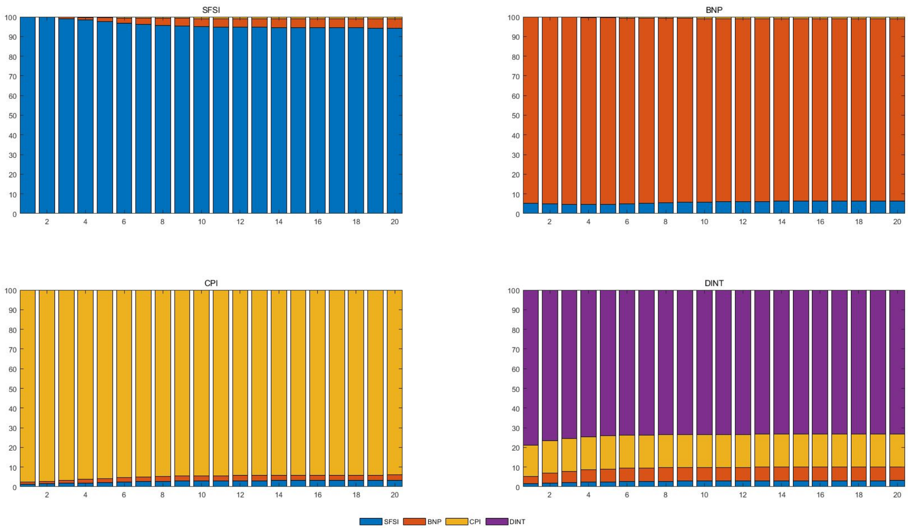

Figure 5: Forecast error variance of all variables, median percentage.

8 Sensitivity analysis

In this section I will present sensitivity analyses of the model, first by dropping the steady state prior to see if the IRFs are consistent and then by changing the recursive ordering of the model and use sign restrictions to see if the results changes or stays consistent.

8.1 Normal diffuse prior

In Villani's mean adjusted Bayesian VAR model one provides a informative prior, the steady-state values of the variables in the system. This assumes that prior information on the steady-state value exists for all variables in the system. This is however not the case for the financial stress index, where there is no prior theory on it's steady state. To test the importance of the steady state for the results, assertion is made by estimating a traditional Bayesian VAR model,

$$\boldsymbol{\Pi}(\boldsymbol{x}_t) = \boldsymbol{\alpha} + \boldsymbol{e}_t. \tag{12}$$

Where $\boldsymbol{\Pi}$, $\boldsymbol{x}_t$ and $\boldsymbol{e}_t$ is defined as in Section 4. $\boldsymbol{\alpha}$ is an $n \times 1$ vector of intercepts, where I set a diffuse prior $\boldsymbol{\alpha} \sim N_n(0, 100\boldsymbol{I}_n)$. I also set the prior mean on the first own lag to unity on all variables.

Given above change on the model, I find that the impulse response functions in Figure 6 are exceedingly similar to those in Figure 9 and that Villani's mean-adjusted Bayesian VAR does not affect the results.

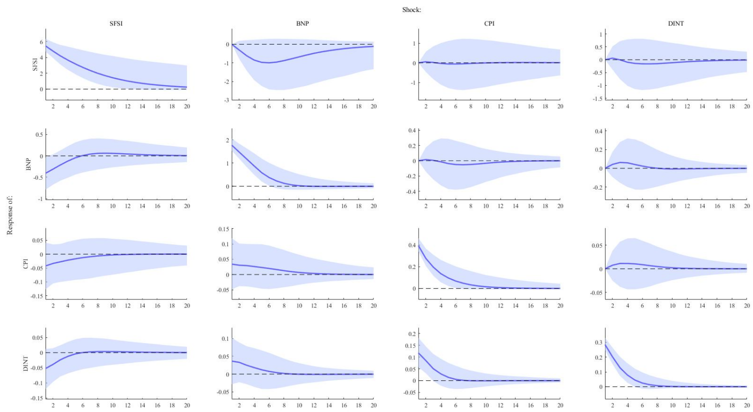

Figure 6: Impulse response functions normal diffuse prior. Solid lines are median response of the endogenous variables to one-standard-deviation shock. Shaded areas represent 95 percent error bands.

8.2 Changing ordering

To verify whether the results are robust or if they are sensitive to the recursive ordering of the Cholesky decomposition, one can estimate a new model with different ordering and see if there is significant difference in the produced IRFs. A common method to order economic variables is to order slow variables first and lastly fast moving variables. An example of this ordering is given by Stockhammer & Osterholm (2017) stating that this ordering is reasonable. Following their reasoning would in this case mean that the financial stress index changes daily taking new information into account, such as GDP, while economic variables such as inflation and GDP are sluggish and information from the financial stress index is not taken into account by firms and consumers in the short term when making investment or consumption decisions.

This results in below order,

$$\boldsymbol{x}_t = (y \quad \pi \quad \Delta i \quad SMSI), \tag{13}$$

where $SFSI$ variables is ordered last entails it does not have a contemporaneous effect on any other variables in the system. The IRFs produced from this model in Figure 7 shows no significant effect on GDP growth from a shock to financial stress compared to the original ordering of the model. Since results are not robust to changes in ordering it implies weak model identification and that the results depend on the assumptions of the contemporaneous effect of the shocks.

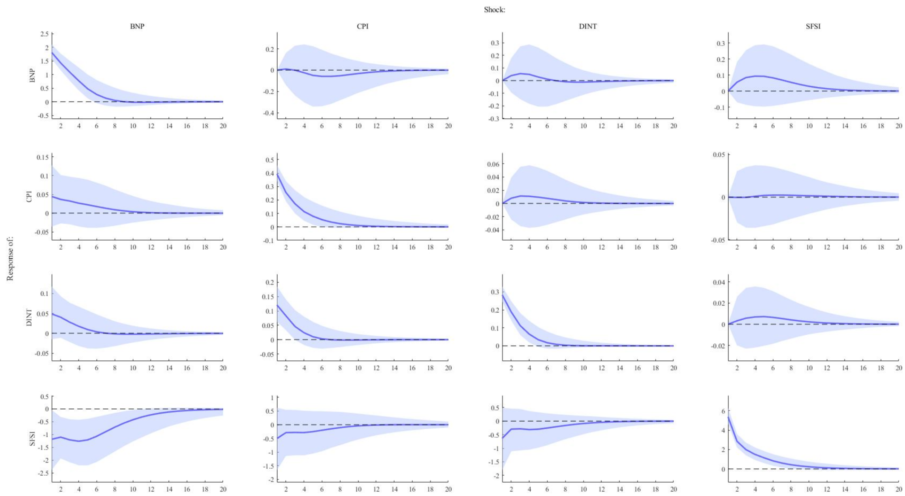

Figure 7: Impulse response functions SFSI ordered last. Solid lines are median response of the endogenous variables to one-standard-deviation shock. Shaded areas represent 95 percent error bands.

8.3 Sign restrictions

In Section 6.3 the identification for the model using sign restrictions was made. From the impulse response functions we see that a positive financial stress shock did not have a significant response to GDP growth or inflation rate. While the response is negative nothing can be said about magnitude of the response, and from Section 6.3 the expectation was that a positive shock to financial stress would reduce GDP growth. Inflation rate also has a negative albeit insignificant response to the shock and given the "inflation puzzle" explained in Section 6.3 the negative sign suggests that financial stress shock acts more as a demand shock than a supply shock. From the forecast error variance in Figure 15 in the Appendix, financial stress shocks are shown to explain up to 12 percent of the variations in GDP growth, staying stable over all periods, where the increased explanatory power of financial stress is true for the other economic variables as well.

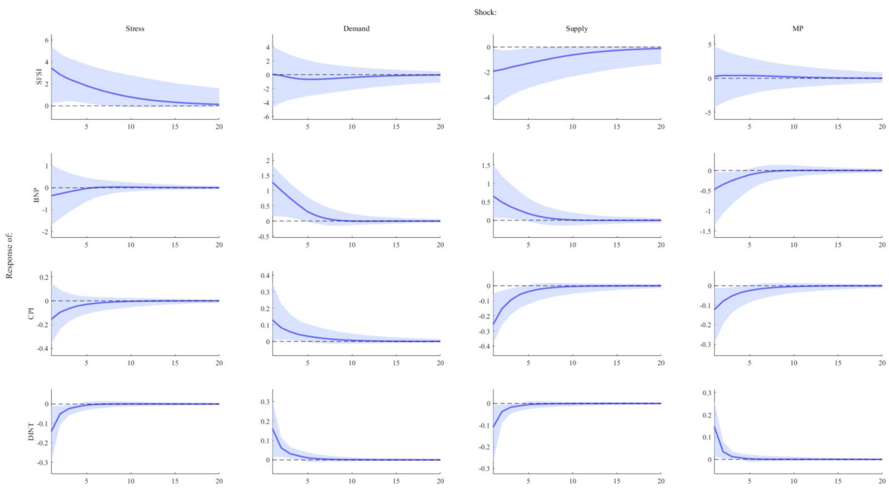

Figure 8: Impulse response functions from sign restriction identification. Solid lines are median response of the endogenous variables to one-standard-deviation shock. Shaded areas represent 95 percent error bands.

9 Discussion

Dropping the steady state prior did not affect the results significantly. Altering the ordering of the variables, following a slow-to-fast specification where the financial stress index is ordered last, resulted in no significant response in any of the economic variables from a positive shock to financial stress. Comparatively with the original ordering in Equation 1, where a positive shock to financial stress had significant effect on GDP growth. Stockhammar & Österholm (2017) found similar results when checking for the robustness of their model studying uncertainty shocks given by CBOE S&P volatility index.

Since ordering of the variables impacted the results, and specifically resulted in no significant responses from any of the economic variables from a shock to financial stress, this implies that the structural shocks are sensitive to the assumptions of the dynamics in the system and that a choice between the models is ambiguous and dependent on the assumed dynamics.

Applying a different identification strategy, mainly sign restriction allow us more flexibility. The advantage of sign restrictions is not having to specify the recursive ordering of the variables. The issue with sign restriction models is to uniquely identify shocks. The shock of interest in this case is a positive shock to financial stress and as stated in Uhlig (2017) one should be reasonably sure that no other shock has the same sign implication. This proposes an immediate threat to the identification since a positive financial stress shocks might have the same sign implication as a negative demand shock, and that events such as the great financial crisis can be seen as both a negative demand shock and positive financial stress shock using this identification. Another threat being Fry & Pagan (2009) pointing out that sign restrictions is rather weak and should be used in conjunction with parametric restrictions. They also point out that both sign restrictions and recursive ordering only solves the structural identification but not the model specification.

Results from previous literature Bloom (2009) finds that the impact of macro uncertainty shock in the US having an effect of lowering aggregate output with 0.98 percentage points. While Stockhammar & Osterholm (2014) found that euro area policy uncertainty shock had an impact of minus 0.1 percent GDP growth in Sweden, Abbate et al. 2020 investigated financial shocks and inflation dynamics on US data and found significant increase in inflation rate of 0.1 percentage points as well as decrease in output of 0.6 percentage points. Further, van Roye (2011) found a significant decrease in both GDP and inflation and interest rates in the euro area to a shock to a financial market stress indicator. Comparing results with previous literature shows mixed results dependent on both area and uncertainty indicator as well as identification assumptions, making it challenging to validate and compare model output with the previous literature.

Other identification method that are more widely adopted, such as narrative shocks and high-frequency identification and external instruments (Proxy SVAR), can be used to provide exogeneity. The challenge using these methods respectively is constructing narrative series and identifying events or having available data. For external instruments, the challenge is having an instrument fulfilling the relevance and exogeneity condition. In this case, that would be an instrument that is correlated with financial stress as well as uncorrelated with other structural shocks, meaning demand, supply and monetary policy shocks. Hence, finding a strong instrument can prove to be extremely challenging.

Identification strategy is important as to be able to argue that shocks are structural and not correlated with each other. In this thesis, it is a potential problem since the financial stress index is endogenous as are other measures of financial stress or uncertainty. This means that it may respond contemporaneously to other variables in the VAR, since the index has been aggregated and data is at a quarterly frequency. Related to that, it is also important to have an exogenous variable or proxy for the particular shock one wishes to study. Since the financial stress index is a composite of different sub-market indicators, mainly implied volatility and spreads, it mainly captures the uncertainty and risk in those markets. This allows us to interpret increased financial stress in the index as increased uncertainty, capturing one of the channels of propagation as laid out by Bjellerup & Shahanazarian (2012). These indicators tend to be driven by several factors that other than financial rigidity, such as sentiment, leverage, macroeconomic risk, investors appetite for risk and firm based decision and productivity. This poses an issue since the financial stress index is not exogenous but confounded by other factors. Bloom (2009) provides evidence that stock-market volatility is linked to other measures of productivity and demand uncertainty.

Another approach one may have in the interest of further studying financial stress, would be to investigate the interaction effect of financial stress as to estimate the simultaneous interaction between financial stress and macroeconomic variables, which can be made using an Interactive Panel VAR model which is a nonlinear framework. This method allows for suggestive answers to questions as to how great the fiscal multiplier is during periods of high financial stress or the effect of monetary policy when there is high financial stress.

10 Conclusions

The purpose of this study was to investigate the dynamics between shocks to financial stress and the Swedish economic variables such as GDP growth, inflation rate and interest rates using a mean-adjusted Bayesian VAR model specification. The findings from the recursive model were not robust to changing the order of the variables, implying weak identification. Changing identification strategy from Cholesky to sign restrictions, produced similar results as the recursive model, main difference being insignificant although negative effects on both GDP growth and inflation rate. Since results were not robust to changes to identifying assumptions in the recursive model and financial stress shocks could not reasonably be distinguished from negative demand shocks using sign restrictions identification, this raises the question on how it can be improved for further studies. Given that one can find an instrument for financial stress to remove contemporaneous shocks that satisfies the exogeneity and relevance condition, a proxy SVAR model would allow for greater inference and macroprudential policy implications to mitigate effects of financial stress and spillovers on the real economy.

References

Angela Abbate, Prieto Eickmeier, and Esteban Prieto. Financial shocks and inflation dynamics. *Macroeconomic Dynamics*, page 29, 2021.

Malin Adolfson, Stefan Laséen, Jesper Lindé, and Mattias Villani. Evaluating an estimated new keynesian small open economy model. *Journal of Economic Dynamics and Control*, 32(8):2690–2721, 2008.

Scott Baker, Nicholas Bloom, and Steven Davis. Policy uncertainty: A new indicator. *CentrePiece*, 16, 2012.

Meredith Beechey and Pär Österholm. Forecasting inflation in an inflation-targeting regime: A role for informative steady-state priors. *International Journal of Forecasting*, 26(2):248–264, 2010.

Allen N. Berger, Richard J. Herring, and Giorgio P. Szegö. The role of capital in financial institutions. *Journal of Banking & Finance*, 19(3):393–430, 1995.

Ben S. Bernanke. Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, 98(1):85–106, 1983.

Mårten Bjellerup and Hovick Shahnazarian. Hur påverkar det finansiella systemet den reala ekonomin? Technical report, Finansdepartementet, Regeringskansliet, 2012. OCLC: 940712633.

Nicholas Bloom. The impact of uncertainty shocks. *Econometrica*, 77(3):623–685, 2009.

Claudio E. V. Borio. Change and constancy in the financial system: implications for financial distress and policy. BIS Working Papers 237, BIS, 2007.

Roberto Cardarelli, Selim Elekdag, and Subir Lall. Financial stress and economic contractions. *Journal of Financial Stability*, 7(2):78–97, 2011.

Vesna Corbo and Ingvar Strid. Maja: A two-region DSGE model for sweden and its main trading partners. Working Paper Series 391, Sveriges Riksbank, 2020.

Thomas Doan, Robert Litterman, and Christopher Sims. Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews*, 3 (1):1–100, 1984.

Heidi Elmér, Gabriela Guibourg, David Kjellberg, and Marianne Nessén. The riksbank's monetary policy measures during the financial crisis – evaluation and lessons learnt. Sveriges riksbank economic review, Sveriges Riksbank, 2012.

J. Peter Ferderer. The impact of uncertainty on aggregate investment spending: An empirical analysis. *Journal of Money, Credit and Banking*, 25(1):30–48, 1993.

Fiorella De Fiore and Oreste Tristani. Optimal Monetary Policy in a Model of the Credit Channel. *The Economic Journal*, 123(571):906–931, 12 2012.

Renée Fry and Adrian Pagan. Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature*, 49(4):938–960, 2011-12-01.

Mark Gertler and Peter Karadi. A model of unconventional monetary policy. *Journal of Monetary Economics*, 58(1):17–34, 2011.

Simon Gilchrist, Jae W Sim, and Egon Zakrajsek. Uncertainty, financial frictions, and investment dynamics. Working Paper Series 69, The Federal Reserve Board, 2014.

Simon Gilchrist, Raphael Schoenle, Jae Sim, and Egon Zakrajšek. Inflation dynamics during the financial crisis. *American Economic Review*, 107(3): 785–823, March 2017.

Luigi Guiso, Paola Sapienza, and Luigi Zingales. Trusting the stock market. *The Journal of Finance*, 63(6):2557–2600, 2008.

Craig S Hakkio and William R Keeton. Financial stress: What is it, how can it be measured, and why does it matter? *CFA Digest*, 40(1):46, 2010.

Tor Johansson and Fredrik Bonthron. Further development of the index for financial stress for sweden. Sveriges riksbank economic review, Sveriges Riksbank, 2013.

Markus Knell and Helmut Stix. Trust in banks - evidence from normal times and from times of crises. Working Papers 158, Oesterreichische Nationalbank, 2009.

Stefan Laséen. Monetary policy surprises, central bank information shocks, and economic activity in a small open economy. Sveriges Riksbank Working Paper Series 396, Sveriges Riksbank, 2020.

Hayne E. Leland. Saving and uncertainty: The precautionary demand for saving. *The Quarterly Journal of Economics*, 82(3):465, 1968.

Caroline Leung. The riksbank's measures during the global financial crisis 2007-2010. Technical report, Sveriges Riksbank, 2020.

Robert B Litterman. Forecasting with bayesian vector autoregressions-five years of experience. *Journal of Business & Economic Statistics*, 4:25–38, 1986.

Césaire A. Meh and Kevin Moran. The role of bank capital in the propagation of shocks. *Journal of Economic Dynamics and Control*, 34(3):555–576, March 2010.

Marco Del Negro, Michele Lenza, Giorgio E. Primiceri, and Andrea Tambalotti. What's up withthe phillips curve? Working Paper 27003, Brookings Papers of Economic Activity Conference Drafts, 2020.

Gert Peersman and Roland Straub. Technology shocks and robust sign restrictions in a euro area SVAR. *International Economic Review*, 50(3):727–750, 2009.

Christopher Sims. Macroeconomics and reality. *Econometrica*, 48(1):1–48, 1980.

Pär Stockhammar and Pär Österholm. The Euro Crisis and Swedish GDP Growth — A Study of Spillovers. Working Papers 134, National Institute of Economic Research, March 2014a.

Pär Stockhammar and Pär Österholm. Effects of US policy uncertainty on swedish GDP growth. *Empirical Economics*, 50(2):443–462, 2014b.

Pär Stockhammar and Pär Österholm. The impact of US uncertainty shocks on small open economies. *Open Economies Review*, 28(2):347–368, 2017.

Harald Uhlig. Shocks, sign restrictions, and identification. In Bo Honore, Ariel Pakes, Monika Piazzesi, and Larry Samuelson, editors, *Advances in Economics and Econometrics*, pages 95–127. Cambridge University Press, 2017. ISBN 978-1-108-22722-3.

Johannes Utland and Björn van Roye. The effects of external shocks on business cycles in emerging asia: A bayesian VAR model. Kiel Working Paper 1668, Kiel Institute for the World Economy, 2010.

Björn van Roye. Financial stress and economic activity in germany and the euro area. *Empirica*, 41(1):101–126, 2014.

Curdia Vasco and Woodford Michael L. Credit spreads and monetary policy. *Journal of Money, Credit and Banking*, 42:3–35, 2010.

Mattias Villani. Steady-state priors for vector autoregressions. *Journal of Applied Econometrics*, 24(4):630–650, 2009.

11 Appendix

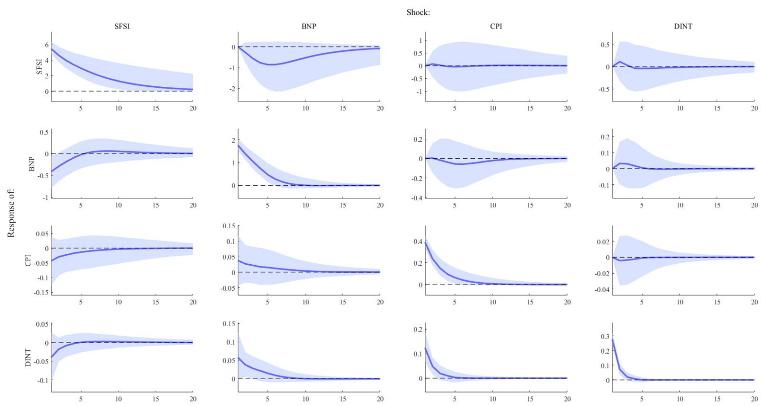

Figure 9: Impulse response functions mean-adjusted model. Solid lines are median response of the endogenous variables to one-standard-deviation shock. Shaded areas represent 95 percent error bands.

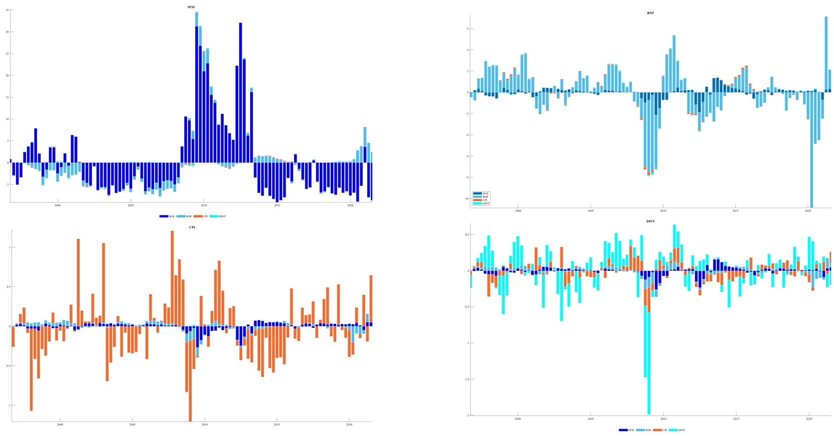

Figure 10: Historical decomposition normal diffuse prior, measured as the median.

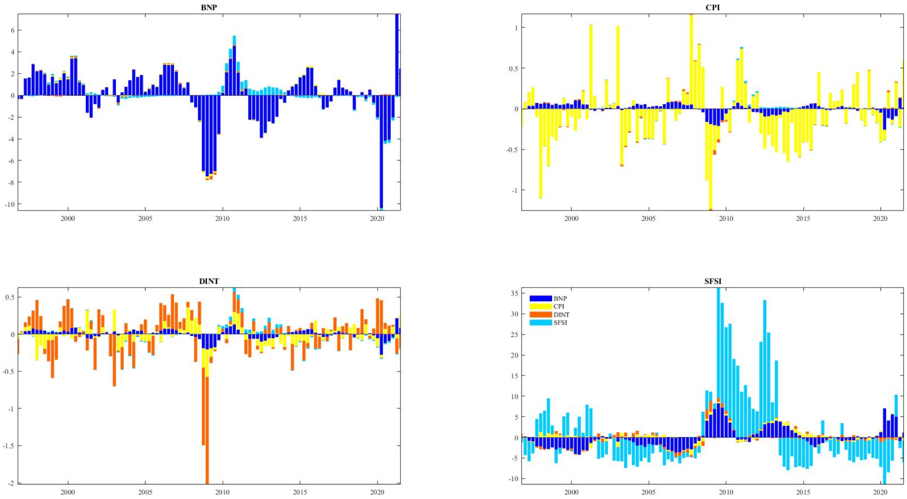

Figure 11: Historical decomposition $SFSI$ ordered last, measured as the median.

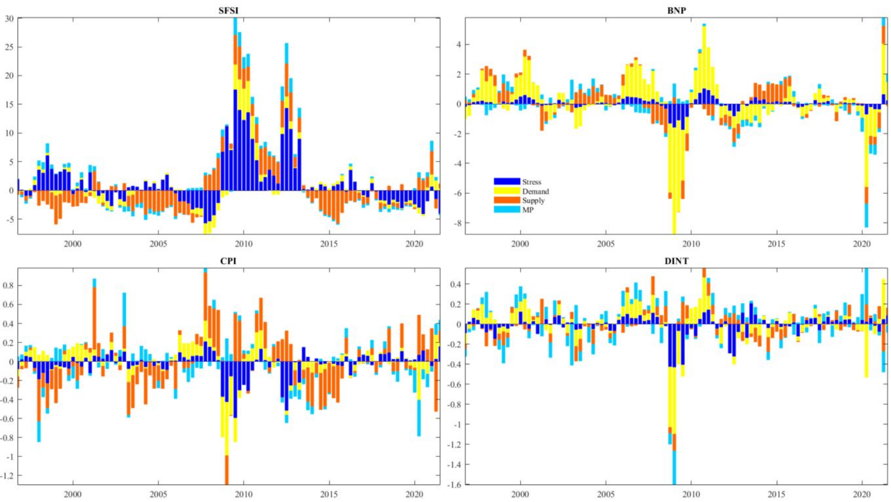

Figure 12: Historical decomposition from sign restrictions identification, measured as the median.

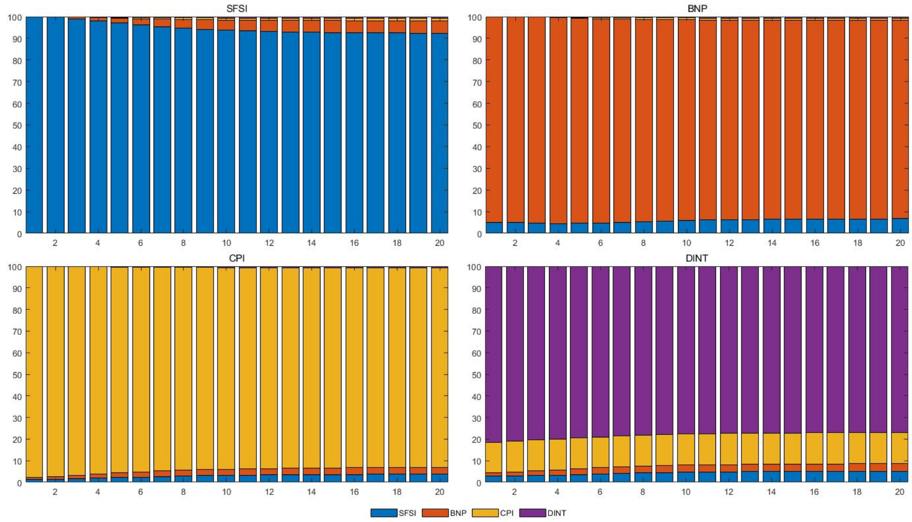

Figure 13: Forecast error variance normal diffuse prior, median percentage.

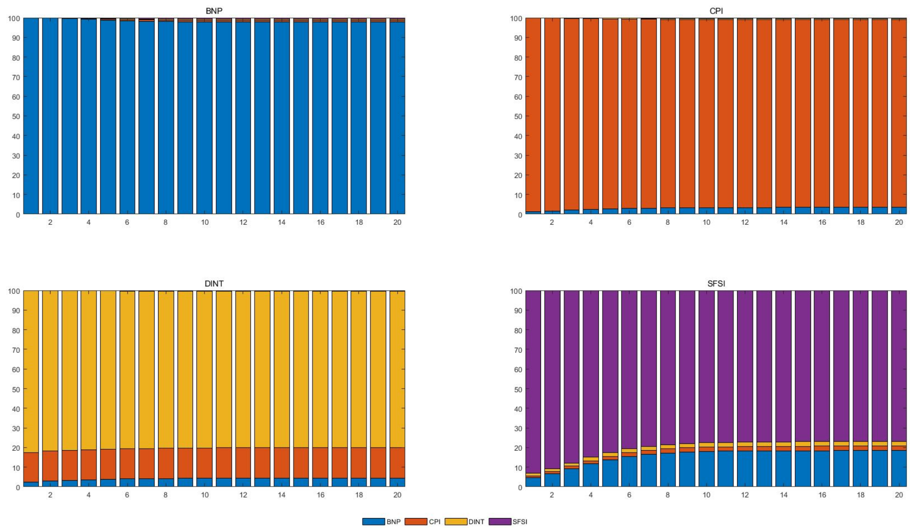

Figure 14: Forecast error variance $SFSI$ ordered last, measured as the median percentage.

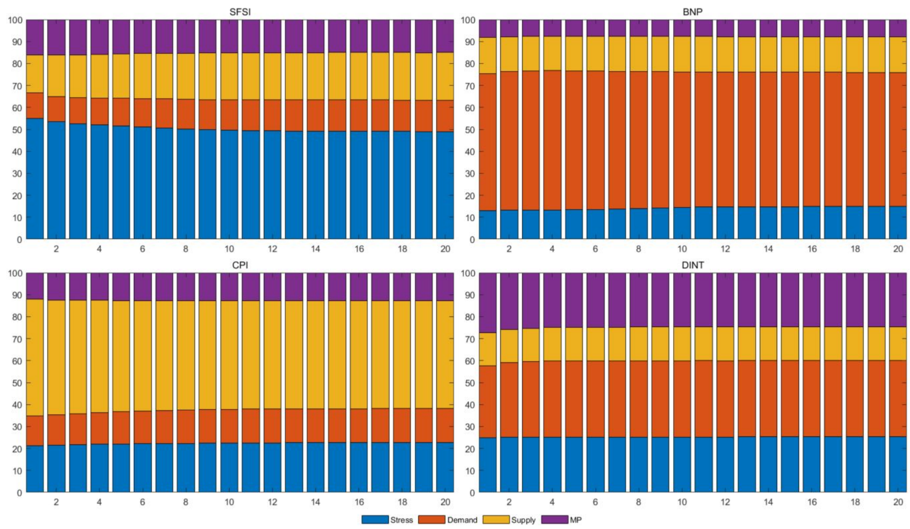

Figure 15: Forecast error variance from sign restrictions identification, measured as the median percentage.