The Inverse Relationship Between Inflation and Unemployment

Abstract:

In this paper, I attempt to verify the inverse relationship between inflation and unemployment rates (the Phillips Curve). Using annual data from the U.S. between 1960 & 2010, I apply vector autoregression and determine there is not a clear inverse relationship, but there is Granger-causality in both directions. The nature of the relationship is difficult to clearly state, but is best illustrated by examining the impulse responses of the variables. I find that the Phillips Curve does not hold over such a long period of observations, but may be possible to confirm over shorter periods.

Introduction:

Since the birth of the Keynesian school of economics, economists have sought to understand forces interacting within an economic system and how a government's fiscal and monetary policies should be tailored to influence forces in the system. Two primary measures which have been studied extensively are unemployment and inflation. In the late 1950's, A.W. Phillips observed an inverse relationship between the two when examining data from the UK (Mankiw, 2019). Although there are myriad studies and papers around this topic, I wanted to investigate for myself if the Phillips Curve holds for a real sample of data.

There is no shortage of existing literature on the unemployment-inflation problem. I'll be reviewing literature on the evolution of the Phillips Curve since its introduction. I'll also explore some papers that approach the issue in a broader scope, taking other factors into account such as GDP and government spending.

In this paper, I will explore inflation and unemployment data from the US from 1960 through 2010. First, I'll use ARIMA modeling to determine behaviors of each set independently. Then I'll employ VAR modeling techniques to discover the relationship between the two time-series sets. After analysing the results of the VAR model, establishing Granger causality, and examining impulse response functions, I will offer conclusions based on those results and compare my results to the expectation of establishing an inverse relationship.

Literature Review:

I want to look first at how perceptions of the Phillips Curve have changed as real world conditions have changed. In its original form, Phillip's theory was very simple and took into account only inflation and unemployment rates. The theory seemed to hold through the 1960s, although some economists argued that the model was overly simplistic and did not hold in the long run. Economic conditions exacerbated by apparent missteps in government policies in the 1970's did show a breakdown in the simple Phillips model. This was evidenced by a contradictory state of high inflation and high unemployment known as stagflation. In the years since, observations have led economists to consider only unemployment that deviates from the natural rate of unemployment, and to include other factors of expectations of inflation and supply shocks when forecasting inflation. Empirical evidence does continue to demonstrate that in any form, the Phillips Curve only holds in the short term (Federal Reserve Bank San Francisco, 2021).

While this slightly more complex model does seem more useful as a predictive tool, some argue that variations of the original Phillips are no more accurate a predictor of inflation rates than inflation rates themselves in the short term. In 2001, Atkenson and Ohanian conducted a study of the predictive accuracy of modern versions of the Phillips Curve against their "naive" model. The naive model stated that the expected rate of inflation would be the same as the inflation over the previous four quarters, simply expressed as $E_t(\pi_{t+4} - \pi_t) = 0$. They compared the naive model against three more complex versions which took into account factors such as unemployment, the PCE deflator, CPI, core CPI, and GNP using regression analysis in the scope of one year. They concluded "for the last 15 years, economists have not produced a version of the Phillips Curve that makes more accurate inflation forecasts than the from a naive model." (Atkenson, A. & Ohanian, L., 2001). The study shows using the Phillips Curve with any variety of factors, including unemployment, there was "no evidence that any such indicator reliably signals short-term changes in inflation." (Atkenson, A. & Ohanian, L., 2001).

Another study examined the predictive abilities of the Phillips Curve over the long run. Yizhuo Qin applied VAR methods to examine inflation and unemployment data in a range similar to ours, from Q2 of 1962 through Q4 of 2019. The model built estimating coefficients of four lags of the first difference of the two variables. The study found that unemployment Granger-causes inflation, but inflation does not Granger-cause unemployment. In testing the impulse response of each variable, Qin found that the Phillips Curve did hold. A positive inflation shock resulted in an initial negative response on unemployment, but became positive in the long term. Likewise, a shock in unemployment resulted in an immediate decrease in inflation, but the result was very short lived and eventually settled to around zero. Based on this analysis, Qin concluded that although its robustness does fade somewhat as the scope of time lengthens, the Phillips Curve holds in both the short and long terms. This implies that governments can in fact use the two indicators to inform policy decisions (Qin, 2020).

A different VAR analysis focusing on the period from Q1 2000 to Q2 2020 found much less promising results. This study seeks to use the Phillips Curve and GDP numbers as a tool to predict the likelihood of recession, particularly in the context of the onset of the Covid-19 pandemic, and offer relevant findings as a guide for advising monetary policy. The model is structured using GDP as a function of itself, inflation, and unemployment with one lag. The findings of the study were insignificant as the model was unable to forecast any predictions reliably. The study's author was reluctant to difference the data for the model, so was subject to outliers that caused residuals to be more significant than white noise (Wessels, 2020). I hope to avoid such a trivial result in my VAR model by differencing the data to ensure stationarity.

Data:

Table 1 - U.S. 1960-2010

Variable	# of Obs	Min	Mean	Max	Standard Deviation
Unemployment Rate (%)	51	3.500	5.982	9.700	1.551606
Inflation Rate (%)	51	-0.356	4.062	13.549	2.863878

Table 1 provides descriptive statistics for the two time-series variables. Annual data regarding unemployment rates were obtained through datahub.io, and annual data on inflation rates were sourced from Worldbank's database.

Chart 1 - Inflation Rates

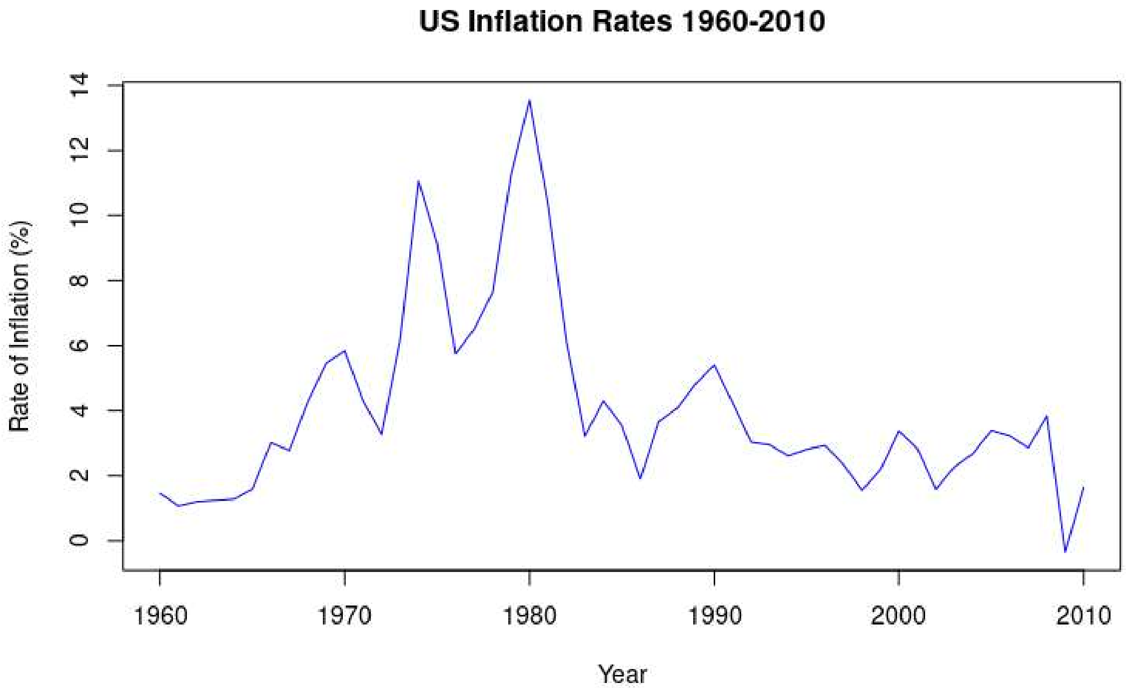
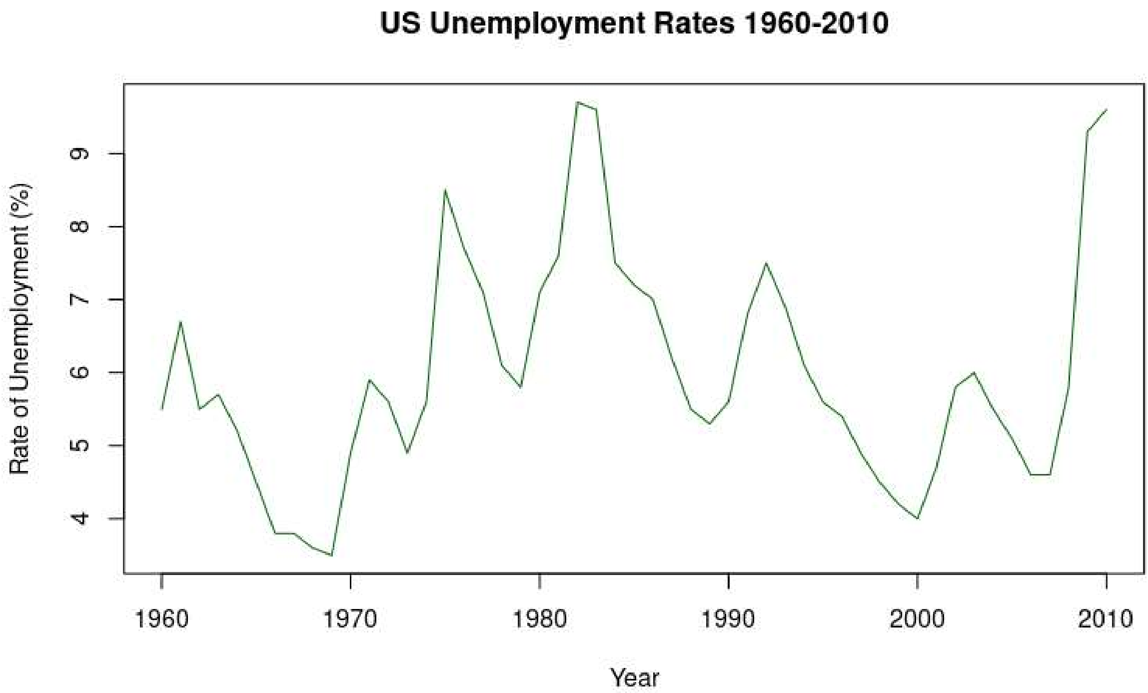


Chart 1 shows the fluctuations in interest rates over a period of 51 years. Graphically, the data seem fairly volatile, especially in the 1970s & early 1980s. Beginning around 1970, inflation rates seem to fluctuate wildly and suddenly until the early 1980s, after which time rates seem to revert around a short-term mean of about 2%.

Chart 2 illustrates the path of the unemployment rate over the same time period. One noticeable feature can give us insight into the existence of an underlying natural rate of unemployment. Unemployment only briefly dips below 4% in the late 1960s, suggesting the natural rate of unemployment is somewhere between 0% and 3.5%. Although the graph doesn’t pin this down to an exact number, it does provide an estimated range.

Also interesting to note is the previously mentioned period of stagflation in the 1970s and early 1980s. This is made apparent by the similar movements in that period on both Chart 1 & Chart 2, where we see the sharp and sudden movements in the same direction for both variables.

Chart 2 - Unemployment Rates



<u>Econometric Model:</u>

The model was built assuming a two equation system for a Vector Autoregressive model, starting with the general form:

$$y_t = \beta_{10} + \beta_{11}\, y_{t-1} + \beta_{12}\, y_{t-2} + \dots + \beta_{1p}\, y_{t-p} + \alpha_{10}\, x_{t-1} + \dots + \alpha_{1p}\, x_{t-p} + \epsilon_t$$

$$x_t = \beta_{20} + \beta_{21}\, y_{t-1} + \beta_{22}\, y_{t-2} + \dots + \beta_{2p}\, y_{t-p} + \alpha_{21}\, x_{t-1} + \dots + \alpha_{2p}\, x_{t-p} + \upsilon_t$$

Rather than considering any other exogenous variables, I wanted to approach each as functions of the other. I first wanted to establish the stationary form for each data set. After visually examining the first difference of both variables, I performed a Dickey-Fuller test to confirm that both data sets were stationary around their first difference (there was no unit root). To get some preliminary idea of the autoregressive and moving average terms, I looked at the ACF and PACF for both variables. The spike patterns suggested AR(1) for both variables (see Appendix A). I also ruled out any autocorrelation for either variable by running a Ljung-Box test. The results were that I could not rule out the null hypothesis that there was no autocorrelation, so I could assume that any residuals were white noise. I confirmed that one lag was optimal by running the varselect command, resulting in the lowest Akaike Information Criteria score at one lag.

I now had a model of the form:

$$\Delta U_t = \alpha_0 + \alpha_1 \Delta U_{t-1} + \alpha_2 \Delta I_{t-1} + \epsilon_t$$
$$\Delta I_t = \beta_0 + \beta_1 \Delta I_{t-1} + \beta_2 \Delta U_{t-1} + \upsilon_t$$

Analysis & Results:

The VAR model yielded the following solutions for the two equation system:

Table 2

Dependent Variable	Coefficient	Value	Independent Variable	Value	Coefficient	Dependent Variable
ΔU_t	α_0	0.036	constant term	0.069	β_0	ΔI_t
	α_1	0.449	ΔU_{t-1}	-0.745	β_2	
	α_2	0.303	ΔI_{t-1}	-0.010	β_1	

The results, although somewhat surprising, are at 95% confidence or greater. It appears that past values for unemployment and inflation positively determine current unemployment, but negatively determine current inflation rates.

I then performed a Granger test on the model. I concluded that inflation Granger-causes unemployment. Having a p-value of 0.0003054, much smaller than the threshold of 0.05, I was able to reject the null hypothesis that inflation does not Granger-cause unemployment. Testing for reverse Granger-causality resulted in a p-value of 0.005297, so I was able to reject the null-hypothesis that unemployment does not Granger-cause inflation.

Lastly, I explored how a shock in one variable impacted the other by examining impulse response functions over a period of 10 years. I found that a shock in inflation resulted in an increase in unemployment over the first 2 years, and decreased thereafter. The confidence interval contained zero after the 3 period, so there was no lingering effect on unemployment after the 3rd year (see Chart 3). A shock in unemployment resulted in a sharp decline in inflation for the first two periods, but again the confidence interval contained zero starting just shy of the 2nd period and continued to do so thereafter.

Chart 3

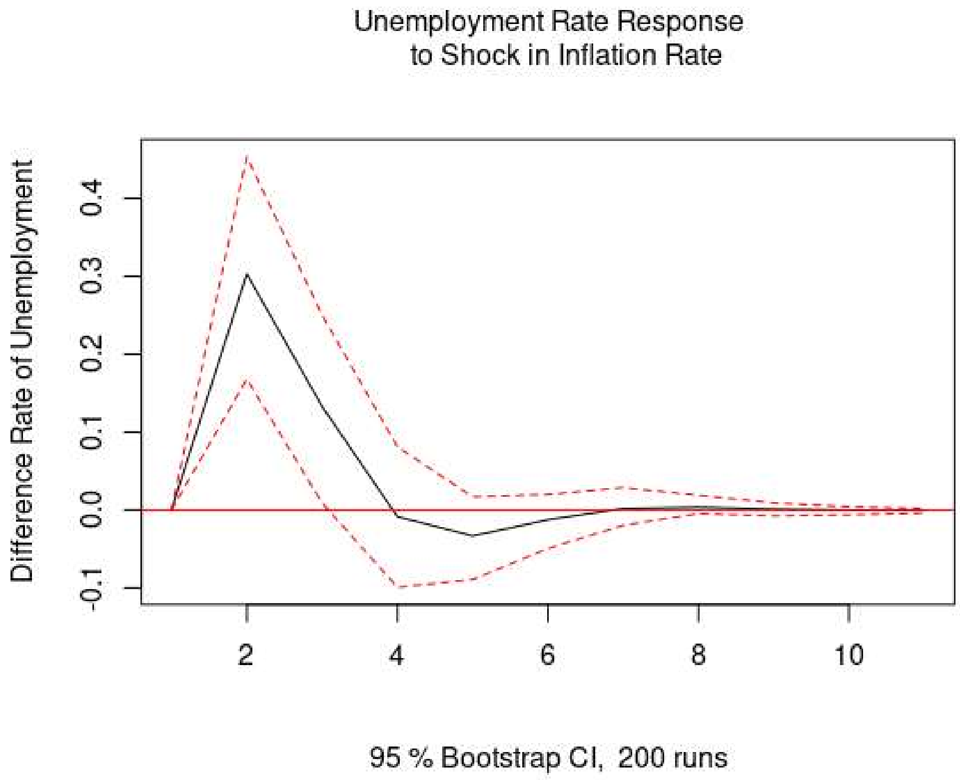
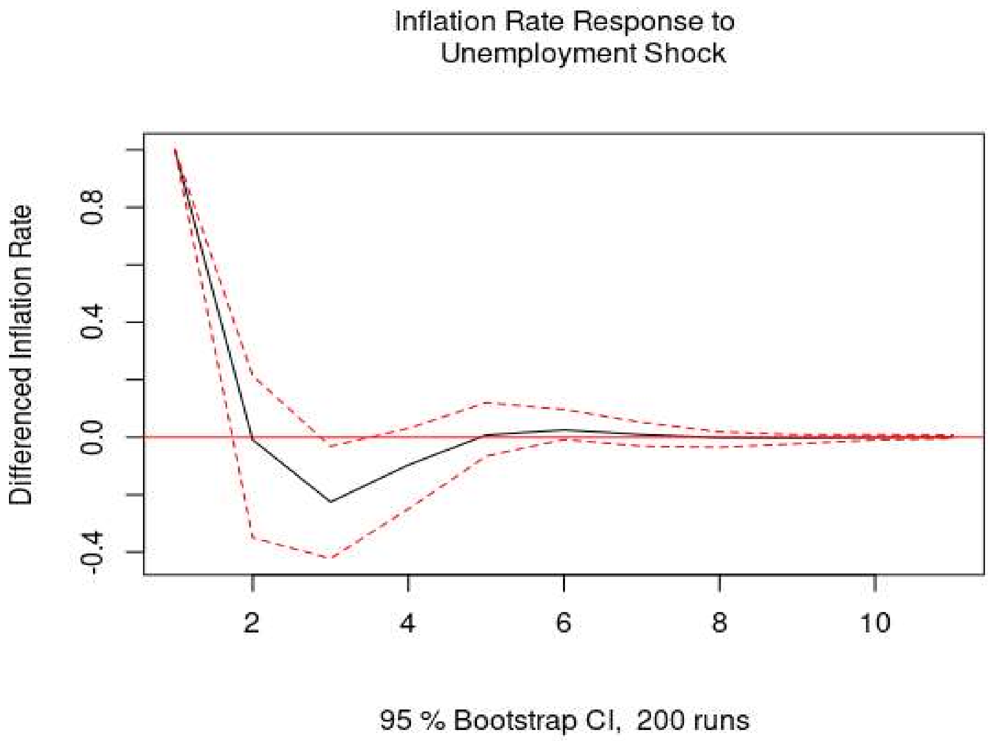


Chart 4



Conclusion:

The goal of this study was to confirm the inverse relationship between inflation rates and unemployment rates, using real data and a simplistic bivariate model. Although I was able to establish Granger causality with both variables, it was not consistent with the hypothesis that the two were inversely related. The coefficients of my VAR model contradicted the Phillips Curve significantly. When looking at inflation as a function of itself and unemployment, I expected a positive coefficient for the inflation variable and a negative coefficient for the unemployment variable. Instead, both coefficients were negative. This somewhat supported our hypothesis, however the model broke down when examining unemployment as a function of itself and inflation. Here, the coefficients were both positive, meaning I've shown a positive relationship between the two variables.
The impulse response functions further showed the model's break from the hypothesis. While the shock to unemployment did show an immediate and severe decrease in inflation, a shock to inflation caused a positive response to unemployment rates. Additionally it should be noted that responses of both were quite short-lived before the confidence intervals inclusion of zero discounted the validity of longer term responses of the model.

The inclusion of data from the period of stagflation likely had a strong influence on my model's robustness as it consisted of a significant portion of all the data (roughly 24%). Knowing that nearly a quarter of the data contradicted the hypothesis, it's not surprising that the model failed to confirm it. I would recommend reexamining the model based on shorter time periods to identify a more consistent version. This would seek to provide for more robust results which could then be used to advise on short term economic objectives regarding inflation and unemployment. A brief look at a particular subset of the data (1963-1969) seems to show that the hypothesis would be strongly supported in the short run (see Appendix A - Chart 5).

I conclude that the Phillips Curve does not hold in the long run in its simple form. Based on existing literature, it's possible that it holds only in the short term, or maybe even not at all. This implies the theory is not useful for informing decisions around monetary or fiscal policies focusing on long run objectives.

References:

Atkenson, A., Ohanian, L. (2001) Are Phillips Curves Useful for Forecasting Inflation? *Federal Reserve Bank of Minneapolis Quarterly Review*. 25(1). 2-11. Available from: DOI https://doi.org/10.21034/qr.2511

Federal Reserve Bank of San Francisco. (2021) *Dr. Econ, what is the relevance of the Phillips curve to modern economics?*. Available from: https://www.frbsf.org/education/publications/doctor-econ/2008/march/phillips-curve-inflation/ [Accessed December 8, 2021].

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Pkgstore.datahub.io. (2021) Available from: https://pkgstore.datahub.io/core/employment-us/at1_csv/data/d7e5ec6ea0340e846fd84ae6a69519c2/aat1_csv.csv [Accessed December 6, 2021].

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Wessels, NT. (2020) *VAR Analysis of Economic Activity, Unemployment, and Inflation during Periods Preceding Recessions in the United States: COVID-19*. Available from: https://econ.unc.edu/wp-content/uploads/sites/38/2020/09/VAR-Analysis-of-Economic-Activity-Unemployment-and-Inflation-during-Periods-Preceding-Recessions-in-the-United-States-COVID-19.pdf [Accessed December 8, 2021].

The World Bank. (2021) Available from: https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?locations=US [Accessed December 6, 2021].

Appendix A - Additional Material

Chart 5

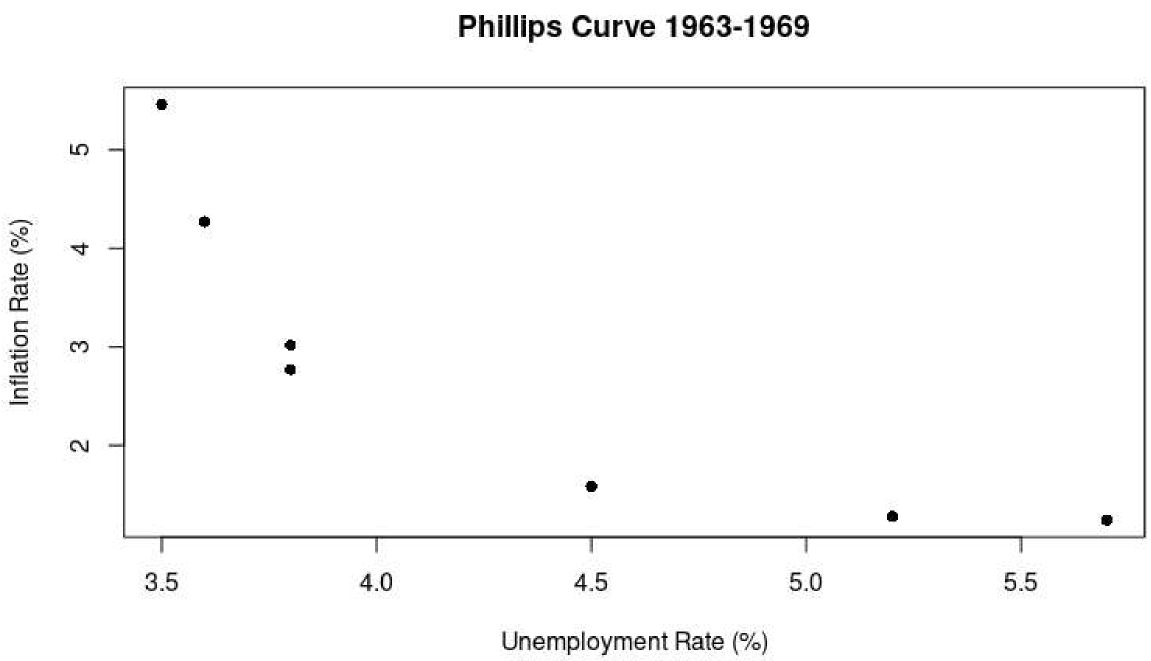

Chart 6 - ACF inflation

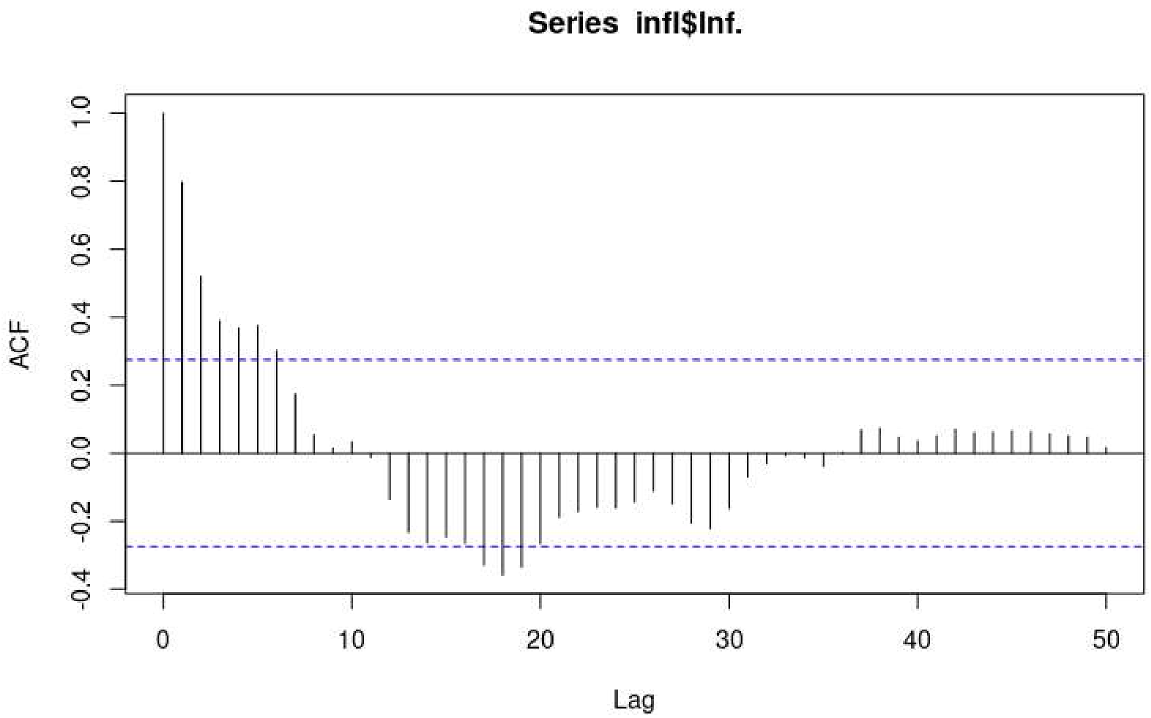

Chart 7 - PACF inflation

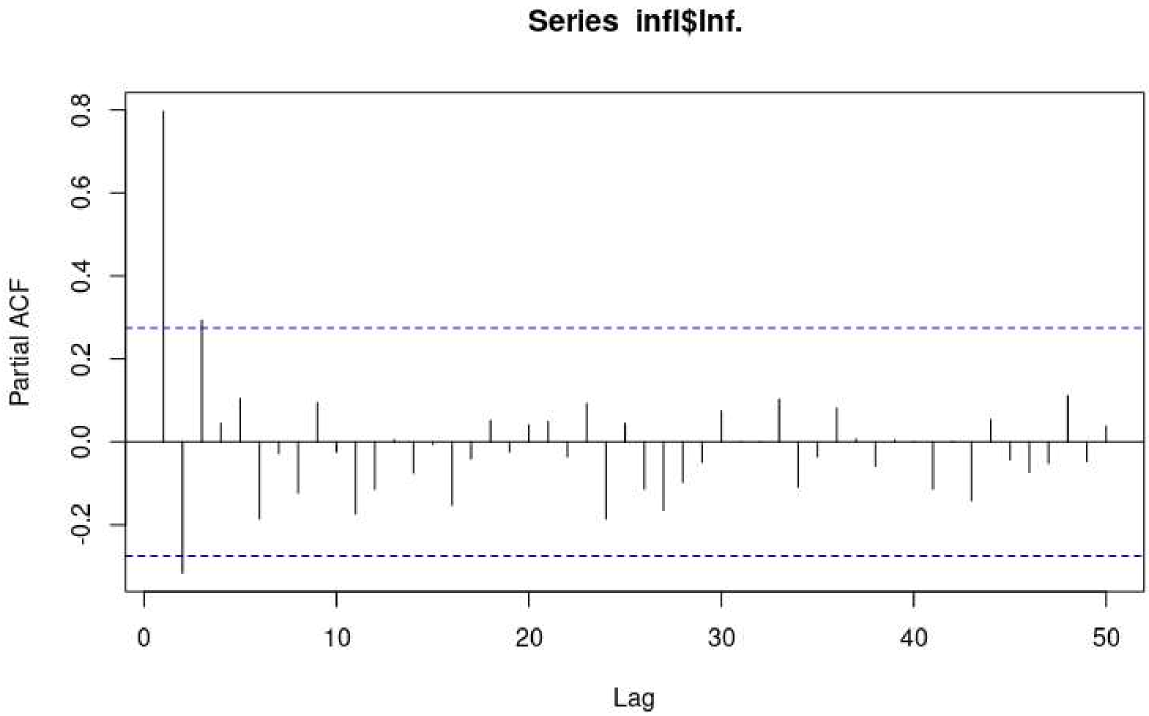

Chart 8 - ACF unemployment

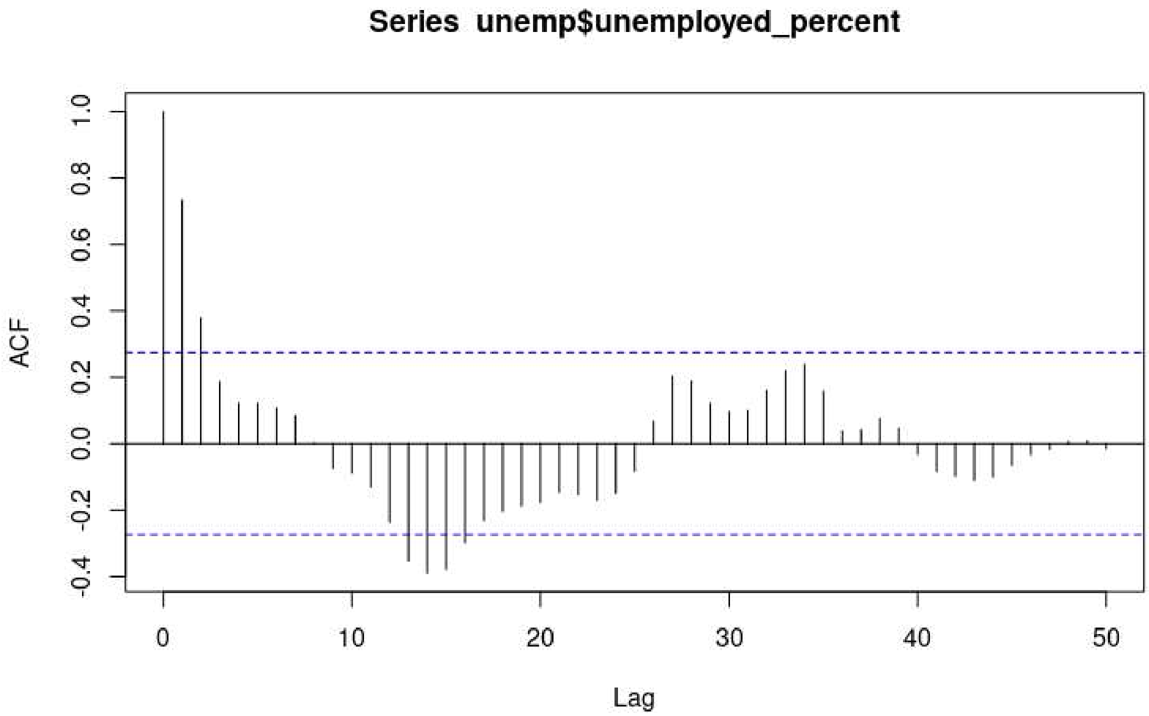

Chart 9 - PACF unemployment

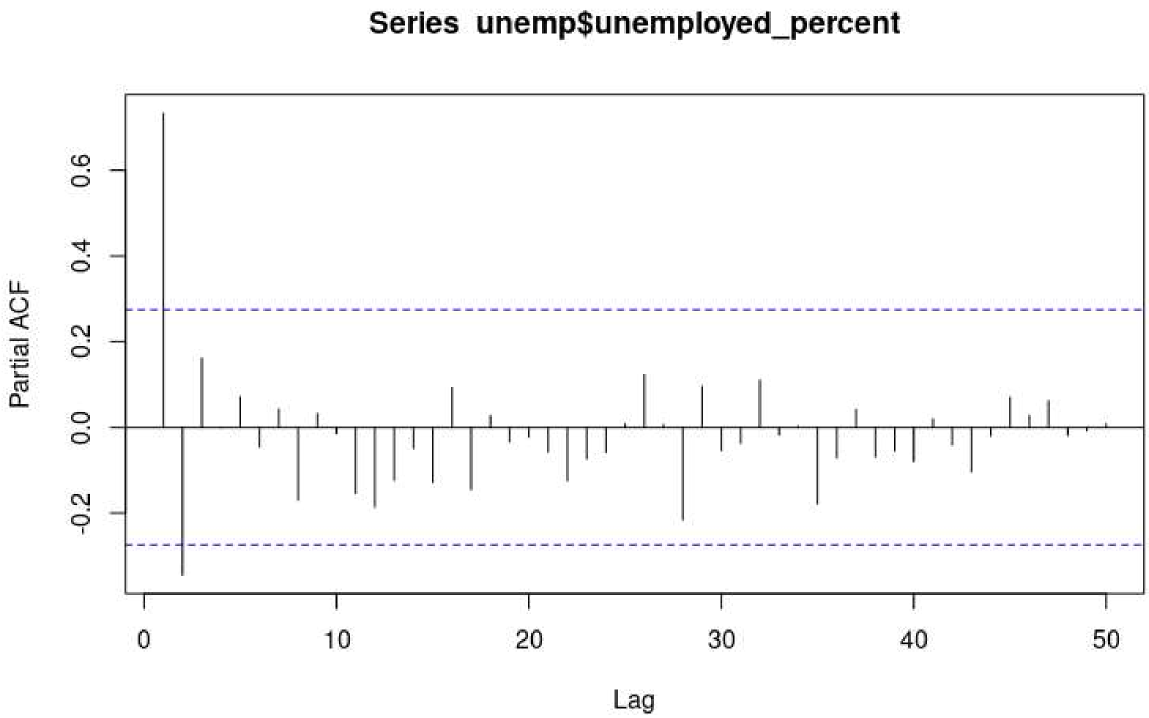

Chart 10 - First difference of inflation

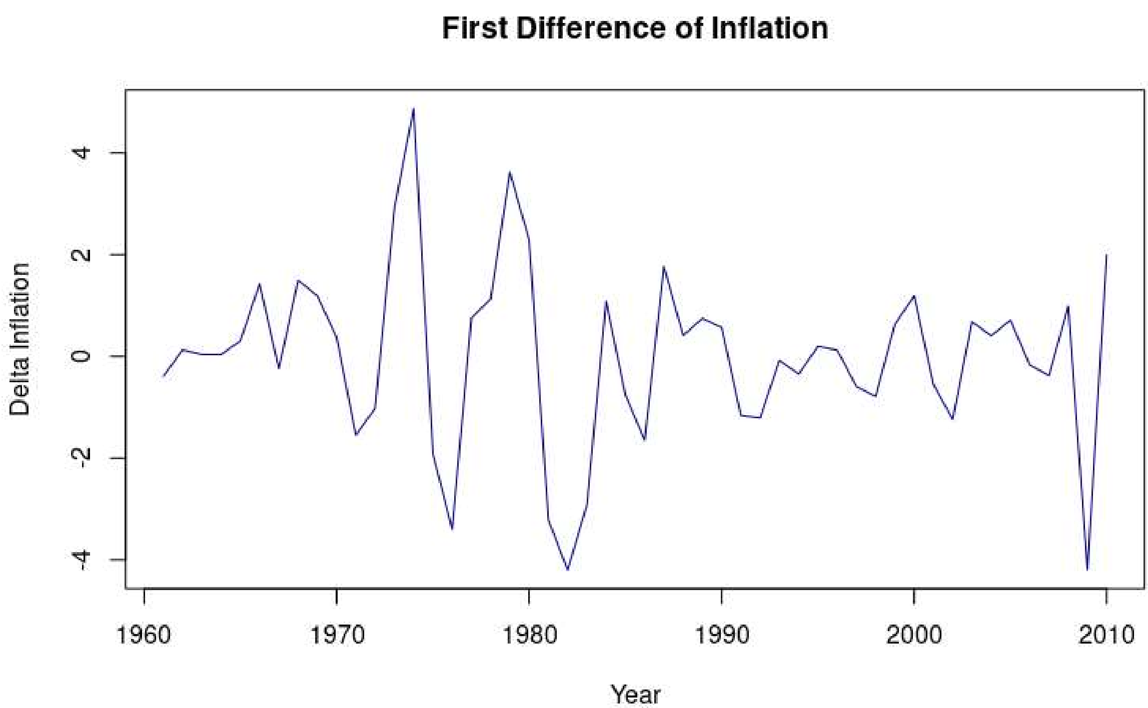

Chart 11 - First difference of unemployment

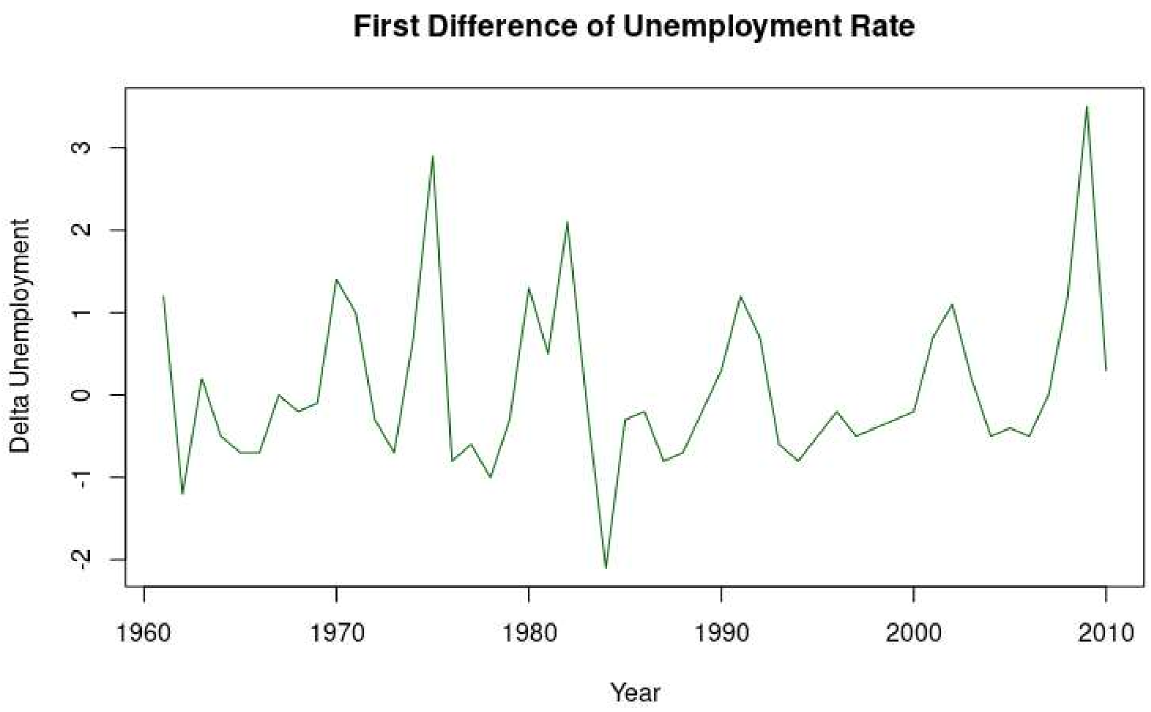

Table 3 - VAR model coefficients from r

	Dependent variable: y (1)	(2)
Dinf.l1	-0.010	0.303***
	(0.148)	(0.078)
Dunemp.l1	-0.745***	0.449***
	(0.255)	(0.134)
const	0.069	0.036
	(0.237)	(0.125)
Observations	49	49
R2	0.179	0.293
Adjusted R2	0.143	0.262
Residual Std. Error (df = 46)	1.657	0.870
F Statistic (df = 2; 46)	5.015**	9.536***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix B - r code

```
setwd("/cloud/project")

install.packages("readr")
install.packages("tidyverse")
install.packages("urca")
install.packages("stargazer")
install.packages("vars")

library(readr)
library(tidyverse)
library(urca)
library(stargazer)
library(vars)
rm(list=ls())

infl <- read.csv("Infl_Emp - Inflation.csv")
unemp <- read.csv("Infl_Emp - Unempl rates.csv")

#scatterplot to see if follows Phillips curve
plot(unemp$unemployed_percent,infl$Inf., main = "Does this look like Phillips curve?")
abline(lm(infl$Inf. ~ unemp$unemployed_percent))

#try limiting data to 1963-1969

unemp60s <- unemp[-c(1:3,11:51), ]
infl60s <- infl[-c(1:3,11:51), ]
plot(unemp60s$unemployed_percent,infl60s$Inf., main = "Phillips Curve 1963-1969",ylab =
"Inflation Rate (%)",xlab = "Unemployment Rate (%)", pch = 16)


#summary stats

summary(unemp)
sd(unemp$unemployed_percent, na.rm = TRUE)
summary(infl)
sd(infl$Inf., na.rm = TRUE)

#look at data visually
plot(infl$Year,infl$Inf.,type = "l", ylab = "Rate of Inflation (%)", xlab = "Year",
    main = "US Inflation Rates 1960-2010", col = "blue")
plot(unemp$Year,unemp$unemployed_percent,type="l", main = "US Unemployment Rates
1960-2010",
    ylab = "Rate of Unemployment (%)", xlab = "Year", col = "darkgreen")
```

```
#neither seem stationary, so taking first difference
Dinf <- diff(infl$Inf.,differences = 1)
plot(infl$Year[2:51],Dinf,type="l", main="First Difference of Inflation", ylab = "Delta Inflation",
    xlab = "Year", col="darkblue")

Dunemp <- diff(unemp$unemployed_percent,differences = 1)
plot(unemp$Year[2:51], Dunemp, type = "l", main = "First Difference of Unemployment
Rate",
    ylab = "Delta Unemployment", xlab = "Year", col="darkgreen")

#first differences look a bit better - both appear to be mean-reverting around zero
#let's run ADF to check for stationarity

DFinf <- ur.df(Dinf,type="none",selectlags = "AIC")
summary(DFinf)
#Value of test-statistic is: -6.6487, & p-value is tiny, so we can reject the null hypothesis
#that data is not stationary
DFune <- ur.df(Dunemp, type = "none", selectlags = "AIC")
summary(DFune)
#again, good results: test-statistic is -5.2364 and p-val tiny, so data is stationary

#now let's get our first differences into their own object to play with
varmod <- data.frame(Dinf,Dunemp)

#let's take a look at potential #s of lags
VARselect(varmod,lag.max = 10,type = "none")

#AIC measure indicates one lag is optimal, so now let's build model on one lag
var_inf_unemp <- VAR(varmod,p=1,type = "const")
summary(var_inf_unemp)

#Check for serial correlation
BGtest <- serial.test(var_inf_unemp,lags.bg = 5, type = "BG")
BGtest
#p-value is 0.7544, meaning we can accept the null hypothesis that there is no serial
correlation

#make pretty
stargazer(var_inf_unemp[["varresult"]],type = "text")

#Look at Granger causality
gtest1 <- grangertest(Dinf ~ Dunemp, order = 1, data = varmod)
#null hypothesis is that Dunemp does not help predict Dinf
gtest1
#p-value is 0.005297 < 0.05, so at 95% confidence, we can reject null hypothesis and
conclude
```

#Dunemp is useful at predicting Ding

gtest2 <- grangertest(Dunemp ~ Dinf, order = 1, data = varmod)
#null hypothesis is that Dinf does not help predict Dunemp
gtest2
#p-value is 0.0003054 < 0.05, so at 95% confidence, we can reject null hyposthesis and conclude
#Dinf is useful at predicting Dunemp

#Unemployment Granger causes inflation, and inflation Granger causes unemployment

#let's do IRFs
irf_Dinf_Dunemp <- irf(var_inf_unemp,impulse = "Dinf", response = "Dunemp", n.ahead = 10,
    ortho = FALSE, runs = 200)
plot(irf_Dinf_Dunemp, ylab = "Difference Rate of Unemployment", main = "Unemployment Rate Response
    to Shock in Inflation Rate")

irf_Dunemp_Dinf <- irf(var_inf_unemp,impluse = "Dunemp", response = "Dinf", n.ahead = 10,
    ortho = FALSE, runs = 200)
plot(irf_Dunemp_Dinf, ylab = "Differenced Inflation Rate", main = "Inflation Rate Response to
    Unemployment Shock")

#For giggles (and more graphs), let's look at ARIMA models for each variable
install.packages("forecast")
library(forecast)

#let's look at ACF and PACF for unemployment to try to determine ARIMA order

acf(unemp$unemployed_percent, lag.max = 50)
pacf(unemp$unemployed_percent, lag.max = 50)
#both graphs highly suggestive of AR(1) and MA(1); let's have r estimate best model
arimaunemp <- auto.arima(unemp$unemployed_percent, trace = TRUE)
summary(arimaunemp)
#indeed, r indicates best model is AR(1) and MA(1)
#check that residuals are white noise using Ljung-Box test
Box.test(arimaunemp$residuals, lag = 10, type = "Lj")
#since p-val is 0.9525, we cannot reject null hypothesis is there is no serial correlation
#so we can presume residuals are white noise

#let's repeat same ARIMA analysis for inflation
acf(infl$Inf.,lag.max = 50)
pacf(infl$Inf.,lag.max = 50)
#again, both ACF and PACF looking very much like AR(1) and MA(1)

```
arimainfl <- auto.arima(infl$Inf., trace = TRUE)
#huh, r says 0,1,0
summary(arimainfl)
#BUT! we notice r didn't try 1,0,1 so let's try manually

arimainflman <- arima(infl$Inf., order = c(1,0,1))
summary(arimainflman)
#hazaa! aic for 1,0,1 is 197.85, which is less that aic for 0,1,0
#let's check for serial correlation now that we have a better fitting model
Box.test(arimainflman$residuals, lag=10, type = "Lj")
#p-val is 0.8516 so we can't reject null hyp that there is no serial corr
#therefore assume residuals are white noise.
```