ERASMUS UNIVERITY ROTTERDAM

Erasmus School of Economics

Bachelor thesis Quantitative Finance

Post-War Monetary Policy in the United States and United Kingdom

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Abstract

This paper researches the possible causes of the high levels of inflation and unemployment in the 1970s and 80s in the United States and United Kingdom. In particular, to which extent monetary policy played a role in this phenomenon. A time varying structural vector autoregression model is used. In both countries, we include the variables inflation, the unemployment rate and the interest rate in the model. We find evidence that the variance of non-systematic policy shocks is larger pre-1985 than after for both the US and the UK. Also, the monetary policy in terms of tackling inflationary pressures has significantly changed since World War II in the United Kingdom.

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Contents

1 Introduction

The years 1965-1980 represents a time of economic uncertainty for a large part of the Western World (Poynter, 2016). This economic uncertainty peaked as a result of the 1973-1975 recession. In the United States (US), there was a substantial increase in unemployment and inflation and their volatility compared to twenty years before and after. Next to this, the United Kingdom (UK) experienced peaks of inflation, which reached a peak of over 25% in the same period.

This thesis aims to analyze the possible causes of the economic conditions of the 1970s and 80s and to what extend monetary policy influenced these conditions for both the US and UK.

Previous literature considers two main classes of explanation for these poor economic conditions. The first class focuses on the heteroskedasticity of exogenous innovations (e.g. Sims and Zha (2006) and Stock and Watson (2002) for the US and Mumtaz (2010) and Benati (2004) for the UK). This is because both the US and UK experienced much more volatile shocks in the 1970s and early 1980s than twenty years before or after. The second class focuses on the way macroeconomic variables react to shocks. As monetary policy has changed in this period of time, this macroeconomic variable is analyzed in this paper.

To analyze the possible causes of the poor economic conditions in the 70s and 80s, we use the time varying structural vector autoregressive (TVP VAR) model introduced in Primiceri (2005). This model combines both classes of explanation for the poor economic conditions. For both the US and UK economy, we use this model and include inflation, unemployment rate and the short-term interest rate. The data is quarterly and ranges from 1953Q1 till 2001Q3. For the estimation, the Gibbs sampler is used. To calibrate the priors, we use OLS point estimates of the first 10 years of the data set.

In the US, we find that the variance of monetary policy shocks was larger in the pre-Volcker and during his first four years as chairman than after. This is consistent with the findings of Bernanke and Mihov (1998b), Sims (1999) and Sims and Zha (2006). Next to this, the monetary policy seems to change somewhat over time. However, this change in monetary policy is not significant between the different periods of time.

The monetary policy shocks in the UK are lower after implementing inflation targeting than before. Again this is in line with previous literature (Benati, 2004). Next to this, there is evidence that the monetary policy has significantly changed after World War II (WWII).

The rest of the paper is structured as follows. Section 2 gives an overview of the previous literature. In section 3, the used data is described. The used model is introduced in section 4, while section 5 gives an overview of the methods used for estimation. The results are shown and elaborated in section 6. Finally, section 7 concludes.

2 Literature

Monetary policy and its effects on inflation and unemployment have been a topic of research for quite some time. In this paper, monetary policy in the period 1953Q1-2001Q3 is analyzed for both the economy of the US and the UK

From an economic point of view, a substantial amount of research has been done on the subject of the high levels of inflation and unemployment in the US in the 1970s and 1980s. A lot of the papers focused on the role of monetary policy as an explanation for these poor economic conditions (e.g. Cogley and Sargent (2001), Favero and Rovelli (2003) and Boivin (1999)). It is argued (by e.g. Boivin and Giannoni (2006) and Cogley and Sargent (2001)) that under the Federal Bank Reserve (FED) chairmanship of Arthur Burns, the monetary policy was less active in combatting rising inflation compared to the periods of chairmanship of Paul Volcker and Alan Greenspan. However, other papers (Bernanke and Mihov (1998a), Hanson (2006) and Leeper and Zha (2003)) argue that there is no evidence that the monetary policy in terms of inflation changed significantly. On the other hand, Cogley and Sargent (2005) focus on the importance of heteroskedasticity in the exogenous shocks. The model used in Primiceri (2005) is inspired by their model. They find evidence for time varying variances. In other words, the volatility of shocks changed over time. Also, they emphasize that even with this model there is still evidence for drifting coefficients.

In terms of the UK, the topic of inflation in the 1970s is researched in e.g. Nelson (2001), Nelson and Nikolov (2002) and Nelson and Nikolov (2003). Mumtaz (2010) and Benati (2004) incorporate a time varying factor augmented VAR model. They focus mainly on the variance of the exogenous innovations and find that the variance of these innovations are lower after the start of inflation targeting in 1992. To be more specific, Benati (2004) finds that the volatility of exogenous shocks has been more stable and lower compared to post-WWII since the introduction of inflation targeting in the monetary policy in 1992.

For the theoretical framework, the model that is used is constructed by combining two different types of models that allow for time variation on multivariate linear structures. In Cogley and Sargent (2001) and Sims (1993) VAR models that allow for time varying coefficients are used. Next to this, VAR models with multivariate stochastic volatility are considered in Harvey et al. (1994), Kim et al. (1998), Jacquier et al. (2002) and Chib et al. (2006). Each of these papers imposes some restrictions on the time varying ability of the variance covariance matrix. Most common is the restriction that the covariances do not vary over time independently of the variances. Cogley and Sargent (2001) introduced a VAR model that allowed for time varying coefficients as well as multivariate stochastic volatility. Here, only the variances were time varying. This means that the simultaneous relationships between the variables, that are in the covariances, are not captured over time. Therefore the model can only be used to analyze of reduced form VARs. This paper aims to analyze if the transmission mechanism or the size of the exogenous innovations changes over time. Therefore a VAR model is used that incorporates time varying coefficients together with a variance covariance matrix that varies over time in its entirety. This model is introduced in Primiceri (2005).

3 Data

In this paper, two different sets of data are used. One represents the US; the other one represents the UK. Both are quarterly data sets which range from 1953Q1 - 2001Q3. The US data is collected from the Federal Reserve Bank of St. Louis[1] (FRED). The variables used are the same three variables as used in Primiceri (2005). Namely, the inflation rate, the unemployment rate, and the short-term interest rate. The variables inflation rate and unemployment rate represent the non-policy part of the model, while the short-term interest rate is added to represent the policy part. The inflation rate is measured as the percentage of annual change in a chain-weighted GDP price index. For the unemployment rate, all workers above the age of 16 are considered. Finally, the yield on the 3-month Treasury bill is used for the short-term interest rate. The used data of the FRED is monthly. The quarterly data is obtained by taking the average of the three months in a particular quarter for all variables.

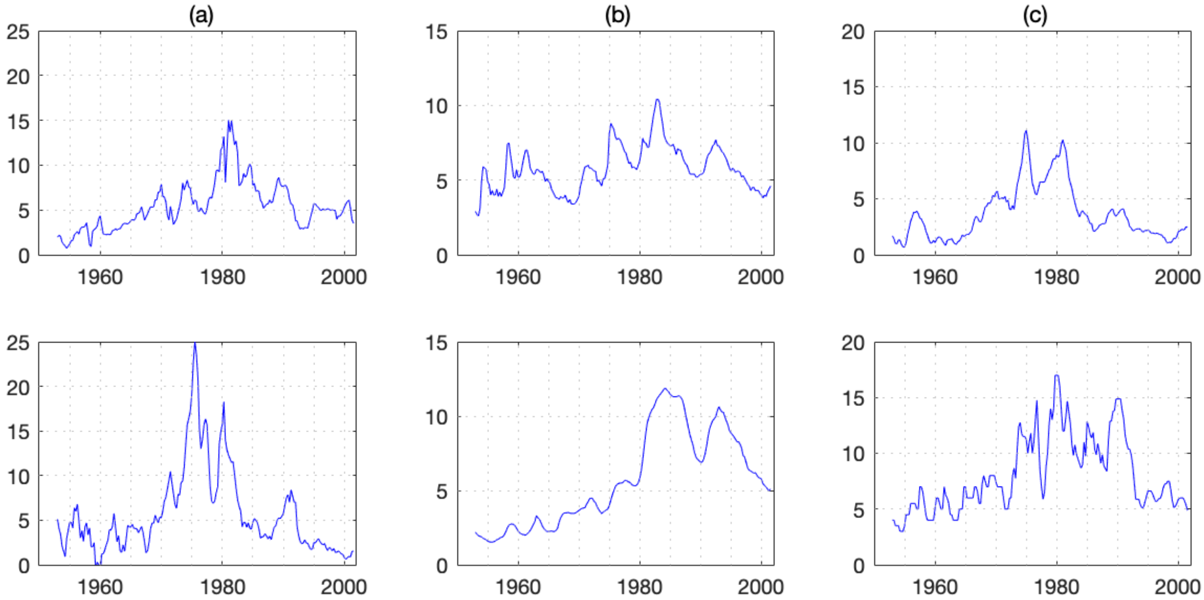
For the UK, the same variables are used. The Bank Rate is chosen as the short-term interest rate and obtained from the Bank of England site. Next to this, the unemployment rate and inflation are obtained from the FRED website.

Figure 1 shows the quarterly US inflation, unemployment, and interest rate for the US and the UK. Inflation peaks in the 1970s and beginning 1980s in the UK, while it peaks in the 1980s in the US. This was due to the rising oil prices, which tripled in the 1970s due to the 1979 energy crisis that was mostly caused by the Iranian Revolution (Abrahamian, 1980). Also, due to rising

[1] https://fred.stlouisfed.org/

wages and powerful unions which bargained for a higher salary to keep up with the rising cost of living, a wage-inflationary spiral was caused in the UK. The rising oil prices also affected the interest rate of the US. As a result, both countries increase their interest rate to control the inflation (Kose et al., 2020). Another result of this recession is the increase in unemployment in both countries.

Figure 1: Quarterly data of the United States in the first row and the United Kingdom in the second row from 1953Q1-2001Q3. (a) is the inflation rate, (b) the unemployment rate, (c) the interest rate



Note. All y-axis represent the percentage of each of the variables.

4 The Model

The model used in Primiceri (2005) is a time varying structural vector autoregression model (TVP-VAR). The model is a combination of two models previously used in literature. First of all, it allows coefficients to change over time. These changes could indicate a changes in monetary policy in the economies. Next to this, it also allows the variance covariance matrix of the additive innovations to change over time, which is studied in Sims (1999), Bernanke and Mihov (1998a), and Bernanke and Mihov (1998b). This is used to check whether the unobservable shocks change over time. Also, it could capture the nonlinearities in the simultaneous relationships between the used variables.

First, we consider the following model:

$$y_t = c_t + B_{1,t} y_{t-1} + ... + B_{k,t} y_{t-k} + u_t \qquad t = 1, ..., T, \tag{1}$$

where y_t is a n x 1 vector of endogenous variables, c_t is a n x 1 vector of time varying coefficients that multiply constant terms. Furthermore, the time varying coefficients $B_{i,t}$ with lags $i = 1, ..., k$, is a n x n matrix. Finally, the time varying shocks are given by u_t. The variance covariance matrix of u_t is given by Ω_t. By triangle reduction, this stochastic variance covariance matrix can be factored as

$$Var(u_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})', \text{with } H_t = \Sigma_t \Sigma_t'. \tag{2}$$

Here, A_t is a time varying lower triangular matrix, and Σ_t is a time varying diagonal matrix, and they are denoted by:

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{nn-1,t} & 1 \end{bmatrix} \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}. \tag{3}$$

Using the triangle reduction of (2) and rewriting (1) in matrix form, we obtain:

$$y_t = X_t' B_t + A_t^{-1} \Sigma_t \varepsilon_t, \tag{4}$$

where $X_t' = I_n \otimes [1, y_{t-1}', ..., y_{t-k}']$, $B_t = vec(c_t, B_{1,t}, ..., B_{k,t})$ and $Var(\varepsilon_t) = I_n$ for each time t. The time varying nature of the model is specified as follows:

$$B_t = B_{t-1} + \nu_t \tag{5}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{6}$$

$$\log\, \sigma_t = \log\, \sigma_{t-1} + \eta_t, \tag{7}$$

where B_t is given in (3), α_t the vector of non-one and non-zero elements of the matrix A_t given in (3) stacked by rows, and σ_t is the vector of the diagonal elements of Σ_t. Together (3), (4), (5) and (6) give the state space model. The vector B_t is modeled as a random walk as well as the free elements of the vector A_t. Next, the vector t is modeled as geometric random walk, indicating the model's stochastic volatility. For the innovations in this model, we assume that their are jointly normal distributed with the following variance covariance matrix,

$$\begin{bmatrix} \varepsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix} \sim N(0, V), \text{ with } V = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}, \tag{8}$$

where Q, S and W are positive definite matrices and I_n is the n identity matrix. For V, we assume the off diagonal elements to be equal to zero. This is not a necessary condition but is used because it decreases the number of parameters in the model. Also, the assumption ensures the possibility of structural interpretation, which will further be explained in section 5.3. Furthermore, the matrix S is assumed to be block diagonal, with each of the blocks corresponding to parameters of separate equations. Again, this assumption is not strictly necessary, but it simplifies the inference and increases the efficiency of the simulation method. The distributions of the positive definite matrices in (8) is shown in section 5.1.

5 Bayesian Inference

In this section, the techniques used to estimate the time varying structural VAR, which is introduced in the previous section, are explained. In this paper, Bayesian methods are used. They are used to evaluate the posterior distribution of the parameters of interest. Namely, B^T, A^T, Σ^T and the hyperparameters of the variance covariance matrix V. There are three reasons why using Bayesian methods is preferred over classical estimation methods. First, the maximum likelihood estimator has a point mass at zero if the variance of the time varying parameters is very small (Stock and Watson, 1998). Second, the high dimensionality and nonlinearity in the model can be a problem for maximum likelihood estimation. A complicated model like this could give uninteresting peaks or peaks that are not in the plausible region of the parameter space. Thirdly, using Bayesian methods is practically more efficient than the maximum likelihood estimation as it is generally computationally hard to maximize over such a high dimensional parameter space. On the contrary, Bayesian methods are very efficient in dealing with the high dimensionality of the parameters. Next to this, the nonlinearity of the model can also be dealt with efficiently. This is because in the Bayesian methods the original estimation problem is splitted into smaller and simpler estimation problems. The Bayesian method that is used in this paper is the Gibbs sampler (Casella and George, 1992). The Gibbs sampler is a variant of the Markov Chain Monte Carlo (MCMC) estimation method. This numerical estimation method is used to estimate the posterior distributions of the parameters of interest described above. The estimation method is more precisely explained in section 5.2. First, we start with the choice of the priors.

5.1 Priors

Before explaining which priors are used, some assumptions must be clarified. We use the priors that are used in Primiceri (2005). Furthermore, the initial state of the time varying parameters B^T, A^T, and Σ^T are assumed to be independent and normally distributed. Next to this, the initial state of the hyperparameters Q, W, and the blocks of S is assumed to be independent inverse Wishart (IW) distributed.

In this paper, the first ten years of data, which is equal to 40 observations, are used to calibrate the prior distributions. With these 40 observations, OLS is performed on the parameters of interest using a time invariant VAR model. As a result, the initial state B_0 is normally distributed with $\widehat{B}_{OLS}$ as its mean and four times $V(\widehat{B}_{OLS})$ as its variance. The prior for A_0 is obtained in the same way. For the prior log σ_0, the mean is equal to the OLS point estimates of log σ while its variance is assumed to be equal to the n identity matrix. As previously stated, the priors of the hyperparameters are IW distributed. Now their degrees of freedom and scale matrices have to be chosen. First of all, it is important to state that when following previous literature (Cogley and Sargent (2001) and Cogley and Sargent (2005)), the means of the prior distributions of the hyperparameters are a multiplication of the variance of the OLS point estimates, which are obtained using the previously mentioned subsample. Next to this, the means are multiplied by a certain constant (k_Q^2, k_W^2, and k_S^2). The chosen values for these constants are elaborated later. For the degrees of freedom, we choose 40 for Q. This is equal to the initial subsample used to calibrate the prior distributions. Next to this, the degrees of freedom for W, S_1 and S_2 are equal to their dimension plus one. In this case 4, 2 and 3, respectively. In summary, the general notation of the distributions of the priors is denoted by

$$
\begin{aligned}
B_0 &\sim N\left(\widehat{B}_{OLS}, 4 \cdot V\left(\widehat{B}_{OLS}\right)\right), \\
A_0 &\sim N\left(\hat{A}_{OLS}, 4 \cdot V\left(\widehat{A}_{OLS}\right)\right), \\
\log \sigma_0 &\sim N\left(\log \widehat{\sigma}_{OLS}, I_n\right), \\
Q &\sim IW\left(k_Q^2 \cdot \tau \cdot V\left(\hat{B}_{OLS}\right), \tau\right), \\
W &\sim IW\left(k_W^2 \cdot (1 + dim(W)) \cdot I_n, (1 + dim(W))\right) \\
S_1 &\sim IW\left(k_S^2 \cdot (1 + dim(S_1)) \cdot V\left(\hat{A}_{1,OLS}\right), (1 + dim(S_1))\right) \\
S_2 &\sim IW\left(k_S^2 \cdot (1 + dim(S_2)) \cdot V\left(\hat{A}_{2,OLS}\right), (1 + dim(S_2))\right).
\end{aligned}
$$

Here S_1 and S_2 are denoted as the two blocks of S. Next to this, $\widehat{A}_{1,OLS}$ and $\widehat{A}_{2,OLS}$ are defined as those two corresponding blocks of A_1. Now, the values of the constants k_Q^2, k_W^2, and k_S^2 have to be chosen. Primiceri (2005) uses $k_Q = 0.01$, $k_W = 0.01$, and $k_S = 0.1$. A more detailed explanation for the choice of these values can be found in his paper.

5.2 Simulation method

As previously mentioned, the method used to evaluate the posterior distributions is the Markov Chain Monte Carlo simulation. In particular, the Gibbs sampler is used. The Gibbs sampler used in Primiceri (2005) consists of four steps. The time varying coefficients (B^T), simultaneous relations (A^T), volatilities (Σ_t) and hyperparameters (V) are drawn conditional on the rest of the parameters and the observed data, in that order. Later, in Del Negro and Primiceri (2015), this approach was corrected. In this paper 'Algorithm 2' of the corrigendum of Primiceri is used. The order of the drawn conditional distributions is more mixed and looks as follows:

1. Initialize A^T, Σ^T, s^T and V
2. Sample B^T from $p\left(B^T \mid y^T, A^T, V, \Sigma^T\right)$, using the Carter and Kohn (CK) (1994) algorithm
3. Sample Q from $p\left(Q \mid y^T, B^T, A^T, \Sigma^T\right)$, which is IW distribution
4. Sample A^T from $p\left(A^T \mid y^T, B^T, V, \Sigma^T\right)$, again using CK
5. Sample S from $p\left(S \mid y^T, B^T, A^T, \Sigma^T\right)$, which consists of several blocks that are IW
6. Sample the auxiliary discrete variables s^T from $p\left(s^T \mid y^T, B^T, A^T, V, \Sigma^T\right)$ for the Kim et al. (1998) algorithm
7. Draw Σ^T from $p\left(\Sigma^T \mid y^T, B^T, A^T, V, s^T\right)$, using CK
8. Sample W from $p\left(W \mid y^T, B^T, A^T, \Sigma^T\right)$, which is IW

9. Go to Step 2.

Sampling B^T from $p\left(B^T \mid y^T, A^T, V, \Sigma^T\right)$ can be done quite easily because of the fact that conditional on A^T and Σ^T, the state space shown (4)-(7) is linear as well as Gaussian. Therefore B^T can be defined as a product of Gaussian densities and drawn by the algorithm proposed in (Carter and Kohn, 1994), which is a standard simulation smoother. The same holds for the posterior A^T conditional on B^T and Σ^T. The draw of Σ^T is not as straightforward as its state space is nonlinear and non-Gaussian. Kim et al. (1998) proposes an algorithm which transforms this nonlinear and non-Gaussian state space form into a linear and Gaussian one. This algorithm also utilizes standard simulation smoothers. For each of the diagonal blocks Q, W, S of V it holds that it's posterior conditional on y^T, B^T, A^T, and Σ^T has an IW distribution, which is independent of the other diagonal blocks. A more detailed explanation for each of the steps is given in Primiceri (2005).

6 Empirical results

In this section the results of the model are shown and explained. To obtain the results the *R* package *bvarsv*[2] from Fabian Krüger is used. For both datasets, we use the lag order $p = 2$. As shown in the data section, for both models three different variables are used. Namely, inflation, umemployment rate and the interest rate. Here, inflation and the unemployment rate are used to represent the non-policy part of the model. The interest rate represents the monetary policy part of the model. Furthermore, for the Gibbs sampler we use 50000 iterations. Of these 50000, the first 5000 are discarded for convergence purposes. In Appendix A the diagnostics of the convergence of the posteriors are given. It shows autocorrelations lower than 0.2 for almost the entire set of parameters which is a satisfactory result.

We focus on non-systematic monetary policy. The non-systematic monetary policy is formulated as all the changes in interest rates that are not due to inflation or unemployment. Also, non-systematic monetary policy should capture the so-called "policy mistakes". As a measure of non-systematic monetary policy actions, we use identified monetary policy shocks. The shocks have to be identified to ensure that the monetary policy actions affect the unemployment and inflation rate after one time period. In other words, the monetary policy shocks have to be isolated. This is done by setting interest rate as the last variable in the model and is in line with

[2]The code can be found on https://cran.r-project.org/web/packages/bvarsv/index.html.

previous literature (e.g. Christiano et al. (1999) and Primiceri (2005)). Furthermore, inflation is set as the first variable while unemployment is set as the second. However, changing these two gives the same results for both the US economy as the UK economy.

The results of both the US economy and the UK economy as well as their differences are shown in the rest of this section.

6.1 US Economy

As we focus on non-systematic monetary policy shocks, the first measure we take into consideration is the time varying standard deviation of the monetary policy shocks. This is displayed in Figure 2c, together with its 16th and 84th standard deviation percentiles. A couple of things stand out in this figure. First, the early 80s exhibit higher variances than the rest of the periods. Inflation was rising during this period of time and to counter this phenomenon the FED tightened their monetary policy, which resulted in an economic recession that lasted till 1983 (Goodfriend and King, 2005). The figure confirms this new regime under chairman Volcker, which lasted from 1979-1987. Furthermore, the variances seem to be higher before the Volcker regime than after it. Since the Volcker regime, the main target of the FED is to keep the inflation levels at 2% and maximize employment. The figure shows that it is likely that the FED took other targets than inflation and unemployment into consideration in the pre-Volcker era. The rest of Figure 2 shows that not only monetary shocks were larger in the pre-Volcker era, also the shocks in inflation and unemployment. To conclude, the fact that the variance of the monetary policy was larger pre-Volker and during his first four years as chairman is robust and consistent with the findings of Sims (1999), Bernanke and Mihov (1998b) and Sims and Zha (2006).

Next to the time varying standard deviation of the monetary policy shocks, we consider the impulse responses to monetary policy shocks for inflation and unemployment. Three different time periods, that represent different economic time periods, are considered. First, for the Burns chairmanship, 1975Q1 is chosen, 1981Q3 for the Volcker chairmanship, and 1996Q1 for the Greenspan chairmanship. The results are given in Figure 2 and 3, together with the differences between each of the time periods and their 16th and 84th percentiles. The impulse responses for all three periods increase in the first five periods after the monetary policy shock. This phenomenon is called the 'prize puzzle'. Also, when comparing the different time periods with each other, non of the periods significantly differ from each other. This indicates that the coefficients do not change much over time. Next to this, it is remarkable how little the response of unemployment to policy shocks changes over time.

In summary, the variance of the monetary policy decreased after the first four years of the Volcker chairmanship. Also, the impulse responses don't suggest that the monetary policy changed significantly over time.

Figure 2: The posterior mean and the 16th and 84th percentiles of the standard deviation of residuals of (a) the inflation equation, (b) the unemployment equation and (c) the interest equation for the US.

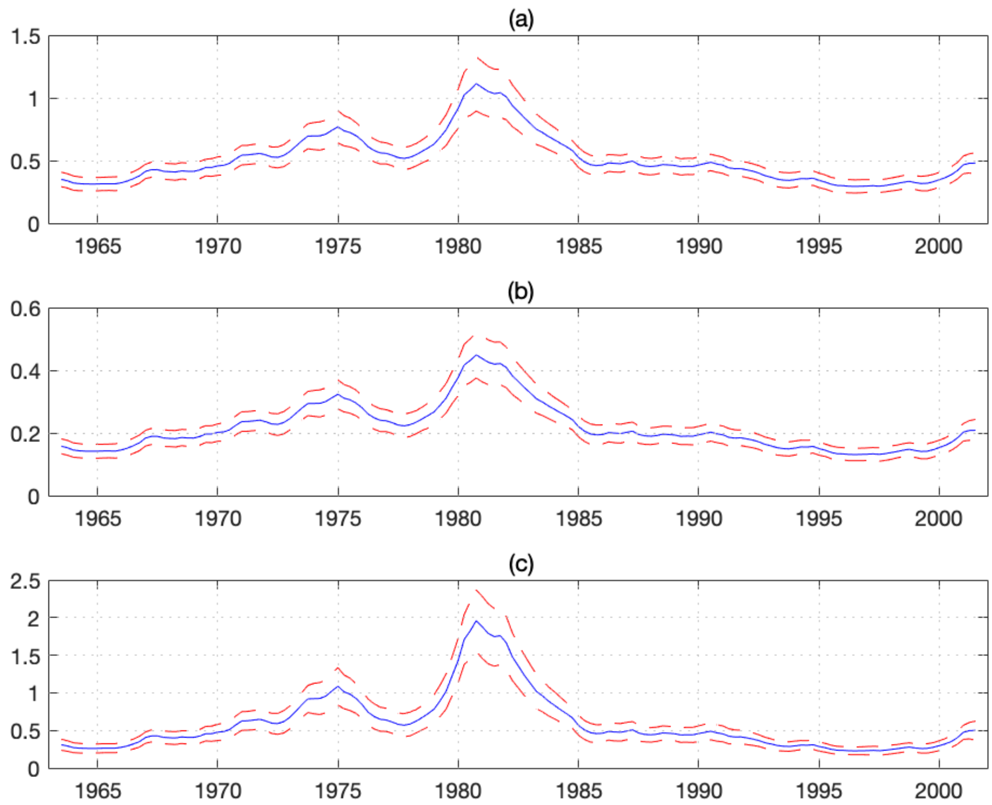


Figure 3: (a) impulse responses of inflation to monetary policy shocks at times 1975Q1, 1981Q3, and 1996Q3, (b) differences in impulse responses between 1975Q1 and 1985Q3 and their 16th and 84th percentiles, (c) differences in impulse responses between 1975Q1 and 1996Q3 and their 16th and 84th percentiles, (d) differences in impulse responses between 1981Q1 and 1996Q3 and their 16th and 84th percentiles.

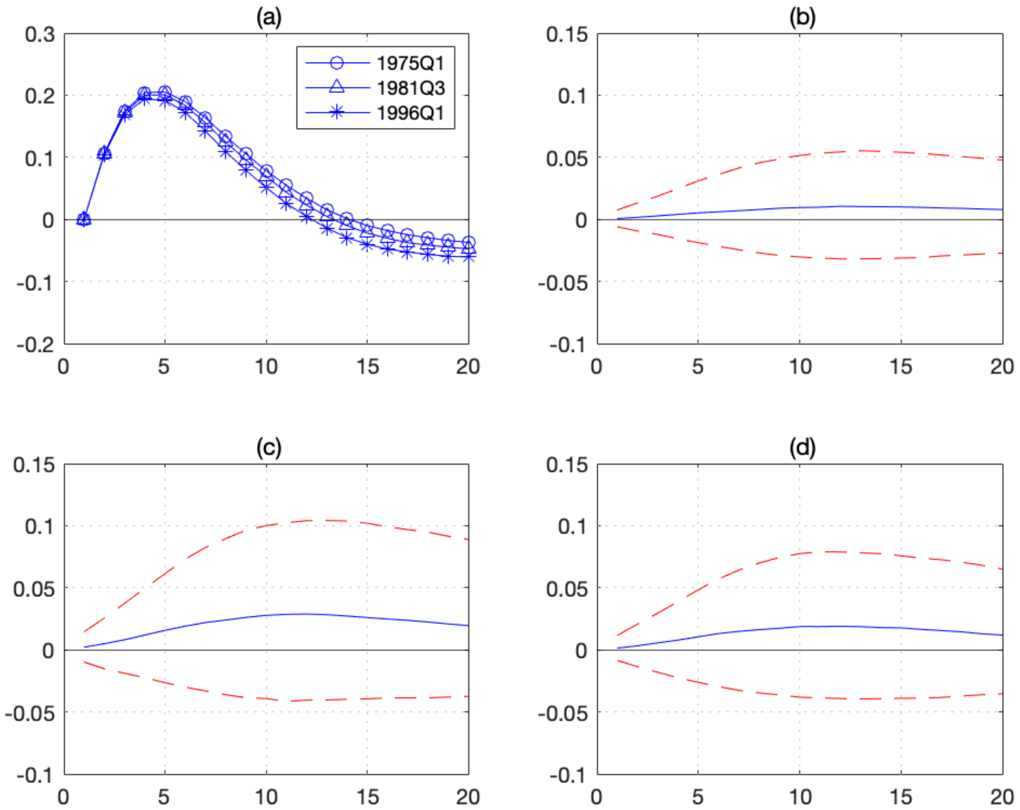
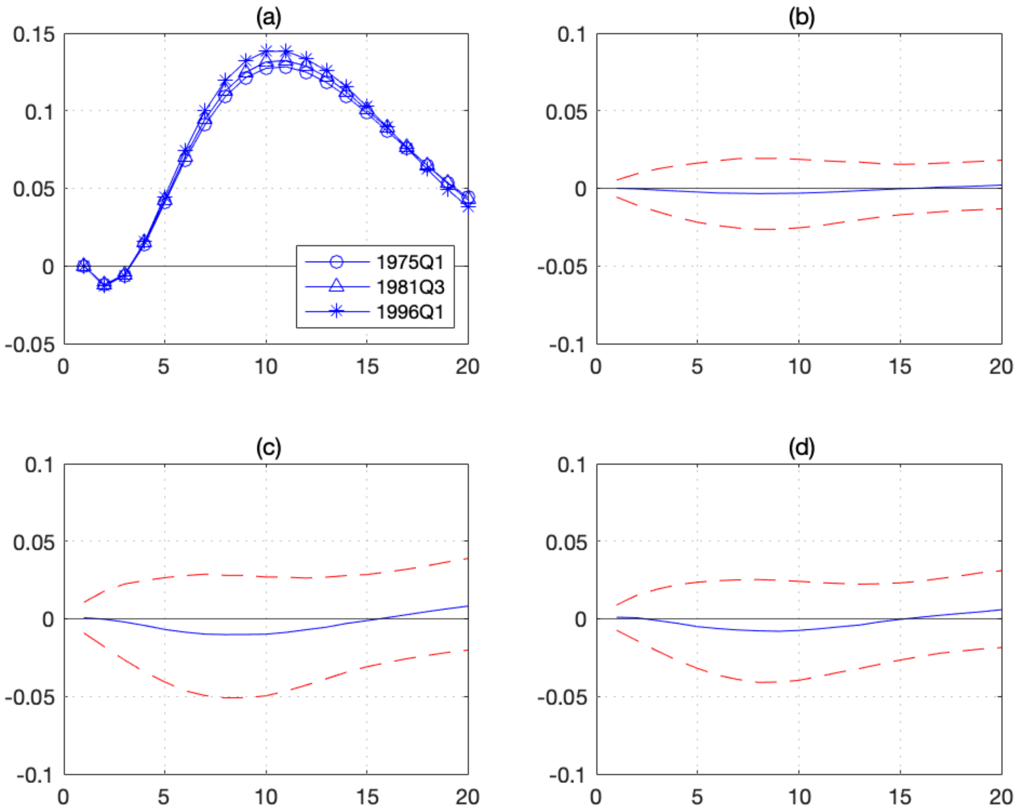


Figure 4: impulse responses of the unemployment rate to monetary policy shocks at times 1975Q1, 1981Q3, and 1996Q3, (b) differences in impulse responses between 1975Q1 and 1985Q3 and their 16th and 84th percentiles, (c) differences in impulse responses between 1975Q1 and 1996Q3 and their 16th and 84th percentiles, (d) differences in impulse responses between 1981Q1 and 1996Q3 and their 16th and 84th percentiles.



6.2 UK Economy

For the economy of the UK, we also focus on non-systematic monetary policy. Again, the time varying standard deviation of the monetary policy is considered. The period 1975-1980 exhibits a higher variance of monetary policy shocks than the rest of the sample. In 1975, the UK's inflation rose to a historical high of over 25%. As a result, the Bank of England changed their monetary policy and started with monetary targeting to reduce inflation (from 1976-87). Monetary targeting is when central banks use monetary aggregates to influence, in this case, inflation. One of those monetary aggregates is the Bank rate, which increased substantially in the late 1970s. This explains the rise of the variance of the monetary policy shocks. Again, just as with the US economy, we see that on average the variance of the monetary policy shocks is lower after the change in monetary policy plus the first couple of years than before. This suggests that it is likely that the Bank of England responded to different targets than inflation. Furthermore, since the introduction of inflation targeting in 1992, the decrease in the variance of the monetary policy shocks has increased. This is robust and consistent with the findings of Benati (2004) and Mumtaz (2010).

Figure 6 and 7 show the impulse responses of inflation and the unemployment rate to monetary policy shocks at different time periods. The choice of these periods has two reasons. First, to compare them with the US economy results in this paper. And second, because each of the periods represent a different form of monetary policy and economic conditions. The first date represents the monetary policy of the floating exchange rates. Income policies (e.g. wage and price controls) delegated the control of inflation in this time period (Nelson and Nikolov, 2003). This lasted till 1976. The next date, 1981Q3, represents the time when the Bank of England used monetary aggregates to reduce inflation. Since 1992, the Bank of England started actively targeting inflation as part of their monetary policy[3]. The date 1996Q1 represents this period.

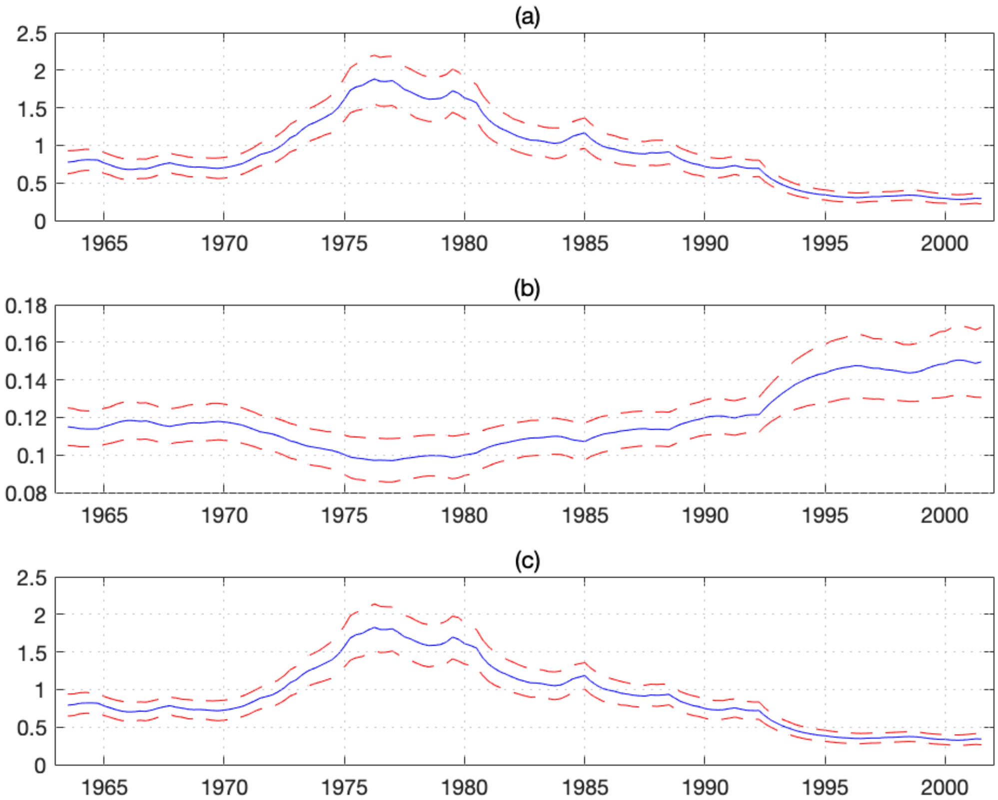
A couple things stand out when considering the impulse response of inflation to a monetary policy shock in Figure 6a. First, the response for each of the different dates s with a prize puzzle. Inflation increases when the bank rate increases. Furthermore, after five time periods, the impulse responses of the different dates behave differently. The difference between the period of inflation targeting compared to the floating exchange rates period is significant after nine quarters. The same holds for the difference between 1981Q3 and 1975Q1, only this time the difference is significant after ten quarters. Even the difference shown in Figure 6d is quite substantial and becomes significant after 20 quarters. This indicates that the estimated coefficients are time varying. This is evidence of changes in monetary policy in response to inflationary pressures over time. Economic theory suggests that an increase in the bank rate should decrease the inflation rate. For 1975Q1 and 1981Q3 this is not the case, while it is for the last period, when inflation targeting was implemented. This could be a sign that the monetary policy that was used in the first two periods was not sufficient. Furthermore, just as in the US part, the unemployment rate is very consistent in its response to monetary policy shocks over time.

To conclude, the impulse response function shows that the estimated coefficients are time

[3]Note that this is different from the policy in the US, where the aim to reduce inflation was equally important as the maximization of employment.

varying and indicate the change in monetary policy in terms of reaction to inflation pressures over the years.

Figure 5: The posterior mean and the 16th and 84th percentiles of the standard deviation of residuals of (a) the inflation equation, (b) the unemployment equation and (c) the interest equation for the US.



Note. The figures (a) and (c) look alike but are not the same.

Figure 6: (a) impulse responses of inflation to monetary policy shocks at times 1975Q1, 1981Q3, and 1996Q3, (b) differences in impulse responses between 1975Q1 and 1985Q3 and their 16th and 84th percentiles, (c) differences in impulse responses between 1975Q1 and 1996Q3 and their 16th and 84th percentiles, (d) differences in impulse responses between 1981Q1 and 1996Q3 and their 16th and 84th percentiles.

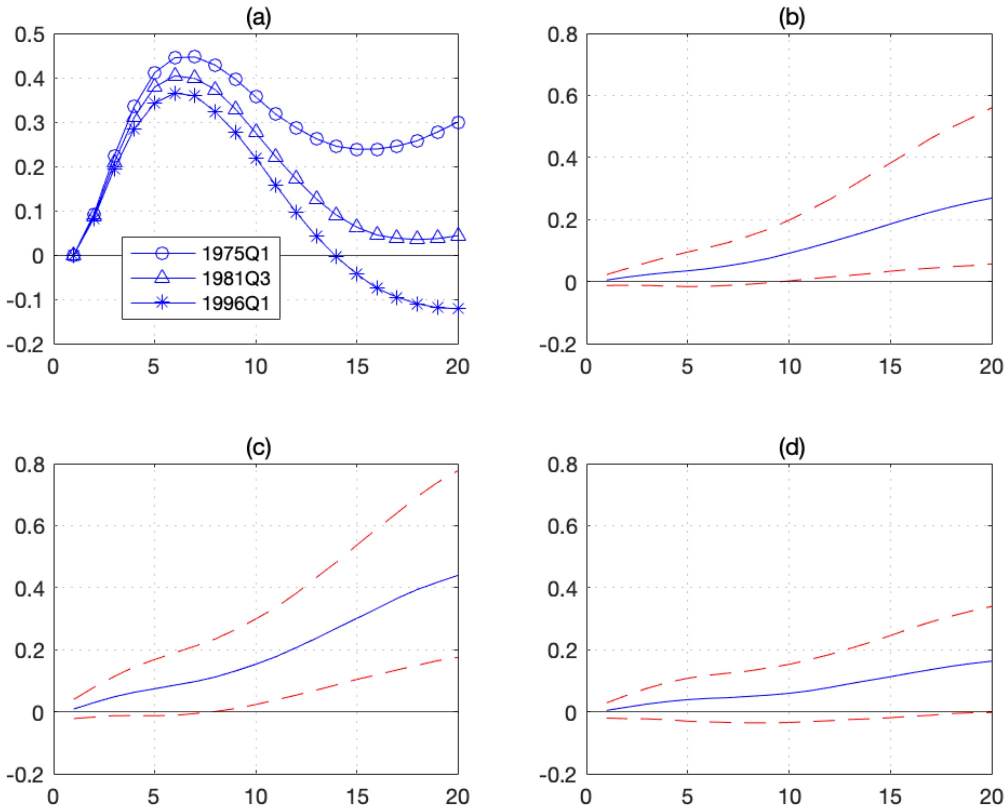
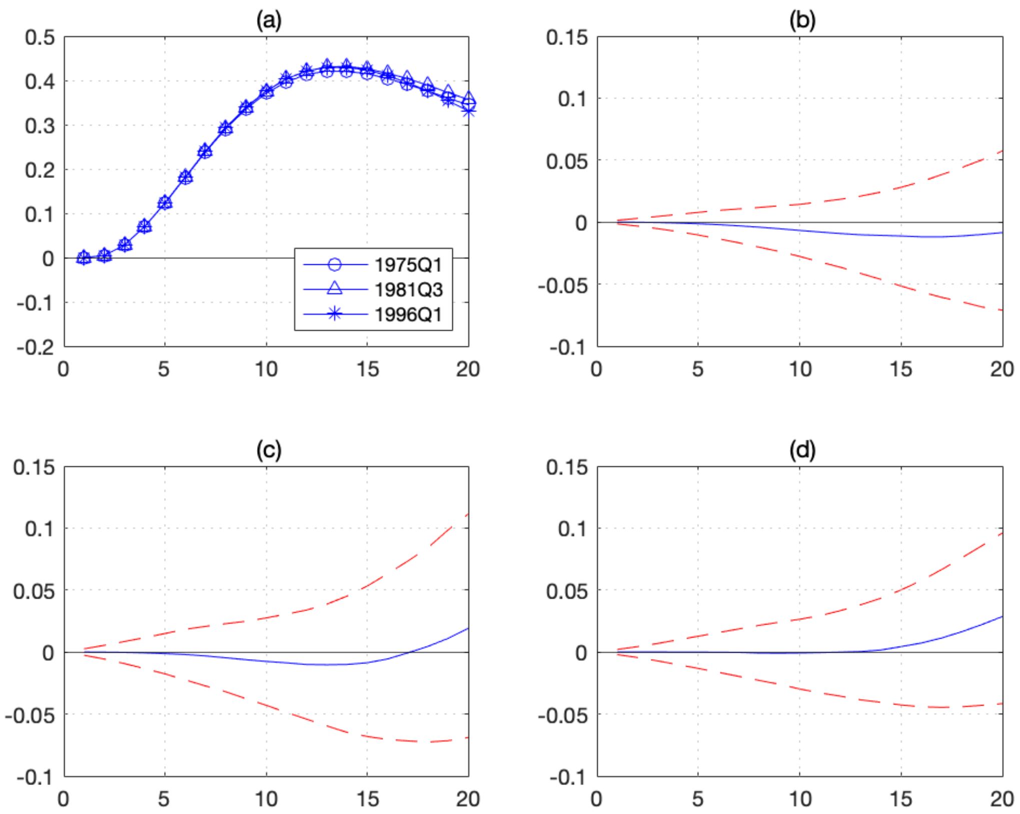


Figure 7: impulse responses of the unemployment rate to monetary policy shocks at times 1975Q1, 1981Q3, and 1996Q3, (b) differences in impulse responses between 1975Q1 and 1985Q3 and their 16th and 84th percentiles, (c) differences in impulse responses between 1975Q1 and 1996Q3 and their 16th and 84th percentiles, (d) differences in impulse responses between 1981Q1 and 1996Q3 and their 16th and 84th percentiles.



7 Conclusion

In this paper, the possible causes of the poor economic conditions in the 1970s and 80s and to which extent monetary policy has had influence in this conditions, is analyzed for both the UK and the US. A TVP-VAR model introduced in Primiceri (2005) is used. For estimation, the Gibbs sampler is used. The variables inflation, unemployment and the short-term interest rate are included in the model for both economies.

The variance of non-systematic monetary policy shocks seems to be lower in pre and in the first four years of Paul Volckers chairmanship in the US, which is consistent with the findings of Cogley and Sargent (2005). Furthermore, we find that the coefficients are time-varying. However, there is no evidence of significant differences in the tackling of inflation under the different chairmanships of the Fed.

In the UK, we find that these non-systematic monetary policy shocks gradually decline from 1980 onwards. Also, with the introduction of inflation targeting the variance of these shocks decline even further. Next to this, there is evidence of significant differences in the approach towards inflation over the years.

For further research, it would be interesting to analyze systematic monetary policy. Also, since the used model only contains three variables it would be interesting to use a model where more variables are included. This is because there are probably more variables that influence or are influenced by monetary policy.

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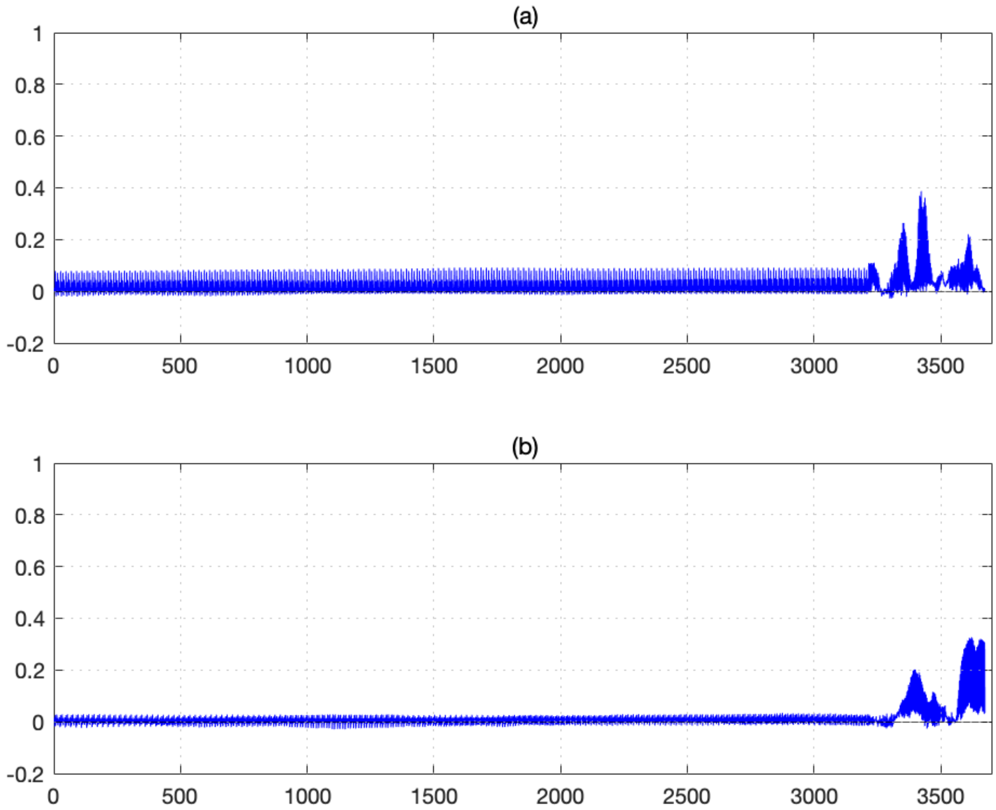
A Convergence Markov Chain Monte Carlo algorithm

This appendix checks the convergence of the Markov Chain Monte Carlo algorithm for both the US and UK data.

To check this convergence, we consider the time varying coefficients of B^T as well as the variances of the residuals. For the time varying coefficients we have 21 variables for 153 periods of time. Therefore the variables 1-3213 are of B^T. Next to this we have 3x153 variances. Variables 3214-3672 represent the variances of the residuals. These variances are computed as $\Omega_t = A_t^{-1} H_t (A_t^{-1})'$, as explained in section 4.

It is common practice to look at the autocorrelation to see how well the chain of draws mixes. Here, it is preferable to have low autocorrelations as this suggests that the draws are almost independent. This then increases the efficiency of the simulations. In Figure 8, the 20th order sample autocorrelations of the draws of the variables explained above. Figure 8a exhibits the results for the U.S dataset. Here we see that the autocorrelation stays below 0.2 for almost all the variables. There are some exceptions for the variances, but overall we can conclude that the convergence diagnostics for the US data set are satisfactory.

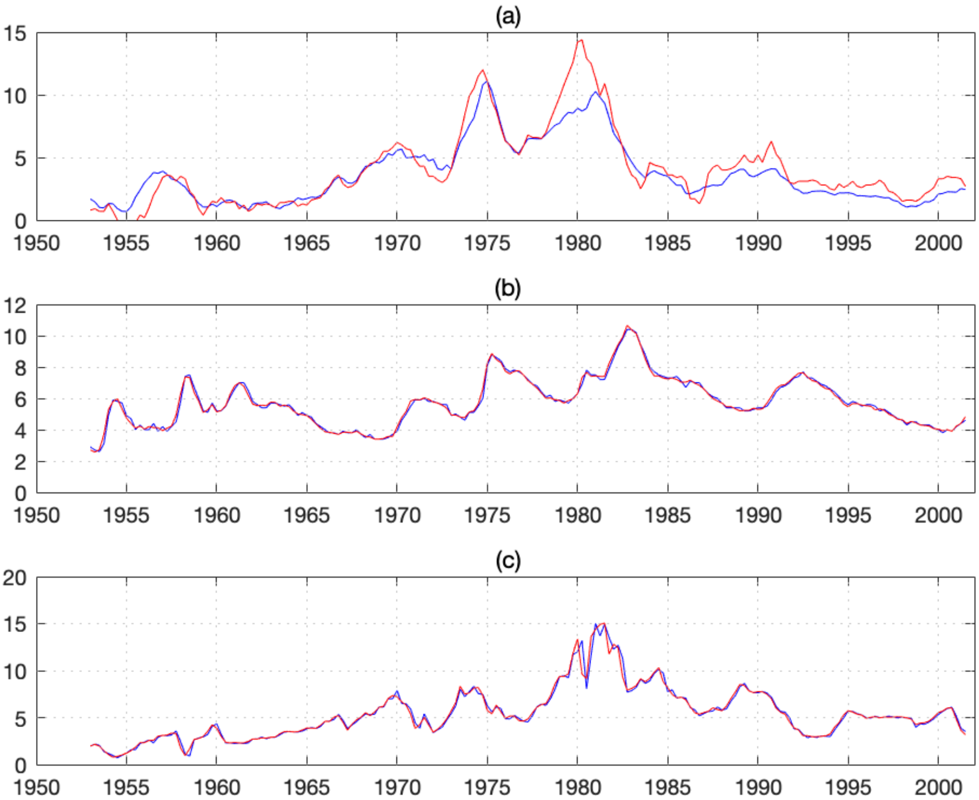
Figure 8: 20th order sample autocorrelations of B^T and the variances of the residuals, with (a) US data, (b) UK data.



B Data Comparison

In this section the data of the package of Fabian Krüger is compared to the data of the Federal Reserve of St. Louis. This is exhibited in Figure 9. The red lines indicate the data of the FRED, while the blue is that of the package. The unemployment rate and the 3-month Treasury bill rate seem to be almost indentical. The inflation rate however seems to be a little bit different at some points. Therefore the impulse response of inflation to monetary policy shocks is a little different that in Primiceri (2005). However, the results are still consistent and robust with Primiceri (2005).

Figure 9: Comparison of data of the package and FRED. Where red indicates FRED and blue the package and (a) as inflation, (b) as unemployment rate and (c) as 3-month Treasury bill rate.



C Code Explanation

As stated in the results section we used the *R* package *bvarsv*from Fabian Krüger. The code to compute the posterior means and impulse responses is also from Fabian Krüger and is obtained from https://sites.google.com/site/fk83research/code. In the RStudio folder both the code for the UK and US can be found. The last part in both scripted is written by myself to compute figure 8 (figure 9c in Primiceri (2005)). The 20th sample autocorrelation for the time varying coefficients is very straightforward. For the variances some computations were needed. First, for every time period t, the variance covariance matrix $\Omega_t = A_t^{-1} H_t (A_t^{-1})'$ is computed. Then for only the variances the 20th sample autocorrelation is computed.

I stored all the needed output in text files. Then computed the graphs in MATLAB. All the necessary code and data can be found in the MATLAB folder of the zip file.