Does the Size of the Government Consumption Multiplier for Finland Vary Over Time?

Elena Ahonen*

January 29, 2020

Abstract

This background paper provides new empirical evidence on the size of the Finnish fiscal policy multiplier for the period from 1975 to 2018. Using the tools of Bayesian time-varying parameters approach, I estimate a time-varying multiplier for government consumption for Finland. Based on the research results, it is not possible to conclude whether the government-consumption multiplier has varied over time or not.

1 Introduction

In this background report, I use a Bayesian time-varying paramaters vector autoregressive model (TVP VAR) to examine whether a government consumption multiplier for Finland has varied over the past 34 years. Despite being introduced more than a decade ago, no one has, to the best of my knowledge, used the TVP VAR model for estimating Finnish government consumption multiplier before. Given the scarce existing literature on government consumption multipliers for Finland, my estimation also provides new empirical evidence on the size of the Finnish government consumption

*This is a background paper based on my three month research internship from June 2019 to September 2019. The results of the study do not present the official views of the Economic Policy Council of Finland. I would like to thank my supervisor Seppo Orjasniemi for his patient guidance, advice and encouragement. I am also grateful for Allan Seuri, the Economic Policy Council, and Jani Luoto, at the University of Helsinki, for their helpful comments

multiplier.

There are several economic theories showing that the size of government spending multiplier can be dependent on a country's monetary system, trade openness and stage of the business cycle. For instance, Michaillant (2014) introduces a New Keynesian model in which the effect of the government policy varies over the business cycle. In his study, variation of the government-unemployment multiplier, a close relative of the government consumption multiplier, is not dependent on countercyclical financial frictions. Christiano, Eichenbaum and Rebelo (2011) argue that government spending multiplier can be large when the nominal interest rate is close to zero and does not respond to an increase in government sepending. The fiscal space theory model by Perotti (1999) suggests that the effect of government expenditure on private consumption differs between normal times and times when public debt or interest rates are high. Empirical evidence of government spending multipliers by Ilzeztki, Mendosa and Végh (2012) shows that the value of government spending multiplier is larger than one for countries operating under predetermined exchange rates. These empirical and theoretical research support the hypothesis of time-varying government consumption multiplier for Finland. Moreover, judging by empirical evidence of time-variation in fiscal policy multipliers for other countries, such as in the euro area, in the United States and in the United Kingdom, my hypothesis seems to be worth of investigating (Kirchner, Cimamodo and Hauptmeier 2010; Pereira and Lopes 2010; Glocker, Sestieri and Towbin 2019).

This paper is organised as follows. In the first section, I shortly discuss the earlier literature on fiscal multipliers for Finland and present the econometric methodology used in this paper. In the second section, I introduce my small model for the Finnish economy. The third section presents the results from the estimation. The fourth section concludes.

1.1 Literature Review

There has been very little research on the size of fiscal policy multiplier for Finland. Furthermore, the Bayesian approach is rarely used to study the size of those multipliers. I narrow the literature review on government spending multipliers because other fiscal multipliers, such as tax multipliers, are not estimated in this paper. More details on the variables used for the estimation can be found in section 2.1. In addition to aforementioned, I focus on literature that employ vector autoregression (VAR) models. The VAR model for econometric was first developed by Sims (1980). Since the 1980s, it has become the workhorse model in modern macroeconometric literature with a wide range of applications. In fiscal policy context, VAR models are used to describe how the economy is responding for a change in fiscal policy. (Auerback and Gorodnichenko 2012; Kilian 2017; Kuismanen and Kämppi 2012; Nakajima 2011; Sims 1980.)

Kuismanen and Kämppi (2010) have been the first to study effects of fiscal policy in Finland. In order to analyse whether fiscal policy decisions have real effects on Finnish economy, Kuismanen and Kämppi use two VAR based econometric approaches: structural vector autoregression (SVAR) and Vector Stochastic Process with Dummy Variables. Their results suggest that an increase in government spending has a negative effect on the GDP of Finland during a period from 1990 to 2007. Moreover, both of the models seem to suggest that an increase in government spending crowds out economic activity in the private sector.

A study by Lehmus (2014) estimates fiscal multipliers for Finnish economy for the time period from 1975 to 2011. In his study, Lehmus uses Blanchard and Perotti's (2002) SVAR approach. Lehmus's becnhmark model specification suggests that the fiscal multiplier for government spending reached its peak value of 1.30–1.56 for five quarters after a positive public spending shock. Afterwards, the multiplier decreases rapidly close to zero. (Lehmus 2014). Likewise, Virkola's (2014) research on the effects of fiscal policy suggests that a positive government spending shock has a positive effect on economic growth of Finland, although it is only around one percent. Similarly to Lehmus, Virkola uses modified Blanchard and Perotti's (2002) SVAR approach in his study. In addition, Virkola finds that public expectations, measured as government spending forecast errors, have no effect on the size of government spending multiplier. Conversely, Haavanlammi suggests in her study on *Kansantaloudellinen aikakauskirja – 4/2017* that a government spending increase as an expansionary fiscal policy action increases GDP by 0.5 times if private agents cannot anticipate the increase. The government spending multiplier is roughly negative for first few years if the increase is anticipated by the agents. (Haavanlammi 2017.)

More extensive research by Kuusi and Keränen (2016) observes that a fiscal multiplier for Finland is larger in recession than in expansion. In their study, Kuusi and Keränen use an augmented version of Auerbach and Gorodnichenko's (2012) nonlinear smooth transition vector autoregressive (STVAR) model to quantify time-varying fiscal multipliers for Finland. The regime–specific government spending and tax multipliers are estimated for the time period from 1972Q2 to 2015Q2. The results of the estimation suggest that the expectation augmented government spending multiplier can rise to two at the bottom of the economic cycle. In the contrast, the spending multiplier can be negative in economic expansion. (Keränen and Kuusi, 2016.) However, the time-variation of the government spending multiplier beyond business cycle dependence is beyond the scope of their study.

The studies presented thus mainly provide the evidence that there is no universal agreement on the size of fiscal multipliers for Finland. Some of the results suggested that the spending multiplier would be larger for Finland than for some other OECD countries (see, for example, Auerbach and Gorodnichenko 2012, and Batini, Eyraud, Forni and Weber 2014, for discussion). Furthermore, there seems to be some evidence indicating that the government spending multiplier is larger in economic recession than in economic expansion (e.g, Keränen and Kuusi 2016). Overall, these studies outlined a need for further research on government spending multipliers for Finland, especially on the size of government spending multipliers for the economy on different phases of economic cycle.

1.2 Econometric Methodology

The model used in this research paper is a multivariate time series model with stochastic volatility. After being introduced by Primiceri (2005), the model has become a broadly used model for estimating the effects of changes in monetary and fiscal policy regimes. Primiceri (2005) allowed stochastic volatility in the variance covariance matrix by assuming its parameters follow a random walk process. This means that the time variation in the model derives from coefficients and the law of motion of variance covariance matrix's innovations. On the contrary, Nakajima et al. (2011) assume all the model's parameters to follow a first order random walk process. This assumption allows the parameters to vary over time both temporarily and permanently. As mentioned by Nakajima et al. (2011), allowing stochastic volatility for all parameters helps to avoid misspeficiation that might be likely if possible variation of the volatility in disturbances is overlooked.[1] Thus, I follow closely Nakajima et al. (2011) in the specification of my model. For more detailed derivation of the model, see the appendix C.

Following Nakajima (2011) and Primiceri (2005), I describe the VAR model of time varying parameters and stochastic volatility as

$$y_t = c_t + B_{1,t}y_{t-1} + ... + B_{s,t}y_{t-s} + e_t, t = s+1, \dots, n. \tag{1}$$

where c_t is a $k \times 1$ vector of time varying coefficients, y_t is a $k \times 1$ vector of endogeneous variables and B_s, $k = 1 \dots, n$ are $n \times n$ matrices of time varying coefficients. I assume that $e_t \sim (0, \Omega)$, where Ω is a $n \times n$ time varying covariance matrix. Futhermore, I consider a simple recursive identification for the VAR system by assuming that

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t', \tag{2}$$

where A_t is the lower triangular matrix with diagonal elements equal to one,

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21,t} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \dots & a_{k,k-1} & 1 \end{bmatrix} \tag{3}$$

and Σ_t is the diagonal matrix

$$\Sigma = \begin{bmatrix} \sigma_{1,2} & 0 & \dots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_{n,t} \end{bmatrix}. \tag{4}$$

[1] A public consumption multiplier for Finnish economy was also estimated using Primiceri's (2005) original model. The estimation results suggested that the fiscal policy of the government has no effect on the economic activity of Finland. However, since there is high volatility in the Finnish data, Primiceri's model might have produced biased estimate of time-varying coefficients because it ignores a possible variation of the volatility in disturbances. Hence, allowing stochastic volatility in all parameters of the model is a sensible choice.

Hence, I can rewrite equation (2) as

$$\Omega_t = A_t^{-1}\Sigma_t\Sigma_t' A_t'^{-1}. \tag{5}$$

All the coefficients on the right hand side of the equation (1) are piled to a vector β_t. I assume that $X_t = I_t \otimes (y_{t-1}', \ldots, y_{t-s}')$, where $\otimes$ stands for Kronecker product. Thus, I can write

$$y_t = X_t'\beta_t + A_t^{-1}\Sigma_t\epsilon_t, t = s+1, ...n, \tag{6}$$

which is a TVP VAR model with stochastic volatility and the time varying parameters β_t, A_t and Σ_t. In addition, I define $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, a_{k,k-1})'$ as a vector of lower triangular elements of A_t and h_t as a vector of logσ_t^2, $h_t = (h_{t1}, \ldots, h_{kt})'$, with h_{jt} =logσ_{jt}^2 for $j = 1, \ldots, k$ and $t = s+1, \ldots, n$. In a similar vein to Nakajima et al. (2011), I assume that the parameters β_t, A_t and Σ_t follow the first order random walk process:

$$\begin{aligned} \beta_{t+1} &= \beta_t + u_{\beta_t}, \\ a_{t+1} &= a_t + u_{at}, \\ h_{t+1} &= h_t + u_{ht} \end{aligned} \tag{7}$$

$$\begin{bmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{bmatrix} \sim N \left[0, \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix} \right], \tag{8}$$

where $t = s+1, \ldots, n$. Also, I assume that initial states of parameters follow normal distribution as $\beta_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$, $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{h_0})$ and $h_{s+1} \sim N(\mu_{h0}, \Sigma_{h_0})$, where Σ_β, Σ_a and Σ_h are assumed to be diagonal matrices. Due to the hierarchical prior in the model's initial states, another prior distribution is assumed for these hyperparameters. I will discuss the choice of prior distributions in sections 1.3.2 and 2.2. The TVP regression forms a state space model, in which I regard a and h as state space variables. The assumption of the lower triangularity of the A_t matrix is a simple recursive identification of the VAR system.

Following Nakajima et al. (2011), the parameters of the model are assumed to follow the random walk process instead of the stationary process. To make the estimation accurate, the parameters of the model have to be decreased by assuming that the innovations of parameters follow random walk process. (Nakajima et al. 2011.) As the TVP VAR model is usually implemented by Bayesian inference, the number of model paramaters chosen to be small in nearly every research. Moreover, the number of autoregressive lags is set to be two by several researches. Undoubtedly, as Kilian and Lütkepohl (2017) mention, a large number of parameters and autoregressive lags causes high dimensionality in the posterior, which would make a Bayesian simulation for the model computationally impractical. As a consequence, a large number of autoregressive lags might lead to misspecification. The role of Bayesian inference in my TVP VAR model is discussed more detail in the next subsection.

1.3 Bayesian inference

1.3.1 MCMC algorithm

As Nakajima (2011) and Primiceri (2005) suggest, the Bayesian approach is more preferable for nonlinear state space models such as TVP VAR than the frequentist approach. In the TVP VAR model, Bayesian methods are used for generating independent samples from the posterior draws. As mentioned by Primiceri (2005), use of Bayesian methods provides more accurate and efficient estimation for models with unobservable components and nonlinearities[2]. Following Nakajima et al. (2011) and Primiceri (2005), I use a popular Bayesian simulation method, MCMC algorithm, for numerical evaluation of the posterior of the model parameters. As a consequence of nonlinearity in the model, the use of other methods such as the linear Gaussian state space method or the standard Kalman filter would be computationally too demanding. In general, MCMC algorithms approximate the exact posterior distribution of the parameters under certain prior probability densities that have been set in advance.

In accordance with the study of Nakajima et al. (2011), I use a joint sampling scheme for $\beta = \beta_{t\,t=s+1}^{\,n}, a = a_{t\,t=s+1}^{\,n}$ and $h = h_{t\,t=s+1}^{\,n}$, and the simulation smoother by Durbin and Koorpman (2002) to sample the time-varying coefficient β and a parameter a. As a result, the TVP VAR model can be written as a linear Gaussian state space form and the sampling of the time-varying

[2]More detailed information about the strengths of Bayesian inference concerning this model can be found in Primiceri (2005, p.7).

parameters becomes efficient. Similarly Nakajima et al. (2011), I evaluate the posterior distribution by using a multi-move sampler, which is developed for linear state space models by Shephard and Pitt (1997) and extended for nonlinear state space models by Watanabe and Omori (2004). (Greenberg 2012; Nakajima 2011; Shephard and Pitt 1998; Watanabe and Omori 2004).

Following the MCMC implementation by Nakajima et al. (2011)[3], I define data as y and let $y = \{y_t\}$ and $\omega = (\Sigma_\beta, \Sigma_a, \Sigma_h)$ and set the prior probability density as $\pi(\omega)$ for ω. A sample from the posterior distribution $\pi(\beta, a, h, \omega|y)$ can be generated following Nakajima et al. (2011):

1. Initialise β, a, h, ω
2. Sample $\beta|a, h, \Sigma_\beta, y$
3. Sample $\Sigma_\beta|\beta$
4. Sample $a|\beta, h, \Sigma_a, y$
5. Sample $\Sigma_a|a$
6. Sample $h|\beta, a, \Sigma_h, y$
7. Sample $_h|h$
8. Go to step 2.

Similarly to Nakajima et al. (2011), the steps from 2 to 8 are looped to generate M = 20 000 sample draws.

1.3.2 Priors

In the Bayesian approach, the posterior distribution is computed from the likelihood function and the prior probability density that is set by a researcher beforehand. Hence, a specification of prior distribution is necessary and an important part of the estimation process. Priors should be chosen carefully to avoid implausible behaviour of the flexible TVP VAR model. As Koop and Korobilis

[3]Details of the multi-move sampler can be found in Nakajima et al. (2011, p. 240–243).

(2010) demonstrate, the choice of prior distribution might have an effect on the estimation results from the model. The prior distribution and hyperparameters can be either specified by utilising all information from previous empirical research and theoretical applications about the subject, or be specified by selecting a portion of the observations as a training sample. Next, the training sample is combined with a relatively uninformative prior to evaluate a posterior distribution, which becomes the prior for actual estimation. (Greenberg 2011; Koop and Koroblis 2010.) Following Nakajima et al. (2011) and Primiceri (2005), I select first ten years from my time series as a training sample to evaluate a prior distribution for the initial states of parameters.[4] The distribution is chosen based on the OLS estimators from a time invariant VAR.

I assume that my model is hierarchical and place another prior distribution for Σ_β in $\beta_{s+1} \sim N(\mu_{a_0}$,for $\Sigma_{a_0})$, for Σ_a in $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{h_0})$ and $h_{s+1} \sim N(\mu_{h0}, \Sigma_{h_0})$. The choice to use a hierarchical prior reflects my uncertainty about the size of the VAR coefficients between the training sample and the actual sample. A distribution confined to positive values such as Inverse-Gamma distribution could suit to the situation since $0 < \Sigma_\beta, \Sigma_a, \Sigma_h < \infty$. (Greenberg 2010; Kirchner, Cimado and Hauptmeier 2010.) The Inverse-Gamma distribution is often used to specify noninformative priors for variance parameters. Since in the Inverse-Gamma distribution the continuous parameters are constrained to be non-negative, it is a plausible choice for my model's hierarchical prior distribution. Also, given the fact that I place the prior distribution for parameters in one dimensional paramater space, the univariate Inverse-Gamma distribution is a natural choice. In recent TVP VAR literature, the hierarchical Inverse-Gamma prior distribution is also placed for the diagonal elements of covariance matrices by, for instance, Bauemaister and Benati (2010) and Kirchner Cimado and Hauptmeier(2010). Furthermore, the Inverse-Gamma distribution is a conjugate prior for the variance of normal distribution, which means that the posterior distribution is in the same family of distributions as the prior. I will discuss about prior distributions, hyperparameters, the calibration process and the robust checks in the section 2.2.

[4] The estimation is also performed for the whole sample from 1975:Q2 to 2018:Q4. In addition, a training sample of five years is being tested. The results suggest that length of the estimation period has a small effect on the size of the government consumption multiplier and the estimation results of the parameters.

2 The TVP VAR model for Finnish economy

In this section I present the TVP VAR model for Finnish economy. In contrast to earlier literature on TVP VAR models with stochastic volatility[5], there are four variables in the model instead of three variables. The model variables are in the following order: inflation p, the real government consumption G, the real private consumption C and the real gross domestic product x. Thus, the TVP VAR model for the Finnish economy can be written as $y_t = (p_t, G_t, C_t, x_t)'$. I assume that the recursive identification of the model is in the same order. The structural interpretation of the model will be discussed in the section 2.2. To avoid misspeficiation of the model, I keep the model relatively small by setting the number of autoregressive lags as two. As Primiceri (2005) mentions, a large number of variables in the model requires tighter priors to avoid bad behaviour of the model. Consequently, I choose a tighter prior for β_t and test the sensitivity of priors with a few robustness checks.

2.1 Data

The data used in this estimation is a quarterly and seasonally adjusted Finnish data for the time period from 1975Q1 to 2018Q4. The data was kindly provided by the Statistics of Finland. Real government consumption, real private consumption and GDP series are divided by the total population of Finland. Subsequently, the series are logaritmised and first order differenced similarly to Nakajima et al. (2011). Finally, the series are multiplied by 100. The inflation series are constructed by taking an annual differential from the GDP deflator, which is calculated by subtracting the real value GDP from the nominal value GDP and multiplying the result with 100.

The model variables are selected on the basis of both Bayesian information criterion and Akaike information criterion, which provide a mean for statistical model selection from a set of data. The procedure is carried out by constructing eight time-invariant VAR models with different set of variables and two autoregressive lags. The model with the smallest BIC and AIC test results is selected. The test results indicate that a four-variable VAR model with inflation, real government consumption, real private consumption and real output has better quality than other models tested,

[5]see for example Cogley and Sargent (2005), Primiceri (2005), Nakajima et al.(2011)

e.g. a four variable VAR model with inflation, real government consumption, net taxes and real output. As a result, the set of variables used in this paper is different from the earlier literature of Finnish fiscal multipliers (see for instance Keränen and Kuusi 2016; Kuismanen and Kämppi 2010 and Lehmus 2014). The time series of the variables are illustrated in Figure 7 in the Appendix B.

2.2 Prior distributions and hyperparameters

I assume that the initial states of paramaters in the model follow the Normal distribution. My assumption is consistent with earlier TVP VAR literature[6]. I verify the assumption by using the Ordinary Least Squares (OLS) estimators that are computed for a time invariant VAR estimated from the training sample. The training sample covers first ten years of the data set (40 observations from 1975:Q1 to 1984:Q4). The assumption of initial state of paramaters following normal distribution is also plausible from the theoretical point of view. As Nakajima et al. (2011) argue, the first order random walk process for all the model parameters requires the normal distributed prior for the initial state of each time varying parameter. Given the aforementioned, I assume that

$$\begin{aligned} \beta_{s+1} &\sim N\big(\mu_{\beta_0}, 3 \times \Sigma_\beta\big) \\ a_{s+1} &\sim N\big(\mu_{a_0}, 10 \times \Sigma_a\big) \\ h_{s+1} &\sim N\big(\mu_{h_0}, 10 \times \Sigma_h\big) \end{aligned} \tag{9}$$

where μ_{β_0}, μ_{a_0} and μ_{h_0} are the OLS estimators for the VAR coefficients β_0, and for vectors of paramaters a_0 and h_0. My choice for degrees of freedom for a_{s+1} and h_{s+1} is arbitrary. However, the same number of degrees for freedom is also assumed for a_0 and h_0 by Kirchner et al. (2010) who examined effects government spending shocks in euro area using a TVP-VAR model. As mentioned by Primiceri (2005) and Nakajima et al. (2011), a tighter prior for the covariance matrix is required as the consequence of time variation in all of the model parameters. Despite the fact that some researchers have claimed this choice to be arbitrary, I follow Primiceri (2005) and Nakajima et al. (2011) and set a tighter prior for β and more informative prior for a_0 and h_0.

[6]For instance, this assumption was made by Bauemaister and Benati (2010), Benati and Mumtaz (2007), Nakajima et al. (2011), Primiceri (2005), Kirchner et al. (2010) and Pereira and Lopes (2010).

As Gelman (2006) mentions, in the hierarchical model, hyperparamaters must be given their own prior distributions. The hyperparameters for the inverse gamma distribution as a prior distribution in hierarchical model can be specified by utilising information from earlier research. Following Cogley, Primieri and Sargent (2010); Baumeister and Benati (2010) and Kirchner et al. (2010), I choose to define the hyperparameters for inverse gamma distribution as follows:

$$\begin{aligned} (\Sigma_\beta)_i^{-2} &\sim Gamma(10, 0.01) \\ (\Sigma_a)_i^{-2} &\sim Gamma(10, 0.01) \\ (\Sigma_h)_i^{-2} &\sim Gamma(10, 0.01) \end{aligned} \tag{10}$$

My choice for scale paramaters $k_\beta, k_a, k_h = 0.01$ is consistent with recent literature. Cogley and Sargent (2001), Primiceri (2005) and Baumeister and Benati (2010) specified their scale paramaters equivalently. Following Baumeister and Benati (2010), I set degrees of freedom for each hyperparameter to 10. Utilising information from researchers that have applied the TVP VAR model for the monetary or fiscal policy of the United States or of the euro area can be criticised as being a naive approach for choosing priors. Hence, I have specified rather uninformative scale parameters to reflect my uncertainty about these values. Nevertheless, due to a lack of earlier research using the TVP VAR models for estimating effectiveness of Finnish fiscal policy, it is inevitable to utilise information from studies concerning other countries.

2.3 Fiscal policy and structural interpretation

In this report, the time-varying government consumption multiplier for Finland is estimated for the sample period in which Finland experienced different phases of business cycle. In the 1980s, Finland experienced a strong economic boom. For this reason one of the identified government consumption shocks is computed for 1986:Q1 to compute the size of the government consumption multiplier for that period. In the early 1990s, the Finnish economy suffered from one of the worst economic recessions in its history. The depression started in 1991 and thus, one of the identified government consumption shocks is computed for 1991:Q1 to estimate the size of the government-consumption multiplier during the depression. The third identified government consumption shock is computed for 2007:Q1, which was also the beginning of the Financial crises. The fourth identified government consumption shock is computed for 2017:Q1 to estimate the size of the government consumption multiplier in the most recent economic expansion.

I investigate the impact of government consumption shocks on real output, private consumption and inflation. Following Nakajima (2011), I assume that contemporaneous interactions between the model variables are recursively identified for simplicity. Thus, no additional identifying restrictions on the matrix B_0 is needed since the recursive identification is sufficient to identify dynamic responses of y_t to government consumption shocks (Christiano, Eichenbaum and Evans 1999).[7] The recursive ordering is a commonly used identification strategy in the previous TVP VAR literature. It is especially assumed by Primiceri (2005) and Cogley and Sargent (2001) in their investigation on the effects of monetary policy. In addition, Kichner et al. (2010) use the approach to estimate time-variation of fiscal policy in the Euro area. The most prominent pitfall of this identification strategy is that the ordering of the variables in the covariance matrix influences the result.

Similarly to Nakajima et al. (2011), I assume that the shocks to the innovations of the time-varying parameters are uncorrelated amongst a_t, β_t and h_t. Since having the ordering of the variables is as aforementioned, I define the innovation in the second equation of the VAR as a structural government consumption shock. Consequently, all variables apart from inflation are allowed to react to the government consumption shock after a quarter. The real government consumption responds to a shock in inflation within a quarter and to shocks in other variables after a quarter. In recursive identification an error term in each regression is assumed to be uncorrelated with the error in preceding equation. If the contemporaneous effect of government consumption shock on inflation was not equal to zero, this assumption would be violated. Thus, the identification strategy would yield inconsistent estimates of the model parameters.

Another possible approach for the estimation would be a nonrecursive identification strategy, for example a procedure introduced by Blanchard and Perotti (2002). In the TVP VAR literature, this

[7] As Kilian and Lütkepohl (2017, p. 215) point out, the SVAR model must have $K(K-1)/2$ restrictions to be identified. Being recursively identified, my model has 6 restrictions which is a sufficient amount for the model to be exactly identified.

identification strategy is used by Pereira and Lopes (2010) in their investigation of time-variation of fiscal policy in the United States. Moreover, the identification strategy is widely used in other macroeconometric literature. In their approach, Blanchard and Perotti use a trivariate AB-model with real taxes per capita, government spending and output. They impose a restriction that the government spending does not respond contemporaneously to prices and output. Variances of shocks are left unrestricted. In the model, government spending follows Cholesky identification being ordered as second. However, the identification strategy by Blanchard and Perotti requires prior information on taxes, transfer and spending programs to construct parameters a_1 and b_1. These elasticities ought to be most preferably determined outside the dataset. Moreover, if the identification scheme by Blanchard and Perotti (2002) was used for estimating time-variation of the Finnish government consumption multiplier, it would require that the tax variable is added in the model. Since the recursive identification strategy is more popular in the recent TVP VAR literature than non-recursive identification strategies, I will use it for my estimation.

2.4 Sensitivity to priors and model robustness checks

In Bayesian statistics, posterior probabilities of models are compared to each other to examine which of the several models is better to supported by the prior beliefs and the observed data (Greenberg 2010). However, I already compare invariant VAR models with AIC and BIC to see which model fits the data best. Therefore, I investigate the model's sensitivity to priors using other estimators. Following Nakajima et al. (2011), the inefficiency factor and the Convergence Diagnosis by Geweke (1999) are used to check plausibility of the posterior inference for the given priors. The estimators are designed to quantify if each parameter has efficiently convergenced by the MCMC iteration. (Nakajima et al. 2011.) The derivation of the estimators can be found in the appendix C.

The model's sensitivity to priors is tested by placing different sets of scale parameters and degrees of freedom (0.01/2,1/2), (1/2,1/2) and (0.001/2, 0.001/2) for the Inverse-Gamma distribution. The model seems to convergence efficiently under each set. Nevertheless, the results from the impulse response analysis and estimation of a cumulative government consumption multiplier are observed to be unrobust to alternative priors. The results from prior comparison based on the inefficiency factor are illustrated in Table 2 in the appendix A. In addition, the government consumption multiplier estimated with the TVP VAR model is compared to the government consumption multiplier estimated with a time-invariant VAR model as a robustness check.

3 Results

3.1 Impulse Responses Analysis

Figure 1 illustrates how the variables respond to unexpected shocks in 1981:Q1, 1991:Q1, 2007:Q1 and 2017:Q1. In accordance with Nakajima (2011), the impulse responses are computed at each quarter based on the average size of the stochastic volatility across the entire sample periods. Furthermore, the posterior mean of time-varying parameters is used for computing the time-varying impulse responses (Nakajima 2011). The results suggest that a positive government consumption shock affects output positively in the first two periods, the output effect reaching its peak of around 0.2. On the third period, the output falls down reaching a value of -0.1, and then increases again to 0.1 on the forth period after the shock. An effect of the government consumption shock to output seems to be vanishing after four quarters for all time periods estimated. Based on Figure 1, there seems to be very little time variation in the response of the output.

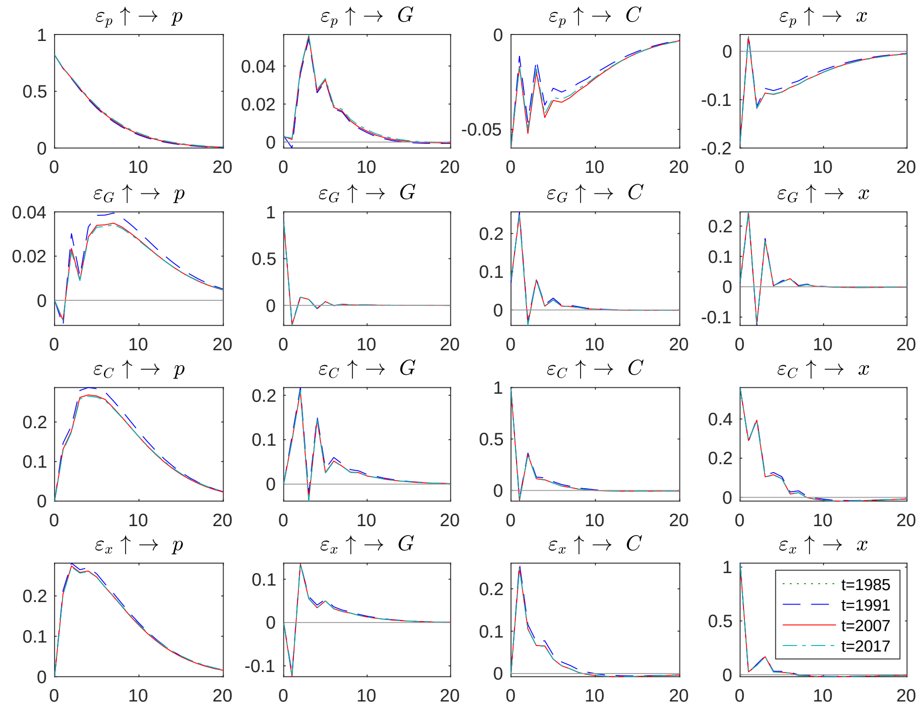

Figure 1: Impulse response of the variables

Similarly to output, private consumption responds positively to a government consumption shock after one period, falling shortly negative on the second period and increasing again on the third period after the shock. The results indicate that there is a correlation between a positive shock in government consumption and an increase in private consumption within a year of the shock. Furthermore, the response of inflation to a government consumption shock is positive after one period of lag. There is very little time variation in the responses of inflation. However, it seems to be slightly difficult to identify time variation of impulse responses based on Figure 1. It is possible that taking log differences has thrown away a lot information. In the following subsection, I investigate the hypothesis of time-variation in the government consumption multiplier more closely.

3.2 Time-variation of the Finnish Government consumption Multiplier

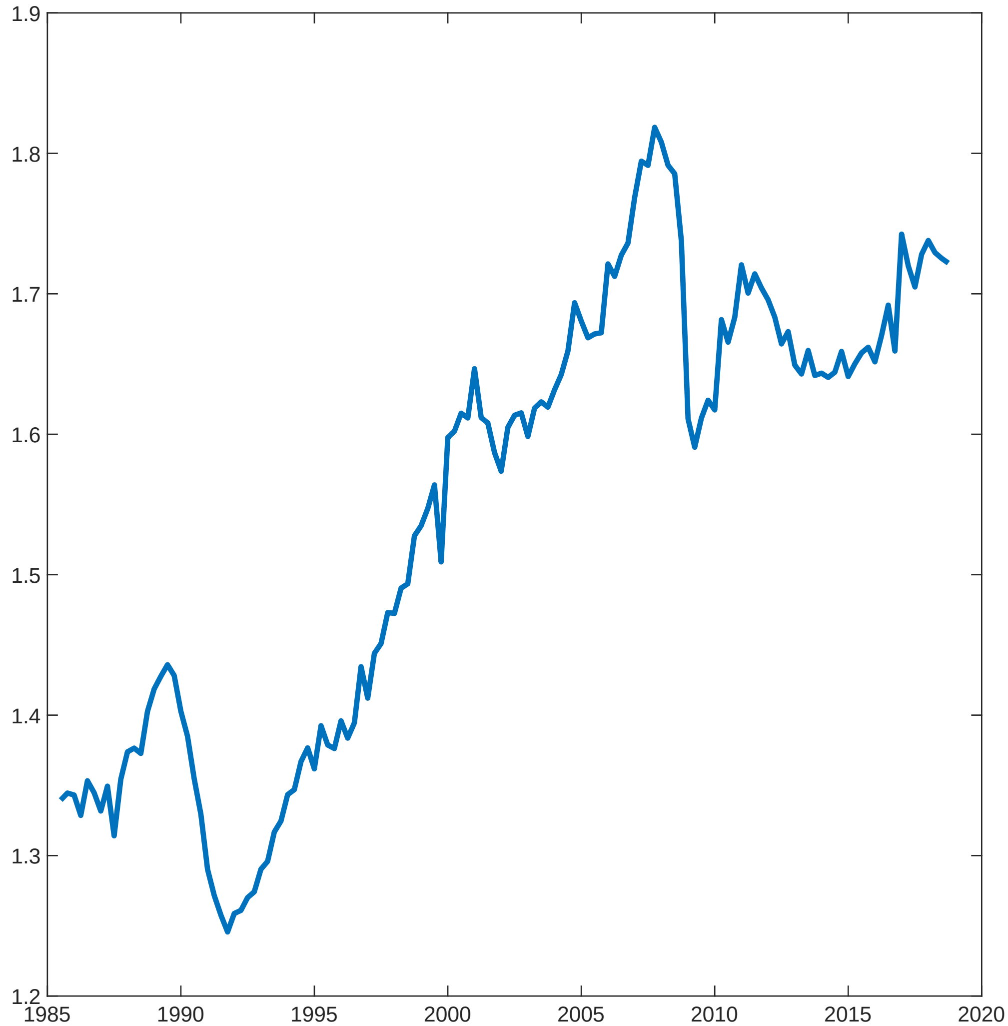

Figure 2: Time-variation of the cumulative Finnish government consumption multiplier

The time variation of the government-consumption multiplier is illustrated in the Figure 2. To report the time-varying government-consumption multiplier, I computed the cumulative response of output to government consumption in a similar vein to Glocker, Sestieri and Towbin (2019). The cumulative consumption multiplier is defined as the cumulative response of output in response to a cumulative increase in government consumption. The initial increase of the government consumption amounts to one percent of GDP. The cumulative responses are computed for a two-year time horizon. However, as mentioned by Glocker et. al. (2019), the results are observed to be robust to alternative time periods. The technical interpretation of the cumulative public consumption multiplier can be found in the appendix C.

Figure 2. shows that the cumulative government-consumption multiplier has varied over time even though there is very little variation in the impulse responses. Since the impulse responses are computed for each quarter based on the average size of the stochastic volatility across the sample period, the time variation of the responses is very modest. On the contrary, the government-consumption multiplier is a cumulative sum of the stochastic volatility of the responses for each quarter, which causes the time variation in Figure 2. The results indicate that the government consumption multiplier varied between 1.2 and 1.5 from 1985 to 1999. It seems that the government consumption multiplier decreased to its lowest value in 1992 and then it started to increase until reaching its peak value of 1.85 in 2008. Interestingly, the multiplier started to shrink after 2008 until 2010 when it started to gradually increase again. In conclusion, the results suggest that the government-consumption multiplier has been fluctuated between 1.2 and 1.5 in 1985–1999 and between 1.5 and 1.85 in 2000–2018.

4 Conclusions

Based on the results from my model, one cannot conclude whether the government consumption multiplier for Finland has varied over time or not. The impulse responses suggest that there has not been any time variation on the effect of the government consumption shock to output. Conversely, my findings suggest that the government consumption multiplier has fluctuated over time between 1.2 and 1.85. It might be that taking log differences has thrown away a lot information from the data. Despite the complexity of the model, it does not provide any clear explanation for the increase of the cumulative Finnish government consumption multiplier. For more credible result the confidence interval bands are needed to present for the impulse responses.

For further research, I suggest two ways to enhance the model. First, an alternative structural identification strategy could be chosen to capture all movements in the A_0 matrix instead of the recursive identification. Second, the scale paramaters and degrees of freedom for the Inverse-Gamma distribution in the hierarchical prior could be estimated using a more complicated method such as the delta-method. This might yield more accurate estimation for the Finnish data.

References

Auerbach, A. and Gorodnichenko, Y. (2012). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, 4:1–27. http://dx.doi.org/10.1257/pol.4.2.1.

Batini, N., Eyraud, L., Forni, L., and Weber, A. (2014). Fiscal multipliers; size, determinants, and use in macroeconomic projections. *IMF Technical Notes and Manuals. International Monetary Fund.*, 4. http://www.imf.org/external/pubs/cat/longres.aspx?sk=41784.

Baumeister, C. and Benati, L. (2010). Unconventional monetary policy and the great recession estimating the impact of a compression in the yield spread at the zero lower bound. *Working Paper Series. European Central Bank.*, 1258. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1258.pdf.

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (2010). Chapter 2. monetary policy shocks: What have we learned and to what end? *Handbook of Macroeconomics*, 3:285–367. https://doi.org/10.1016/B978-0-444-53238-1.00007-7.

Cogley, T., Primiceri, G. E., and Sargent, T. J. (2005). Inflation-gap persistence in the us. *Review of Economic Dynamics*, Vol. 8. Issue 2:262–302. https://doi.org/10.1016/j.red.2004.10.009.

Cogley, T. and Sargent, T. J. (2010). Drifts and volatilities: monetary policies and outcomes in the post wwii us. *American Economic Journal: Macroeconomicss*, Vol. 2. No. 1:43–69. https://www.jstor.org/stable/25760284.

Durbin, J. and Koopman, S. (2002). A simple and efficient simulation smoother for state space time series analysis. *Biometrika*, Volume 89. Issue 3:603—-616. https://doi.org/10.1093/biomet/89.3.603.

Galí, J., Vall's, J., and López-Salido, J. D. (2007). Understanding the effects of government spending on consumption. *Journal of the European Economic Association*, 5:227—-270. https://doi.org/10.1162/JEEA.2007.5.1.227.

Gelman, A. (2006). Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis*, 3:515—-533. https://projecteuclid.org/euclid.ba/1340371048.

Geweke, J. (1999). Using simulation methods for bayesian econometric models: inference, development,and communication. *Econometric Reviews*, 18. Issue 1:1–73. https://doi.org/10.1080/07474939908800428.

Glocker, C., Sestieri, G., and Towbin, P. (2019). Time-varying government spending multipliers in the uk. *Journal of Macroeconomics*, 60:180–197. https://doi.org/10.1016/j.jmacro.2019.02.003.

Greenberg, E. *Introduction to Bayesian Econometrics.* Cambridge University Press. 2nd edition. 271 pages. ISBN-13: 978-1107015319.

Haavanlammi, K. (2017). Julkisten menojen ennakointi ja finanssipolitiikan vaikutusten arviointi. *Kansantaloudellinen aikakauskirja*, 4:557–571. https://www.taloustieteellinenyhdistys.fi/wp-content/uploads/2017/12/LOW3$_3$0616645_KAK_sisus_4_2017_176x245 $-$ 1 $-$ 101 $-$ 115.pdf.

Ilzeztki, E., Mendoza, E. G., and Végh, C. A. (2016). How big (small?) are fiscal multipliers? *Journal of monetary Economics*, 60:239–254. https://doi.org/10.1016/j.jmoneco.2012.10.011.

Keränen, H. and Kuusi, T. (2016). The eu's fiscal targets and their economic impact in finland. *Etla Working Papers*, 33. http://pub.etla.fi/ETLA-Working-Papers-33.pdf.

Kilian, L. and Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis.* Cambridge University Press. https://sites.google.com/site/lkilian2019/textbook/preliminary-chapters.

Kirchner, M. J. C. and Hauptmeier, S. (2010). Transmission of government spending shocks in the euro area – time variation and driving forces. *Working paper series. European Central Bank.*, 1219. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1219.pdf.

Koop, G. and Korobolis, D. (2010). Bayesian multivariate time series methods for empirical macroeconomics. *Foundations and Trends in Econometrics*, 3. Issue 4:267–358. http://dx.doi.org/10.1561/0800000013.

Kuismanen, M. and Kämppi, V. (2010). The effects of fiscal policy on economic activity in finland. *Economic Modelling*, 27. Issue 5:1315–1323. https://doi.org/10.1016/j.econmod.2010.01.010.

Lawrence, C., Eichenbaum, M., and Rebelo, S. (2011). When is the government spending multiplier large? *Journal of Political Economy.*, 119. No 1.:78–121. https://www.journals.uchicago.edu/doi/abs/10.1086/659312.

Lehmus, M. (2014). Finnish fiscal multipliers with a structural var model. *Working Papers. Labour Institute for Economic Research*, 296. http://www.labour.fi/english/publications/working-papers/working-papers-293/.

Michaillat, P. (2014). A theory of countercyclical government multiplier. *American Economic Journal: Macroeconomics*, 6:190–2017. https://www.aeaweb.org/articles?id=10.1257/mac.6.1.190.

Nakajima, J. (2011). Time-varying parameter var model with stochastic volatility: An overview of methodology and empirical applications. *IMES Discussion Paper Series. Institute for Monetary and Economic Studies, Bank of Japan.*, 11–E–09. http://www.imes.boj.or.jp/research/papers/english/11-E-09.pdf.

Nakajima, J., Kasuya, M., and Watanabe, T. (2011). Bayesian analysis of time-varying parameter vector autoregressive model for the japanese economy and monetary policy. *Journal of the Japanese and International Economies*, Volume 25. Issue 3. https://doi.org/10.1016/j.jjie.2011.07.004.

Pereira, M. C. and Lopes, A. S. (2010). Time-varying fiscal policy in the u.s. *Bank of Portugal Working papers*, 21. https://www.bportugal.pt/sites/default/files/anexos/papers/wp201021.pdf.

Perotti, R. (1999). Fiscal policy in good times and bad. *The Quarterly Journal of Economics*, 114. No. 4:1399—-1436. https://doi.org/10.1162/003355399556304.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, 72. No. 3:821–852. https://www.jstor.org/stable/3700675.

Shephard, N. and Pitt, M. K. (1997). Likelihood analysis of non-gaussian measurement time series. *Biometrika*, Volume 84. Issue 3:653–667. https://doi.org/10.1093/biomet/84.3.653.

Sims, C. A. (2005). Macroeconomics and reality. *Econometrica*, 48. No. 1:1–48. https://www.jstor.org/stable/1912017.

Virkola, T. (2014). Exchange rate regime, fiscal foresight and the effectiveness of fiscal policy in a small open economy. *Etla Raportit*, 20. https://www.etla.fi/wp-content/uploads/ETLA-Raportit-Reports-20.pdf.

Watanabe, T. and Omori, Y. (2004). A multi-move sampler for estimating non-gaussian time series models: Comments on shephard pitt (1997). *Biometrika*, Volume 91. Issue 1:246—248. https://doi.org/10.1093/biomet/91.1.246.

Appendices

A Estimation results for the model paramaters

The MCMC iteration is computed for M = 20000 draws after the initial 1000 draws is being discarded. The posterior means, standard deviations, the 95 percent credible interval, the Convergence diagnostics factor by Geweke (1999) and the inefficiency factor for each parameter of the model are reported in the table 1. Convergence diagnosis for each parameter is plausible apart from Σ_{h_2}. However, the inefficiency criterion is very low, less than 100 for each paramater, which indicates that sampling for the parameters is efficient. Nonetheless, the posterior means, standard deviations and the 95 percent credible interval seem to be really tight.

Parameter	Mean	St.dev	95 % U	95 % L	CD	In.ef
Σ_{β_1}	0.0034	0.0009	0.0022	0.0054	0.537	39.89
Σ_{β_2}	0.0034	0.0009	0.0022	0.0056	0.631	28.62
Σ_{a_1}	0.0035	0.0009	0.0022	0.0057	0.933	33.45
Σ_{a_2}	0.0035	0.0010	0.0022	0.0058	0.159	42.06
Σ_{h_1}	0.0035	0.0009	0.0023	0.0059	0.013	37.89
Σ_{h_2}	0.0034	0.0009	0.0022	0.0055	0.593	27.86

Table 1: Estimation Result for Each Parameter in the Model

Sample autocorrelation, the sample paths and posterior densities of the benchmark model variables are illustrated in the Figure 3. Sample paths in the middle of the picture seem to stable and the posterior densities at the bottom of the picture are decreasing rapidly, which indicates that the samples drawn by the MCMC sampling are uncorrelated.

Posterior means and one-standard deviation bands for $\sigma_{it}^2 = exp(h_{it})$, a_t and for the free elements of A_t^{-1} illustrated in Figure 4, Figure 5 and Figure 6, respectively.

The inefficiency factors computed for different sets of prior distributions are shown in Table 2.

The inefficiency factor shows the number of uncorrelated samples in the MCMC iteration. According to Nakajima et. al. (2011), the inefficiency factor less than 100 is considered to be good. Even though the size of the inefficiency factor differs from each M = 20 000 computed, it suggests if the posterior inference is plausible for given priors.

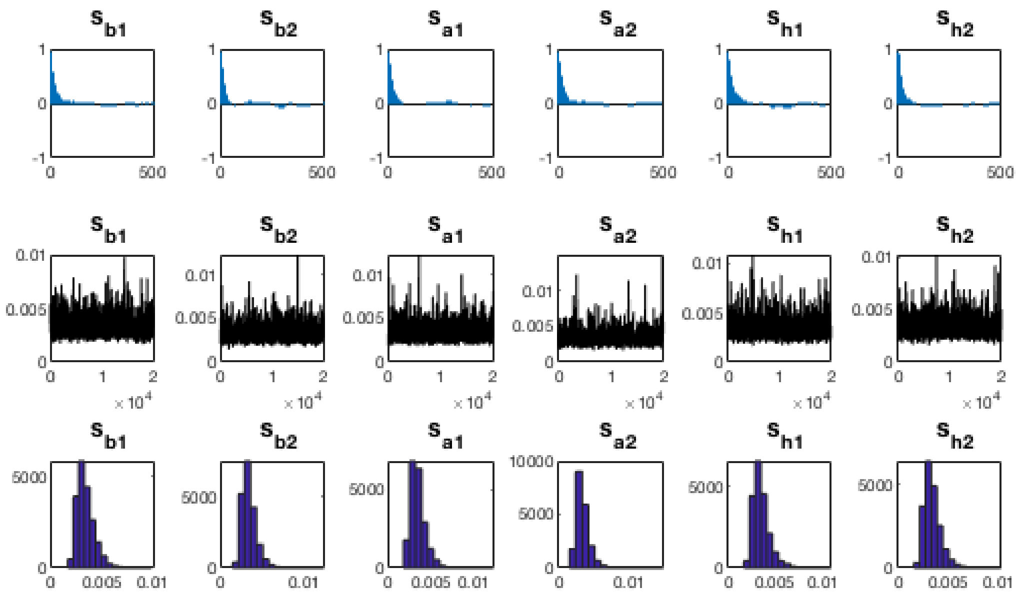

Figure 3: Sample autocorrelation (top), the sample paths (middle) and the posterior densities (bottom)

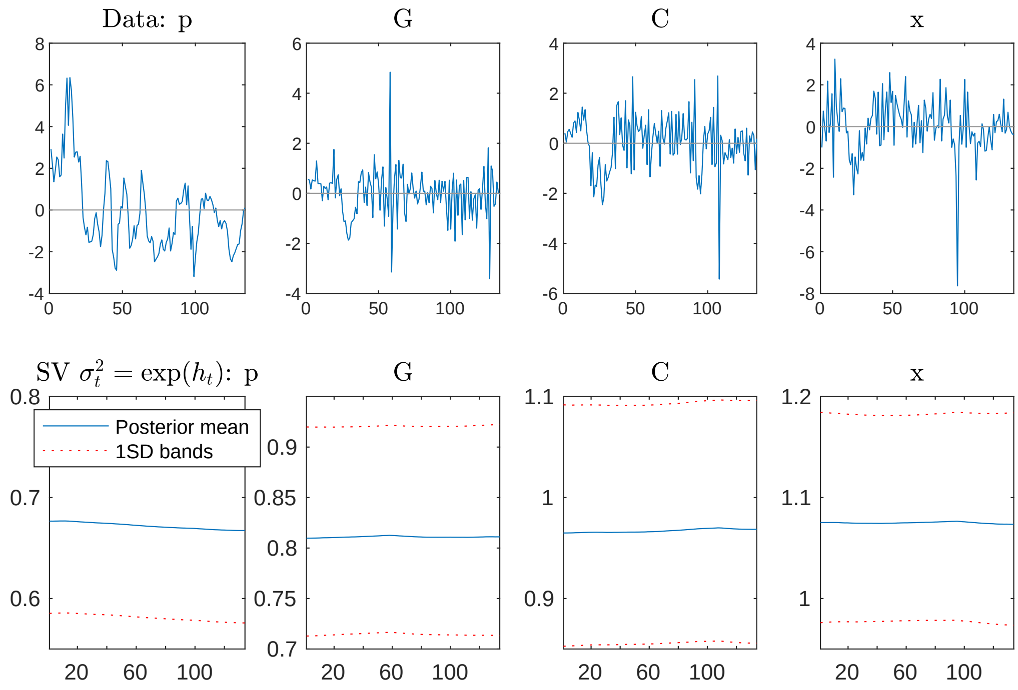

Figure 4: Posterior mean and one-standard deviation bands for $\sigma_{it}^2 = exp(h_{it})$

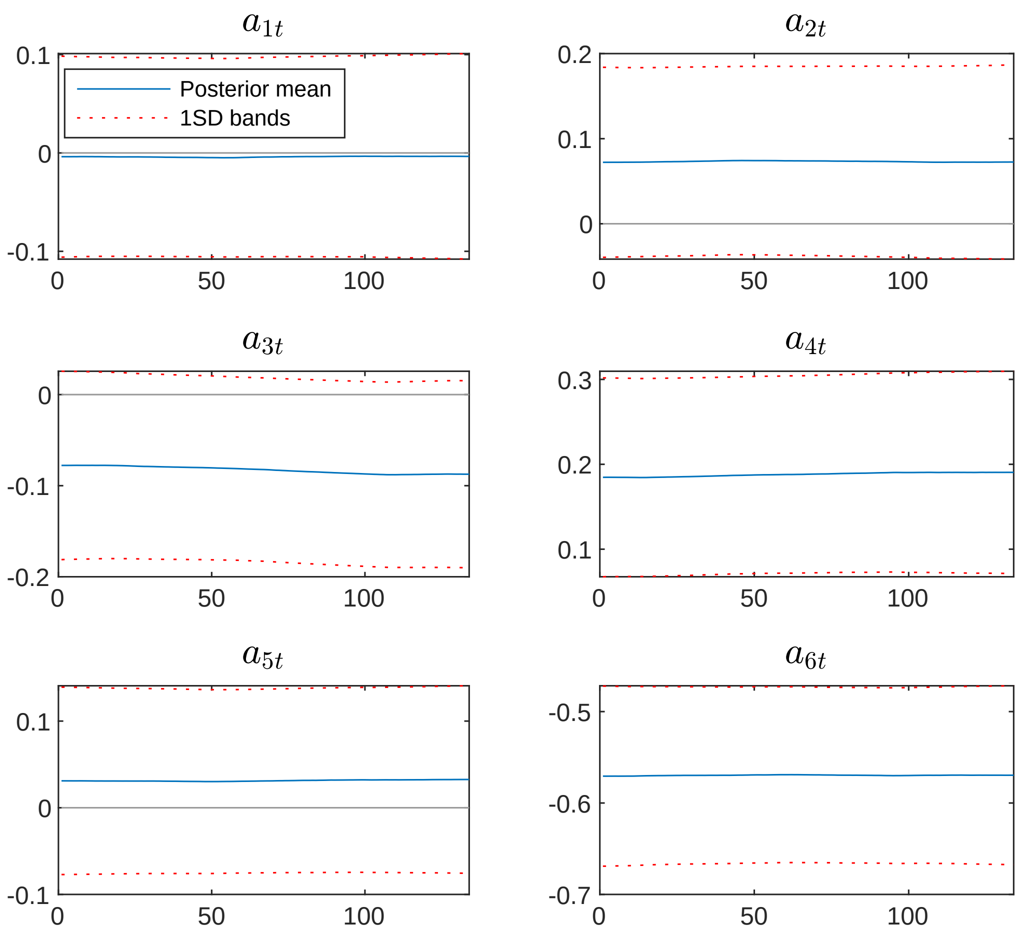

Figure 5: Posterior mean and one-standard deviation bands for a_t

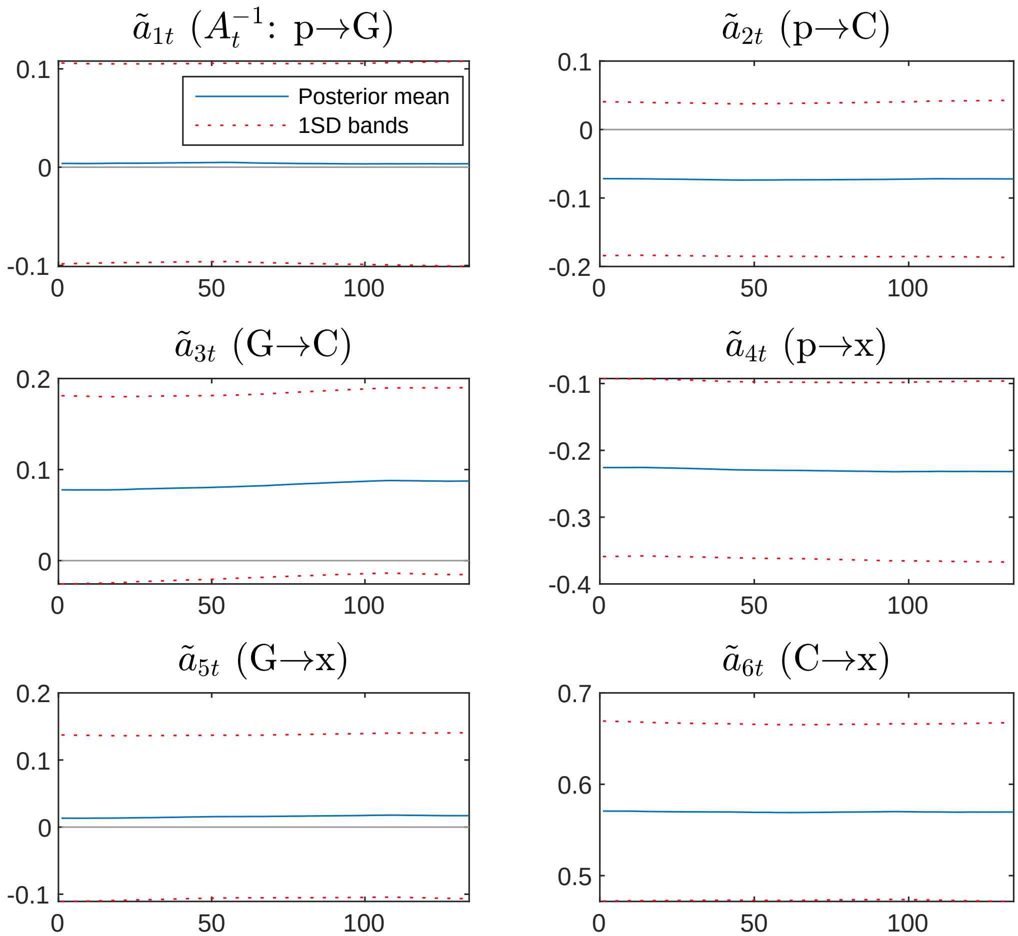

Figure 6: Posterior mean and one-standard deviation bands for A_t^{-1}

Parameter	$\mathrm{IG}(0.01/1, 10/2)$	$\mathrm{IG}(0.01/2, 1/2)$	$\mathrm{IG}(1/2, 1/2)$	$\mathrm{IG}(0.001/2, 0.001/2)$
Σ_{β_1}	39.89	1.45	1.80	32.14
Σ_{β_2}	28.62	1.02	1.44	32.08
Σ_{a_1}	33.45	36.01	29.11	43.83
Σ_{a_2}	42.06	30.81	41.37	42.12
Σ_{h_1}	37.89	56.86	36.48	32.70
Σ_{h_2}	27.86	35.62	35.80	30.11

Table 2: The inefficiency factors

B Data

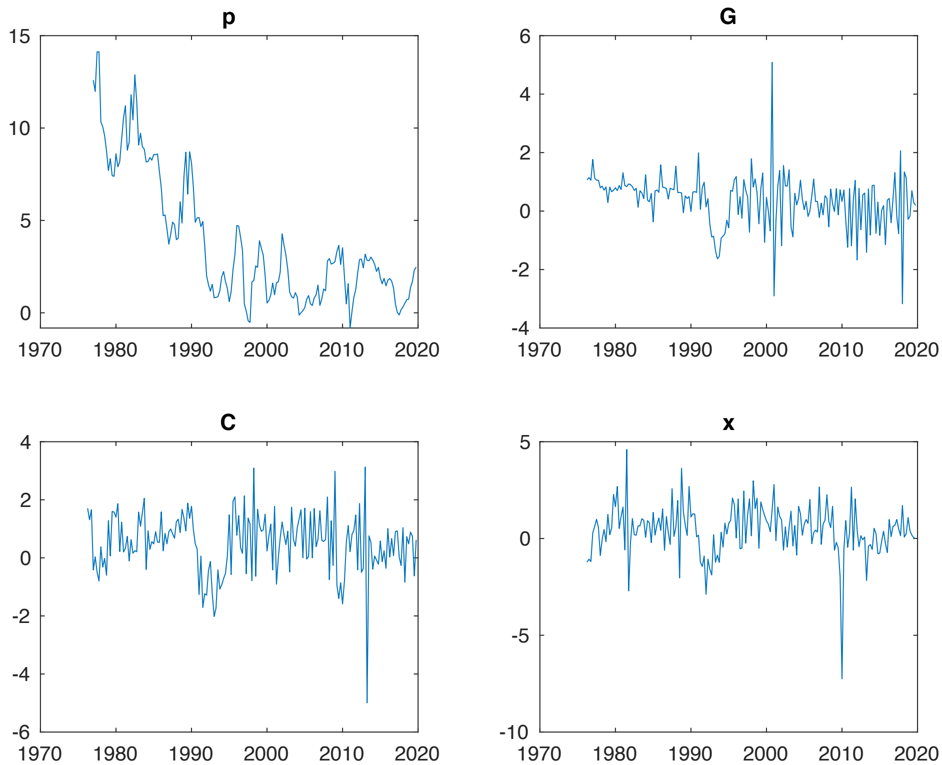

Figure 7: The constructed time series of the model variables (p = inflation, G = real government consumption, C = private consumption and x = real GDP)

Time series of the model variables are illustrated in Figure 7. The series of real government consumption G_t, real private consumption C_t and real GDP series x_t are divided by the total population of Finland, logaritmised and first order differenced. Finally, the series are multiplied by 100. The inflation series p_t are constructed by taking an annual differential from the GDP deflator, which is calculated by subtracting the real value GDP from the nominal value GDP and multiplying the result with 100.

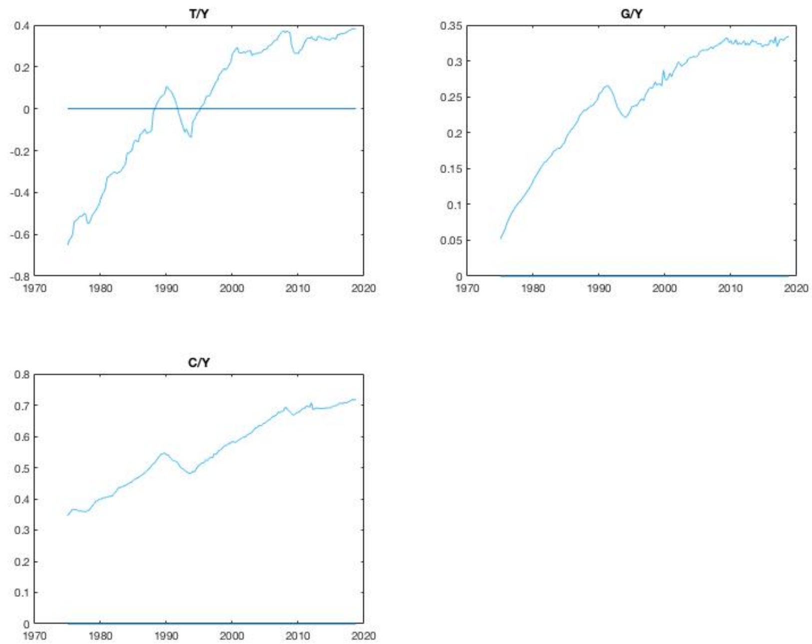

Figure 8: The ratios of tax series and GDP series T/Y, real private consumption series and GDP series C/Y and real government consumption series and GDP series G/Y.

The ratios of nominal net tax income series and GDP series T/Y, real private consumption series and GDP series C/Y and real government consumption series and GDP series G/Y are illustrated in Figure 8. The tax series is constructed by subtracting tax transfers from tax revenues.

C Theoretical Framework

C.1 The Derivation of the Model

My model is a slightly modified version of the TVP VAR model used by Nakajima et al. (2011). Following Nakajima (2011) and Primiceri (2005), I start with writing a basic VAR model

$$Ay_t = F_1 y_{t-1} + \cdots + F_s y_{t-s} + u, t = s + 1, ...n \tag{11}$$

where y_t is a $kx1$ vector of variables and A and F_1, F_2,...F_s are kxk matrices of coefficients. Following Nakajima et al (2011) and Primiceri (2005), I assume that A is a lower triangular matrix

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21,t} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \dots & a_{k,k-1} & 1 \end{bmatrix}. \tag{12}$$

Hence, the simultaenous relations of the structural shocks are specified by recursive identification. I also assume that $u_t \sim (0,\Sigma\Sigma)$, where

$$\Sigma = \begin{bmatrix} \sigma_{1,2} & 0 & \dots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_{n,t} \end{bmatrix}. \tag{13}$$

In accordance with the study of Nakajima et al. (2011), the model (11) can be written in the reduced form VAR model:

$$\begin{aligned} y_t = B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1}\Sigma\varepsilon_t, \\ \varepsilon_t \sim N\big(0, I_k\big). \end{aligned} \tag{14}$$

In the reduced form VAR model, $B_i = A^{-1}F_i$ for $i = 1, \dots s$. Following Nakajima et al. (2011), I stack all the elements of the B_i to the form $\beta\big(k^2 s \times 1$ vector$\big)$. I also define $X_t = I_k \otimes \big(y'_{t-1}, \dots, y'_{t-s}\big)$ where $\otimes$ is the Kronecker product.

Next, the the model can be written in a time-invariant VAR form:

$$y_t = X_t\beta + A^{-1}\Sigma\varepsilon_t \tag{15}$$

By allowing the all the paramaters to change over time $t = s+1, \dots, n$, the time-invariant model can be transformed to a TVP VAR model with stochastic volatility:

$$
\begin{aligned}
y_t = X_t\beta_t + A^{-1}\Sigma_t\varepsilon_t, \\
t = s+1, \dots, n.
\end{aligned}
\tag{16}
$$

In addition, I define $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, a_{k,k-1})'$ as a vector of lower triangular elements of A_t and $h_t = (h_{t1}, \dots, h_{kt})'$ with $h_{jt} = log\sigma^2_{jt}$ for $j = 1, \dots, k$ and $t = s+1, \dots, n$. In the similar vein to Nakajima et al. (2011), I assume that the parameters β_t, A_t and Σ_t follow the first order random walk process:

$$
\begin{aligned}
\beta_{t+1} &= \beta_t + u_{\beta_t}, \\
a_{t+1} &= a_t + u_{at}, \\
h_{t+1} &= h_t + u_{ht}
\end{aligned}
\tag{17}
$$

$$
\begin{bmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{bmatrix} \sim N \left[0, \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix} \right],
\tag{18}
$$

where $t = s+1, \dots, n$. Also, I assume that initial states of parameters follow normal distribution as $\beta_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$, $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{h_0})$ and $h_{s+1} \sim N(\mu_{h0}, \Sigma_{h_0})$, where Σ_β, Σ_a and Σ_h are diagonal matrices.

C.2 The Theoretical Framework of the Estimators

I use the Convergence diagnosis by Geweke (1999) and the inefficiency factor defined by Nakajima et al. (2011) to check the plausibility of the posterior inference. In the accordance with Nakajima et al. (2011), I compute the CD statistics by $CD = \left(\bar{x_0} - \bar{x_1}\right) / \sqrt{\sigma_0^2/n_0 \hat{+} \sigma_1^2/n_1}$, where $\bar{x_j} = \frac{1}{n_j}\sum_{i=m_j}^{m_j+n_j-1} x^{(i)}$. $x^{(i)}$ is the ith MCMC draw and $\sqrt{\hat{\sigma_j^2/}n_j}$ is the standard error of $\bar{x_j}$ for $j = 0, 1$. Following Nakajima et al. (2011), I set $m_0 = 1, n_0 = 1000, m_1 = 5001$ and $n_1 = 5000$ and compute the $\hat{\sigma_j^2}$ using a Parzen window with bandwith $B_m = 500$. (Nakajima et al. 2011)

Following Nakajima et al. (2011), I define the inefficiency factor as $1 + 2 \sim \sum_{s=1}^{B_m} \rho_s$, where ρ_s is defined as the sample autocorrelation at lag s.

C.3 The Technical Definition of the Cumulative Government Consumption Multiplier

I follow Glocker et al. (2019) to compute the cumulative government consumption multiplier for Finland. In their paper, the cumulative government consumption multiplier as is defined as follows:

$$CM_{P|t} = \frac{\sum_{j=1}^{P=1} x_j\left(\Xi_t\right)}{\sum_{j=1}^{P=1} g_j\left(\Xi_t\right)} * \frac{1}{\mu_t} \tag{19}$$

where $x_k\left(\Xi_t\right)$ is the impulse response function of output at horizon k in period t, $g_t\left(\Xi_t\right)$ is the corresponding government consumption response. Ξ_t consists of all coefficients and variance-covariance matrix estimates of the TVP-VAR model. $1/\mu_t$ is a conversion factor that rescales the impulse responses of output(in percent) to a government consumption shock (in percent) by the inverse of government consumption share. P denotes the time horizon that the government consumption multiplier is reported. (Glocker et al. 2019.)