Master Thesis

Henry Svedberg

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1 Introduction

Inflation refers to the general rise in prices, which erodes purchasing power and results in consumers being able to buy fewer goods and services with the same amount of money. It can arise from various factors such as increased demand for goods and services, rising production costs like higher wages, or anticipations of future price increases that lead consumers and businesses to change their spending behaviors accordingly. While these basic concepts are widely recognized, they form the foundation of understanding the critical role that central banks play in managing inflation.

Monetary policy is the most important factor policy makers can use to control the price (Tran 2018). Central banks rely on it in order to steer the inflation by adjusting policy rates, which influence a broader variety of economic acitvity suich as borrowing, spending and investment both by firms and individuals alike. For example, lowering the policy rate can stimulate economic activity by making borrowing cheaper, potentially leading to higher inflation if demand outstrips supply. Conversely, raising the policy rate tends to cool down an overheating economy, thereby reducing inflationary pressures. Many central banks rely on the technique called inflation target, where they try to steer the inflation rate to a specific threshold predetermined threshold value such as 2 percent, by estimating and projecting how the inflation is going to develop in the future and then using their monetary policy to steer it toward the target rate. This is to make it more predictable.

There exists a large literature on monetary policy and the mechanisms through which it affects inflation and economic activity; the transmission mechanism of the monetary policy has been thoroughly examined due to its importance for various reasons. Policymakers must have an adequate assessment regarding how the monetary policy affects the economy as well as the timing of the effects to determine the monetary policy at a specific point in time (Boivin et al. 2010). A brief summary of the transmission mechanism is given in section 2.3. Much of the previous research about the inflation rate and interest rates has typically revolved around making predictions. Usually by methods such as estimating VAR models and Granger causality for time series data, for example, revolving around analyzing monetary shocks.

Although these types of analyses have their usage, these are more oriented towards causal discovery, which is the task of identifying and understanding causal relationships in the data. However, such methods lack causal effect estimation, which is the estimation of the actual effect of a policy or treatment on a target variable. This is instead commonly done by other methods using metrics such as Average Treatment Effect (ATE), commonly associated with the causal inference framework as laid out by the Rubin Causal model. Whereas it has seen some use concerning policy rate and inflation, for example Angrist & Kuersteiner 2011. These are not as common as those based on Granger causality, and they still seem to be heavily focused on monetary shocks specifically.

This paper then, will try to fill in this gap in the literature that exists for the causal effect estimation of the policy rate on inflation. More specifically, this study aims to estimate d $E\left[(Y(R_1|x) - Y(R_0|x)\right] = \eta(R_1, R_0, x)$ the causal dose-response curve and obtain the full density of the causal dose-response curve. By doing so, this study will provide an alternative way of seeing the actual causal effect of the policy rate on the inflation

2 Previous research and theoretical framework

2.1 Monetary policy based on macroeconomic theories

This paper will not go into all the specific details about the monetary policy and its effects through which it affects the inflation rate by adjusting the policy rate. but a brief summary is as follows: The traditional view of monetary policy and the transmissions through which it affects the economy is based on the neoclassical channels, which are built on the neoclassical models of investment, consumption, and international trade (Gertler & Karadi 2015). Setting the short-term nominal interest rates gives the central banks control over the contemporaneous real rates as well as the expected rates in the future for some horizon ahead (Gertler & Karadi 2015). It is the real interest rates, hence not the nominal interest rates, that affect other asset pricing as well as the spending through the transmission channels. Furthermore, it is not only the current value of the interest rates but also the expected interest rates that affect economic activity (Gertler & Karadi 2015). However, it should also be noted that there are several different mechanisms through which the monetary policy affects inflation. These act in parallel and with different time frames. This section will limit it to mention the most frequently discussed channels.

In accordance with the traditional Keynesian models, monetary policy affects inflation through the interest rate channel; it can either be by adjusting the nominal money stock which affects the interest rate or more directly by through the policy rate by steering the overnight rate , which are the daily interest rates that typically banks use when lending and borrowing to one another, this, in turn, affects other interest rates in the economy such as the banks and mortgage institutions. In any event though, practically they fulfill same effects in that it impacts the aggregate output, employment and overall price levels (Mishkin 2016). The demand for capital is dependent on the price of the user capital, whether it be investment goods, residential housing or consumer durable. (Jorgenson 1963). Typically, businesses and households tend to look at the long horizon when factoring variation in interest rates into investment decisions. Although an increase of the policy rate increases the short-term nominal interest rates, it also increases the longer-term nominal interest rate, for example due to investors seeking to eliminate disparities of risk-adjusted expected return. This in turn will translate into changes in the real interest rates as well. Hence the user capital cost rises and the capital asset demand decreases due to increasing borrowing costs for both firms and individuals leading to lower spending on investment and in turn a decline in the aggregate spending and demand, which has a dampening effect on the inflation (Ireland 2010).

Another way that the transmission mechanism works is through the exchange rate channel for open economies; as a result of falling interest rates, the domestic currency depreciates vis-à-vis other currencies. This is due to the return on domestic assets decreasing compared to that of foreign assets. Hence the value of domestic assets decreases relative to other currency assets. This in turn causes domestic goods to be cheaper compared to foreign goods and an increase in foreign demand for domestic goods, thereby leading to expenditure switching - a switch between foreign and domestic goods - and hence a rise in net exports. Thus the increase in economic activity as a result from the higher aggregate demand raises the inflation. Hence, the exchange rate channel plays an important role in how monetary policy affects the economy (Taylor 2001).

Another example is the asset price channel described by Tobins q-theory (Tobin 1969), where tobins q is a ratio of the market value of a company's assets divided by the replacement cost of those assets. Low interest rates typically increase the q ratio by raising market values and lowering replacement costs, while high interest rates typically decrease the q ratio by lowering market values and raising replacement costs. For example, When q is lower, each firm has to issue more new shares of stock to finance any new investment project, making investment more expensive for the firm. Consequently, across all firms, investment projects that were only marginally profitable before monetary tightening now go unfunded due to the decline in q. This results in a decrease in output and employment (Ireland 2010).

Aside from those channels, there are others as well with one example being the credit channel. It will not be expanded upon here, but see for example Bernanke & Gertler (1995) or Kashyap & Stein (1994) for further details. However, the main point moving forward is that the way monetary policy works is an incredibly complex phenomenon and it is difficult to single out each individual effects. Nevertheless, the mechanism mentioned here are simply the main ones commonly mentioned within the literature. Furthermore it should also be noted that there there are other factors affecting the interest rates in a country and not only its monetary policy. For example, the general level of global interest rates. Hence the policy rate is not solely responsible for being the factor which affects the inflation rate, but it does nevertheless play an important role.

2.2 Causality debate

Though the causal relationship about interest rates as a tool for monetary policy to steer the inflation is widely known and accepted, there are some debate about its actual effectiveness; especially for developing countries (Islam & Ahmed 2023). A key aspect is the financial structure is different: for example the absence of effective and functional markets for things such as fixed income securities, equities and real estate. Furthermore, even though banks are the largest financial institutions, the financial system typically is small in relation to the total economy (Mishra & Montiel 2013). Developing countries typically have limited and imperfect connections with private international capital markets, leading their central banks to heavily intervene in foreign exchange markets.(Mishra et al. 2012). This distinct institutional context indicates that the monetary transmission mechanism in low-income countries may significantly differ from that in advanced and emerging economies. However, as this study is limited to only US and Swedish data, this aspect is not further analyzed since these are considered advanced economies as per the IMF definition (Nielsen 2011), (IMF 2023). Although one should keep in mind moving forward that potential results may not be generalize for other countries, it may be even more so for developing countries. For the remainder of the study though, it is assumed based on the macroeconomic theories that there already is an established causal relationship between interest rate and inflation.

Hence this study will consider three variables, inflation rate, unemployment rate and the policy rate. Although in some literature, a larger collection of variables are used, such as for example in Leeper et al. (1996), much of the literature considers these variables in particular such as for example one notable being Stock & Watson (2001). Also one reason to not include more variables is to try and keep the number of parameters low for the models used.

here i will expand some more later, especially whit regards to unemployment rate. Maybe i will write it in theory

2.3 literature overview

As mentioned in section 1, in general there has been a lot of research regarding the causality of interest rate and inflation. However, this section will limit this literature overview to focus on the statistical and econometrics literature. For a long time this methodological framework has been traditionally dominated by the use of VAR models, which began with the works by Sims (1980) and granger causality.

The concept of Granger causality is that some variable X is said to Granger to cause some other variable Y if past values of X help explain future values of Y, that is, it contains information about Y that is not available in Y's past (Moraffah et al. 2021). This is typically modeled by VAR models as:

$$Y_t = \sum_{\tau=1}^{\tau_{\max}} \phi(\tau) Y_{t-\tau} + e_t,$$

where $Y_t = (Y_{1t}, \ldots, X_{nt})$ indicates time series Y at time step t, $\phi(\tau)$ is the $N \times N$ coefficient matrix at lag $\tau, \tau_{\max}$ denotes the maximum time lag, and e represents an independent noise. Using this equation, we say $_i$ Granger causes Y_j with lag τ if any of the coefficients in $\phi_{ji}(\tau)$ is nonzero. This relationship can be shown by $Y^i_{t-\tau} \rightarrow Y^j_t$ which demonstrates the causal link between Y_i and Y_j at lag τ.

Some examples of the use of VAR models on this area are Arnoštová & Hurník (2005) and Tran (2018).

will probably fix this section a bit to make it more flowing

Adolfson et al. (2007) makes the argument that although models such as VARs may have good statistical properties and can be useful as a way to make good forecasts, they come with little economic theory and a drawback is that they typically are over parameterized. Having a large number of parameters causes imprecise estimates leading to large intervals for the pulse response functions. Hence VAR models cannot give more in depth answers about the monetary transmission mechanism and thus actual effect of monetary policy is not captured. One proposed solution is to instead incorporating Bayesian methods such as Bayesian Retrogressive (BVAR) models. These models are able to include some macroeconomic theory by the use of priors, for example such as the concept of the steady state of the system (Villani 2006). Another example is Berger & Österholm (2011), where they use BVAR to determine whether money growth Granger-causes inflation based on US data, for which including interest rate consistently gave better results.

However, with regards to casualty, it should also be noted that the results from these model cannot be attributed an direct causal interpretation, although they offer an in-depth analysis of varying statistical dependencies within a set of economic variables to better evaluate causality (Doan et al. 1984).

Nevertheless, others have also studied the relationship between interest rates and inflation by other methods. For example, in Fama (1975) found significant results in his hypothesis testing for the inflation and interest rates relationship

$$\mathbb{E}\left(X_i \mid \mathcal{I}_{i-1}\right) = \alpha + \sum_{j=1}^{p} \phi_j X_{i-j} + \sum_{r=1}^{q} \beta_r R_{i+1-r}, \tag{1}$$

for some order (p, q).

,

But as Xu et al. (2022) points it, there are limitations with this type of linear regression based framework: most importantly that there is reason to suspect that the relationship between inflation and interest rates may not be constant over a longer period of time. furthermore, The conditional mean represents the average return, but it doesn't provide much insight into the distribution of the return. Two distributions can have the same mean yet exhibit very different shapes, and overlooking these differences can lead to incorrect conclusions. In their work, Xu et al. (2022) used locally stationary quantile regression instead to model inflation and interest rates and came to two conclusions: the first was that inflation rate is positively correlated with one month lagged inflation rate for the quantiles considered. The second conclusion was the the relation between inflation and interest rates exhibits more complicated quantile-specific and time-varying features.

Depending on the final methods used,, i will try to add some more litterature related to that, as for example specific density estimation or such

3 Method

The method used for this paper can be split into two different parts. The first part is about testing the null hypothesis that the density is flat. This is done in section [to be filled in later]. Given that some results are found, then the next part consist of estimating the density itself, which is done in section3.2.

3.1 Non parametric test of the causal null

The following procedure and test are based upon the work done by Westling (2022). The main reason for this is that there is a severe gap in the literature regarding causal inference with nondiscrete exposures, hence the methods used by Westling can be seen as something new and something to later be expanded upon..

Whether an exposure of interest has a causal effect on a given outcome. In classical statical methods for association , causality can often be asserted due to randomization. In the case with observational data its more difficult due to potential confounding between the exposure and outcome. As Westling argues, in the stetting where the exposure is discrete there has been previous work done by others such as using matching estimators as done by Rubin (1973), or inverse probability weighted (IPW) estimators as laid by Horvitz & Thompson (1952). However, for settings where the exposure is continuous rather than discrete, there exist much less work.v Typically in the literature, the researcher transforms the exposure variable to a discrete variable ; this is not without drawbacks though, as depending on the decimalization the results will vary and also such tests tend to have less power than other tests based on the original continuous exposure, since making it discrete causes information loss Westling (2022).

In this case with the interest rate as a continues exposure and inflation as a continues outcome, we want to estimate the causal dose-response curve, which for each value of the exposure is the average outcome if all units are assigned to that value of exposure. If there is a causal relationship between the exposure and outcome, then it corresponds to the dose-response curve being non-flat. As Westling argues, one possibility of estimating the dose-response curve would be to assume that the regression for the outcome on the exposure and potential confounders follows al inear model. Given that the model is correctly specified, this would mean that the coefficient for the exposure corresponds to the slope of the dose-response curve. However, if the model is not correctly specified, the results would be inconsistent . Although IPS may be used, it would also inconsistent results if teh model for the propensity score was wrong. Hence this study will use non-parametric methods, as they are more robust due to them making less assumptions.

Moving foward, we denote $A \in \mathcal{A}$ = exposure of interest with support $A_0 \subseteq \mathcal{R}$. Based on the Neyman-Rubin potential outcomes, then for each

for each $a \in \mathcal{A}_0$, , we have that $Y(a) \in \mathcal{Y} \subseteq \mathcal{R}$ is a unit's potential outcome by setting exposure to $A = a$. Then we have that $:m(a) := E[y(a)]$ is the average outcome under assignment of the entire population to exposure level $A = a$. This leads to the causal dose-response curve: $m : \mathcal{A} \rightarrow \mathcal{R}$.

We want to test the null hypothesis: s: $m(a) = \gamma_0$ for all $a \longrightarrow \mathcal{A}_0$ and some $\gamma_0 \in \mathcal{R}$, that is, the dose-response curve is flat.

This is true if and only if the value of exposure assigned to units does not influence the average value of the potential outcomes. However, due to the fact that we cannot observe $Y(a)$ for all units, but instead the outcome $Y := Y(A)$. Hence, m is not actually a mapping of the joint distribution of the pair (A, y), with the consequence that the null hypothesis of it begin flat cannot actually be tested by the observed data. In order to do make this testable, we first need to make some assumptions:

1. Each unit's potential outcomes are independent of all other unit's exposure

2. The observed outcome Y almost surely equals $Y(A)$.

Then assuming both assumptions hold, we further have that:

3. $Y(a) \perp\!\!\!\perp A$ for all $a \in \mathcal{A}_0$,

If this is all true, then m would be identifiable using univariate regression,, and the null hypothesis would be testable using parametric approaches. The problem here however, is that the third assumptionis only valid where A is randomly assigned, which is not the case for observational studies where the problem of confounding variables affecting both A and $Y(a)$ causing nonparametric regression to have invalid type 1 error rates.

If we instead have a collection $W \in \mathcal{W} \subseteq \mathbb{R}^p$ of confounds, then given that assumption 1 and 2 we also the following assumptions:

4. $Y(a) \perp\!\!\!\perp A \quad W$ for all $a \in \mathcal{A}_0$, (no unmeasured confounding)

5. all $a \in \mathcal{A}_0$ are in the support of the conditional distribution of A given $W = w$ for almost every w

In that case, then $m(a = \theta_0(a) := E\left[E(Y|A = a, W), \right]$, which is a G-computed regression function, from the work developed by Robins (1986).

Hence giving that all assumption 1-2, and 4-5 hold, then m is flat on $\mathcal{A}_0$ if and only if θ_0 is flat on $\mathcal{A}_0$

Note, I don not intend to simply leave it like for all the steps mentioned below. However, this is the steps that Westling highlights in his article and which i don't fully understand.

Step 1: Split the sample into V sets $\mathcal{V}_{n,1}, \ldots, \mathcal{V}_{n,V}$ of approximately equal size.

Step 2: For each $v \in \{1, \ldots, V\}$, construct estimates $\mu_{n,v}$ and $g_{n,v}$ of the nuisance functions μ_0 and g_0 based on the training set $\mathcal{T}_{n,v}$ for fold v.

Step 3: For each a in the observed values of the exposure $\mathcal{A}_n := \{A_1, \ldots, A_n\}$, use $\mu_{n,v}$ and $g_{n,v}$ to construct $\Omega^\circ_n(a)$ as defined in (2).

Step 4: Let $T_{n,\alpha,p}$ be the $1-\alpha$ quantile of $\left(\frac{1}{n}\sum_{i=1}^{n}|Z_n(A_i)|^p\right)^{1/p}$ for $p<\infty$ or $\max_{a\in\mathcal{A}_n}|Z_n(A_i)|$ for $p=\infty$, where, conditional on $O_1,\ldots,O_n$, $(Z_n(A_1),\ldots,Z_n(A_n))$ is distributed according to a mean-zero multivariate normal distribution with covariances given by $\Sigma_n\left(A_i,A_j\right):=E\left[Z_n(A_i)Z_n\left(A_j\right)\mid O_1,\ldots,O_n\right]=\frac{1}{V}\sum_{v=1}^{V}\mathbb{P}_{n,v}D^*_{A_i,n,v}D^*_{A_j,n,v}$ for $D^*_{a_0,nv}(y,a,w)$ equal to

$$
\begin{aligned}
&\left[I_{(-\infty,a_0]}(a)-F_{n,v}(a_0)\right]\left[\frac{y-\mu_{n,v}(a,w)}{g_{n,v}(a,w)}+\theta_{n,v}(a)-\gamma_{n,v}\right]\\
&+\int\left[I_{(-\infty,a_0]}(u)-F_{n,v}(a_0)\right]\mu_{n,v}(u,w)F_{n,v}(du)\\
&-2\Omega_{\mu_{n,v},F_{n,v},Q_{n,v}}(a_0)
\end{aligned}
$$

where $\theta_{n,v}(a):=\int\mu_{n,v}(a,w)dQ_{n,v}(w)$ and $\gamma_{n,v}:=\iint\mu_{n,v}(a,w)dF_{n,v}(a)dQ_{n,v}(w)$

Step 5: Reject H_0 at level α if $n^{1/2}\left\|\Omega_n^\circ\right\|_{F_n,p}>T_{n,\alpha,p}$.

3.2 Density estimation

In order to estimate the density, we use non parametric methods.

Density estimation is the process of estimating some underlying probability density function by using the obserbed data. There are various methods; both parametric methods where the data generating process is from a known family of distribution, or nonparametric methods which are able to more flexible estimate unkown distributions

Nonparametric smoothing regression is a type of regression analysis used to estimate the relationship between a dependent variable and one or more independent variables without assuming a predefined form (like a linear or polynomial form) for the relationship. This flexibility allows the model to adapt more closely to the actual data, making it particularly useful in situations where the relationship between variables is complex or unknown.

Nonparametric estimation makes it possible to model relationships among variables while robust against functionfal form of misspecification, making it able to detect structure that may otherwise not would be detected Racine & Li (2004).

Smoothing refers to that predictions being weighted averages of the observed responses in the training data:

$$
\widehat{r}(x)=\sum_{i=1}^{n}y_i w\left(x,x_i,b\right) \tag{2}
$$

where h is the bandwidht that controlls the degree of smoothing

Smoothing very little ($h \to 0$), means that the model is able to very small details of any potential "true" regression function- Less smoothing leads to less bias. However, it also causes each of the predictions to be an average of fewer observations, making the predictions more noisy. Hence smoothing increases the variance.

Since we have the relationshjip: Total error = noise + bias^2 + variance, and that changing the amount of smoothing affects both bias and variance, there is an optimal amount of smoothing which we want to find. This is done by cross-validation, and the bandwidth with the lowest error under cross-validation is then used to fit the regression curve for all the data.

More specifically in order to estimate the density by adaptting a Cross-validated local linear estimator with the method developed by Racine & Li (2004) and Li & Racine (2004).

Consider a non parametric regression model

$$y_j = g\left(x_j\right) + u_j, \quad j = 1, \ldots, n, \tag{3}$$

Here we have that x_j is a continuous random vector of dimension q. . Then the derivative of $g(x)$ is defined as $\beta(\boldsymbol{x}) \stackrel{\text{def}}{=} \nabla g(\boldsymbol{x}) \equiv \partial g(\boldsymbol{x})/\partial x(\nabla g(\cdot)$ is a $q \times 1$ vector).

Then

$$\delta(x) = (g(x), \beta(x)')'$$

Hence, $\delta(x)$ is a $(q+1) \times 1$ vector-valued function whose first component is $g(x)$ and whose remaining q components are the first derivatives of $g(x)$.

By Taylor expanding $g(x_j)$ at x_i, the result is:

$$g\left(x_j\right) = g\left(x_i\right) + \left(x_j - x_i\right)' \beta\left(x_i\right) + R_{ij} \tag{4}$$

where $R_{ij} = g\left(x_j\right) - g\left(x_i\right) - \left(x_j - x_i\right)' \beta\left(x_i\right)$.

Then equation 3 can be rewritten as:

$$\begin{aligned} y_j &= g\left(x_i\right) + \left(x_j - x_i\right)' \nabla g\left(x_i\right) + R_{ij} + u_j \\ &= \left(1, \left(x_j - x_i\right)'\right) \delta\left(x_i\right) + R_{ij} + u_j. \end{aligned} \tag{5}$$

A leave-one-out local linear kernel estimator of $\delta(x_i)$ is obtained by a kernel weighted regression of y_j on $\left(1, \left(x_j - x_i\right)'\right)$ given by

$$\begin{aligned}\hat{\delta}_{-i}(x_i) &= \begin{pmatrix}\hat{g}_{-i}(x_i)\\ \hat{\beta}_{-i}(x_i)\end{pmatrix}\\ &= \left[\sum_{j\neq i} W_{h,ij}\begin{pmatrix} 1, & \left(x_j - x_i\right)' \\ x_j - x_i, \left(x_j - x_i\right)\left(x_j - x_i\right)' & \end{pmatrix}\right]^{-1} \sum_{j\neq i} W_{h,ij}\begin{pmatrix}1\\ x_j - x_i\end{pmatrix} y_j,\end{aligned} \tag{6}$$

where $W_{h,ij} = \prod_{s=1}^{q} h_s^{-1} w\left(\left(x_{js} - x_{is}\right)/h_s\right)$ is the product kernel function and $h_s = h_s(n)$ is the smoothing parameter associated with the s th component of x.

Define a $(q+1)\times 1$ vector e_1 whose first element is one with all remaining elements being zero. The leave-one-out kernel estimator of $g(x_i)$ is given by $\hat{g}_{-i}(x_i) = e_1'\hat{\delta}_{-i}(x_i)$, and we choose $h_1, \ldots, h_q$ to minimize the least-squares crossvalidation function given by

$$CV\left(h_1, \ldots, h_q\right) = \sum_{i=1}^{n} \left[y_i - \hat{g}_{-i}(x_i)\right]^2. \tag{7}$$

We use $\hat{h} = \left(\hat{h}_1, \ldots, \hat{h}_q\right)$ to denote the cross-validation choices of $h_1, \ldots, h_q$ that minimize equation 6. Having computed $\hat{h}$ we then estimate $\delta(x)$ by

$$\begin{aligned}\hat{\delta}(x) &= \begin{pmatrix}\hat{g}(x)\\ \hat{\beta}(x)\end{pmatrix}\\ &= \left[\sum_{i=1}^{n} W_{\hat{h},ix}\begin{pmatrix} 1, & (x_i - x)' \\ x_i - x, (x_i - x)(x_i - x)' & \end{pmatrix}\right]^{-1} \sum_{i=1}^{n} W_{\hat{h},ix}\begin{pmatrix}1\\ x_i - x\end{pmatrix} y_i\end{aligned}$$

where $W_{\hat{h},ix} = \prod_{s=1}^{q} \hat{h}_s^{-1} w\left((x_{is} - x_s)/\hat{h}_s\right)$, and we estimate $g(x)$ by $\hat{g}(x) = e_1'\hat{\delta}(x)$.

4 Data

The data set used for this is Panel data obtained by combining several different individual monthly time series data for the inflation rate, policy interest rate as well as the unemployment for USA and Sweden. Originally the individual time series for the different variables have different lengths since the starting years for each of them vary, but they all end in either December 2023 or January 2024. However, the data for the Swedish policy rate is the shortest of the individual time series due to it starting in June 1994 since that is when the data consistently started being tracked monthly. Hence, for the combined panel data used in this study, the other time series have been limited to also start from June 1994 to make it more comparable.

All the data is collected from various public governmental sources. The Swedish policy interest rate is from the Swedish Central Bank Riksbanken, and the inflation rate as well as the unemployment rate is retrieved from Statistics Sweden (Statistika Centralbyrån, SCB). The US Fed Funds rate is retrieved from the US Federal Reserve Bank, and the data for the unemployment and consumer price index is retrieved from the U.S. Bureau of Labor Statistics.

For both the US and Swedish data, the concept of inflation is operationalized through the consumer price index CPI, which is a measurement of the change in prices of goods and services acquired for private domestic consumption, based on weighted averages for specific sets or baskets of products (U.S. Bureau of Labor Statistics), (Statistics Sweden). Hence this is used as a proxy for the overall rate of inflation. There are different measurements one can use for the CPI such as the actual CPI value, or for example monthly differnces. For this study, the focus will be on the 12 month percentage change. That is, the difference percentage difference for one month compared ot the same month one year ago, since this is the measurement commonly used when referring to the inflation rate Sweden (2024).

Regarding the unemployment rate, it should be noted that whereas they are roughly similarly defined in the Swedish and US cases, there are some differences in some of the details. In general, the unemployment rate for both countries refers to the people who are part of the labor force, meaning that they do not currently have a job but are actively seeking a job. Hence, people without jobs but who are not actively seeking jobs are not considered unemployed. For the US data, this data is originally collected from surveys done by Bureau of Labor Statistics, whereas the Swedish data is obtained from Arbetskraftundersökningarna (AKU), a survey done by Statistics Sweden. Thus there are some differences in the exact method by which the surveys were done such as the target population for the survey as well as some of the definitions used in the surveys. There have also been some changes over the years. For example, in 2021 AKU made some changes due to a new framework law implemented by the EU; this included changes in the target population of the surveys as well as some definitions used, and hence comparisons between the periods before and after this date are not strictly straightforward, (SCB 2023) However, SCB has worked on making the time series comparable through different means such as imputations. Nevertheless, overall this is considered a minor problem for this study, and potential differences are not further analyzed for this study.

4.1 Summary statistics

Table 1: Summary statistics for the different variables

	n	mean	sd	median	min	max	skew	kurtosis
swe_CPI	355	1.72	2.25	1.40	-1.90	12.30	2.46	7.47
us_CPI	355	2.53	1.64	2.30	-2.00	9.00	1.22	3.26
us_interest	355	2.45	2.24	1.75	0.05	6.54	0.37	-1.52
swe_interest	355	2.26	2.30	2.00	-0.50	8.91	0.84	0.39
us_unemployment	355	5.62	1.82	5.20	3.40	14.80	1.43	2.27
swe_unemployment	355	7.60	1.16	7.60	4.90	10.50	0.15	-0.66

Table 1 shows some summary statistics for the different variables. Comparing the Swedish and US data it can be seen that the US inflation rate on average is higher than the Swedish inflation rate at 1.72 compared to 0.21 as defined by their respective consumer price indices (CPI). These values seem reasonable with the inflation target rate of 2 percent in mind. Furthermore, the Swedish inflation rate exhibits more variation as indicated by the higher standard deviation at 2.25 compared to 1.64, as well as having a higher degree of asymmetry as indicated by the higher skewness. The Swedish CPI shows relatively high kurtosis at 7.47 and compared to 3.26 for the US, indicating a relatively fat tail for its distribution.

Comparing the interest rates, it can be seen that they are considerably closer to each other with regard to almost all aspects.

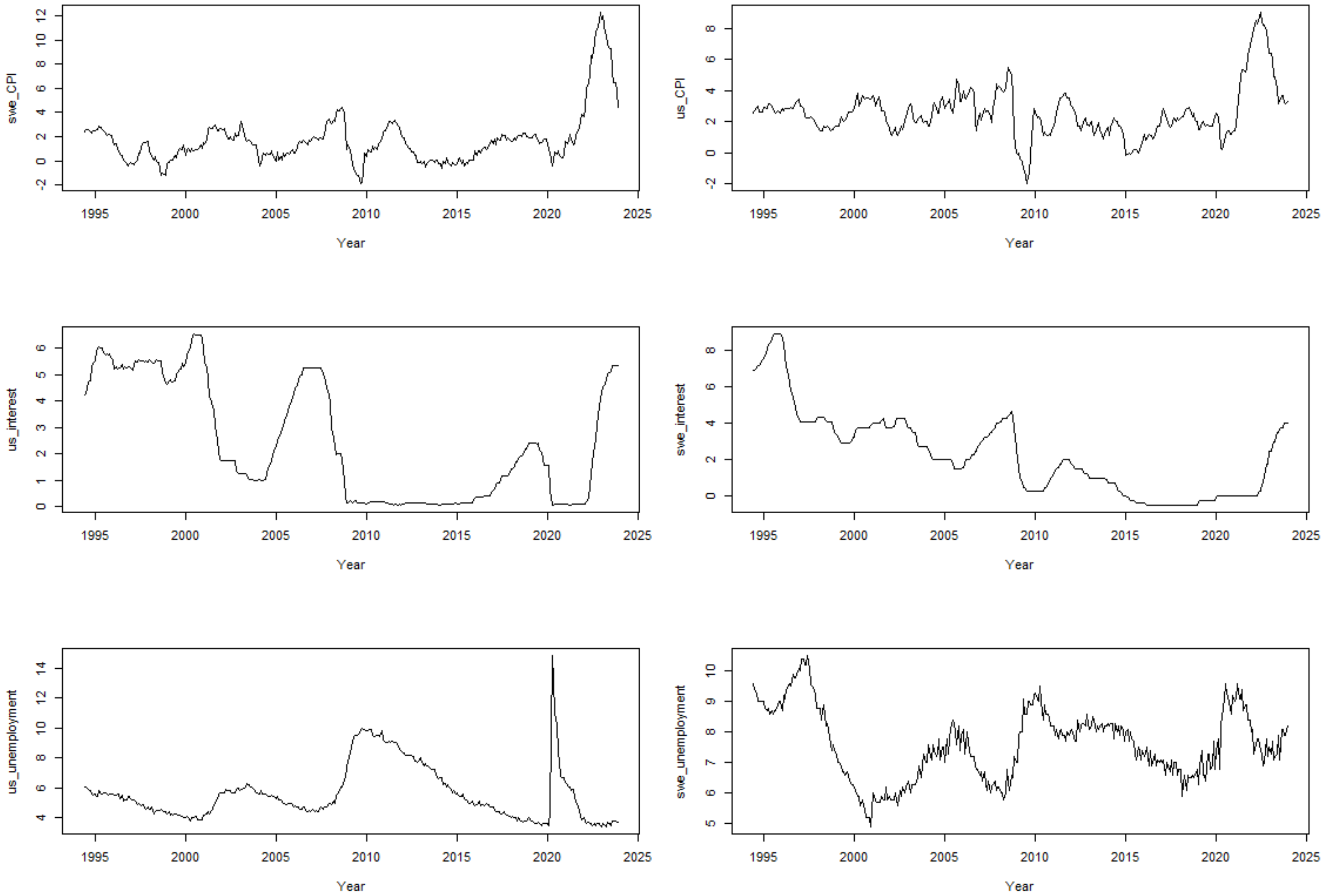

Figure 1: Variables over time

Figure 1 shows the different variables plotted over time. The visualized plots seem consistent with the results in table 1; the inflation rate for both countries seems fairly stable over time, though for the Swedish CPI there is one noticeable outlier for December 2022 at 12.3 percent. The interest rates are unemployment rates for both countries seem to roughly follow a similar pattern to each other concerning the overall trend and their different peaks during the different years. This is likely due to both countries following the same economic cycle and thus having both of the respective central banks taking similar action.

5 Results

Table 2: Ljung-Box test for white noise

	statistic	parameter	p.value
swe_CPI	2379	12	0.00
us_CPI	113	12	0.00
us_interest	3444	12	0.00
swe_interest	3410	12	0.00
us_unemployment	2386	12	0.00
swe_unemployment	2899	12	0.00

Example results of density: Swe data

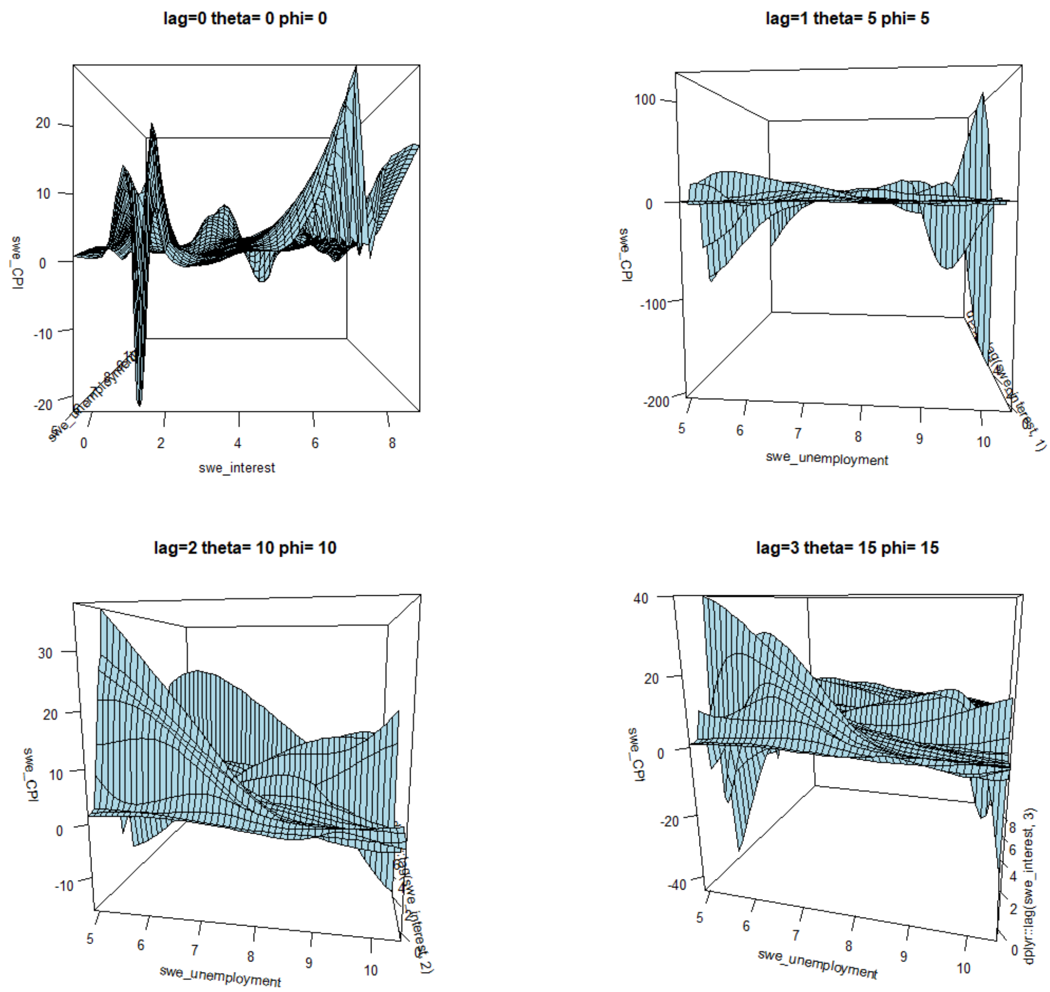

Figure 2: swe1

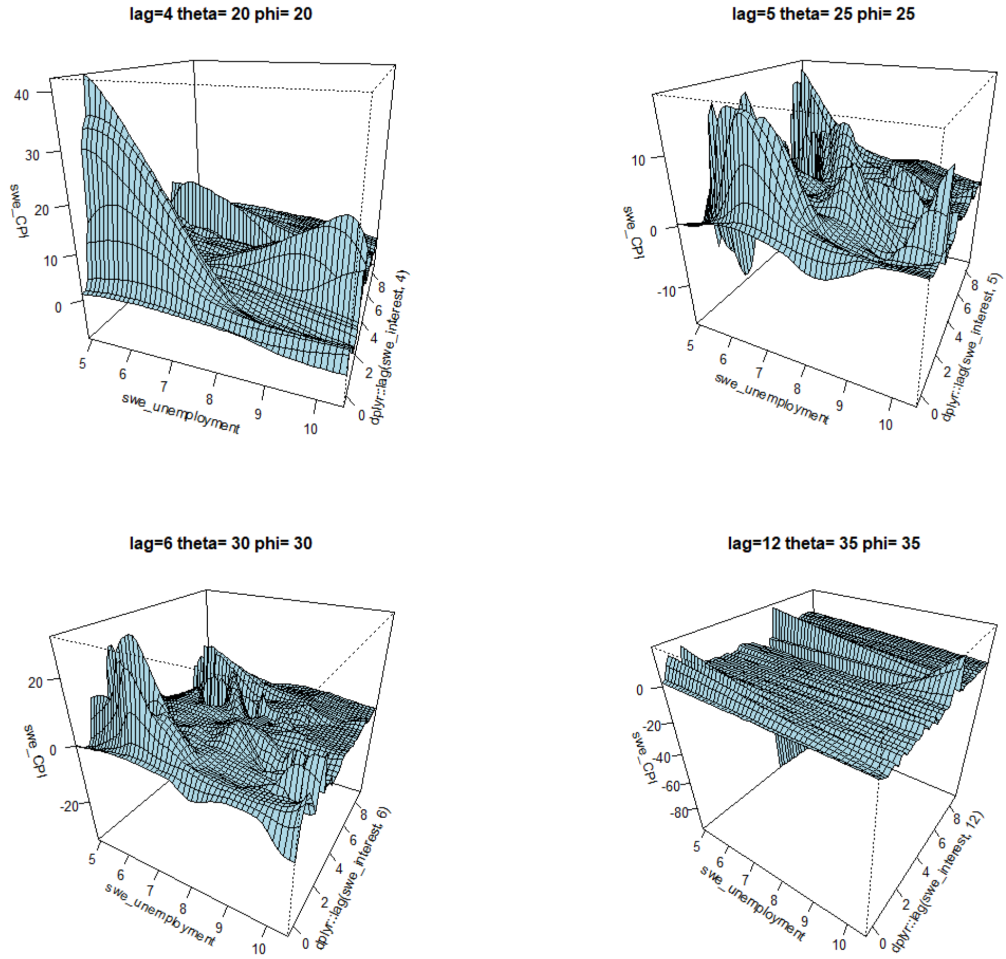

Figure 3: swe2

US results:

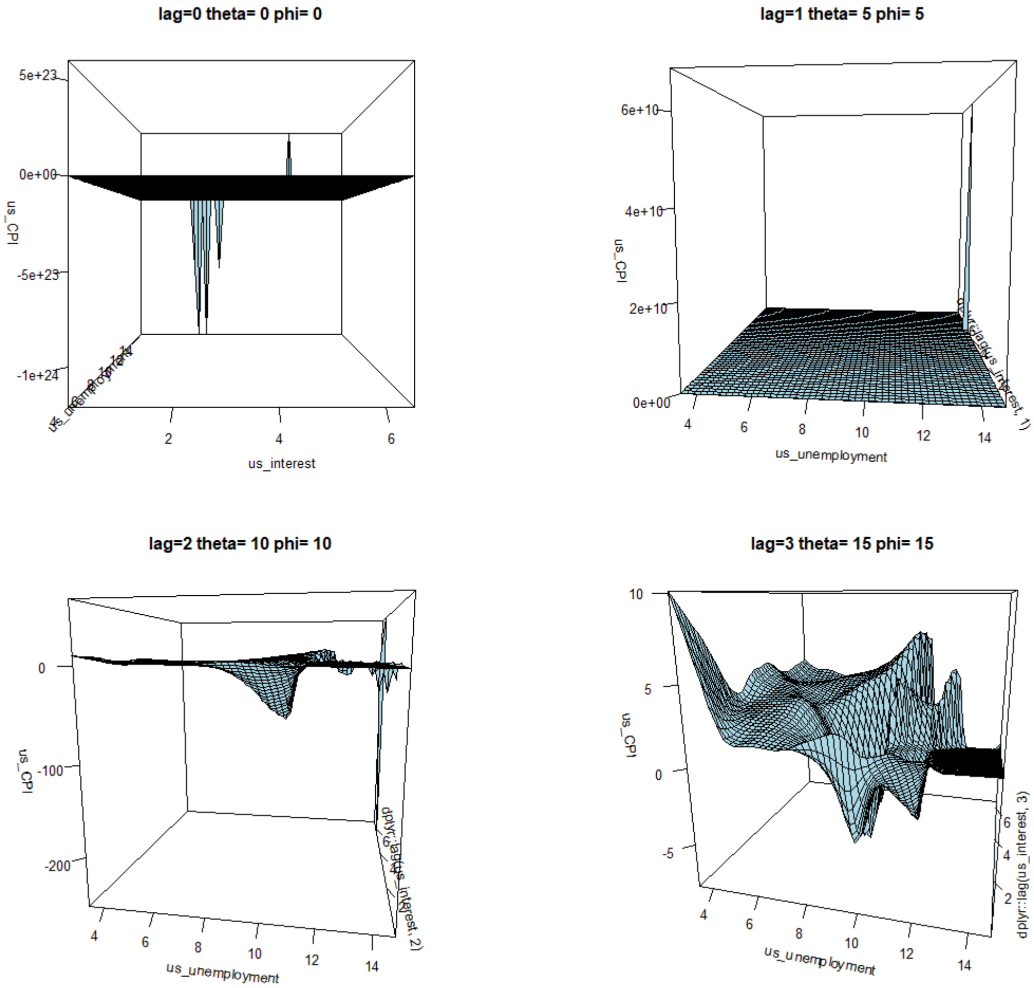
lag=0 theta= 0 phi= 0
5e+23
0e+00
-5e+23
-1e+24
us_CPI
us_interest
2
4
6
lag=1 theta= 5 phi= 5
6e+10
4e+10
2e+10
0e+00
us_CPI
us_unemployment
4
6
8
10
12
14
lag=2 theta= 10 phi= 10
0
-100
-200
us_CPI
us_unemployment
4
6
8
10
12
14
dplyr::lag(us_interest, 2)
lag=3 theta= 15 phi= 15
10
5
0
-5
us_CPI
us_unemployment
4
6
8
10
12
14
dplyr::lag(us_interest, 3)
2
4
6

Figure 4: us1

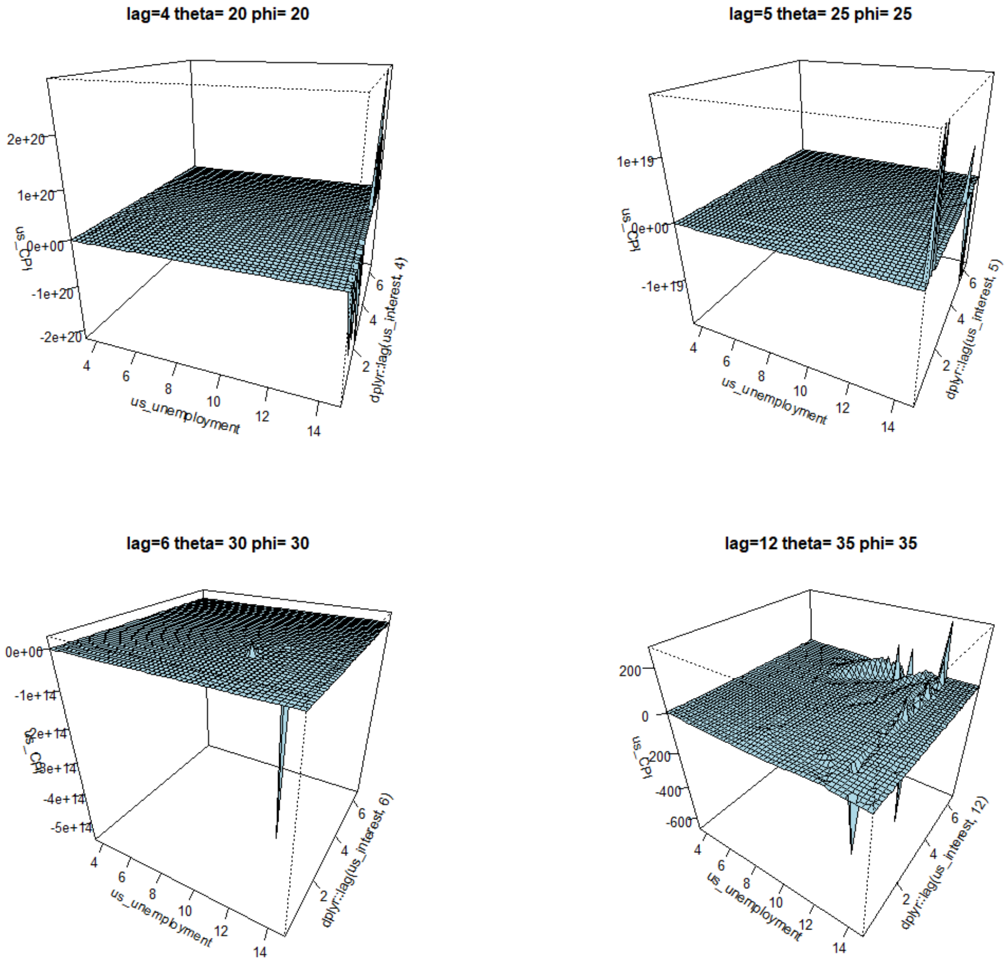
lag=4 theta= 20 phi= 20
us_CPI
2e+20
1e+20
0e+00
-1e+20
-2e+20
us_unemployment
4
6
8
10
12
14
dplyr::lag(us_interest, 4)
2
4
6
lag=5 theta= 25 phi= 25
us_CPI
1e+19
0e+00
-1e+19
us_unemployment
4
6
8
10
12
14
dplyr::lag(us_interest, 5)
2
4
6
lag=6 theta= 30 phi= 30
us_CPI
0e+00
-1e+14
-2e+14
-3e+14
-4e+14
-5e+14
us_unemployment
4
6
8
10
12
14
dplyr::lag(us_interest, 6)
2
4
6
lag=12 theta= 35 phi= 35
us_CPI
200
0
-200
-400
-600
us_unemployment
4
6
8
10
12
14
dplyr::lag(us_interest, 12)
2
4
6

Figure 5: us2

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