The Relevance of Phillips Curve in Italy

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Abstract

Using Italian data, the relationship between unemployment and inflation was examined building on the principles of Phillips curve. The findings of the present study revealed that while the Phillips curve was relevant in explaining inflation in the past, it is now less relevant since the last decade. Future research is needed to investigate the indicators of inflation that are more suitable for this century.

1 Introduction

Since the end of World War II, the nation of Italy has seen the formation of 66 governments (approximately one every 1.14 years) each with their own manifestos. Nevertheless, two very common mandates the new federation usually aims to achieve involve unemployment and inflation rates. Ideally, low unemployment is preferable; specifically, unemployment should be lower than the non-accelerating inflation rate of unemployment (NAIRU), which can be challenging as evidently, NAIRU is constantly changing (Staiger et al., 1997). Furthermore, low to moderate inflation rate is favourable. However, as solidly established in literature, for example, in one of the earliest paper by Phillips (1958), there is a negative relationship between unemployment and inflation rate. This means that it is impossible for governments to strive for both low unemployment and low inflation rates; instead, they would have to somehow find middle ground. By making the different unemployment rate-inflation rate combinations accessible, the Phillips curve is thus, a useful tool for policy makers to decide the desired trade-off. This then leads to the research question of: "How well does the Phillips curve apply to the economy of Italy, and is unemployment still a significant factor of explaining inflation?"

2 Theoretical Background

There are quite a number of empirical challenges when it comes to modelling inflation. Besides unemployment, there are many other different factors, both direct and indirect, that explain inflation; these include lagged variables of inflation itself as well as lagged variables of other economic indicators. One prominent factor of inflation could be crude oil prices, as crude oil is a very important commodity used in the manufacturing of many daily life objects such as plastics, synthetic materials, asphalt, roads, plane fuel and more. It is commonly subjected to supply shocks (e.g. natural disasters, war, etc.) which in turn, affects inflation (Álvarez et al., 2011). Another potential factor of inflation may be short-term interest rates. In particular, as interest rates decrease and more people take out loans, for every loan a bank receives, money is created out of thin air according to the Credit Creation Theory well documented by Werner (2014). This newly unproductive created money then goes into the stock market and other speculative assets, increasing the money supply and ultimately leading to positive asset inflation, bubbles and banking crises. Similarly, other researchers (eg. Lavoie, 1995) have suggested that interest rates stimulate economic growth which in turn, influences inflation.

3 Empirical model and data

The provisional model is a general dynamic model explained with contemporaneous variables for unemployment, oil prices and interest rates, followed by a few lag of the aforementioned variables and inflation:

$$\pi_t = \alpha + \delta\pi_{t-1} + \beta u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \beta_3 i_t + \beta_4 p_t + \xi_t$$

This model may yield biased results, mainly due to disturbance possibly correlating with other disturbance terms (autocorrelation), hence further lags were added depending on the various econometrical tests. For simplicity's sake, normality was assumed in the error term. The data set used in this analysis is taken and combined from multiple sources, namely OECD (2021a, 2021b & 2021c) for inflation rates (monthly behavior of *CPI* growth rate is shown in Appendix), short-term interest rates, and unemployment rates, and U.S. Energy Information Administration (2021) for crude oil prices. All data are monthly and seasonally adjusted (excluding oil prices and inflation) over a period of 25 years (between January 1994 and December 2018). Inflation data was manually seasonally adjusted on R Core team (2020) with TRAMO/SEATS+ adjustment method developed by Quartier-la-Tente et al. (2021) that adjusts for the impact of weekends, public holidays and the Leap Day. The final data set consists of 300 observations. The variables used in the system are as follows:

$\boldsymbol{\pi}$: Price inflation is measured as the monthly change in price of all items (including energy and food); *CPI index;*

$\boldsymbol{u}$: Unemployment is measured as the ratio of people of working age who are without work, are available for work, or have taken specific steps to find work to the labor force;

$\boldsymbol{i}$: Short-term interest rate is measured as the short-term treasury bill rate being traded in the market in percentage point;

$\boldsymbol{p}$: Brent Europe crude oil prices is measured in dollars per barrel.

4 Results

The provisional model above failed all one to four lag Breusch-Godfrey Serial Correlation LM Test ($p < .001$). With the introduction of once lagged variables of interest and oil price, twice and four times lagged variable of inflation as well as thrice lagged variable of unemployment, the model passed all one to four lag autocorrelation tests ($p = .068, p = .186, p = .080, p = .053$, see Table 2). The finalised equation is:

$$\pi_t = \alpha + \delta\pi_{t-1} + \delta_1\pi_{t-2} + \delta_2\pi_{t-4} + \beta u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \beta_3 u_{t-3} + \beta_4 i_t$$
$$+ \beta_5 p_t + \beta_6 i_{t-1} + \beta_7 p_{t-1} + \xi_t$$

Independent	Inflation_t
Inflation_{t-1}	1.020 (0.056)
Unemployment_t	-0.047 (0.057)
$\text{Unemployment}_{t-1}$	0.154 (0.070)
$\text{Unemployment}_{t-2}$	-0.166 (0.070)
$\text{Unemployment}_{t-3}$	0.055 (0.057)
Oil Price_t	0.011 (0.002)
Interest Rate_t	0.197 (0.052)
N after adjustment	296
AIC	-156.5144

Table 1: Shorten Regression Output

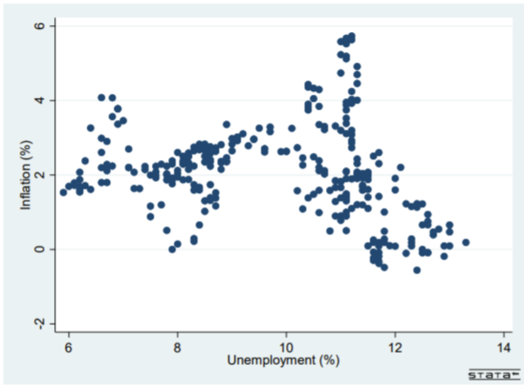

Figure 1: Scatterplot of Inflation and Unemployment

A scatter plot, in figure 1, between inflation and unemployment shows an unclear relation for unemployment rate lower than 10%, whereas for unemployment above 10% a clear relation can be observed. Table 1 reports a shortened version of the OLS regression output; a Breusch-Pagan test for heteroskedasticity suggested at 95% confidence that the error terms have constant variance ($\chi^2 = 15.72, p = .152$), hence standard OLS errors were reported instead of White (1980) heteroskedastic-consistent standard errors. Interestingly, only the once ($t = 2.19, p = .029$) and twice lagged ($t = -2.37, p = .019$) unemployment coefficients were significant albeit having opposite relationships with inflation, while the contemporaneous ($t = -.84, p = .404$) and thrice lagged ($t = .98, p = .330$) unemployment coefficients were insignificant. A one percent increase in unemployment the month before causes inflation to rise 0.154% the month after and a one percent increase in unemployment two months ago causes inflation to drop 0.166% two months later. On the other hand, all lag inflation coefficients were significant ($p < .001$), with the exception of the twice lagged inflation coefficients ($t = 1.59, p = .113$). Oil price and interest rate as well as their respective lags were significant too ($p < .001$). Furthermore, for every one percent increase in contemporaneous interest rate, inflation increases significant by 0.197% ($t = 3.77, p < .001$). In contrast, one percent increase in once lagged interest rate significantly reduces inflation the next month by 0.175% ($t = -3.31, p = .0011$).

A Chow-Breakpoint test was conducted to investigate potential structural break on January

2013, which is a month after the official end of the Great Recession in Europe. The test was significant ($f = 2.26, p = .0097$), confirming that with 95% confidence that there is a difference between the coefficients before and after January 2013. As a result, two OLS regressions were carried out on two respective samples with shortened results shown in Table 2.

Table 2: Regression two subsamples

Independent	Inflation$_t$ (1994-2012)	Inflation$_t$ (2013-2018)
Inflation$_{t-1}$	1.051 (0.064)	0.779 (0.126)
Unemployment$_t$	-0.125 (0.064)	-0.0026 (0.1254)
Unemployment$_{t-1}$	0.191 (0.084)	0.079 (0.135)
Unemployment$_{t-2}$	-0.114 (0.085)	-0.097 (0.140)
Unemployment$_{t-3}$	0.058 (0.065)	0.095 (0.134)
Oil Price$_t$	0.0093 (0.0023)	0.011 (0.006)
1 lag Autocorrelation Test (P-value)	0.169	0.790
2 lag Autocorrelation Test (P-value)	0.288	0.376

Standard Error in parenthesis

What is interesting is that the coefficients in the 2013-2018 subsample is no where near as pronounced as the 1994-2012 subsample. Additionally, only once lagged inflation ($p < .001$) and contemporaneous oil price ($p = .0425$) were significant in explaining inflation in the 2013-2018 subsample whereas similar variables that were significant in the combined regression were also significant in explaining inflation in the 1994-2012 subsample.

5 Conclusion

The main goal of this study was to build on the standard Phillips curve and to investigate how well it performs in the economy of Italy. To some extent, unemployment is consistent with previous literature (Gali, 2011; Phillips, 1958) at least with regard to the direction of the relationship between unemployment and inflation. The findings of the present study show that for more recent data, unemployment does not seem to play a significant part in explaining inflation. This suggests that unemployment may not be a suitable indicator of inflation. However, regardless of time, the one variable that is highly significant in explaining inflation is the once lagged of itself. This is a reasonable result as after all, governments will definitely monitor the inflation rate a period ago before deciding what actions to take for the next period. Moreover, the results showed that the contemporaneous interest rates positively explain inflation. While this result contradicts classic economic theories, it could be explained by central banks responding to greater inflation by raising interest rates.

This study is limited in a few ways. First, endogeneity bias caused by the simultaneity effect between inflation and unemployment could be present. For example, having high inflation might raise the input costs, which may trigger employers to resort to cheaper alternatives, ultimately causing unemployment to rise. Another possible limitation would be the measurement error of the inflation *CPI*. The best real indicator of incoming inflation may well be when governments adjust the basket of goods and services used to measure *CPI*. This is because the difference in product quality is not taken into account when calculating *CPI*, so it is not reasonable to investigate inflation solely using differences in prices of goods and services.

Additionally, as hinted in the analysis above, neither unemployment, oil prices, nor interest rates may be relevant for forecasting inflation. Rather, technology shocks such as the introduction of cryptocurrency could stimulate a chain reaction leading to inflation. In particular, Bitcoin prices could be a very important indicator of future inflation, as more and more people, hedge funds and even national governments are investing in Bitcoin in anticipation of inflation. Perhaps a more accurate approach for future research would be to place greater emphasis on the role of quantities, especially the quantity of credit, which is the source of the money supply. After all, 97% of the money supply is created by banks when they give out loans, making them the major players that contribute to inflation and not the financial intermediaries people commonly believe them to be.

6 References

Álvarez, L. J., Hurtado, S., Sánchez, I., & Thomas, C. (2011). The impact of oil price changes on Spanish and euro area consumer price inflation. *Economic modelling*, *28*(1-2), 422-431.

Galí, J. (2011). The return of the wage Phillips curve. *Journal of the European Economic Association*, *9*(3), 436-461.

Lavoie, M. (1995). Interest rates in post Keynesian models of growth and distribution. *Metroeconomica*, *46*(2), 146-177.

OECD (2021a). *Inflation (CPI) (indicator)* [Data set]. doi: 10.1787/eee82e6e-en

OECD (2021b). *Short-term interest rates (indicator)* [Data set]. doi: 10.1787/2cc37d77-en

OECD (2021c). *Unemployment rate (indicator)* [Data set]. doi: 10.1787/52570002-en

Quartier-la-Tente, A., Michalek, A., Palate, J., & Baeyens, R. (2021). *RJDemetra: Interface to 'JDemetra+' Seasonal Adjustment Software, (R package version 0.1.7)*. https://CRAN.R-project.org/package=RJDemetra

R Core Team (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/

Staiger, D., Stock, J. H., & Watson, M. W. (1997). The NAIRU, unemployment and monetary policy. *Journal of economic perspectives*, *11*(1), 33-49.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861-1957. *Economica*, *25*(100), 283-299.

U.S. Energy Information Administration (2021). *Crude Oil Prices: Brent - Europe, (MCOILBRENTEU)* [Data set]. Federal Reserve Bank of St. Louis.
https://fred.stlouisfed.org/series/MCOILBRENTEU

Werner, R. A. (2014). Can banks individually create money out of nothing? The theories and the empirical evidence. *International Review of Financial Analysis*, *36*, 1-19.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, *48*, 817–838.

7 Appendix

Figure 2: Monthly inflation rate (%)

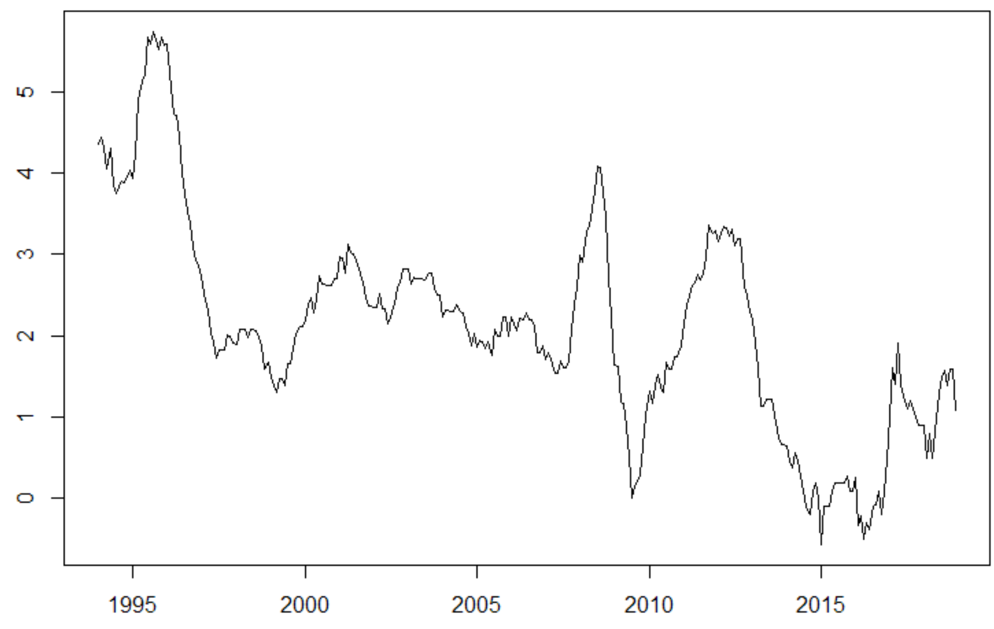

Table 3: Regression on full sample

Independent	Inflation_t
Inflation_{t-1}	1.020 (0.056)
Inflation_{t-2}	0.117 (0.073)
Inflation_{t-4}	-0.196 (0.036)
Unemployment_t	-0.047 (0.057)
$\text{Unemployment}_{t-1}$	0.154 (0.070)
$\text{Unemployment}_{t-2}$	-0.166 (0.070)
$\text{Unemployment}_{t-3}$	0.055 (0.057)
Oil Price_t	0.011 (0.002)
Oil Price_{t-1}	-0.010 (0.002)
Interest Rate_t	0.197 (0.052)
$\text{Interst Rate}_{t-1}$	-0.175 (0.053)
Constant	0.079 (0.076)
Observations after adjustment	296
AIC	-156.5144

Standard errors in parentheses

Table 4: Breusch–Godfrey LM test for autocorrelation

lags(p)	F-stats	df 1	df 2	P-value
1	3.3564	1	283	0.0680
2	1.6922	2	282	0.1860
3	2.2788	3	281	0.0797
4	2.3648	4	280	0.0532

H_0: no serial correlation

Table 5: Regression of two subsamples

Independent	(1994-2012) Inflation$_t$	(2013-2018) Inflation$_t$
Inflation$_{t-1}$	1.051 (0.064)	0.779 (0.126)
Inflation$_{t-2}$	0.097 (0.083)	0.134 (0.156)
Inflation$_{t-4}$	-0.206 (0.040)	-0.085 (0.099)
Unemployment$_t$	-0.125 (0.064)	-0.0026 (0.1254)
Unemployment$_{t-1}$	0.191 (0.084)	0.079 (0.135)
Unemployment$_{t-2}$	-0.114 (0.085)	-0.097 (0.140)
Unemployment$_{t-3}$	0.058 (0.065)	0.095 (0.134)
Oil Price$_t$	0.0093 (0.0023)	0.011 (0.006)
Oil Price$_{t-1}$	-0.0083 (0.0023)	-0.0066 (0.0058)
Interest Rate$_t$	0.178 (0.047)	1.861 (1.585)
Interst Rate$_{t-1}$	-0.160 (0.048)	-2.606 (1.516)
Constant	-0.057 (0.092)	-1.175 (1.303)
R-squared	0.978	0.908
1 lag Autocorrelation Test (P-value)	0.169	0.790
2 lag Autocorrelation Test (P-value)	0.288	0.376
3 lag Autocorrelation Test (P-value)	0.382	0.560
4 lag Autocorrelation Test (P-value)	0.532	0.199

Standard errors in parenthesis