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Catch Me if You Can – the Phillips Curve

A Structural Vector Autoregressive Analysis of the Flattening Phillips Curve Hypothesis for Norway over the Past Fifty Years

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Abstract

This thesis examines if the Phillips curve in Norway has flattened over the past fifty years, and what implications this could have for the conduct of monetary policy. Several research papers have estimated that the slope of the Phillips curve for many advanced economies have flattened over time. However, the research is limited in the case of the Norwegian economy. The starting point of the analysis is estimation of various correlation coefficients. Building on the International Monetary Fund (2013), Blanchard et al. (2015) and Blanchard (2016), the Phillips curve relation is thereafter modelled using Ordinary Least Squares regressions (OLS) and rolling regressions. Building on Neri (2004) and Bjørnland (2009), Structural Vector Autoregression (SVAR) models with short-run restrictions and Cholesky decompositions are then applied. The correlation coefficient, regressions and impulse responses are used to evaluate potential changes in the slope coefficient of the Phillips curve and the behavior of inflation expectations.

Consistent with prior research, the empirical results indicate that the slope of the Phillips curve in Norway has decreased in the period 1982 – 2012. The empirical results involving the last decade are more ambiguous. Rolling regression results considering the behavior of inflation expectations suggest that expectations have become more firmly anchored since Norges Bank became independent in 1985. Stable inflation expectations after 1985 further indicate stable inflation dynamics induced by a flatter aggregate supply curve. Impulse responses of inflation suggest a reduced responsiveness of inflation to demand shocks. The real economy remains reactive to the shocks in before and after 1992. The findings implicate a weakening of the demand channel to inflation in the inflation targeting monetary policy model. This implies that it has become harder to control the rate of inflation through changes in the real economy. Subsequently, this indicate that larger variations in the real economy is necessary to bring inflation back to target.

Keywords – Inflation, the Phillips curve, anchored expectations, monetary policy.

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1. Introduction

Low inflation and low unemployment rates are important goals of stabilization policies. The Phillips curve, which depicts the relation between inflation and economic slack, is a standard macroeconomic model used for forecasting and policy advice in central banks. However, recent findings suggest a breakdown in the inflation-slack relationship. The Phillips curve appears to have weakened or even disappeared over the years.

Several papers estimate that the slope of the Phillips curve has flattened over time (Ball & Mazumder, 2011; IMF, 2013; Blanchard et al., 2015; Blanchard, 2016; Del Negro et al., 2020). Other research points to a flatter aggregate demand curve as a potential explanation of the phenomenon (McLeay & Tenreyro, 2020). Anchored inflation expectations are also highlighted by the literature as a central explanation (Orphandies & Williams, 2005; Blanchard, 2016; Jørgensen & Lansing, 2020; Ascari & Fusso, 2021). The literature focuses on three main hypotheses for the apparent inflation puzzle: (i) the mismeasurement of either economic slack or inflation, (ii) a flatter aggregate supply curve, or (iii) a flatter aggregate demand relationship caused by improved stabilization policies.

The mainstream literature focuses on the US economy, but the same phenomenon has been found in several other countries as well (Beaudry & Doyle, 2000; IMF, 2013). The findings could have major implications for monetary policy, as a disconnect in the relationship challenges the relevance of the macroeconomic model. It would further call in to question the rationale for independent, inflation-targeting central banks.

This paper investigates how the Phillips curve in Norway has developed over the past fifty years. In doing so, this paper aims to answer if the Phillips curve has flattened in the case of the Norwegian economy, and what implications this will have for the conduct of monetary policy. To answer this, a simple econometric framework is first applied to interpret the behavior of the Phillips curve slope estimates and the role of inflation expectations over the chosen sample period. Thereafter, structural vector autoregressive models are applied to test the behavior of the relationship more formally before and after 1992.

Due to the large scope of this topic, with various hypotheses and empirical explanations for the disconnect phenomenon, clear delimitations are set for this thesis. This paper focuses on examining if the price Phillips curve in Norway has flattened over the past fifty years and the role of inflation expectations behavior over the same period. Thus, this paper mainly builds on the literature exploring the flattening supply curve hypothesis and anchoring of inflation expectations. The research question was chosen due to the lack of research on this topic for Norway. The recent rise in inflation further motivated the choice.

The rest of the paper is organized as follows: Chapter 2 presents how this thesis connects to the theoretical and empirical literature on the Phillips curve and recent inflation-slack disconnect literature. Chapter 3 examines the central theoretical frameworks and hypotheses applied in this paper. Chapter 4 gives an overview of the datasets and provides a detailed description of the data collection. In addition, it explains the applied data processing techniques and finally, presents a discussion on the validity and reliability of the data. Chapter 5 presents the methodologies applied in the analysis, i.e., the Correlation coefficient and Ordinary Least square to examine the inflation-unemployment relationship as well as the Structural Vector Autoregression (SVAR) framework which is applied to examine effects of shocks to inflation and the real economy. Chapter 6 presents the empirical results. Chapter 7 presents the limitations and further research needed, and finally chapter 8 concludes the thesis.

2. Literature Review

This chapter gives a brief overview of the relevant theoretical and empirical literature on the disconnect phenomenon and the Phillips curve framework.

2.1 Disconnect between inflation and market slack

The empirical disconnect between inflation and various measures of slack has been widely discussed in the aftermath of the Great Recession. The potential causes of any weakening in the Phillips Curve relationship have been an important topic of discussion amongst policymakers (Bernanke, 2007; Draghi, 2017; Carney, 2017, Powell, 2018). A change in the Phillips Curve relationship could have major implications for monetary policy, as it is one of the building blocks of the standard macroeconomic models used in forecasting and policy advice in central banks.

A number of research papers interpret the empirical disconnect as evidence that the Phillips curve has weakened or even disappeared (Ball & Mazumder, 2011; IMF, 2013; Hall, 2013, Blanchard et al., 2015; Coibion & Gorodnichenko, 2015; Blanchard, 2016; Harding et al., 2020). Several papers have found that there has been a reduction in the cyclical correlation between inflation and real activity since the 90s (Akteson & Ohaninian, 2001; Stock & Watson, 2007; Stock & Watson, 2008; Stock & Watson, 2020).

There is also a large amount of literature highlighting the role of inflation expectations and their apparent anchoring (Del Negro et al., 2020). Examples of papers examining the anchoring of inflation expectations are Orphandies & Williams (2005), Ball et al. (2011), Blachard et al. (2015), Blachard (2016), Jørgensen and Lansing (2020), Ascari & Fusso (2021). The empirics suggest that expectations are now less volatile than they were before the 1990s.

The influential paper by McLeay and Tenreyro (2020) finds that the empirical disconnect between inflation and slack is a result to be expected when monetary policy is set optimally. The paper further argues that the finding is consistent with an underlying stable and positively sloped Phillips curve. This suggests a flatter demand curve relationship, due to more aggressive inflation targeting monetary policy. The role of monetary policy on inflation dynamics in simple New Keynesian models with Taylor rule is highlighted by Roberts (2006), Carlstrom, et al. (2009) and Bullard (2018). Phillips curve identification in a similar setup is explored by Nason and Smith (2008), Mavroeidis et al. (2014) and Krogh (2015).

2.2 The history of the Phillips Curve

This thesis builds on the vast empirical and theoretical literature on the Phillips curve. The inverse relationship between inflation and unemployment was first proposed by Phillips (1958), who identified an empirical relationship between the level of aggregate unemployment and aggregate wage growth. Phillips found that higher rates of wage gains were associated with lower rates of unemployment (Phillips, 1958). The relationship between unemployment and wage growth, introduced by Phillips (1958), gave rise to the Phillips curve. The same term is however used for the relationship between the unemployment rate and price changes rather than changes in wages. More specifically, low rates of unemployment tend to be associated with large wage increases/increments of an inflationary character. This relation was introduced by Samuelson and Solow (1960), who baptized the curve.

2.2.1 The Phillips Curve Tradeoff

Samuelson and Solow (1960) replicated Phillip's exercise and found a negative correlation between inflation and the unemployment rate. The Phillips curve was a fixed inflation-unemployment trade-off and thus, a specific level of unemployment was reflected in a consistent level of inflation. Samuelson and Solow (1960), furthermore, presented the curve as a «menu» for monetary policy, where the policy makers could choose which combination of inflation and unemployment they wanted along the curve. A lower level of unemployment could be attained by the cost of higher inflation. Thus, the relation was also referred to as the Samuelson-Solow-menu (Gordon, 2012).

The insights from the Samuelson-Solow Phillips curve gave Keynesian economists a way to measure how far the economy was from full capacity, as the Phillips curve related price inflation to the resource slack of the economy given by the level of unemployment. Subsequently, making it possible to make quantitative predictions about how inflation would be affected by the level of aggregate demand. Inflation was conceived as affected by policy, whether monetary or fiscal, via a causal chain, from aggregate demand, to the level of output and employment – and thereby unemployment – to the rate of inflation (Gordon, 2012).

2.2.2 Expectations Augmented Phillips Curve

The idea of a stable trade-off between inflation and the output was, however, criticized by Friedman (1968) and Phelps (1967). Friedman (1968) and Phelps (1967) studied how the Phillips curve reacted to changes in inflation expectations, and if the curve would remain stable if inflation expectations changed. They concluded that the relation would not hold in the long run and thus, expanded the Phillips curve to embed expected inflation as an additional explanatory variable of inflation formation. This gave rise to the Expectations Augmented Phillips curve and the Accelerationist Phillips curve with adaptive expectations. Lucas (1972) and Sargent and Wallace (1975) introduced the mechanisms of rational inflation expectations.

2.2.3 New Keynesian Phillips Curve

The Phillips curve has a long and fascinating history marked by heated policy debates and landmark contributions. The literature is so comprehensive that it makes it impossible to address all major contributions in the limiting scope of this paper. Instead, this thesis focuses on the New Keynesian Phillips curve – henceforth NKPC – which is currently the most widely used model in relation to the Phillips curve (Mankiw, 2003; Mavroeidis et al., 2014; Bjørnland & Thorsrud, 2015). The model has gained its popularity from its theoretical micro foundation and early empirical success (Mavroeidis et al., 2014; Bjørnland & Thorsrud, 2015).

The NKPC theory was introduced in the 1980s and 1990s and is now a standard feature of modern macroeconomics (Mavroeidis et al., 2014). Key properties are that inflation is primarily a forward-looking process driven by expectations of future real economic activity (Mavroeidis et al., 2013). This limits the scope of actively exploiting the Phillips curve trade-off from a policy perspective. However, the forward-looking behavior provides a central role for monetary policy rules by introducing the possibility of expectations management and communications as monetary policy tools (Mavroeidis et al., 2014). These key properties have led to the widespread adoption of the NKPC as the key price determination equation in policy models used at central banks around the world (Mavroeidis et al., 2014).

3. Theory

This chapter presents central theoretical frameworks and hypotheses applied in this paper.

3.1 The natural rate hypothesis

Friedman (1968) and Phelps (1967) introduced what is now known as the natural rate hypothesis in relation to the Phillips curve. The natural rate of unemployment is the hypothetical and unobserved level of the unemployment rate, that would prevail in the absence of cyclic variations. In other words, the natural rate of unemployment is the average rate of unemployment in which the economy fluctuates around (Mankiw, 2003). The natural rate is never zero, as unemployment would not disappear even in stable economic conditions and thus, all free-market economies experience unemployment to some degree (Mankiw, 2003). The Phillips curve is thus given by:

$$\pi_t = \pi_t^e + \beta(\mu_t - \mu_t^*) + \varepsilon_t , \qquad \beta < 0 \tag{1}$$

where π_t is the current rate of inflation and $\pi^e$is the expected rate of inflation. The unemployment rate is given by μ_t, the natural rate of unemployment is μ_t^* and ε_t is the error term. This modification of the Phillips curve can be interpreted as the curve only providing a temporary «tradeoff» between unemployment and inflation (Mankiw, 2003; Gordon, 2011). It suggests that unemployment below its natural rate can only be achieved temporarily by generating inflation that is higher than what economic agents anticipate. When expectations adjust towards the higher inflation rate, workers bargain for higher nominal wages as a response to the higher inflation. Consequently, unemployment moves back to its natural rate and a new equilibrium is established at a higher rate of inflation. This version of the curve also implies that a rise in unemployment above its natural rate is necessary to reduce the rate of inflation.

If economic activity is stimulated by monetary policy such that the rate of inflation is raised, the stimulus will only last until inflation expectations have been fully adjusted upwards to the actual rate. Wages will rise to an extent that will eliminate the stimulus to employment. The unemployment goes back to its natural rate as inflation expectations adjust. Thus, the Phillips curve becomes vertical in the long term. Friedman (1968) and Phelps (1968) consequently argued that the Phillips curve is a short-term phenomenon.

3.2 Short-run and long-run Phillips curve

The analysis by Friedman (1968) and Phelps (1967) provided a distinction between the «short-run» and the «long-run» Phillips curve. If the average rate of inflation remains fairly constant as it did in the US during the 1960s for example, inflation and unemployment will be inversely related. However, if the average rate of inflation changes which will be the result when policymakers persistently try to push unemployment below the natural rate, then unemployment will return to its natural rate after a period of adjustment. In other words, the natural rate of unemployment will be compatible with any level of inflation when economic agents' expectations of inflation have had time to adjust. Hence, the long-run Phillips curve will become a vertical line above the natural rate. Consequently, the original Phillips curve can, according to this belief, only be applied to brief, transitional periods and will shift with any persistent change in the average of inflation.

The short-run and long-run relations are combined in a single «expectations-augmented» Phillips curve. The quicker worker's inflation expectations adapt to changes in the actual rate of inflation, the quicker the unemployment rate will return to its natural rate. The quicker the unemployment rate returns to its natural rate, the less successful policymakers will be at reducing unemployment through monetary and fiscal policies.

3.3 Behavior of expectations

Friedman (1968) went a step further and specified the behavior of expectations. He argued that «unanticipated inflation generally means a rising rate of inflation» and thus, that expected inflation is well-proxied by past inflation. Following this assumption, equation (1) becomes:

$$\pi_t = \pi_{t-1} + \beta(\mu_t - \mu_t^*) + \varepsilon_t , \tag{2}$$

where π_{t-1} denotes past inflation. The equation is called the accelerationist Phillips curve, and is often expressed in the following form:

$$\pi_t - \pi_{t-1} = \beta(\mu_t - \mu_t^*) + \varepsilon_t , \tag{3}$$

where the dependent variable is the unanticipated inflation denoted by $\pi_t - \pi_{t-1}$. There are two main reasons for why rational workers and firms have backward-looking expectations over forward-looking expectations (Gordon, 2012):

1) Economic agents have no reason to believe that changes to unemployment will be permanent, as there have been fluctuations in the economy before.
2) The existence of long-term wage and price contracts would prevent actual inflation from responding immediately to a possible permanent change.

Thus, economic agents expect price and wages to adjust gradually, and the actual speed of the adjustments cannot be predicted in advance (Gordon, 2012). The most well-known form of backward-looking expectations are adaptive expectations. The concept of adaptive expectations is plausible, but assuming that inflation expectations are only based on past or recently observed inflation is a simplification of reality (Mankiw, 2003).

3.4 Rational expectations hypothesis

The alternative approach is to assume that people have rational expectations. Lucas (1972) and Sargent and Wallace (1975) added another dimension to the Phillips curve by including a rational inflation expectations term. These papers argued that workers and firms would work out implications of an observed fall or rise in wages on the overall wage level based on historical knowledge. Thus, the price level was purely forward-looking in the early rational expectation's models of Lucas (1972) and Sargent and Wallace (1975). This implied that prices were flexible and could jump in response to shocks. The rational expectations theory assumes that economic agents use all available information to form expectations about the future (Mankiw, 2003). The information includes current government policies, as inflation expectations should be dependent on such policies in effect due to monetary and fiscal policies influence on inflation.

3.5 Stagflation

The 1970s, with several periods with steep simultaneous increases in both unemployment and inflation, gave Friedman and Phelps' critics of the original curve with a stable inflation-unemployment trade-off, empirical evidence. The combination of high inflation, high unemployment and low (or stagnating) economic activity is defined as stagflation (Grytten & Hunnes, 2016). It is in other words, the combination of stagnation and inflation in an economy.

In this type of economic scope/situation, the stable inflation-unemployment trade-off in the Phillips curve breaks down.

The breakdown in the inflation-unemployment trade-off was explained, among other factors, by changes in the expectations for inflation. The prices in the US had been stable before the 1960, and thus the expectations for inflation were constant and equal to zero. The inflation could, therefore, be associated with a certain level of unemployment. However, as the prices started to increase steadily for years, the inflation expectations became systematic and raised the level of actual inflation, independent of any level of unemployment. The changes in expectations in addition to the increase in oil prices were the main reasons for the high inflation in the 1970s in many western countries (Bovet, 1983; Bruno & Sacha, 1985).

3.6 New Keynesian Phillips curve

The NKPC is a key equation in modern macroeconomic models. The NKPC equation relates inflation dynamics to anticipated future inflation and some measure of overall real economic activity (Bjørnland & Thorsrud, 2015). The relation is founded on micro economic principles and assumes staggered price settings by forward looking individuals and firms. The relation can be expressed as the provided example by Galí et al. (2001):

$$\pi_t = \beta_1 \pi^e{}_t + \beta_2 \widehat{mc}_t \tag{4}$$

where π_t denotes inflation, $\pi^e{}_t$ is the conditional expectation at time t of future inflation and $\widehat{mc}_t$ denotes excess demand or marginal cost. The latter is typically measured as the wage share, the output gap or unemployment (Bjørnland & Thorsrud, 2015). The output gap is defined as the difference between actual and potential output often measured as actual GDP and the natural rate of GDP (Hagelund et al., 2018). The unemployment gap is defined as the difference between the actual unemployment rate and the «natural» rate of unemployment. Actual unemployment and output will increase or decrease depending on the cyclical conditions of the economy. The natural rate can be viewed as the trend rate, which changes over time, independent of the cyclical conditions of the economy. The natural rate of unemployment is often measured by the Non-Accelerating Inflation Rate of Unemployment (NAIRU) (Atkeson & Ohanian, 2001).

The slope coefficient, β_2, in the NKPC represents the sensitivity of inflation to excess demand or marginal cost – here measured as the difference between unemployment and the natural rate of unemployment. The NKPC is a formal statement of the common intuition that if the economy is booming and demand is high, it will lead to workers seeking higher wages and firms to raise prices. The intuition behind it is simple. As marginal cost pressures rise, firms seek to push some of their costs on to customers by rising prices. Thus, marginal cost pressures are associated with rising inflationary pressure.

The most widely applied version of the NKPC includes a supply shock (cost-push shock) in the model. The relation can be expressed as follows:

$$\pi_t = \beta_1 \pi_t^e + \beta_2(\mu_t - \mu_t^*) + v \tag{5}$$

where v denotes a supply shock to the economy. The other parameters are as previously stated. The marginal cost variable is measured as the unemployment gap.

3.6.1 Causes of rising and falling inflation

The forces that can change the rate of inflation are thus given by the second and third terms in the NKPC given by equation (5) (Jones, 2018). The second term, $\beta_2(\mu_t - \mu_t^*)$, exerts what is called a demand-pull shock on inflation, while the third term, v, exerts what is called a cost-push shock on inflation.

Demand-pull inflation

The Keynesian economists believe that the deviation of unemployment from its natural rate – the cyclical unemployment, denoted by the second term, $\beta_2(\mu_t - \mu_t^*)$, in equation (5) – exerts upward or downward pressure on inflation. High aggregate demand is responsible for this type of inflation, it is referred to as demand-pull inflation. Low unemployment pulls the inflation rate up, and high unemployment pulls the inflation rate down. The parameter β, the slope parameter, measures how responsive inflation is to cyclical unemployment (Mankiw, 2003).

Cost-push inflation

The monetarists, however, believe that inflation rises and falls due to supply shocks. An adverse supply shock implies a positive value of the third term, v, in equation (5). An example of this type of shock is the rise in world oil prices in the 1970s. Adverse supply shocks typically are events that push up cost of production, hence is it called cost-push inflation (Mankiw, 2003).

The demand shocks and supply shocks consequently have opposing effects on the relationship between the unemployment gap and inflation. Demand shocks create a negative relation, while the supply shocks create a positive relation. In other words, there is a negative trade-off between unemployment and inflation created by demand shocks, and supply shocks create a positive relation between unemployment and inflation (Gordon, 2012). This is evident in the 1970s when sharp increases in oil prices created a simultaneous rise in unemployment and inflation. The same state was found in Norway in the late 1970s and early 80s (Grytten & Hunnes, 2016).

3.7 Okun's Law

As the unemployment rate is inversely related to the output gap, the economy's prosperity can be described by either low unemployment or a high output gap (Gordon, 2012). Any factor that raises aggregate demand will boost the output ratio and reduce unemployment (Mankiw, 2003; Gordon, 2012). Okun's law gives a negative relation between the output ratio and the unemployment gap. A version of Okun's law can be expressed as:

$$(\mu - \mu^*) = -\frac{1}{2} \times (y - y^*) \tag{6}$$

where, μ, denotes the unemployment rate and μ^*, the natural rate of unemployment. The output gap is given by $(y - y^*)$. The relation states that for each percentage point that output is below potential, the unemployment rate exceeds its natural rate by half a percentage point (Mankiw, 2003; Jones, 2018).

3.8 New Keynesian Phillips curve and monetary policy

3.8.1 Closed Economy Model

Inflation targeting monetary policy in Norway, is built on an expanded aggregate demand-supply (AD-AS) model, which can be described by three equations (Røisland & Sveen, 2018). The first is the aggregate demand (AD) curve, represented by the following Investment-Savings (IS) equation:

$$y = -\alpha(i - \pi^e - p) + v \quad (7)$$

where y represents the output gap, i is the nominal interest rate, π^e is inflation expectations and $(i - \pi^e)$ denotes the real interest rate which henceforth will be denoted r. The long-term equilibrium rate is given by p and v represents a demand shock (Røisland & Sveen, 2018). The equation expresses that a higher real interest rate will reduce demand and lower the output gap. A lower interest rate will work expansionary and create a higher output gap.

The aggregate supply (AS) curve is the price-setting equation used by firms in the economy (Jones, 2018), and is represented by the following Phillips curve equation (Røisland & Sveen, 2018):

$$\pi = \pi^e + \gamma y + u \quad (8)$$

where u represents an inflation shock, which can be a surprising increase in energy prices or wages. Demand pressures bring gradual increases in prices, as the Phillips curve is based on the assumption of rigidity in prices and wages. A similar version of the Phillips curve is central in New Keynesian theory (Røisland & Sveen, 2018). Pressures in the economy, meaning a positive output gap, generates an increase in inflation.

High demand for goods and services allows firms to increase their profit margins by rising prices for their goods and services. Increased economic activity normally increases the cost level, for example low unemployment rates put pressure on wages. Higher wages are generated by unions demanding higher wage increases/increments and employers trying to outbid each other when competing for labor (Røisland & Sveen, 2018).

In the closed economy model, there are two channels the monetary policy work through:

1) The interest rate channel to aggregate demand.
2) The demand channel to inflation.

When the nominal interest rate is lowered, the real interest rate subsequently falls, due to sticky inflation and inflation expectations. The reduction in real interest rates leads to increased demand for goods and services. This reflects the interest rate channel to aggregate demand given by the IS equation. An increase in demand subsequently implies an increase in the rate of inflation, which represents the demand channel to inflation.

The monetary policy regime presented here is described for a central bank with an explicit inflation target. The inflation target is specified by the following loss function:

$$L = \frac{1}{2}[(\pi - \pi^*)^2 + \lambda y^2] \tag{9}$$

where the parameter λ measures how much weight is assigned to the production stability relative to the price stability by the central bank. $\lambda = 0$ implies strict inflation targeting, which means that the central bank aims to achieve the inflation target quickly and sets interest rate accordingly. This might result in large fluctuations in the real economy, as it requires large and frequent changes in interest rates (Røisland & Sveen, 2018). A positive λ implies flexible inflation targeting. Norway introduced inflation targeting monetary policy in 2001 (Eitrheim & Qvigstad, 2020).[1] Since then, the inflation targeting has become gradually more flexible, which entails that the central bank moves more gradually to avoid excessive fluctuations in output and employment.

The loss function is dependent on the difference between the actual inflation level and the inflation target. The central bank's task is to minimize the function. Thus, the goals are to:

1) Stabilize inflation around the target.
2) Stabilize production around potential production.

The quadratic form of the loss function implies that a balanced development of the inflation and output gaps is preferred by the central bank, as large gaps result in proportionally larger losses. The central bank set the interest rate to minimize the loss function. The first order condition for minimum loss is given by:

$$(\pi - \pi^*)\frac{d\pi}{dr} + \lambda y \frac{dy}{dr} = 0 \tag{10}$$

The derivatives, $\frac{d\pi}{dr} = -\alpha$ and $\frac{dy}{dr} = -\alpha\gamma$ given by equation (7) and (8), summarize the transmission mechanism. The parameter α measures the strength of the interest rate channel

[1] Norway made a transition to inflation targeting in 1999, which officially came into act in 2001 (Eitrheim & Qvigstad, 2020).

and the parameter γ measures the strength of the demand channel. The first order condition can be expressed as:

$$\pi - \pi^* = -\frac{\lambda}{\gamma} y \tag{11}$$

The equation states that the monetary policy is optimal if there is a negative relationship between the inflation gap and the output gap, or if both are zero. The optimality condition with respect to the output gap, is given by:

$$y = -\frac{\gamma}{\lambda}(\pi - \pi^*) \tag{12}$$

The equation shows the extent the central bank is willing to drive the economy into a recession when inflation is above target. This depends on the relative weight put on avoiding fluctuations in the real economy and on the strength of the demand channel to inflation (Røisland & Sveen, 2018). If the central bank focuses on avoiding fluctuations in the real economy, it will be less willing to bring the economy into a recession when inflation increases due to a cost-push shock.

The equilibrium values of inflation and the output gap, can be given as the following equations:

$$\pi = \pi^* + \frac{\lambda}{\lambda + \gamma^2}[(\pi^e - \pi^*) + u] \tag{13}$$

$$y = -\frac{\gamma}{\lambda + \gamma^2}[(\pi^e - \pi^*) + u] \tag{14}$$

The equilibrium value of the nominal interest rate is found by combining the IS equation (7) and equation (13):

$$i = \bar{r} + \pi^e \frac{\gamma}{\alpha(\gamma^2 + \lambda)} u + \frac{\gamma}{\alpha(\gamma^2 + \lambda)} (\pi^e - \pi^*) \tag{15}$$

The short-run neutral nominal interest rate is denoted by $(\bar{r} + \pi^e)$, and is the short-run neutral real rate plus the expected inflation. The equation reflects that the central bank should raise the nominal interest rate one-for-one with changes in the neutral nominal interest rate (Røisland & Sveen, 2018). This indicates that demand shocks should be neutralized. The rate is also raised if an inflation shock or a confidence shock occur. Confidence shocks occur if there is a lack of credibility that the central bank is able to meet its target. Thus, agents in the economy expect inflation above the inflation target. This leads to raised interest rates. A confidence shock result in the same type of reaction as an inflation shock. The confidence of economic agents or level of anchored inflation expectations in the economy, is influenced by the central bank's reaction pattern and communication.

3.8.2 Open Economy Model

The New Keynesian Phillips curve in an open economy model henceforth OE-NKPC, differs from its closed economy counterpart, as the exchange rate and prices on imported goods are included as additional influencers of domestic inflation dynamics (Røisland & Sveen, 2018). Norway is a small open economy, in the sense that it has negligible effects on international economic developments, but is influenced by international trade in goods, services and capital (Røisland & Sveen, 2018).

The aggregate demand function (IS curve) is expanded in the open economy model, to consider how the exchange rate affects the level of activity. Following Røisland and Sveen (2018), the IS curve of the open economy is assumed to be represented by the following equation:

$$y = -\alpha_1(r - p) + \alpha_2 e + v \tag{16}$$

where $e = s + p - p*$ denotes the logarithm of the real exchange rate. s is the logarithm of the nominal exchange rate, which increase in value represents a depreciation or weaker currency. $p*$ denotes the logarithm of the price of foreign goods measured in foreign currency and p denotes the price of domestically produced goods.

The open economy Phillips curve is described in the following equation:

$$\pi = \pi^e + \gamma_1 y + \gamma_2 e + u \tag{17}$$

where π is the consumer price inflation, given by the following equation (Røisland & Sveen, 2018):

$$\pi = \psi\pi^F + (1 + \psi)\pi^H \tag{18}$$

π^F and π^H denotes imported and domestic inflation, respectively and ψ is the share of imports in the consumption basket. e denotes the real exchange rate and γ_2 the degree of pass-through inflation from imported inflation from the share of imports in the consumption basket. γ_1 measures the pass-through from domestic inflation in the consumption basket. The rest of the variables are as previously stated for the closed economy model. This thesis assumes that uncovered interest rate parity holds. Further details on the variables included in the expanded Phillips curve in the open economy model are not elaborated on, as the most important mechanisms are already explained for the closed economy model.

This paper excludes the variable of financial instability in the loss function, as it is not as relevant in the context of answering the research question. The loss function for the open economy model is therefore equal to the closed economy loss function.

4. Data

This section provides a detailed description of the data which creates the foundation of the analysis. First, an overview of the datasets with coherent descriptive statistics and the chosen sample period and sub-periods, is introduced. Then, the data used to model the Phillips curve is described in more detail. Following this, a discussion on the validity and reliability of the data is presented and finally, the methodology used to process the data is explained.

4.1 Data overview

The empirical analysis is based on quarterly data that spans the period 1972Q1 – 2022Q3. The data is sourced from Statistics Norway (SSB), the central bank of Norway (Norges Bank), the Organization for Economic Cooperation and Development (OECD), the Organization of the Petroleum Exporting Countries (OPEC) and the Saudi Central Bank (SAMA). Table 4.1 presents an overview of the data series included in the analysis. A detailed description of the data series is presented in Section 4.2.

Table 4.1: Overview of data series.

Data	Notation	Time period	Source	Series No.
Consumer price index	Index (2015=100)	1971M07–2022M10	SSB	08183
Unemployment rate	1000 persons	1972 – 2022 (2022Q1–2022Q3)	SSB	08518
Gross Domestic Product	Fixed prices (2015=100)	1970 – 2022	SSB	09189
Real Wages	Index (2010=100)	1972 – 2022	SSB	09786
Hours	Index (2010=100)	1972 – 2022	SSB	09174
Labor share			Constructed	-
Key policy rate		1970 – 2016, 2016M01 – 2022M10	NB, SSB	09381, 10701
Real oil prices	OPEC Basket (2017=100)	1972 – 2022 (2022M01– 2022M10)	OPEC, SAMA	-
Import price index	Index (2015 = 100)	1970Q1 – 2022Q4	OECD	-
Exchange rate	NOK per USD	1970Q1 – 2022Q4	OECD	-

Note: The table numbers of the data series sourced from SSB, are in the Series No. column.

For the first part of the analysis, the data is divided into five sub-periods to map the Phillips curve over the following five decades:

1) 1972Q1 – 1981Q4

2) 1982Q1 – 1991Q4

3) 1992Q1 – 2001Q4

4) 2002Q1 – 2011Q4

5) 2012Q1 – 2022Q3

The second part of the analysis divides the sample period into two sub-periods. The first, pre-1992, ranging from 1972Q1 to 1991Q4 and the second, post-1992, ranging from 1992Q1 to 2022Q3.

4.2 Data collection

4.2.1 Inflation

Monthly and seasonally unadjusted data on the consumer price index (CPI) for Norway is obtained from SSB, as a measure of inflationary pressures (SSB, 2022a). Data for the sample period 1971M01 – 2022M10, is converted to quarterly data and seasonally adjusted. Following Boug et al. (2011) and Mavroeidis et al. (2014) inflation is measured by the CPI rather than by the GDP deflator. The actual prices that economic agents set, are not on value added but on gross output. Deflators based on value added are typically residuals in the national accounts, and hence, the GDP deflator is less related to the micro price setting behavior compared to other concepts within the national account (Boug et al., 2011). Consequently, this thesis argues that the CPI is a more relevant price series for evaluating the Phillips curve for Norway than the GDP deflator. However, there are possible downsides to the use of CPI as a measure of inflation pressures. A more elaborate discussion of its limitations is presented in the Data validity and reliability chapter.

4.2.2 Market slack

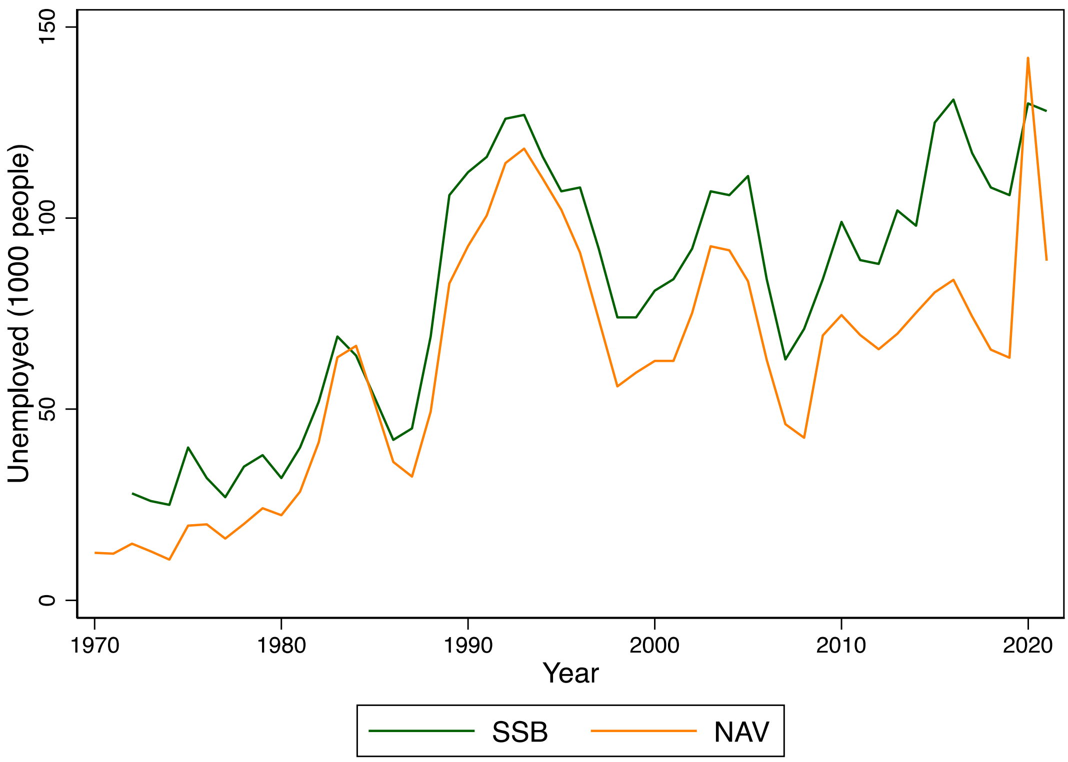
There is no perfectly accurate measure of economic slack when modeling the Phillips curve relation. This problem is mentioned in the literature as a reason for why research find that the

Phillips curve relation has disappeared (Del Negro et al., 2020; Bergholt et al., 2022). This thesis primarily focuses on the relationship between inflation and unemployment, over the relation between inflation and the output gap as a measure of market slack. Unemployment is chosen as the preferred measure, as it is arguably the most straightforward and widely discussed measure of the health of the real economy (Del Negro et al., 2020). The unemployment rate is also a commonly used interdependent variable in Phillips curve regressions.

Unemployment gap

There are two possible measures of labor market slack for the Norwegian economy. Either the unemployment rate as measured by SBB in the «Abriedskraftsundersøkelsen», abbreviated AKU, or the number of the unemployed registered at the labor market offices, published by the Norwegian labor and welfare administration (NAV). A problem with the data published by NAV is the change in propensity to register over time, which may violate the data if no correction is possible (Stølen, 1990).

Figure 4.1: SSB and NAV's measures of number of unemployed (1000 persons).



Note: Data applied in the Figure 4.1 is sourced from SSB (2022b) and NAV (2022).

The unemployment rate, as reported in AKU – equivalent to the Labor Force Survey (LFS) – is however a more volatile measure in the short term and has been at odds with other indicators for the labor market, including employment from the national accounts, over some periods according to Brubakk et al. (2018). Nevertheless, AKU gives a more integral measure of unemployment as it is also composed of unemployed people that apply for work without being registered at NAV (SSB, 2020). The development in unemployment is also presented in a holistic system by dividing the labor force into the following three groups: 1) employed, 2) unemployed or 3) outside the work force. Hence, the unemployment rate as measured by SSB will be applied in this thesis, as it gives a more precise estimate of the actual labor market slack in the Norwegian economy compared to the measurement by NAV.

To construct the unemployment gap, quarterly, seasonally unadjusted data on the unemployment rate is sourced from SSB (SSB, 2022b). The time series dates back to 1972Q1. Consequently, this becomes the starting point of the sample period for this thesis. The data is subsequently seasonally adjusted and detrended. Applied data preparation techniques are presented in Section 4.3. The extrapolation method is applied to calculate the missing values of the unemployment rate in 1971Q3 and 1971Q4 to be able to seasonally adjust the time series. The time series is thereafter detrended to construct the NAIRU, based on the idea that the NAIRU is the long-term trend of the unemployment rate and thus can be used as a proxy for the natural rate of unemployment. The unemployment gap estimates are subsequently generated by retrieving the cyclical component of the unemployment rate. Consequently, in contrast to some of the NAIRU estimates in the established literature, the unemployment gap is not directly dependent on the price growth (Brubakk et al., 2018). This is considered an advantage as the aim is to investigate how and if the price growth is driven by changes in unemployment.

Output gap

The gross domestic product (GDP) is an indicator that measures the total value creation in a country (Grytten, 2004; 2022). GDP is a standard measure for the output of an economy (Gordon, 2012). The output in this paper is based on the GDP for mainland Norway in constant 2015 prices retrieved in yearly data from SSB (2022c) for 1970 – 2021. Mainland GDP for Norway measures all productivity excluding the petroleum-based offshore sector (SSB, 2022c). Mainland GDP is utilized in this paper to avoid skewness of the value creation in Norway due to the large impact of petroleum production in the Norwegian economy. GDP given in constant prices is chosen as it reflects the real value creation in the economy and possesses the best ability to study the progression over time.

The data series is converted to GDP per capita following the calculation method applied by Ola Honningdal Grytten in Norges Bank's publication «Historical Monetary Statistics for Norway 1819 - 2003» in the following chapter: «The gross domestic product for Norway 1830-2003»[2] (Grytten, 2004; 2022). GDP per capita removes expansion in GDP created by population growth. Consequently, the actual pattern in economic activity is better reflected and GDP per capita is thus viewed as the best measure of activity. Thereafter, the series is quarterly adjusted and the missing values for 2022Q1, 2022Q2 and 2022Q3 are extrapolated by utilizing the CPI index measured in 2015 prices to assure that the data is comparable to the earlier series[3]. Potential output is obtained by applying the Hoderick-Prescott filter on the GDP per capita series. Subsequently, the output gap is computed as the difference between the logarithm of the time series and its polynomial trend.

4.2.3 Inflation expectations

There is a considerable difficulty in modeling the Phillips curve with rational inflation expectations since the expectations are not directly observable. Most studies apply survey-based measures of inflation expectations. This has two main shortcomings. The first is that surveys usually only report expectations of professional forecasters, rather than perceptions of the public at large. This might not be a representative for the overall economy (Coibon et al., 2018). The second shortcoming involves limited historical survey expectations data. Most of the surveys do not go back far in time. The Expectations Survey conducted by Norges Bank, is based on social partners expectations at the start of the year (Ipsos, 2020; Norges Bank, 2022a). The survey data only dates back to 2002, which means there is a lack of available data for the sample period, which limits the econometric analysis.

The chosen proxy for inflation expectations is therefore the low frequency component of consumer price index changes, generated by the Hodrick-Prescott (HP) filter – following Tease

[2] The time series on population data applied in the calculations of GDP per capita, is obtained from SSB (2022d) for the period 1972 – 2022 – Series No. 05803.
[3] The extrapolated GDP per capita values for 2022, is cross-checked by acquired monthly – thereafter quarterly adjusted – data for 2022 on Mainland GDP in constant 2020 prices from SSB. The 2022 data is subsequently divided by the extrapolated missing middle population value for 2022 to generate the GDP per capita values.

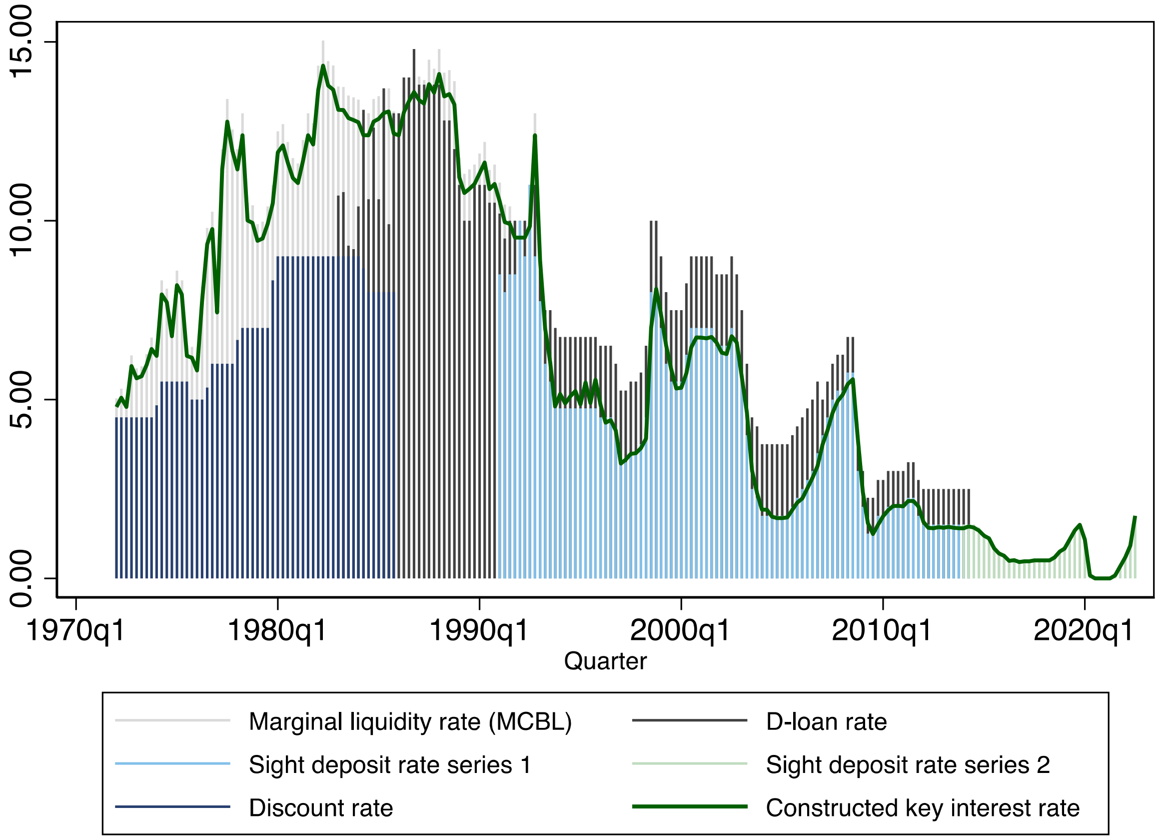
et al. (1991) and Orr et al. (1995). Short-run inflationary expectations have been generated from autoregressive models by for example Blanchard and Summers (1984), Atkinson and Chouraqui (1985) and Barro and Martin (1990). The choice of generation technique is unlikely to alter the longer-term trends in the data (Atkinson & Chouraqui, 1985; Tease et al., 1991). It may nevertheless affect the timing of the turning points, which can be a limitation of the constructed inflation expectation series. Backward- and forward-looking information is relevant when economic agents form rational expectations, due to sticky prices and slow adjustments (Roberts, 1995). Consequently, the HP filter method is considered a good choice to estimate the inflation expectations, as the low frequency component generated by the HP filter is a two-sided average of the observed inflation. Thus, data from the Consumer Price Index (CPI) is used to construct an inflation expectation series by applying the HP filter (SSB, 2022a). The filter properties of the HP method are described in detail in Section 4.3.5.

4.2.4 Key policy rate

The main instrument for stabilizing inflation and developments in the Norwegian economy is the key policy rate. Primarily, the policy rate and expectations of the policy rate influence interbank rates and banks' interest rates on customer deposits and loans. In return, market rates affect the NOK exchange rate, security prices, credit demand, house prices, consumption, and investment (Norges Bank, 2022b). The policy rate can furthermore influence inflation expectations and economic developments. The system through which NB has affected bank liquidity, has been subject to large changes and revisions over the sample period. The system has changed from one based on direct or indirect regulatory instruments, to one based on market-oriented instruments (Eitrheim & Klovland, 2007). Hence, constructing a precise key interest rate series for the sample period, in which it is possible to correctly compare the response of the variables of interest to monetary policy shocks, is challenging. Thus, the data series constructed in this paper is viewed as an estimate.

Before the sight deposit rate was introduced in 1993 there was no standardized key policy rate per definition. Before 1986, discount rates functioned as a key signal rate indicating the lower end of the whole structure of administratively determined interest rates (Eitrheim & Klovland, 2007). From 1986 until May 1993, the D-loan rate was the operating policy rate of NB (Norges Bank, 2021). The D-loan rate is Norges Bank's overnight lending rate – the interest rate banks are charged to cover negative balances overnight on their accounts. From May 1993 the key policy rate has been the sight deposit rate. The sight deposit rate is the interest rate on banks overnight deposits in Norges Bank up to a specified quota (Norges Bank, 2021).

Figure 4.2: Constructed key interest rate and other central interest rate series over the sample period.



Note: Data series sourced from SSB (2022) and Eitrheim & Klovland (2007).

The data series on the key policy rate applied in this thesis is constructed by the following two interest rate series; 1) the Marginal Central Bank liquidity rate and 2) the sight deposit rate (Eithrheim & Klovland, 2007; SSB, 2014; SSB, 2022e). The Marginal Central Bank liquidity rate – henceforth the MCBL rate – series is constructed by Eitrheim & Klovland (2007), published in Norges Bank Occasional paper No. 38 «*Historical Monetary Statistics for Norway, Part II*». The MCBL rate is constructed from several different series[4] (Eitrheim & Klovland, 2007). The series is given in quarterly averages of monthly figures. The data series on the sight

[4] Before 1976 the MCBL rate was sat equal to the Central Bank loan rate. From 1977 the MCBL rate is estimated by the maximum of the effective yield on NB's market paper and the marginal rate on Central Bank loans. The principle was followed until March 1986. Until 1993 it is set equal to the F-loans, except for 1992 and the first five months of 1993, when the D-loan rate is applied. From July 1993 it is estimated by the maximum of the interest rate on F-loans and the interest rate on F-deposits (Eitrheim & Klovland, 2007).

deposit rate is sourced from SSB (2014) in quarterly data for the period 1991Q2 to 2014Q2, and monthly data for the sample period 2014M1 to 2022M10 (SSB, 2022e).

From 1996 onwards, the rate of marginal liquidity has only temporarily deviated from the sight deposit rate. The deviation periods are typically periods such as 1998 – 1999 when oil prices dropped significantly which caused turbulence in the foreign exchange markets for a prolonged period (Eitrheim & Klovland, 2007). The sight deposit rate series is thus applied from 1996. The marginal liquidity rate series is spliced with the sight deposit series to construct a key interest rate series for the entire sample period. The splicing technique is presented in Section 4.3.3. Missing quarterly figures for the marginal liquidity rate series, in 1981K4, 1982K4 and 1983K2, are calculated by quarterly adjusting the yearly figures for the marginal liquidity rate in 1981, 1982 and 1983. The yearly figures are sourced from Eithrheim & Klovland (2007).

4.2.5 Exchange rate

The trade-weighted exchange rate (TWI) published by Norges Bank (2020), would be the preferred measure for the exchange rate. The multilateral index is based on the NOK exchange rate weighted against the currencies of Norway's 25 most important trading partners (Norges Bank, 2020). However, there is limited data available for the index, as it only goes back to 1981. Thus, NOK exchange rate measured against the US dollar is considered the best alternative when comparing sample periods with different exchange rate policy regimes. As the US economy has a large impact on the Norwegian economy and the NOK exchange rate, it further motivates this choice (Smets, 1997). The exchange rate, given as NOK per US dollar is obtained from OECD' monthly monetary and financial statistics (MEI), for the period 1970Q1 – 2022Q3 (OECD, 2022a). The obtained quarterly data is calculated as monthly averages (OECD, 2022a).

4.2.6 Import price index

The relative consumer price index sourced from OECD, is included as an import price measure. The index is a competitiveness-weighted relative consumer price index for Norway in dollar terms. The competitiveness weights accounts for the structure of competition in both export and import markets of the goods sector of 49 countries (OECD, 2022b). An increase in the index indicates real effective appreciation and deterioration of the competitive position of

Norway. Quarterly data for the sample period 1970Q1 – 2022Q3 is collected. The data is given in NOK per US dollar, with 2015 as the reference year.

4.2.7 Oil prices

Data on the OPEC Reference Basket in real terms is obtained from the Organization of the Petroleum Exporting Countries (OPEC) as a measure of real oil prices (OPEC, 2022). The data series is given in Dollars per barrel with reference year 2017 = 100 and is a weighted average of oil prices collected from OPEC member countries. The real oil price is based on combined indices of currency exchange rates of the countries set forth in the modified Geneva I Agreement and weighted average consumer prices indices of modified Geneva I countries and the US (OPEC, 2022). The series serves as a reference point for oil prices. The data is given in yearly figures spanning the time period 1972 – 2021.

Missing values for 1971 and 2022 are retrieved from the Saudi Central Bank (SAMA) and OPEC, respectively (SAMA, 2022; OPEC, 2022). The data value on basket real oil price for 1971 is calculated by using the OPEC basket deflator with base year 2005 = 100 (SAMA, 2022). The 1971 value is spliced with the data series retrieved from OPEC and thus rebased to 2017 as reference year. The data series is subsequently quarterly adjusted.

4.2.8 Real economy and marginal cost measures

Due to limited time, the quarters for 2022 are dropped in the Real economy model presented in Section 5.5.3. SVAR Model 3 is only applied to investigate how inflation responds to shocks to the real economy and marginal costs variables before and after 1992. Thus, dropping 2022Q1, 2022Q2 and 2022Q3 is considered to not make that much of a difference to the results.

Real wages

Yearly data on real wages in fixed 2010 prices, is collected from SSB (2022f). The data is subsequently quarterly adjusted and HP-filtered.

Hours

Yearly data on hours, measured by the per-capita hours worked in the total economy at the end of the year, is collected from SSB (2022g). The data is quarterly adjusted and HP-filtered.

Labor share

According to Del Negro et al. (2020), marginal cost pressures measured by comparing wages to labor productivity, can provide a comprehensive view of cost pressures faced by firms. Following Del Negro et al. (2020), this paper assumes that a firm's log marginal cost is proportional to its log unit labor cost, when there are constant returns to scale production. By further assuming homogenous factor markets, the marginal cost is equalized across firms, so that the aggregate log labor share is proportional to the average real marginal cost (Del Negro et al., 2020). The aggregate log labor share is thus given by the following equation:

$$Labor\ share = Wage + Hours - GDP - CPI$$

4.3 Data preparation

In this section the data preparation methods applied to the time series are presented in more detail. First, the quarterly adjustment techniques are introduced. Thereafter, the extrapolation method and the splicing method is described. Following this the seasonal adjustment and detrending method is explained.

4.3.1 Quarterly adjustment

To capture more of the movement in the data, it is beneficial to transform the yearly data to quarterly data. The quarterly data is constructed by using fixed rates for each quarter. The first quarter and second quarter are calculated by multiplying the preceding year by 0.33 and 0.20, and the present year by 0.67 and 0.8, respectively. The third quarter is set equal to the present year's value, and the fourth quarter is calculated by a rate of 0.8 for the current year and 0.2 for the following year. Some of the data is collected as monthly figures and is thus, converted to quarterly figures by finding the monthly averages for each quarter.[5]

[5] The quarterly adjustment for monthly data is applied with the following mean formula: $\bar{X} = \frac{\sum_{i=1}^{N} x_i}{N}$

4.3.2 Extrapolating

Extrapolating is a method used to calculate missing values outside an interval of known values. The method assumes that the observed trend continues outside the known area of the time series. To calculate the missing values, CPI is utilized to extrapolate backwards in time – which is a commonly used practice (Mouyelo-Kataoula & Hamadeh, 2012). The neighboring value of the known interval is used as a base year, x_b, to construct the missing values. The base value is fitted by the coherent CPI value of the missing quarters, x_n, given by:

$$x_n = x_b \times \left(\frac{CPI_n}{CPI_b}\right) \tag{19}$$

4.3.3 Splicing technique

Many of the times series applied in this paper are constructed over a period where different estimation and processing practices have been applied. This creates a risk of heterogeneity in the data. Different data preparation practices can result in exogenous noise, which makes it difficult to compare the different time series. Splicing different time series allows for correction of possible deviations between overlapping time periods. The method involves splicing the end of one year to the beginning of another year when there is considerable difference in the levels of the time series (Moreno, 2014).

The applied splicing technique adjusts the level of the older time series to the more recent time series' level by creating a joint splicing factor. To construct the splicing factor (SF), the most recent overlapping years of the time series are utilized. The splicing factor in year t for variable I is calculated by dividing the new data on data for corresponding years of the old time series:

$$SF_t^i = \frac{x_t^{iN}}{x_t^{iE}} \tag{20}$$

The joint splicing factor is found by calculating the average of the splicing factors for the overlapping years.

$$\overline{SF}^i = \frac{\sum_{i=1}^{n} SF_i}{n} \tag{21}$$

To adjust the older time series to the same level as the newer time series, the older time series data is multiplied by splicing factor:

$$x_{S_t}^i = x_t^{i^E} \overline{SF}^i \tag{22}$$

The splicing technique adjusts the data and makes it possible to get a representative picture of the change in a variable over time.

4.3.4 Seasonal adjustment

In this section the seasonal adjustment technique applied to the time series is explained. Seasonal adjustment techniques are methods of measuring seasonal variation in time series to subsequently remove the seasonal variation (Pindyck & Rubenfeld, 1991). Seasonal adjustment is a form of smoothing technique that removes seasonal fluctuation in the time series without removing the irregular temporary fluctuations. By adjusting the data series, it is easier to differentiate between trend and cycle in the time series (Pindyck & Rubenfeld, 1991). Seasonal adjustment techniques are based on the idea that a time series y_t is a product of four components:

$$y_t = L \times S \times C \times I \tag{23}$$

where L = the value of the long-term secular trend in the time series

S = the value of the seasonal component

C = the cyclical component

I = the irregular component

First, to reach the objective of eliminating the seasonal component S, the combined long-term trend and cyclical components $L \times S$ must be isolated. The combined seasonal and irregular components $S \times I$ is therefore removed from the original time series y_t, by using a smoothing procedure involving computing a four-period moving average $\tilde{y}_t$ for the quarterly data:

$$\tilde{y}_t = \frac{1}{4}(y_{t+1} + y_t + y_{t-1} + y_{t-2}) \tag{24}$$

The moving average estimate $\tilde{y}_t$ is presumed to be relatively free of seasonal and irregular fluctuations and is thus an estimate of $L \times C$. To obtain an estimate of the combined seasonal and irregular components $S \times I$, the original data is divided by the estimate of $L \times C$:

$$\frac{L \times S \times C \times I}{L \times C} = S \times I = \frac{y_t}{\tilde{y}_t} = z_t \tag{25}$$

The irregular component I is thereafter eliminated to obtain the seasonal index. This is done by averaging the values of $S \times I$ corresponding to the same quarter. The seasonal-irregular percentages z_t are averaged for each quarter and thus the irregular fluctuations are largely smoothed out:

$$\tilde{z}_t = \frac{1}{n}(z_1 + \cdots + z_n) \tag{26}$$

The four obtained averages $\tilde{z}_1$, $\tilde{z}_2$, $\tilde{z}_3$ and $\tilde{z}_4$ are estimates of the seasonal indices and should sum to 4. However, they will not sum to 4 if there is any long-run trend in the data. The final seasonal indices denoted by $\bar{z}_1, \bar{z}_2, \bar{z}_3$ and $\bar{z}_4$ are then computed by multiplying the indices in equation (26) by a factor that brings their sum to 4. Finally, each value in the original time series y_t is divided by its corresponding seasonal index to remove the seasonal component and thereby deseasonalize it (Pindyck & Rubenfeld, 1991). The seasonally adjusted series then become $y_1^a = y_1/\bar{z}_1$, $y_2^a = y_2/\bar{z}_2$,$\cdots$,$y_{20}^a = y_{20}/\bar{z}_{20}$, etc.

4.3.5 Hodrick - Prescott filter

The following section elaborates on the Hodrick-Prescott filter method. The Hodrick-Prescott (HP) filter proposed by Hodrick and Prescott (1997) has been used extensively in applied econometric work, to detrend economic variables and to assist in the measurement and analysis of business cycles. The method assumes that a single observation (x_t) in a time series can be decomposed into a trend component (g_t), a cyclical component (c_t), a season-based component (s_t), and an irregular component (i_t). Hence, each individual observation is a function of the mentioned components or the sum of the components, as shown by equations (27) and (28):

$$x_t = f(g_t, c_t, s_t, i_t) \tag{27}$$

$$x_t = g_t + c_t + s_t + i_t \tag{28}$$

The filter is applied to seasonally adjusted time series derived from the method presented in Section 4.3.4. Hence, the season-based component is removed from the time series. To simplify, the irregular component is hereafter thought of as an error term and Equation 4.10 thus becomes:

$$x_t = g_t + c_t \tag{29}$$

The HP filter allows for variation over time in the underlying growth trend, but additionally ensures that the short-term fluctuations are categorized as temporary cyclical deviations from trend (Hodrick & Prescott, 1997). Consequently, making it possible to distinguish between a permanent and temporary component in a time series. From a technical viewpoint, the method estimates a trend component by minimizing the quadratic difference between the actual values and the trend, as shown by the following equitation (Benedictow & Johansen, 2005):

$$\text{HP} = \sum\nolimits_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum\nolimits_{t=2}^{T-1} ((g_{t+1} - g_t) - (g_t - g_{t-1}))^2 \tag{30}$$

The first part of the expression indicates the cycle component and the second indicates the differences in the trend growth rate where λ penalizes variability in the second difference of the trend component (Kolio & Grytten, 2019). Thus, the positive parameter λ determines the extent of smoothness in the growth component. The extreme λ = 0, means that all changes in the original time series can be interpreted as changes in the trend component (Grytten & Hunnes, 2016). A high λ value, the other extreme, implies that trend growth in a borderline case may equal the average for the projection period.

In consequence, as λ tends to infinity, the HP-trend tends toward a linear deterministic time trend. The established standard for λ values based on Hodrick and Prescott's (1997) original proposition, is λ=100 for yearly data, λ=1600 for quarterly data and λ=14 400 for monthly data. However, according to Johansen and Eika (2000) and Benedictow and Johansen (2005), it can be argued that Norwegian data series should utilize lambda values that are 25 times higher.

The HP-filter makes a new time series with the trend component g_t, and the unique solution to the minimization problem can be identified as:

$$g = (I_n - \lambda F)^{-1} x \tag{31}$$

where I_n is an identity matrix with $n * n$ dimensions, and F constitutes the penta-diagonal $n * n$ matrix. This yields the following theoretical and numerical example for the F matrix, following Kolio and Grytten (2019):

$$F = \begin{pmatrix} f & 0 & 0 & & 0 & 0 & 0 \\ 0 & f & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & f & & 0 & 0 & 0 \\ & \vdots & & \ddots & & \vdots & \\ 0 & 0 & 0 & & f & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & f & 0 \\ 0 & 0 & 0 & & 0 & 0 & f \end{pmatrix} \quad F = \begin{pmatrix} 1 & -2 & 1 & & 0 & 0 & 0 \\ -2 & 5 & 4 & \cdots & 0 & 0 & 0 \\ 1 & -4 & 6 & & 0 & 0 & 0 \\ & \vdots & & \ddots & & \vdots & \\ 0 & 0 & 0 & & 6 & -4 & 1 \\ 0 & 0 & 0 & \cdots & 4 & 5 & -2 \\ 0 & 0 & 0 & & 1 & -2 & 1 \end{pmatrix} \tag{32}$$

When the growth trend is fitted, the estimates of the times series cyclical component is obtained by rearranging equation (29) to get the following:

$$c_t = x_t - g_t \tag{33}$$

To underscore percentage deviations from relevant trend the results will be presented as natural logarithms, and thus the following expression is arrived at:

$$Log(c_t) = Log(x_t) - Log(g_t) \tag{34}$$

The HP filter will be applied for the following four purposes in the empirical analysis:

1) to produce stationary time series applicable for regression analysis.
2) to generate estimates of the NAIRU and subsequently the unemployment gap.
3) to generate estimates of potential output and subsequently the output gap.
4) to estimate a proxy for data on rational inflation expectations.

Limitations

There are, however, several shortcomings associated with the HP-filter which are important to underline. Firstly, although the filter is widely acknowledged, it has a lack of theoretical foundation. Secondly, the filtering method cannot capture structural breaks in the trend of the economic time series (Sørensen & Whitta-Jacobsen, 2010). Such as, labor market reforms which leads to a significant one-time shift in the level of the natural unemployment rate. The change in structural unemployment will only slowly and gradually be picked up by the estimated HP trend in unemployment. Hence, the estimation of the NAIRU as the proxy for the natural unemployment rate, might be imprecise when generated with assistance of the HP-filter. The mentioned reforms during the 1970s and 1980s can further induce uncertainty in the data series.

Another disadvantage of the HP-filter is that the division between trend and cycle is arbitrary as it depends on the smoothing parameter λ (Gottfries, 2013). The λ must be given a preassigned value and there is no objectively correct value of the parameter. The arbitrariness in the choice of λ creates additional uncertainty to the measures of cyclical fluctuations based on the HP filter. Kydland and Prescott (1990) further argue that assuming a constant value of λ implicitly assumes that the relative variances of supply and demand disturbances to a time series are invariant, which can limit the analysis of this thesis.

The filtering method additionally induces endpoint problems, as it gives imprecise estimates of the trend at the endpoints of time series (Sørensen & Whitta-Jacobsen, 2010; Grytten & Hunnes, 2014). The filter is a two-sided filter in the sense that it averages data before and after each data point. Consequently, the method is necessarily one-sided at the endpoints of the sample period and thus estimation errors are caused towards the ends of a dataset (Baxter & Kind, 1995). The limited availability of Norwegian data for some of the applied time series in addition to real time data problems, might constitute as an analytical speedbump. An example is the large negative output gap at the end of the sample period – illustrated in Figure A.1 in Appendix A – most likely due to endpoint problematics. Sørensen & Wittha-Jacobsen (2010) further underlines the considerable uncertainty regarding the size of the output gap. Thus, the potential gap between instrumental trends and natural trends, are further underscored by the limited quantum of data for some of the data sets applied in this analysis.

4.4 Data validity and reliability

The data presented in this chapter is retrieved from reliable sources and adjustments to the data are not done without consulting industry experts, or the providers of the data. The adjustments that are applied are thus considered to not affect the results to a large extent. The data series are therefore viewed as valid and reliable for the analysis of the research problem. Most of the data series are cross-checked, both by comparison with results from existing literature, but also through using several sources for the same data. The adjustments to the applied data sets and other assumptions are minimized, and only used as a last resort.

4.4.1 Variables and chosen sample period

An issue with the broad CPI as an inflation measure is that idiosyncratic factors in food and energy markets can bias estimation results for reasons that are not represented in the standard Phillips curve. Thus, core inflation which attempts to differentiate between persistent and temporary causes of price changes is often preferred over headline inflation due to occasional high volatility of food and energy prices. The CPI is also affected by changes in e.g., VAT and other indirect taxes, which can induce temporary noise in the index and make it difficult to isolate the response of inflation to monetary policy shocks (Bjørnland, 1997). However, choosing a measure of underlying (core) inflation like CPIXE or CPI-ATE that permanently excludes a selection of price subgroups, can lead to the risk of not capturing structural changes in the CPI especially when expanding the analysis to include cost-push shocks in the NKPC framework. There is furthermore uncertainty to the inflation expectations measure as expectations are not directly observable.

Another possible challenge with the data collection is that when a specific time-period is chosen, it can bias the result as the sample could be chosen to give specific outcomes. Thus, the results might contain a degree of bias due to sample period selection. The time-period examined in this thesis is however limited by the applied data series. The AKU conducted by SSB started in 1972 and limits the sample period.

4.4.2 Structural breaks and changes in data collection practices

An issue with using historical data is the length of the series, as longer time periods encompass structural breaks in the trend due to major economic and political occurrences. This might contribute to uncertainty in the estimates of the time series cyclic behavior and consequently, regression estimators. According to Mavroeidis (2004) estimates of the NKPC are less reliable when the sample covers periods in which inflation has been under effective policy controls. The Norwegian economy in the 1970s and early 1980s is characterized by massive government price controls (Boug et al., 2011). This might lead to uncertainty in the results and is a limitation of the data. The key policy rate series are also subject to uncertainty as there was no standardized key policy rate before 1993 and the time series is constructed with two different rate series.

Another consequence of a sample period of 52 years is changes in both definitions and construction practices of the collected data series. As a result, it can weaken the credibility of the data material and hence, the interpretation of the results of the analysis. Collection and construction of time series will always induce the possibility of data errors. Possible sources of errors in the data preparation are errors in collection of the data, misinterpretations of the data or definitions, seasonal and quarterly adjustment calculation errors, errors in extrapolation and filtering calculations, and unrealistic assumptions. The economic and monetary variables are nevertheless collected from official and trustworthy sources. The sources present detailed and open information on the collection of the data in addition to the methods and changes applied to the data sets. This strengthens the reliability of the data. The data collection and preparation conducted in this paper is extensively documented and explained. Overall, the data's validity and reliability are considered satisfactory.

5. Method

This chapter presents the methods applied in the analysis. The empirical approach of this thesis will first employ Correlation coefficient and Ordinary Least Square to examine the inflation-unemployment relationship, building on IMF (2013), Blanchard et al. (2015) and Blanchard (2016). Thereafter, the Structural Vector Autoregression (SVAR) framework is applied to examine effects shocks to inflation and the real economy.

5.1 Correlation coefficients

The Phillips curve and the theoretical foundation behind inflation targeting implies that there is a systemic positive (negative) relationship between short-term fluctuations in inflation and output (unemployment). Hence, a clear positive (negative) correlation between the variables should be present. The following section thus presents the methodology for the correlation coefficient estimate analysis. To study to what extent the cyclical component of an economic variable (x_t) moves in the same direction as or opposite to the cyclical component of the variable of interest (c_t), the empirical covariance between x_t and c_t is introduced. The empirical covariance is defined as:

$$s_{xc} = \frac{1}{T-1}\sum_{t=1}^{T}(x_t - \bar{x})(c_t - \bar{c}), \qquad \bar{c} \equiv \frac{1}{T}\sum_{t=1}^{T} c_t \tag{35}$$

The covariance measures the degree to which the two variables move together (Sørensen & Whitta-Jacobsen, 2010). It is however preferable to normalize the observations of $x_t - \bar{x}$ and $c_t - \bar{c}$ by the respective standard deviations s_x and s_c, to obtain an indicator which is independent of the choice of units. Thus, to study the covariation of the normalized deviations $\frac{x_t - \bar{x}}{s_x}$ and $(c_t - \bar{c})/s_c$, the mentioned procedure produces the coefficient of correlation between x and c, defined as:

$$\rho(x_t, c_t) = \frac{s_{xc}}{s_x s_c} = \frac{\sum_{t=1}^{T}(x_t - \bar{x})(c_t - \bar{c})}{\sqrt{\sum_{t=1}^{T}(x_t - \bar{x})^2} \cdot \sqrt{\sum_{t=1}^{T}(c_t - \bar{c})^2}} \tag{36}$$

The coefficient of correlation assumes a value within an interval ranging from minus one to plus one and measures the strength of the linear relationship between two variables (Sørensen & Whitta-Jacobsen, 2010; Wooldridge, 2020). The variables x_t and c_t are perfectly positively correlated if $\rho(x_t, c_t)$ is equal to one. If $\rho(x_t, c_t)$ equals minus one, the two variables are perfectly negatively correlated. In both cases there is a strict linear relationship between the two variables. A positive value of $\rho(x_t, c_t)$ indicates that x and c move in the same direction, i.e., x tend to vary procyclical. The co-movements will be more systematic the smaller the deviation of $\rho(x_t, c_t)$ is from one. Contradictory, if $\rho(x_t, c_t)$ takes a negative value, the two variables tend to move in the opposite direction – x moves in a countercyclical fashion. If, however, $\rho(x_t, c_t)$ is 0 or close to 0, it indicates that there is no systematic relationship between x and c.

5.1.1 Assumptions and limitations

The variables applied in the correlation analysis are assumed to be stationary. A more detailed discussion of stationarity is presented in Section 5.5.4. It is important to state that correlation does not mean that there is a causal relationship between two variables (Pripp, 2018). Two variables that are correlated, do not have to influence each other. It is thus possible to get positive or negative coefficients of correlation, even if the variables have no relation. The coefficient of correlation does not describe if there is a relation between changes in the two variables. In other words, correlation does not determine cause and effect between two variables. The key limitation of the correlation analysis can be emphasized with a common phrase used in statistics: «correlation does not imply causation». Hence, it is important to execute caution when interpreting coefficients of correlation.

5.2 Ordinary Least Square

To examine if there is a causal relationship between the unemployment gap and inflation, and to generate and interpret slope estimates of the Norwegian Phillips curve, the Ordinary Least Square (OLS) method will be applied. The OLS method minimizes the sum of squared residuals to produce estimates of the unknown parameters in the regression model (Wooldridge, 2020). The simple static OLS regression is presented in the following expression:

$$y_t = \alpha_0 + \beta_i x_t + \varepsilon_t, \quad t = 1,2,\dots,n \tag{37}$$

The dependent variable, y_t, is dependent on the changes in independent variable x_t. α_0 is the constant and the error term is expressed by ε_t and captures the variation in the dependent variable related to omitted variables (Wooldridge, 2020). The slopes estimate coefficients is β_i, and can be written as:

$$\hat{\beta}_i = \frac{\Delta \hat{y}}{\Delta x} , \tag{38}$$

The equation describes the amount by which $\hat{y}$ changes when the independent variable x increases by one unit. Equivalently, this can be expressed as follows:

$$\Delta \hat{y} = \hat{\beta}_i \Delta x \tag{39}$$

5.3 OLS Model specifications

The model employed in the OLS regression analysis is based on the original Phillips curve (the Phillips curve tradeoff) and NKPC. The baseline model is estimated in three stages. The first stage involves estimating the original Phillips curve without any inflation expectations, over the five sub-periods. In the second step, the OLS estimates of the NKPC framework are presented for each of the five sub-periods. Finally, the third step involves estimating rolling regression of the NKPC. Thus, mapping the slope coefficient of unemployment and rational inflation expectation on inflation, over the sample period. The baseline model is algebraically expressed as follows:

$$\ln(\pi_t) = \alpha_0 + \beta_1 \ln(\pi_t^e) + \beta_2 ln(\mu_t - \mu_t^*) + \varepsilon_t \tag{40}$$

In the expression, π_t is the current rate of inflation, $\pi^e$is the expected rate of inflation, and $(\mu_t - \mu_t^*)$ is the cyclical unemployment – or the unemployment gap measured by the log difference between actual unemployment and the NAIRU level for Norway. The parameter ε_t, is a stochastic error term assumed to have a constant variance and a zero mean. β_2 gives how inflation adapts to deviations in unemployment from trend, β_1 denotes how inflation adapts to changes in inflation expectations, and α_0 is the intercept of the Phillips curve.

5.3.1 OLS Model 1: Original Phillips curve

The original Phillips curve assumes that economic agents do not form any expectation on prices. Thus, the coefficient of the inflation expectation variable in the baseline model is equal to zero. The baseline model then simplifies to the following expression:

$$\ln(\pi_t) = \alpha_0 + \beta_1 ln(\mu_t - \mu_t^*) + \varepsilon_t \tag{41}$$

The variables are as previously defined in the baseline model. Fitted OLS regression lines of the original Phillips curve model given in (5.7), are plotted against the scatter plot for each of the five sub-period.

5.3.2 OLS Model 2: NKPC

OLS Model 2 differs from the standard NKPC literature in two ways; 1) The rational inflation expectations of economic agents are assumed to be based on both their expectations on future prices in addition to past inflationary experience. This in addition to all other information available. Thus, the model assumes both backward- and forward-looking expectations. 2) The supply shock is not included. OLS Model 2 is given by:

$$\ln(\pi_t) = \alpha_0 + \beta_1 \ln(\pi_t^e) + \beta_2 ln(\mu_t - \mu_t^*) + \varepsilon_t \tag{42}$$

In the expression, π_t^e represents the rational expectations, and the rest of the variables are as previously defined in the baseline model. ε_t, denotes the disturbance term. The rolling regressions of OLS Model 2 given by equation (42) is applied with a rolling window of 20 and 40 periods, which corresponds to five- and ten-year rolling regressions. The method thus regresses OLS Model 2 for the period starting 1972Q1, to 1977Q1 for the five-year rolling regression, and to 1982Q1 for the ten-year rolling regression. The next regression starts in 1972Q2 and so forth, until the end of the sample period. Each regression report β_1 and β_2 at each starting point of a new regression.

5.3.3 Assumptions and limitations

The variables included in the OLS analysis are assumed to be stationary. Following Blanchard et al. (2015), the unemployment gap, $(\mu_t - \mu_t^*)$, is assumed to be uncorrelated with the error term in the Phillips curve for the OLS regressions. This implies that the OLS estimators of the equations are unbiased. This assumption is standard in the literature, but it is rarely examined (Blanchard et al., 2015). The assumption that the disturbance term is uncorrelated with the regressor in the Phillips curve regression is a strong assumption to make. As unemployment correlates with many other factors in the economy, the explanatory variable included in the regression will be biased when applying OLS. Thus, the expected value of the slope estimator will also be biased.

The model will also contain multicollinearity, as the inflation expectation variable is constructed from the CPI index included as the dependent variable in the OLS models. This paper assumes that a β_1 close to one indicates a perfect collinearity between inflation and inflation expectations and can be interpreted as a one-to-one change in the variables. Another problem with regressing the Phillips curve relationship is that past values of inflation – the dependent variable is believed to affect the current values of inflation. If inflation was high the previous year, economic agents will expect prices to rise fast this year and consequently demand higher factor payments (wages), and in turn driving inflation. Vector autoregressive models address both the endogeneity problem and the autocorrelation problem. Thus, the Structural Vector Autoregression (SVAR) method introduced by Sims (1980) will be applied to address the omitted variable bias and autocorrelation problems.

5.4 Structural Vector Autoregression

Structural vector autoregression (SVAR) models have been extensively applied in empirical macroeconomics, since Sims's (1980) pioneering contribution to the literature (Bjørnland & Thorsrud, 2015). As it allows variables of interest to be interconnected and infer economic meaning to structural shocks, the approach is beneficial for assessing causal relationships and effects of demand, supply and monetary policy shocks (Bjørnland & Thorsrud, 2015). The ways that the different shocks to demand and supply affect inflation, thus further motivates the use of a SVAR model in the analysis. The approach treats all variables as jointly endogenous and allows each variable to depend on its past realizations and the past realizations of other variables in the system (Enders, 2015). Thus, the problems faced in the OLS method involving autocorrelation and endogeneity are solved. Multicollinearity is not allowed in the SVAR model, and thus inflation expectations are excluded from the analysis.

Building on Neri (2004) and Bjørnland (2009), this paper assume that the Norwegian economy can be described by the following structural dynamic vector equation:

$$A(L)y_t + c = v_t \tag{43}$$

where y_t denotes a vector of N economic variables, v_t denotes a vector of structural shocks that can be given an economic interpretation, and c denotes a vector of constant. A(L) is given by:

$$A(L) = A_0 - A_1L - A_2L^2 -..-A_pL^p \tag{44}$$

where L denotes the lag operator and $A_i(i = 0, p)$ are NxN matrices. All variables except for the interest rate are expressed in logs. The interest rate is expressed in levels. The structural shocks are assumed to be mutually independent and serially uncorrelated. The reduced form of the VAR is expressed by the system of equations given by:

$$y_t = c + B(L)y_t + u_t \tag{45}$$

where $B(L)$ is given by

$$B(L) = B_1L - B_2L^2 -..-B_pL^p \tag{46}$$

and u_t denotes the vector of residuals. The residuals are related to the structural shocks by the relationship expressed in equation (47):

$$u_t = {A_0}^{-1}v_t \tag{47}$$

The structural coefficients that link the variables of vector y_t contemporaneously, is given by matrix A_0. The coefficients are of main interest and can be identified by orthogonalizing the reduced form variance covariance matrix of the VAR residuals by using a Cholesky decomposition (Bjørnland & Thorsrud, 2015). This amount to assuming a recursive structure of the A_0matrix for the models. A recursive structure implies only imposing restrictions on the contemporaneous (short run) relations among the VAR variables. The long-run behavior of the model is left unrestricted.

In a Cholesky decomposition, the order of the estimated equations matters, as it puts restrictions on how the different variables influence each other. A variable will influence the following variables contemporaneously, but do not influence preceding variables. Variables assumed to be the most exogenous are therefore placed first in the ordering and the least exogenous variables are ordered last. The ordering is decided based on economic theory, empirics and prior knowledge. The confidence interval is set to 68 percent, as suggested by Sims and Zha (1999) for SVAR analysis.

5.5 SVAR Model specification

5.5.1 SVAR Model 1: The Original Phillips curve

Based on the original Phillips curve, the first SVAR model is constructed as a simple bivariate SVAR model only containing two variables – inflation and the unemployment gap.[6] Vector y_t for SVAR Model 1 thus include the unemployment gap (u) and inflation (π).

$$\begin{bmatrix} v_u \\ v_\pi \end{bmatrix} = \begin{bmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} u_u \\ u_\pi \end{bmatrix} \tag{48}$$

Matrix (48) implies that the following restrictions on the variables are assumed:

- Only shocks to the unemployment gap (u_u) can affect the unemployment rate contemporaneously.
- Only shocks to the unemployment gap and inflation (u_π), can affect inflation contemporaneously.

5.5.2 SVAR Model 2: Open Economy New Keynesian Phillips curve

Vector y_t for Model 2 contains the following variables: the real oil price (o), the unemployment gap (u), the output gap (y), inflation (π), the key policy rate (i), and the exchange rate (e), in that order.[7] The structural shocks to the variables in vector y_t are an oil price shock (v_o), a labor supply shock (v_u), a productivity shock (v_y), an inflation shock (v_π), a monetary policy shock (v_i) and a risk premium shock (v_e), respectively.

[6] Originally, SVAR Model 1 was supposed to include an additional variable of inflation expectations. However, multicollinearity is not allowed in SVAR and thus, the variable was excluded. Some researchers use lags of inflation as an alternative proxy for inflation expectations (Galí and Gertler, 1999). Thus, including lags in the models can be argued to replicate some degree of inflation expectation dynamics.

[7] Another SVAR model where the oil price was replaced with an import price variable in Model 2, was modelled and tested. Following Bjørnland (1998), an approximation of the relative consumer price index for trading partners was included. Shocks to this variable would thus have been interpreted as imported inflation shocks. Due to multicollinearity problems in the model at various lag lengths, the model was discarded.

$$\begin{bmatrix} v_o \\ v_u \\ v_y \\ v_\pi \\ v_i \\ v_e \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{bmatrix} u_o \\ u_u \\ u_y \\ u_\pi \\ u_i \\ u_e \end{bmatrix} \tag{49}$$

Matrix (49) implies that the following restrictions on the variables are assumed:

- Only shocks to the oil price (u_o) can affect the oil prices contemporaneously.
- Only shocks to the oil price and the unemployment gap (u_u) can affect the unemployment rate contemporaneously.
- Only shocks to the import price, the unemployment gap and the output (u_y) can affect output contemporaneously.
- Only shocks to the oil price, the unemployment gap, the output gap and inflation (u_π) and affect inflation contemporaneously.
- Only shocks to the oil price, the unemployment gap, the output gap, inflation and the interest rate (u_i), can affect the interest rate contemporaneously.
- Only shocks to the oil price, the unemployment gap, the output gap, inflation, the interest rate and the exchange rate (u_e) can affect the exchange rate contemporaneously.

The oil price is placed at the top of the ordering to reflect that the exogenous oil price shock can only affect the oil price contemporaneously (Bjørnland, 1996a). As Norway is a small open economy it is reasonable to assume that the oil price is given externally as the oil price is decided by the world market or much larger economies as the US on the world market. The oil price is a financial spot price and thus it responds quickly to news. Thereafter the unemployment gap, the output gap, and inflation are placed next.

The following variable is the interest rate. Ordering the monetary policy shock below the monetary policy target variables, corresponds to the implications of an inflation targeting regime (Bjørnland & Thorsrud, 2015). Monetary policy can react immediately to inflation deviations from the inflation target or output deviations from trend. The monetary policy will have a simultaneously lagged effect of at least one period, i.e., a quarter, on the variables. As Norges Bank expects its policy to impact the economy within a medium-term horizon and not immediately, this assumption is plausible (Bjørnland & Thorsrud, 2015; Røisland & Sveen, 2018). The importance of using demand shocks as instruments to trace the slope of the Phillips curve is stressed by Barnichon and Mesters (2020). According to Barnichon and Mesters (2020) a shock to monetary policy should be viewed as a demand shock instrument in SVAR Model 2.

The exchange rate variable is included last as the most endogenous variable, implying that the Norwegian krone can appreciate or depreciate on impact in response to a monetary policy shock. Including an exchange rate variable is supported by Smets (1997). Smets (1997) argues that small open economies are better modelled with VARs when the exchange rate index is introduced and that it is particularly justified for European economies which strongly depend on the US economy.

5.5.3 SVAR Model 3: The Real Economy Model

Following Del Negro et al. (2020) a SVAR model including the following real economy measures are included: real wage, hours, and labor share. The unemployment gap, inflation and the key policy rate is included as specified in Model 2. Following Bjørnland (1998), wages are assumed to be the most exogenous of the variables, indicating that only shocks to the real wage can affect the real wage contemporaneously. The ordering of variables in the matrix induces the same restrictions to the variables included in SVAR Model 3 as previously stated in SVAR Model 1 And SVAR Model2. This yields the following matrix for SVAR Model 3:

$$\begin{bmatrix} v_w \\ v_h \\ v_{ls} \\ v_u \\ v_\pi \\ v_i \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{bmatrix} u_w \\ u_h \\ u_{ls} \\ u_u \\ u_\pi \\ u_i \end{bmatrix} \tag{50}$$

5.5.4 Assumptions and Misspecification tests

Stationarity

According to Bjørnland and Thorsrund (2015), regression analysis might induce spurious regressions when time series are non-stationary. To ensure stationarity, the time series are detrended by applying the HP-filter. Following Hodrick and Prescott (1997) proposal, the ad-hoc smoothness parameter, λ, is set to 1600 for detrending quarterly data for all variables except inflation expectations and the output gap. To generate the estimates of the rational inflation expectations, λ is set equal to ten. The output gap is estimated using λ = 40 000, following Johansen and Eika (2000) and Benedictow and Johansen (2005). The robustness of the results is tested with different lambda values. The detrended time series are in Appendix A.

Thereafter, each time series is subject to an Augmented Dicky Fuller (ADF) test to determine its stationarity (Wooldridge, 2020). The procedure developed by Dickey and Fuller (1979) tests the null hypothesis of non-stationarity – meaning that the time series does contain a unit root – against the alternative of stationarity. The tests confirm that the null hypothesis of a unit root can be rejected at a one percent significance level for all the detrended time series, except the oil price and hours variables. The unit root tests are reported in Table B0.1 – B0.11 in Appendix B0. For the oil price, the null hypothesis is rejected at a five percent significance level. To be able to reject the null hypothesis at a one percent level, the lambda value is reduced to 1300 (Table B0.4). The estimated cycle is thus less volatile. The null hypothesis is rejected at a ten percent significance level for the hours variable. To be able to reject the null hypothesis at a five percent level, the lambda value is reduced to 900 (Table B0.10). The time series in question, more specifically their deviations from trend, are subsequently assumed stationary.

Lag order selection and Autocorrelation

When SVAR is applied, determining the proper lag length is essential (Bjørnland & Thorsrud, 2015). A model with an insufficient number of lags can generate autocorrelated residuals and omit important information. On the other hand, including too many lags can result in increased estimation errors in the model as more coefficients are estimated than necessary (Bjørnland & Thorsrud, 2015). Lag lengths between one and eight orders are considered, following Bjørnland (1998). The optimal lag order is determined by utilizing the four following formalized lag-order selection statistics:

1) the Final Prediction Error (FPE)
2) Aikaike Information Criterion (AIC)
3) Schwarz's Bayesian Information Criterion (SBIC)
4) the Hannan and Quinn Information Criterion (HQIC)

The BIC and HQIC will be given stronger emphasis, as the AIC does not penalize as much as BIC for including more lags. The lag-order selection tests are presented in Table B1.1 – B1.3 in Appendix B1.

For SVAR Model 1 a lag length of one is found at a five percent significance level by all the lag-order selection statistics. Even though a too short lag duration may omit important dynamics, SVAR Model 1 only contains two variables and thus including a longer lag length might induce the risk of overestimating the model. There should be no autocorrelation at the selected lag length. The Lagrange multiplier test indicates no autocorrelation in the residuals for both sample periods when one lag is applied for SVAR Model 1, as the null hypothesis cannot be rejected at the selected lag order. The Lagrange-multiplier test outcomes for SVAR Model 1, SVAR Model 2 and SVAR Model 3 are reported in Appendix B3 in Table B3.1 – B3.6.

The FPE and AIC suggest a lag order of eight for SVAR Model 2 (Table B1.2). However, when testing for autocorrelation the Lagrange Multiplier test indicates that the null hypothesis of no autocorrelation at the second and third lag order can be rejected. The test thus indicates misspecification of the model. The HQIC test suggests a lag order of two and SBIC suggests a lag order of one. When running the test on the subsamples, the HQIC criteria suggests a lag length of five. For SVAR Model 2, the Lagrange-multiplier test implies that the null hypothesis of no autocorrelation in the residuals for any of the five orders tested cannot be rejected, and thus the test gives no hint of model misspecification at the chosen lag-order (Table B3.3 and B3.4). This holds for both sample periods.

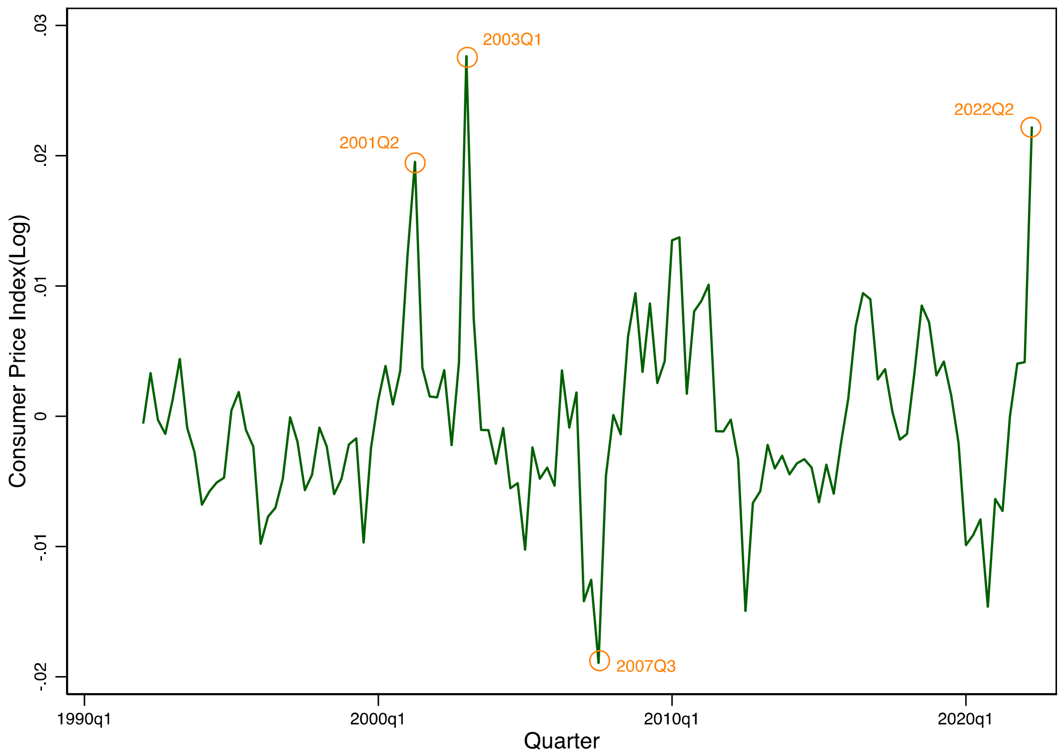
For SVAR Model 3, SBIC suggests a lag length of one, while HQIC and FPE suggest a lag length of five (Table B1.3). Both alternatives induce autocorrelation at lag length one and two. AIC suggests a lag length of six. When applying the lag-selection test for each period separately, SBIC suggests five lags, HQIC suggests six, while AIC and FPE suggest eight lags. The Lagrange-multiplier test implies that the null hypothesis of no autocorrelation cannot be rejected at any of the six lag orders (Table B3.5 and B3.6), and thus a lag length of six is chosen.

Normality

The Jarque-Bera non-normality test suggests that there are outliers in the inflation (CPI), output gap (GDP), wage and policy rate variables. Non-normality indicates that the residuals of the variables are not normally distributed (Bjørnland and Thorsrud, 2015). The Jarque-Bera test results for all models are presented in Table B2.1 – B2.6 in Appendix B.2. CPI does not pass the normality test in the post-92 sample in Model 1 – in other words the variable does not have normally distributed residuals. Following Bjørnland (1998), intervention dummies are included as exogenous variables in the post-92 sample for SVAR Model 1. Dummies are included for 2001Q2, 2003Q1, 2007Q3, and 2022Q2 illustrated in Figure 5.1. The dummies are one or minus one in the year where an outlier is detected, and zero otherwise. Following this, the null hypothesis of normality cannot be rejected at a five percent significance level. Thus, there is no violation of the normal distribution assumption of the error term in SVAR Model 1. However, testing for including and excluding dummies show that the empirical results are virtually unchanged.

In the pre-1992 sample for SVAR Model 2 the non-normality test suggests that there are outliers in the oil price and policy rate variable. Dummies for extreme values in the oil price and policy rate variables are included as exogenous variables. A complete dummy overview is included in Appendix C. Dummies are also included in SVAR Model 2 in the post-1992 sample, to account for outliers in CPI, GDP and policy rate variables. After the dummies are included, the results are more satisfactory. However, there is still some evidence of non-normality in the system. This is most likely due to large volatility in the oil price and interest rate equations.

Figure 5.1: Extreme values in the detrended Consumer Price Index series included as dummy variables in Model 1.



For the pre-1992 sample in SVAR Model 3 the wage and CPI variables are found to be non-normal. Dummies are included in 1976Q3 and 1977Q1 to account for outliers in wage. To account for outliers in CPI, dummies are included in the following four quarters: 1979Q3, 1979Q4, 1979Q2 and 1980Q1. In the post-92 sample the null hypothesis of normality cannot be rejected for all variables except for the key policy rate variable. Dummies are included for the five extreme points found in SVAR Model 2 (See Appendix C), in addition to a fifth one in 1993Q4. The dummies do not alter the results in terms of non-normality for the variable. Following Bjørnland (1998) the remaining non-normality in SVAR Model 2 and SVAR Model 3 is ignored to minimize the use of dummies.

Stability

Lastly, an eigenvalue stability condition test is employed to test the stability of the models (Bjørnland and Thorsrud, 2015). All eigenvalues lie inside the unit cycle for SVAR Model 1 when the chosen lag length of one is applied. The eigenvalue stability condition tests are presented in Table B4.1 – B4.3 in Appendix B4. For SVAR Model 2 the eigenvalues lie inside the unit cycle at the chosen lag length of five, indicating that SVAR Model 2 also satisfies the stability condition. For SVAR Model 3, at least one eigenvalue lies outside the unit circle in the model for the pre-1992 sample. Thus, this induces a limitation of the SVAR Model 3 results. The post-1992 sample in SVAR Model 3 satisfies the stability condition.

6. Empirical results and analysis

This section presents the empirical findings and analysis. First, the correlation coefficient results and OLS regression results for the five sub-periods presented in Chapter 4.1 are introduced. Following this, the empirical results from the SVAR models are presented. The SVAR model results divide the sample period into two adjacent sub-periods with a break in 1992.

6.1 Correlation coefficient results

To explore how the different variables linear relationship variates over the past fifty years, the correlation analysis focuses on comparing the correlation coefficients over the five sub-periods. The correlation analysis is conducted by applying the cyclical values of the variables, to prevent serial correlation problems in the results. The key policy rate is excluded from the analysis as it is set by policy makers and not fit for this kind of analysis. Pairwise correlation results for the variables for the five sub-periods, are presented in Table 6.1 – 6.5.

Table 6.1: Pairwise correlation coefficient results for the period 1972 - 1982

1972-1982	Inflation	Unem.	Output	Wage	Hours	Labor share	Oil price	Import price
Inflation	1.000							
Unem.	0.229	1.000						
Output	-0.067	-0.274	1.000					
Wage	0.552^{***}	0.069	0.480^{**}	1.000				
Hours	0.445^{**}	-0.226	-0.010	0.004	1.000			
Labor sh.	-0.667^{***}	-0.166	0.449^{**}	0.182	-0.283	1.000		
Oil price	0.194	-0.159	0.040	-0.192	0.340^{*}	-0.359^{*}	1.000	
Import p.	0.789^{***}	0.024	0.115	0.490^{**}	0.268	-0.572^{***}	0.260	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.2: Pairwise correlation coefficient results for the period 1982 - 1992

1982-1992	Inflation	Unem.	Output	Wage	hours	Labor share	Oil price	Import price
Inflation	1.000							
Unem.	0.441**	1.000						
Output	-0.564***	-0.693***	1.000					
Wage	-0.606***	-0.740***	0.882***	1.000				
Hours	-0.092	-0.686***	0.689***	0.730***	1.000			
Labor s.	-0.734***	-0.499**	0.639***	0.785***	0.576***	1.000		
Oil p.	-0.017	0.404**	-0.470**	-0.631***	-0.782***	-0.548***	1.000	
Import p.	0.593***	0.400*	-0.484**	-0.616***	-0.177	-0.416**	0.245	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.3: Pairwise correlation coefficient results for the period 1992 - 2002

1992-2002	Inflation	Unem.	Output	Wages	Hours	Labor share	Oil price	Import price
Inflation	1.000							
Unem.	0.093	1.000						
Output	-0.014	-0.431**	1.000					
Wages	-0.144	-0.102	0.190	1.000				
Hours	0.009	-0.514***	0.759***	0.556***	1.000			
Laborshare	-0.586***	-0.269	0.286	0.756***	0.626***	1.000		
Oil Price	0.293	0.422**	-0.099	-0.453**	-0.289	-0.443**	1.000	
Import p.	0.039	0.224	-0.078	-0.107	-0.365*	-0.284	-0.037	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.4: Pairwise correlation coefficient results for the period 2002 - 2012

2002-2012	Inflation	Unem.	Output	Wages	Hours	Labor share	Oil price	Import price
Inflation	1.000							
Unem.	0.380*	1.000						
Output	-0.379*	-0.625***	1.000					
Wages	-0.125	-0.367*	0.148	1.000				
Hours	-0.219	-0.674***	0.801***	0.549***	1.000			
Labor sh.	-0.375*	-0.283	0.005	0.754***	0.466**	1.000		
Oil price	-0.367*	-0.413**	0.495***	0.227	0.516***	0.108	1.000	
Import price	0.267	0.064	-0.250	0.252	-0.112	0.002	0.104	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.5: Pairwise correlation coefficient results for the period 2012 - 2022

2012-2022	Inflation	Unem.	Output	Wages	Hours	Labor share	Oil Price	Import Price
Inflation	1.000							
Unem.	-0.273	1.000						
Output	0.067	-0.233	1.000					
Wages	-0.695***	0.154	-0.148	1.000				
Hours	0.367*	-0.510**	0.566***	0.048	1.000			
Laborsh.	-0.865***	0.304	-0.306	0.875***	-0.266	1.000		
Oil Price	0.181	-0.730***	0.270	0.155	0.618***	-0.163	1.000	
Import Price	0.401*	-0.421*	0.318	-0.095	0.446**	-0.385*	0.687***	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table 6.1 – 6.5 present pairwise correlations between variables for the five sub-periods: 1972-1982, 1982-1992, 1992-2002, 2002-2012 and 2012-2022. Lambda value = 1600 for all variables except the output gap (Lambda = 40 000), the oil price (Lambda = 1300) and hours (Lambda = 900). Variables are given in quarterly cyclic values in log.

The correlation analysis for the five sub-periods find that inflation and the unemployment gap tend to vary procyclical for Norwegian data. The findings suggest a weakening in the strength of the correlation between inflation and unemployment gap. Only considering the significant coefficients, the correlation coefficient decreases from 0.441 at a one percent significance level in the 1982-1992 sub-period (Table 6.2), to 0.38 at a five percent significance level in the 2002-2012 sub-period (Table 6.4). The same is evident for the inflation-output relation. The strength of the correlation coefficient decreases from -0.564 at a 0.1 percent significance level in the 1982-1992 sub-period (Table 6.2), to -0.379 at a five percent significance level in the 2002-2012 sub-period (Table 6.4). Looking at the correlation coefficient estimates between inflation and the output gap, the relationship is found to be strongly negative or close to zero over the five sub-periods.

Coefficient estimate results suggest a surprising negative wage-inflation correlation over all sub-samples, except in 1972-1982. The correlation between wages and inflation is found to increase in strength from -0.606 at a 0.1 percent significance level in the 1982-1992 sub-period (Table 6.1), to -0.695 at a 0.1 percent significance level in the 2012-2022 sub-period (Table 6.5). The correlation coefficients for the intermediate sub-periods are found to be insignificant. The findings further suggest a negative wage-unemployment correlation at varying significance levels for sub-periods 1982-1992 and 2002-2012, in line with theory (Phillips, 1985). The coefficient's strength is reduced from -0.740 at a 0.1 percent significance level in 1982-1992 (Table 6.2) to -0.367 at a five percent significance level in 2002-2012.

Hours are found to be strongly correlated with both the unemployment and output gap over all sub-periods except for the former (1972-1982). The correlation coefficients are of opposite relation. While the unemployment gap varies countercyclical with hours, the output gap tends to vary in a procyclical fashion. The labor share, which is a proxy for marginal cost pressure, is found to strongly correlate with inflation over all sub-periods. Indicating a strong linear real economy-inflation relation. The correlation coefficient suggests that labor share and inflation tend to move in a countercyclical fashion.

The oil price correlation with inflation is only found to be significant in the 2002-2012 sub-period (Table 6.4). However, unemployment and the oil price strongly correlate over all sub-periods except 1972-1982, at either a one percent or 0.1 percent significance level. The import price strongly correlates with inflation in the first sub-period (Table 6.1), the second (Table 6.2) and not until the most recent sub-period (Table 6.5). The findings can however not be interpreted as causal.

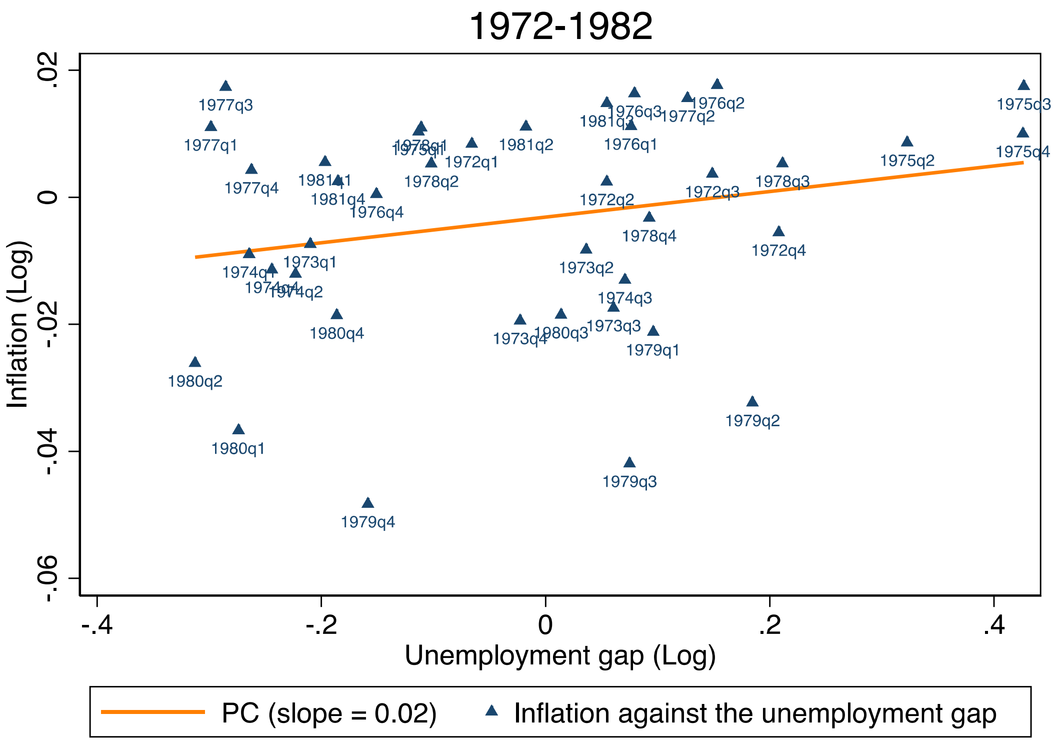
6.2 OLS regression results

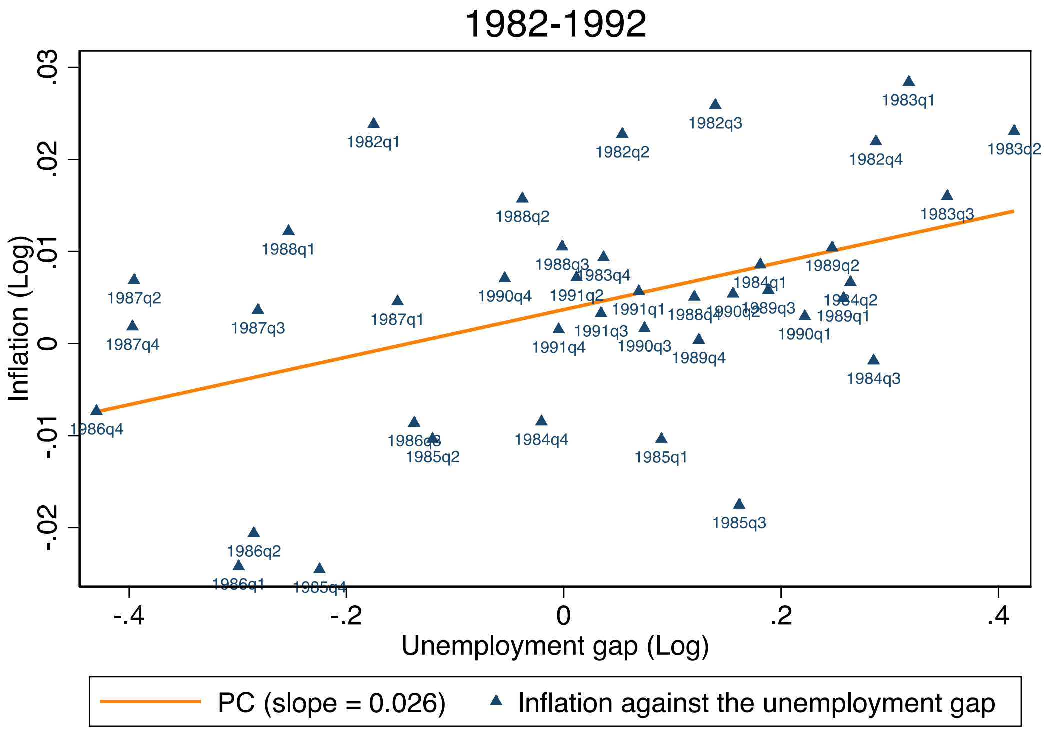
The first pass at estimating the causal Phillips curve relation starts with simple OLS regression, following IMF (2013), Blanchard et al. (2015) and Blanchard (2016). The first regression model is run on the detrended and assumed to be stationary time series of inflation and the unemployment gap. The results of the OLS estimates of OLS Model 1 are presented in Table 6.6. The regression lines of OLS Model 1 are also plotted in Figure 6.1 to illustrate the evolution of the Phillips curve over the five past decades. Thereafter, the OLS model is augmented to include an inflation expectations variable, thus replicating a NKPC. The regression results of OLS Model 2 are given in Table 6.7.

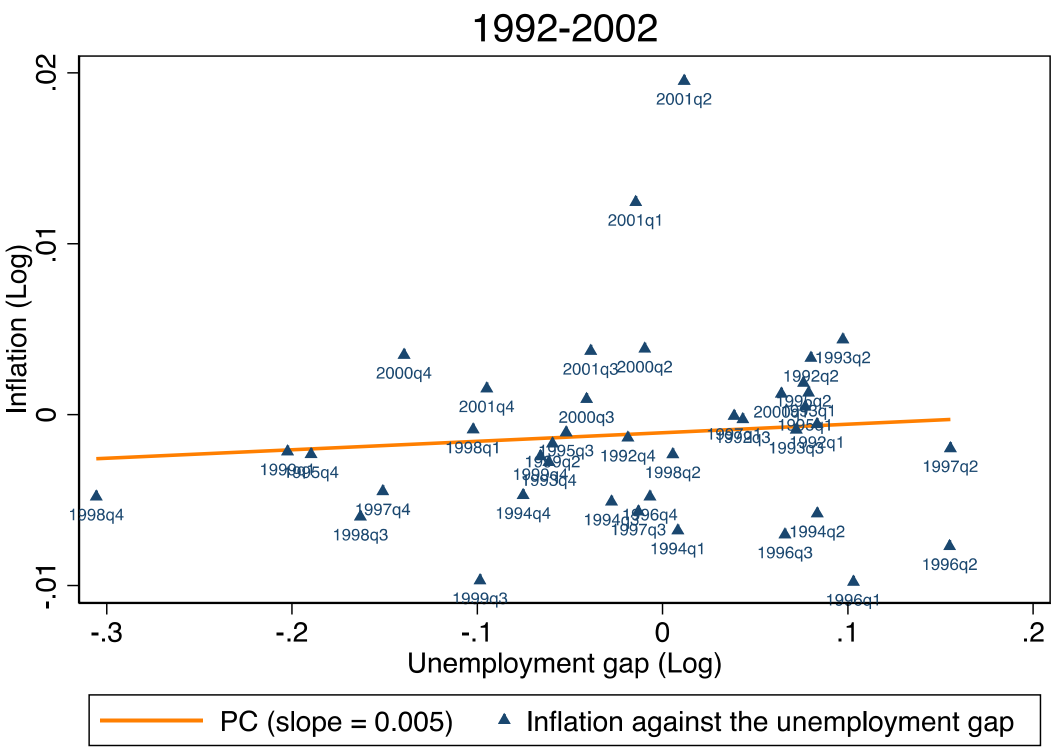
6.2.1 Results OLS Model 1: The Original Phillips curve

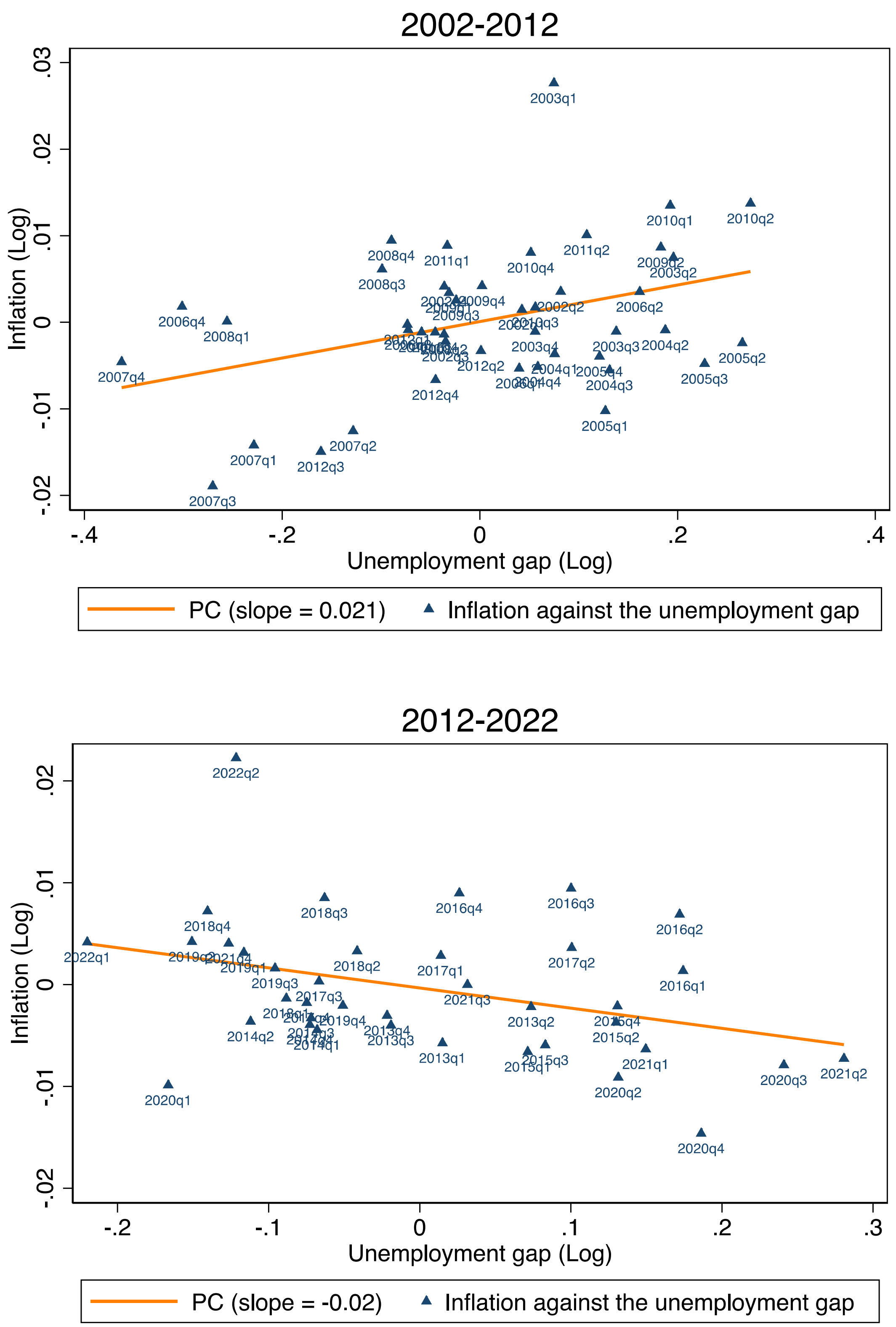
To examine how the Phillips curve slope estimate changes over the chosen sub-periods, the OLS regression lines are presented in Figure 6.1.

Figure 6.1: *OLS Model 1 regression lines and scatter plots for the Phillips curve over the five sub-periods.*




1982-1992
Inflation (Log)
.03
.02
.01
0
-.01
-.02
-.4
-.2
0
.2
.4
Unemployment gap (Log)
PC (slope = 0.026)
Inflation against the unemployment gap


1992-2002
Inflation (Log)
.02
.01
0
-.01
-.3
-.2
-.1
0
.1
.2
Unemployment gap (Log)
PC (slope = 0.005)
Inflation against the unemployment gap



Note: Figure 6.1 shows scatter plots of quarterly inflation against the constructed unemployment gap, split by five sub-periods. Variables are given as the cyclical components of inflation and the unemployment gap in logarithms. The unemployment gap is derived by subtracting the NAIRU estimates from the unemployment rate data. The Phillips curve slopes coefficients and regressions are estimated using OLS.

The OLS estimation results of the original Phillips curve are given in Table 6.6. The estimated slope parameter is found to be significant for the full sample, in addition to the sub-period 1982-1992 and 2002-2012, with varying significance levels. The correlation coefficient is found to be positive for the significant periods except in the sub-period 2012 to 2022. This contradicts the belief of an inverse inflation-unemployment trade-off. The 2012-2022 sub-period shows a negative slope of the Phillips curve, in line with theory (Phillips, 1958; Samuelson & Solow, 1960). The results suggest a flattening of the Norwegian Phillips curve when comparing a slope coefficient of 0.026 for the 1982-1992 sub-period and a slope coefficient of 0.021 in the 2002-2012 sub-period and -0.02 for the 2012-2022 sub-period. The results indicate a reduction in the Phillips curve slope estimate in the period 1982-2012/2022. The results align with the correlation analysis.

Table 6.6: OLS Model 1: The original Phillips curve

	(1) Full sample	(2) 1972-1982	(3) 1982-1992	(4) 1992-2002	(5) 2002-2012	(6) 2012-2022
Unem. gap	0.018^{***}	0.020	0.026^{**}	0.005	0.021^{*}	-0.020^{*}
	(0.005)	(0.014)	(0.009)	(0.009)	(0.008)	(0.008)
Constant	-0.000	-0.003	0.004	-0.001	0.000	-0.000
	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
N	202	40	40	40	44	38
r2	0.07	0.05	0.19	0.01	0.14	0.13
F	15	2	9	0	7	5

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2.2 Results OLS Model 2: NKPC

Table 6.7 presents the results from the OLS Model 2 regressions, which includes rational expectations as an explanatory variable in the relation. The rational inflation expectations estimates are significant for all sub-periods. For the full sample the elasticity for the rational expectation's variable is 1.41. This means that a 1 percent increase in rational expectations is associated with a 1.41 percent increase in inflation, on average. The results indicate a steepening of the Phillips curve from the first sub-period to the second. However, the results are insignificant in the first sub-period. Comparing the slope estimates for the following sub-periods, the findings suggest a decrease in the slope estimate from the second sub-period (1982-

1992) to the fourth sub-period (2002-2012). Thus, a flattening of the Phillips curve is evident from the 1982-1992 period to the 2002-2012 period.

Table 6.7: OLS Model 2: NKPC

	(1) Full sample	(2) 1972-1982	(3) 1982-1992	(4) 1992-2002	(5) 2002-2012	(6) 2012-2022
Unemp. gap	0.012**	0.009	0.023**	-0.001	0.013*	-0.019**
	(0.004)	(0.012)	(0.008)	(0.006)	(0.005)	(0.006)
Inflation Expect.	1.411***	1.565***	1.749**	1.229***	1.121***	1.542***
	(0.153)	(0.413)	(0.515)	(0.186)	(0.157)	(0.287)
Constant	-0.000	-0.003	0.003*	-0.001	0.000	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
N	202	40	40	40	44	38
r2	0.35	0.32	0.39	0.54	0.62	0.52
F	53	9	12	22	33	19

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The findings are in line with those of Ball & Mazumder (2011) for the US, which report that the curve steepened from 1960-72 to 1973-84 and then flattened in the period 1985-2010. IMF (2013), Balanchard et al. (2015) and Blanchard (2016) find that the slope in the US fell from approximately -0.7 in the 1970s to around -0.2 from the 1990s and onwards. McLeay and Tenreyro (2020) find Phillips curve slope estimates around 0.2-0.17 by employing output as the measure of slack. They further conclude that the estimates suggest that the slope is flatter and not always significant.

6.2.3 Rolling regression estimates of β_1 and β_2

Rolling regressions are performed to further evaluate how the Phillips curve slope estimate evolves and to account for how the structural breaks can influence it with regressions for specific sub-periods. The rolling regressions estimate the Phillips curve slope coefficient and the inflation expectations coefficient over five- and ten-year periods with starting points in each quarter over the sample period. The results are presented in Figure 6.2 – Figure 6.5.

Figure 6.2: Five year rolling regression estimates of β_2 (Phillips curve slope estimate).

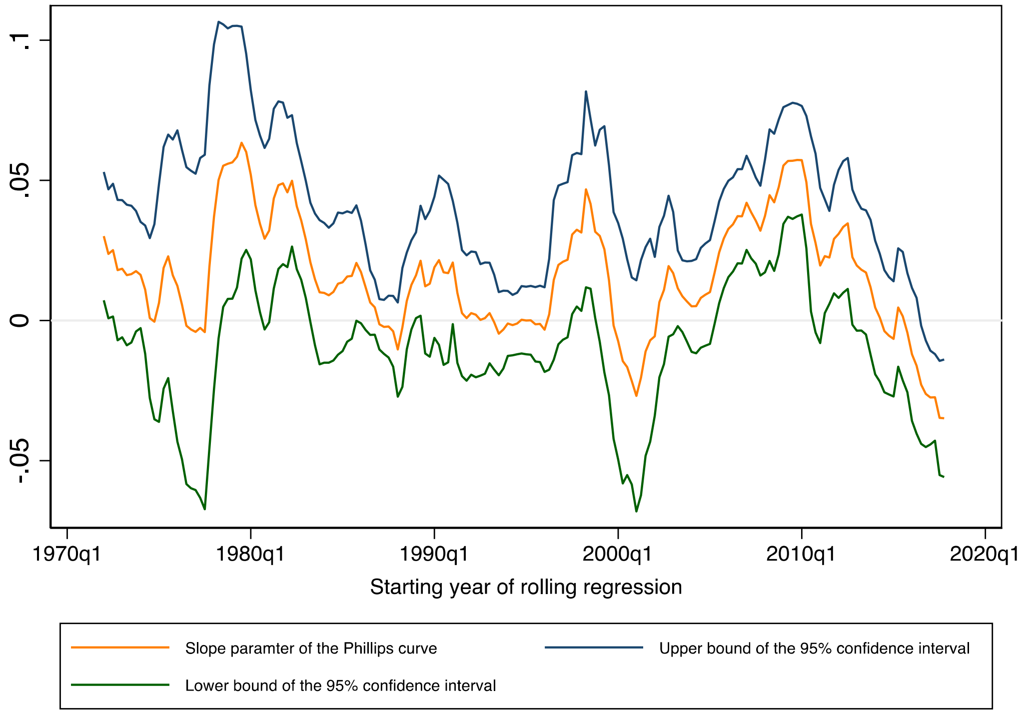


Figure 6.3: Five year rolling regression estimates of β_1 (inflation expectations coefficient).

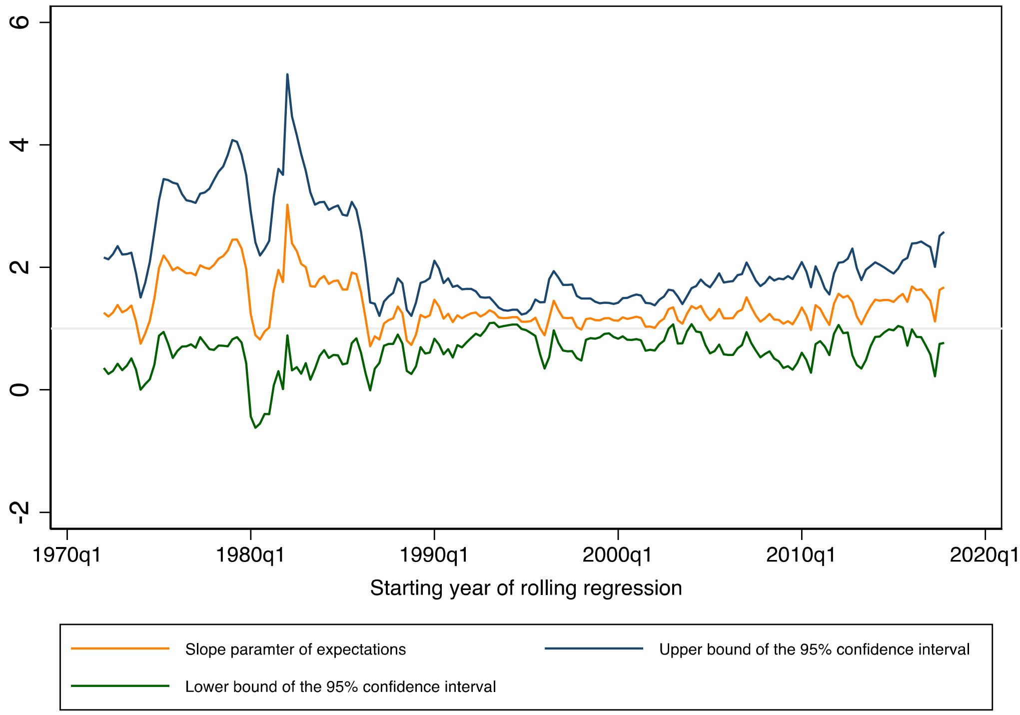
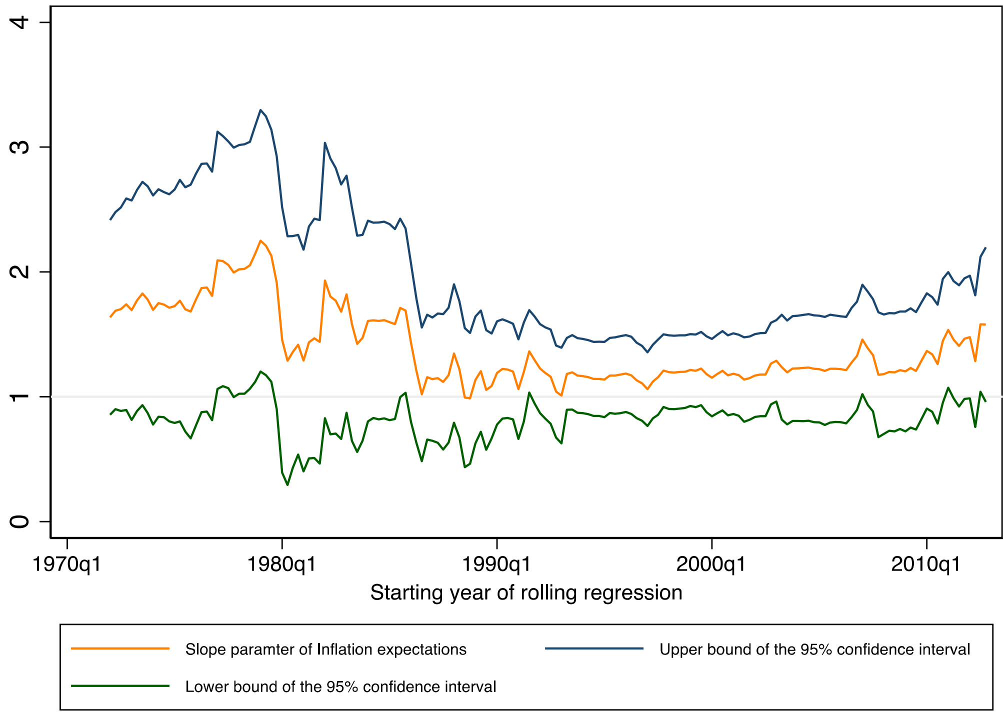


Figure 6.4: Ten year rolling regression estimates of β_2 (Phillips curve slope estimate).

Figure 6.5: Ten year rolling regression estimates of β_1 (inflation expectations coefficient).



The Phillips curve slope parameter β_2

Figure 6.2 and Figure 6.4 show the evolution of β_2, the slope of the Phillips curve – given in equation (42). The estimates of the rolling regressions indicate that the slope of the Norwegian Phillips curve is small and that it was small even during the 1970s. The slope increased from the beginning of the 1970s until the mid-1970s, then steadily decreased until the late 1990s. Looking at the ten-year rolling regression it has remained roughly constant and low from the late 1990s to the mid 2000s. Since the mid-2000s it has steadily increased until a sharp decline happened around 2010.

The slope estimates of both the five- and ten-year rolling regression show an estimate close to zero, with some noticeable deviations, over the whole sample period. This indicates that the Phillips curve has been relatively flat over the full sample period. The flattening aggregate supply curve hypothesis gets more support in the ten-year rolling regression. There is a slight tendency of a downward trend in the slope coefficient estimates of β_2 in the ten-year rolling regression. Given expected inflation, an increase in the unemployment gap was associated with an increase in inflation of 0.03 percent in the mid-1970s. The effect is closer to 0.002 percent in the mid-2000s. Looking at the 95 percent confidence interval lower bounds the slope estimate is close to insignificant over the full sample period. The estimate is mostly positive until the sharp decline towards the end, indicating a negative β_2 in the 2010s and onwards.

Anchoring of inflation expectations and β_1

A second critical element in exploring recent inflation dynamics is the anchoring of inflation expectations. Figures 6.3 and 6.5 illustrate the evolution of rational inflation expectations coefficient estimates over the sample period – estimated by five- and ten-year rolling regressions respectively. The results suggest a drop in the inflation expectations coefficient around 1986Q2/1986Q3. Figures 6.3 and 6.5 show that the expectations coefficient estimate, β_1, has stayed close to one since the change. A β_1 close to one suggests perfect collinearity between inflation and inflation expectations. The results thus indicate that from 1986, inflation moves one for one with changes in inflation expectations.

The Norwegian central bank became independent in 1985. Thus, the findings suggesting a change in inflation expectations behavior in the following year, points to more firmly anchored inflation expectations. The findings are in line with the theory. More trust in the stabilization policy of the central bank, results in more firmly anchored inflation expectations (Røisland & Sveen, 2018). The findings also indicate that the inflation expectations have been more stable since 1986. Improved central bank credibility can explain this change, but stable inflation expectations might also reflect stable inflation due to a flatter Phillips curve. The results are in line with those of Blanchard (2016) for the US economy and Blanchard et al. (2015) for the US and German economy. Their findings suggest that expectations have become more anchored from the mid-1980s and onwards.

The results from the rolling regression analysis implies that only a modest fraction of the large changes in inflation in the late 1970s and early 1980s, can be accounted for by the effect of increasing unemployment working through the slope of the Phillips curve. On the contrary, the data suggests that the movements in inflation expectations were large over this period. The findings are also in line with Del Negro et al. (2020). Their results suggest that expectations are less volatile now than before 1990. Del Negro et al. (2020) further argue that the change in behavior of inflation expectations reflects the inflation stability induced by the flattening of the aggregate supply curve.

6.3 SVAR Model results

To examine changes in the impulse response functions of inflation and market slack before and after the 1990s the SVAR models are estimated for two adjacent sample periods[8]:

1) 1972Q1 - 1991Q4
2) 1992Q1 - 2021Q3

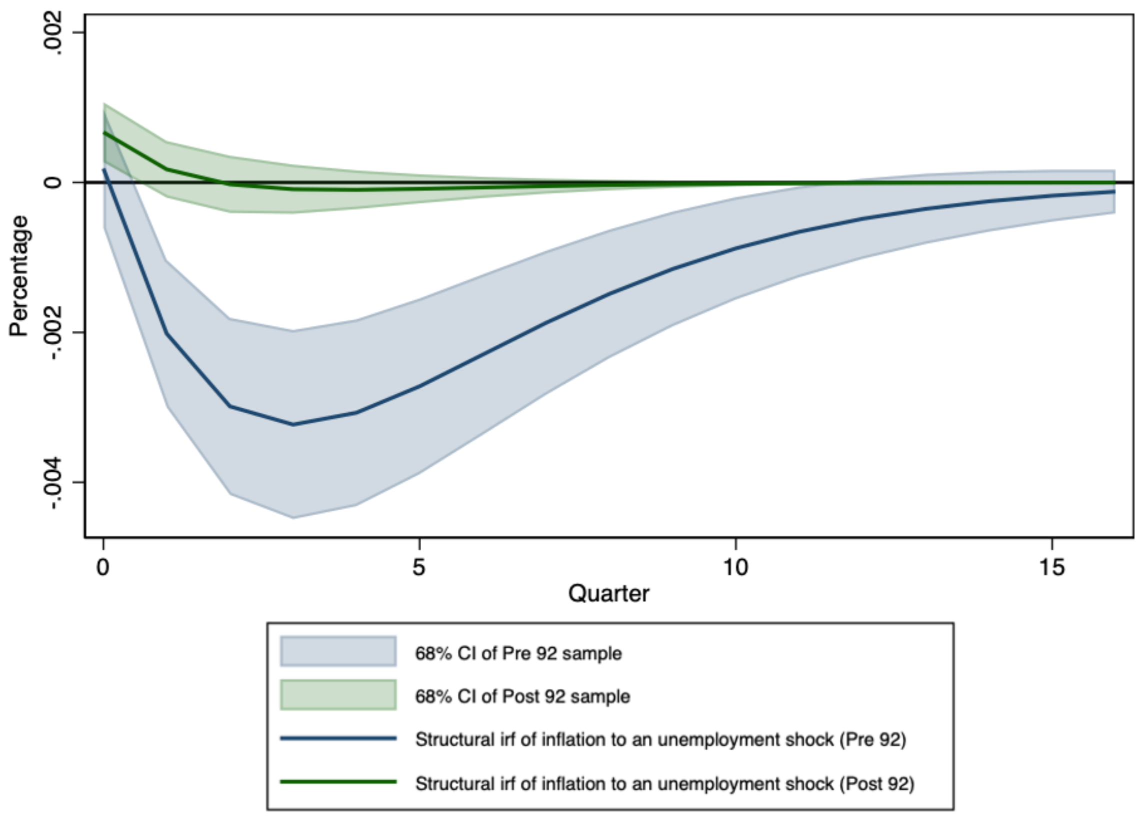
The responses are further compared with predictions from theory and empirical findings. Fluctuations in the data are decomposed into different shocks to the Norwegian economy. All shocks are positive with the magnitude of one standard deviation. As depicted on the horizontal axes of the impulse responses presented in Figure 6.6 – 6.12, the estimated responses are presented over a 16-quarter forecast horizon. This amounts to four years. The vertical axes represent the percentage response to a shock as a decimal. Meaning that 0.01 on the axes reflects a response of one percent. This follows for results from SVAR Model 1, 2 and 3.

[8] The choice of break in the sample period is motivated by the fact that there was a breakdown in the European Monetary System (EMS) which led to the adoption of a managed float regime in the late 1992 (Eitrheim & Qvigstad, 2020). In addition to the sight deposit rate being introduced in 1993.

6.3.1 SVAR Model 1 results: The Original Phillips curve

The impulse response of inflation in SVAR Model 1 shows a contemporaneously opposite effect of an innovation to unemployment, i.e., a positive unemployment shock with the magnitude of one standard deviation, between the two sample periods. Before 1992, inflation decreased by approximately 0.3 percent over the first three quarters before rising again. The finding that higher unemployment leads to a decrease in inflation is consistent with the downward sloping Phillips curve and the inverse inflation-unemployment relation (Phillips, 1958; Samuelson & Solow, 1960). Significant labor market slack, due to for example cutbacks during or following a recession, suggests a decrease in wage and price pressures in the economy.

Figure 6.6: Impulse response of inflation to a shock to the unemployment equation in SVAR Model 1.

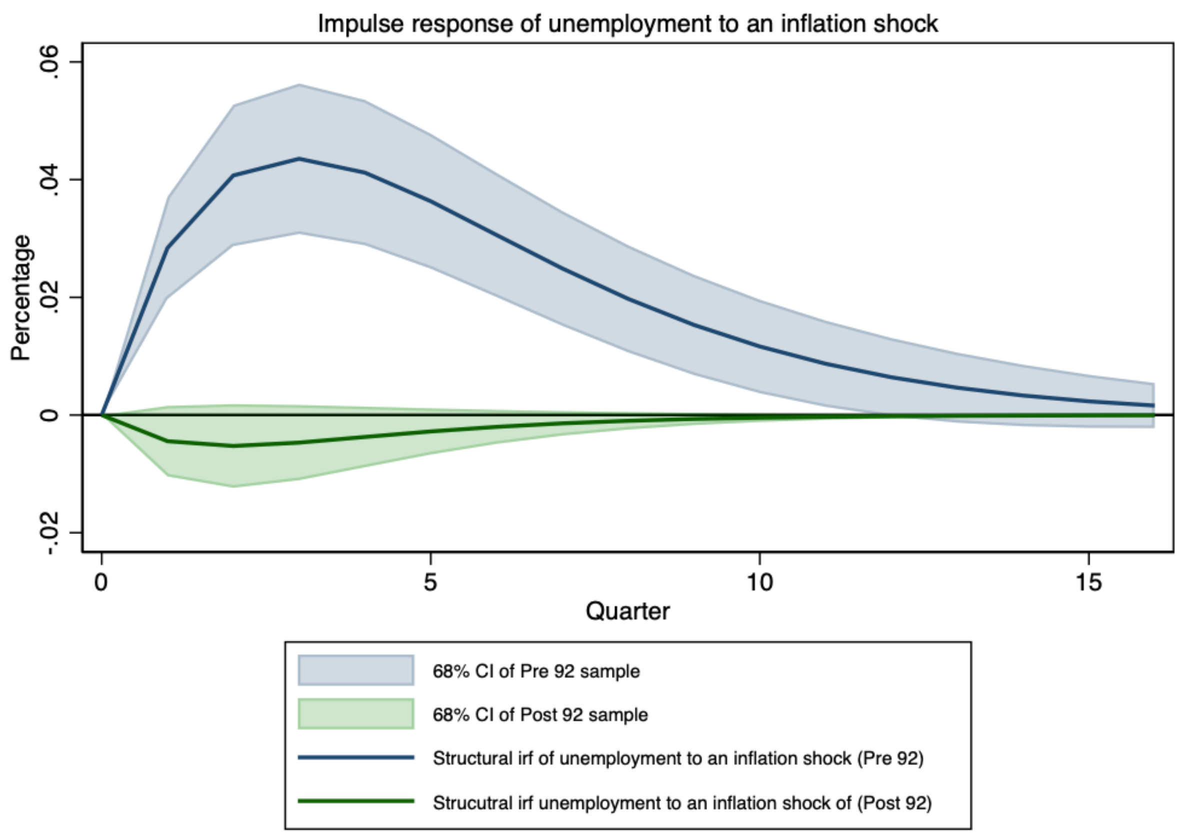


Note: The responses in Figure 6.6 and Figure 6.7 are from SVAR Model 1 for the pre- and post-1992 sample periods. The shocks are identified using a Cholesky strategy, with unemployment ordered first. The shaded areas correspond to the 65- standard error confidence intervals or credible regions, while the solid lines are posterior medians. The pre and post 1992 samples consist of data from 1972Q3 to 1991Q4 and 1992Q1 to 2022Q2, respectively.

Contradictory, the impulse response function of inflation in the post-92 sample, suggests that inflation has a contemporaneously positive response to an innovation to unemployment of approximately 0.15 percent. The effect reverses to zero within half a year (two quarters). The rather weak effect of inflation to a shock to the real economy variable in the post-92 sample compared to the pre-1992 sample, indicates that the Phillips curve has flattened. The findings also suggest that the Phillips curve is slightly upward sloping for the post-92 sample.

Figure 6.7 shows that the response of unemployment to an inflation shock is loosely mirrored for the two sample periods. In the pre-1992 sample the unemployment gap reacted contemporaneously and increased by approximately four percent over the following two to three quarters after the shock. The effect dies down after approximately three years (12 quarters). Contradictory, in the post-92 sample the unemployment gap decreases vaguely, but the response is insignificant. This implies that the relation has inverted from the first to the second sample period. The unemployment gap reacts less in the post-92 sample, indicating a weaker inflation-slack relation and flatter curve.

Figure 6.7: Impulse response function of unemployment to a shock to the inflation equation in SVAR Model 1.



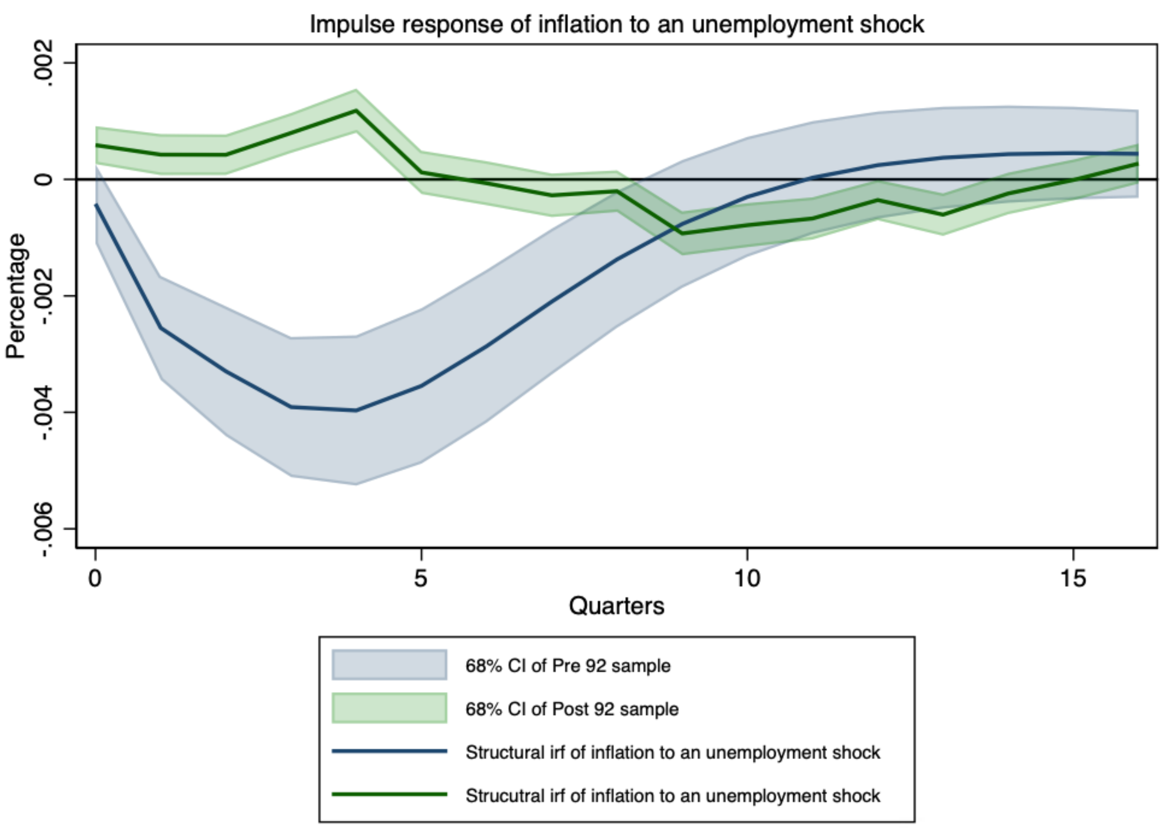
6.3.2 SVAR Model 2 results: NKPC

In this section, SVAR Model 1 is augmented with data on oil prices, the output gap, the key policy rate and the exchange rate. SVAR Model 2 models the inflation-slack relation (NKPC) in a small open economy model. The model is introduced to examine if demand shocks to the economy have a weaker effect on inflation relative to the real economy variables, output and unemployment in the post-1992 sample. The hypothesis is that if inflation has a reduced sensitivity to a demand shock in the post-1992 sample relative to the pre-1992 sample – while the real economy variables are as reactive as in the pre-1992 sample, it suggests that the connection between inflation and the real economy has weakened. Subsequently, indicating a flatter Phillips curve.

Unemployment shock

To test the hypothesis the impulse response of inflation to an unemployment shock in SVAR Model 2 is presented in Figure 6.8. The response to a change in slack is a lot more muted in the post-1992 sample.

Figure 6.8: Impulse response of inflation to an unemployment shock in SVAR Model 2.



Note: The impulse responses in Figure 6.8 – 6.11 are from SVAR Model 2 for the pre- and post-1992 sample periods. The shocks are identified using a Cholesky strategy, with the oil price ordered first. The shaded areas correspond to the 65- standard error confidence intervals or credible regions, while the solid lines are posterior medians.

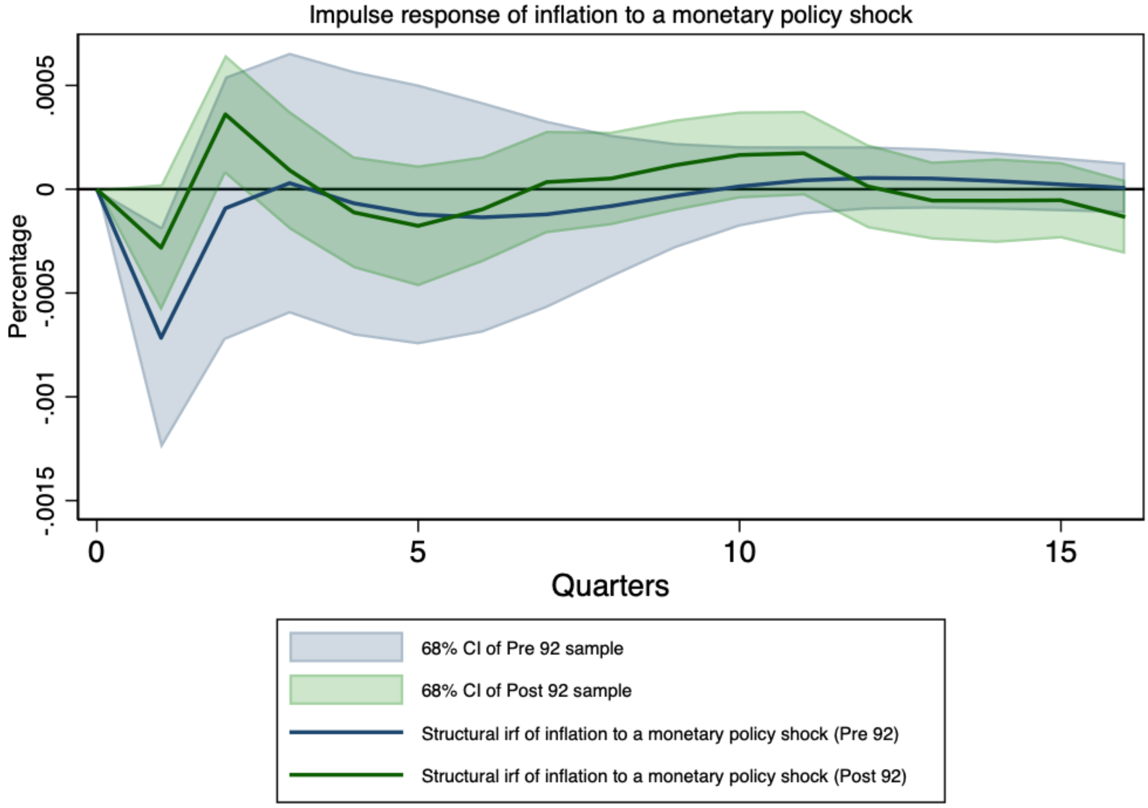
Additionally, the findings suggest that a higher level of unemployment or labor supply induces an increase in inflation in the post-1992 sample. The increase is significant over five quarters, meaning over a year after the shock is induced. The responses are inverse between the two samples, as found in SVAR Model 1. As it is outside the scope of the of this thesis, the inverse response is not elaborated on.

Monetary policy shocks

To capture the price inflations' response to a demand shock before and after 1992, a monetary policy shock was introduced. A monetary policy shock is defined as a contractionary monetary policy shock with a change of 100 basis points or one percent in the key policy rate. The results suggest a weaker response in inflation in the post-92 sample compared to the pre-1992 sample. On impulse, inflation decreases by 0.05 percent in the first quarter after the policy rate is raised, in the pre-1992 sample. The response of inflation is found to be insignificant in the post-1992 sample. The findings are in line with those of Del Negro et al. (2020) for the US economy. Del Negro et al. (2020) find that inflation barely reacts to shocks to the excess bond premium in the post 1990s sample. A shock to the excess bond premium is a shock that propagates through the economy like a typical demand shock.

The findings from SVAR Model 2 indicate that monetary policy has little to non-effect on inflationary pressures in the post-1992 sample. This suggests that the demand channel that the policy is meant to work through, might be disconnected with inflation. To further investigate this finding, impulse responses of the real economy measures, the output gap and the unemployment gap, are introduced in the following paragraphs. Additionally, other real economy measures are included in SVAR Model 3 presented in Section 6.3.3.

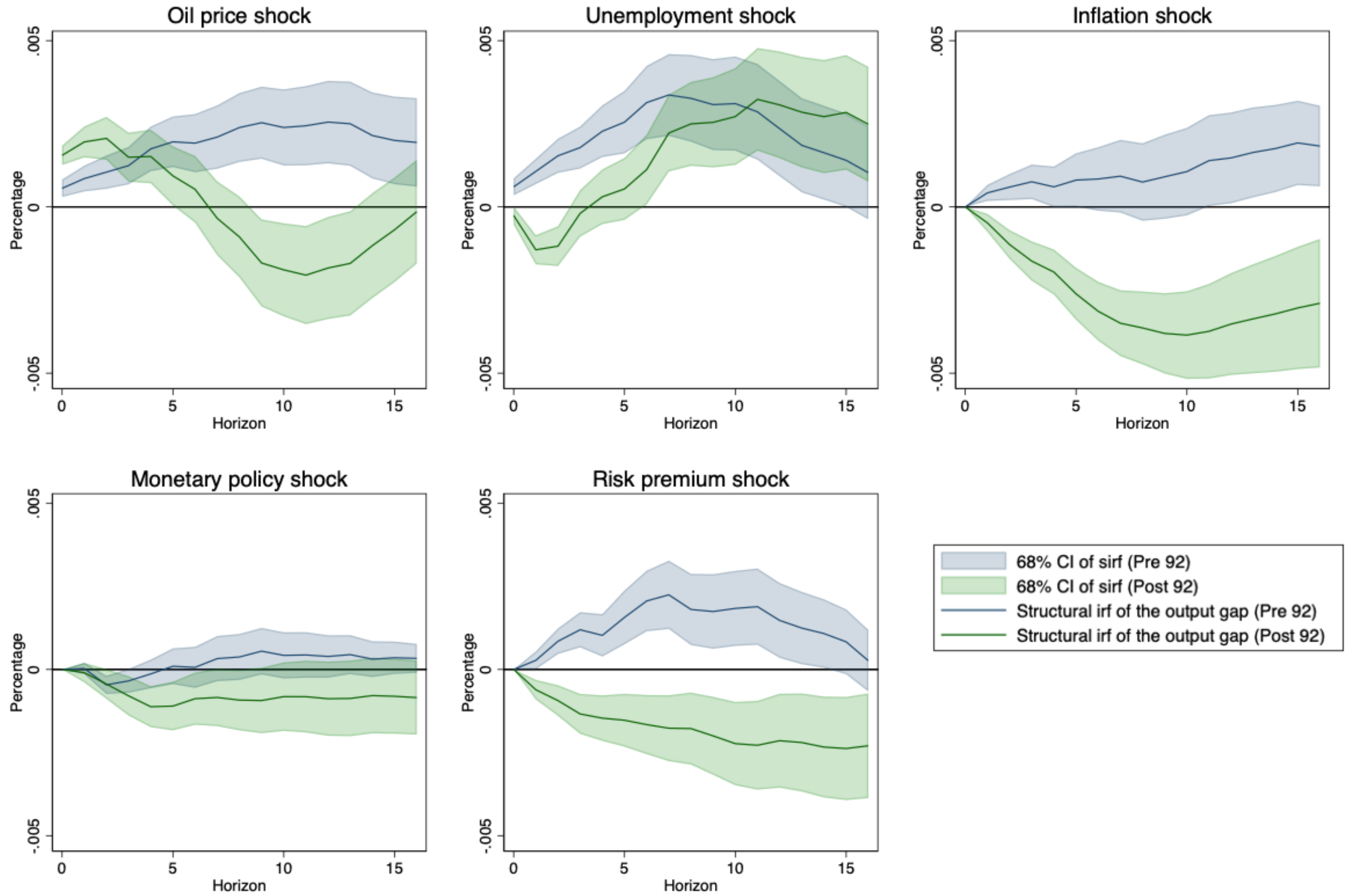
Figure 6.9: The impulse response of inflation to a monetary policy shock in SVAR Model 2.



Impulse responses of the output gap and the unemployment gap

Figure 6.10 plots the impulse response functions of output to various shocks to the Norwegian economy. The response to a monetary policy shock, seems to have a larger effect in the most recent sample compared to before 1992. The findings suggest that a rise in the key policy rate is associated with a decrease of approximately 0.1 percent in economic activity. This indicates that the real economy remains reactive to a demand shock to the economy, as opposed to inflation. Outputs' response to an inflation shock is surprisingly found to have the opposite effect before and after 1992. On impulse, output decreases by approximately 0.4 percent in the post-1992 sample, compared to an increase of 0.063 percent in the pre-1992 sample. The effect is also found to be stronger in the most recent sample. This suggests that activity is dampened in response to an increase in the overall price level in the economy.

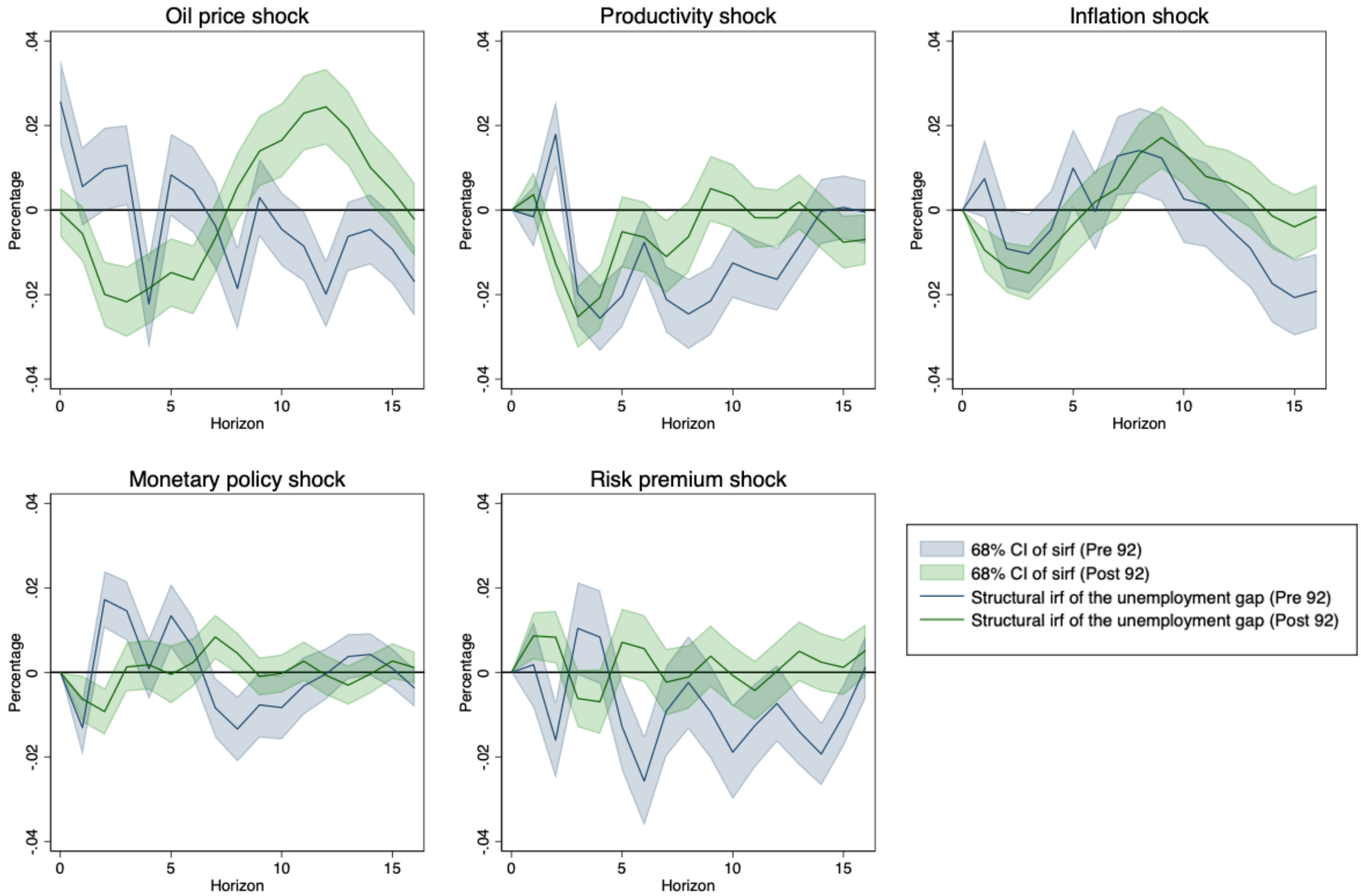
Figure 6.10: Impulse response function of the output gap in SVAR Model 2.



Note: Figure 6.10 shows the impulse response function of the output gap in SVAR Model 2 for the pre- and post-1992 sample periods. The shocks are identified using a Cholesky strategy, with the oil price ordered first. The shaded areas correspond to the 65- standard error confidence intervals or credible regions, while the solid lines are posterior medians.

The impulse response of the unemployment gap to a monetary policy shock (Figure 6.11) suggests a similar response in both sample periods, but the effect is somewhat reduced in the post-1992 sample. Figure 6.11 further shows that a productivity shock to the economy, seems to have the same effect on unemployment before and after 1992. This indicates that the unemployment gap's receptiveness to demand shocks remains persistent, even though it is somewhat reduced in the case of a monetary policy shock.

Figure 6.11: Impulse response of the unemployment gap in SVAR Model 2.



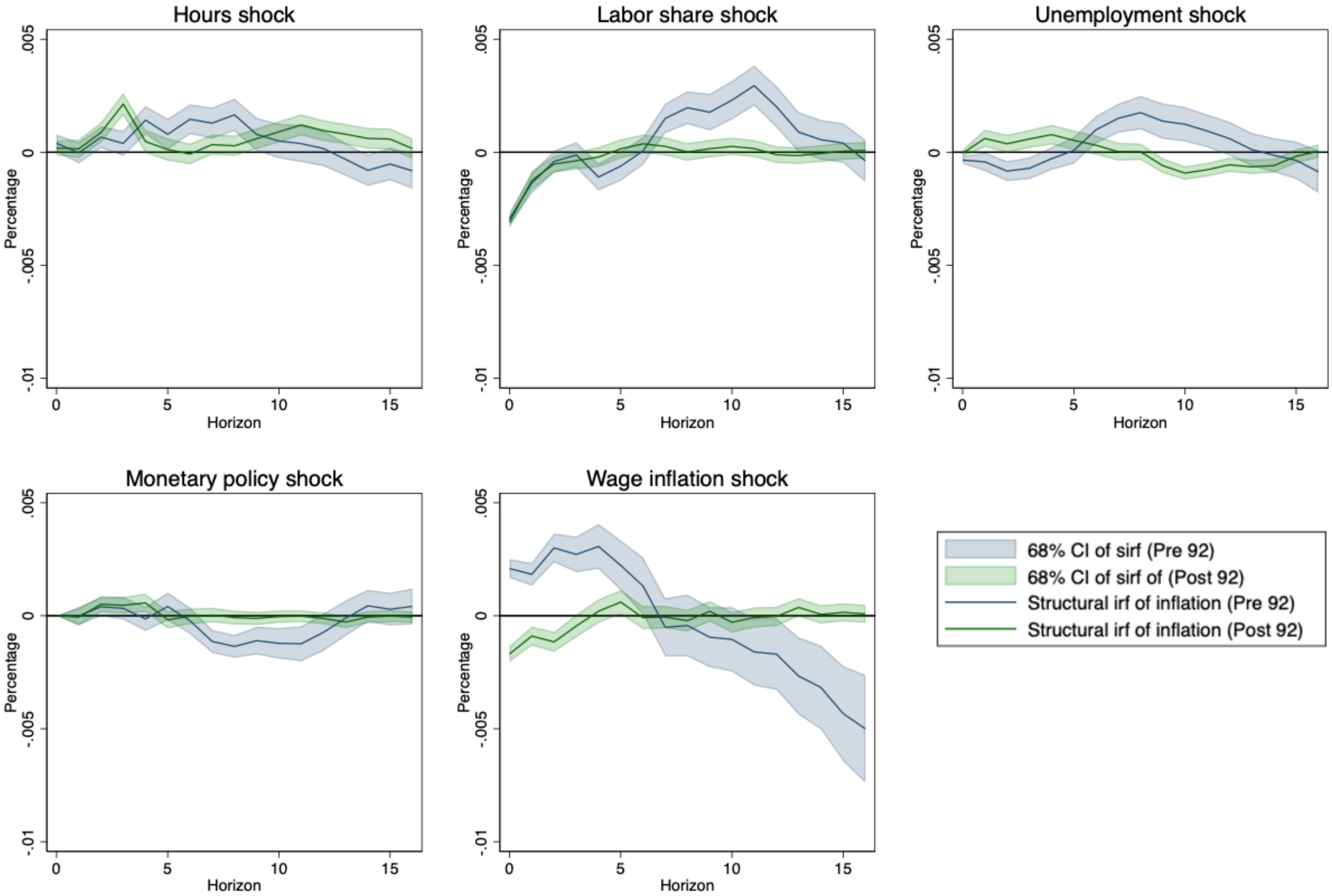
Note: Figure 6.11 shows the impulse response function of the unemployment gap to a positive shock to the oil price, the output gap, inflation, the policy rate and the exchange rate, with the magnitude of one standard deviation. Results are from SVAR Model 2 for the pre- and post-1992 sample periods. The shocks are identified using a Cholesky strategy, with the oil price ordered first. The shaded areas correspond to the 65- standard error confidence intervals.

Even though there are some contradictions in the results from SVAR Model 2, the findings suggest that inflation's response to monetary policy shocks has mitigated in the most recent sample. Meanwhile, the real economy variables remain reactive. The results highlight a reduced sensitivity of inflation to a demand shock, which suggests that the slope of the Phillips curve has fallen in the post-92 sample. The findings are in line with those of Bergholt et al. (2022) for the US. Their findings indicate that inflation's sensitivity to a demand-induced cost pressure is reduced, while the real economy measures are still reactive.

6.3.3 SVAR Model 3 results: Real economy

SVAR Model 3 examines how shocks to the real economy variables: hours, labor share, unemployment and real wage affect inflation dynamics before and after the 1990s. The impulse response functions are presented in Figure 6.12.

Figure 6.12: Impulse response of inflation to real economy shocks in SVAR Model 3.



Note: Figure 6.12 shows the impulse response function of inflation in SVAR Model 3 for the pre- and post-1992 sample periods. The shocks to hours, labor share, unemployment, rate and real wage, are identified using a Cholesky strategy, with the real wage ordered first. The shaded areas correspond to the 65- standard error confidence intervals or credible regions, while the solid lines are posterior medians.

The impulse response functions of inflation show that there is a reduction in price inflation responsiveness to marginal cost pressures in the economy in the post-1992 sample compared to the pre-1992 sample. Shocks to hours show a larger increase in inflation between the second and fourth quarter in the post-1992 sample. However, the response is temporary and the responsiveness over the rest of the horizon is more dampened than in the pre-1992 sample. The response of inflation to a wage inflation shock is the most surprising. Sensitivity of inflation to a wage inflation shock is severely reduced in the post-1992 sample, but the response is also inversed between the two samples. The same response is found for the unemployment shock.

The findings are in line with those of Del Negro et al. (2020). Their results suggest that the sensitivity of price inflation in relation to labor market slack has diminished after 1990. Various explanations have been offered for this evolution. A central explanation is that, as the level of inflation has decreased and stabilized, wages and prices are being changed less often, leading to a smaller response of inflation to labor market conditions. The literature further attributes a reduction in response of prices to marginal costs, to the increased relevance of global supply chains, heightened international competition and other effects of globalization (Sbordone, 2007; Forbes, 2019; Obstfeld, 2019; Ascari & Fosso, 2021).

6.4 Implications for monetary policy

A weaker relation between inflation and market slack raises challenges for monetary policymaking. Although inflationary effects of expansion can be mitigated by a flatter Phillips curve, it also induces risks associated with implementing appropriate monetary tightening in response to persistently rising inflation (IMF, 2013; Røisland & Sveen, 2018). A flattening aggregate supply curve could lead policymakers to place greater weight than optimal on avoiding volatility in both employment and output relative to inflation (Blanchard et al., 2015; McLeay & Tenreyro, 2020). McLeay and Tenreyro (2020) further argue that evidence of a weaker link between inflation and real activity could be interpreted as a sign that there is no short-run policy trade-off between the two goals. This can lead policy makers to abandon the natural rate hypothesis (McLeay & Tenreyro, 2020).

With a flatter Phillips curve in Norway, stabilizing inflation may involve much larger swings in economic activity than in the past, as central banks need to effect larger changes in economic slack to obtain a given change in inflation (IMF, 2013). According to Wren-Lewis (2013) central banks might end up stabilizing inflation at the cost of economic growth, under economic circumstances that entails a flatter Phillips curve and persistent shocks to inflation that are unrelated to domestic cyclical conditions. This could result in stagflation and dis-anchoring of inflation expectations (IMF, 2013). The former is a potential threat facing the Norwegian economy as of late. Thus, the findings of a potentially reduced Phillips curve slope in Norway suggests the need to reconsider how monetary policy can best contribute to general economic welfare.

7. Limitations and further research

However, there are shortcomings with the empirical results and analysis presented in this paper. A central limitation of this paper's analysis is that interpretation of SVAR results is challenging, as it is based on assumptions on the underlying mechanisms of the models. One can only speculate on the mechanisms behind the impulse response function results. As a consequence, the found reduced sensitivity of inflation to the real economy in SVAR Model 1, SVAR Model 2 and SVAR Model 3, could be due to differences in monetary policy or in other aspects of the economy.

The findings from SVAR Model 2 suggesting a negative inflation-output relation (Figure 6.10) indicates support in favor of the flattening aggregate demand curve hypothesis highlighted in the literature as an explanation of the disconnect phenomenon. The impulse response function results from Model 2 indicate that a productivity shock leads to a decrease in inflation. In other words, a negative correlation between inflation and the output gap emerges. This result is in line with the findings of McLeay and Tenreyro (2020) and Bergholt et al. (2022) for the US economy.

McLeay and Tenreyro (2020) argue that under optimal monetary policy the residual variation in output and inflation is driven only by cost-push shocks. In turn, a negative correlation between inflation and the output gap emerges, which blurs the identification of the positively sloped Phillips curve in the data. Thus, optimally set policy could induce the disappearance of the Phillips curve. Meaning that the inflation-slack relation is still alive and well, but it is harder to trace in the data. The data trace out the optimal targeting rule and not the Phillips curve (McLeay & Tenreyro, 2020; Bergholt et al., 2022).[9]

The models applied in this analysis are not equipped to conclude on this alternative hypothesis. Further research should thus evaluate the possibility of a flatter aggregate demand curve in Norway as an explanation for the inflation-slack disconnect. By introducing different types of demand shocks in the SVAR models, the variation in inflation and the real economy conditional on demand and supply shocks could be better isolated and identified. Making it easier to

[9] For a broader explanation of this hypothesis see McLeay and Tenreyro (2020), Del Negro et al. (2020) and Bergholt et al. (2022).

distinguish between the flattening aggregate supply curve and the flattening aggregate demand curve hypotheses.

Another central shortcoming of the analysis is the potential mismeasurement of time series variables included in the models. Wrongly constructed data series or chosen market slack and inflation measures could induce errors in the estimated relations and impulse response functions. The instability found in the first sample model of SVAR Model 3, in addition to non-normality problems in SVAR Model 2 are other limitations of the analysis. Further research should conduct robustness checks of the applied models with other measures of inflation, short-term interest rates, inflation expectations and market slack.

8. Conclusion

This paper has examined the hypothesis of a flattening Phillips curve for the Norwegian economy. A correlation analysis was first employed to analyse how the strength of the linear relationships of interest have evolved over the last five decades. Following the IMF (2013), Blanchard et al. (2015), and Blanchard (2016), Ordinary Least Square (OLS) regressions were then applied to examine the Phillips curve slope coefficient and inflation expectations behaviour over the sample period.

Finally, three Structural Vector Autoregression (SVAR) models were introduced to investigate how variables of interest have responded to different shocks to the Norwegian economy before and after the 1990s. Following Neri (2004) and Bjørnland (2009), SVAR models with short-run restrictions and a Cholesky decomposition were utilized. Monetary transmission mechanism variables including the key policy rate, inflation, the unemployment gap, the output gap, and the exchange rate were employed. An oil price variable was also included to replicate a cost-push shock in the Norwegian economy. The third model examined inflation dynamic responses to various real economy shocks and marginal cost pressures before and after 1992.

The findings of the correlation and OLS analysis indicate a reduction in the Phillips curve slope estimates for Norway from the 1982-1992 sub-sample until the 2012-2022 sub-sample. The findings are confirmed by the rolling regression results. Additionally, the rolling regression analysis suggests that inflation expectations have become more firmly anchored after 1992. The results indicate stable inflation expectations due to stable inflation dynamics induced by a flatter Phillips curve. Empirical results from SVAR Model 2 suggest a dampened response of inflation to a monetary policy shock after 1992, while the real economy variables are still reactive. SVAR Model 3 further corroborates the findings from SVAR Model 2 of a reduced sensitivity in inflations' responsiveness to the real economy after 1992. The findings suggest a decreased slope of the Phillips curve.

The findings imply a higher sacrifice ratio associated with bringing inflation back to its target for Norway. This could lead policymakers to place greater weight than optimal on avoiding volatility in both employment and output relative to inflation (Blanchard et al., 2015; McLeay & Tenreyro, 2020; Del Negro et al., 2022). This thesis concludes that the Phillips curve relation is still evident in the Norwegian economy, but its apparent flattening and small slope coefficient raises serious challenges for the conduct of monetary policy.

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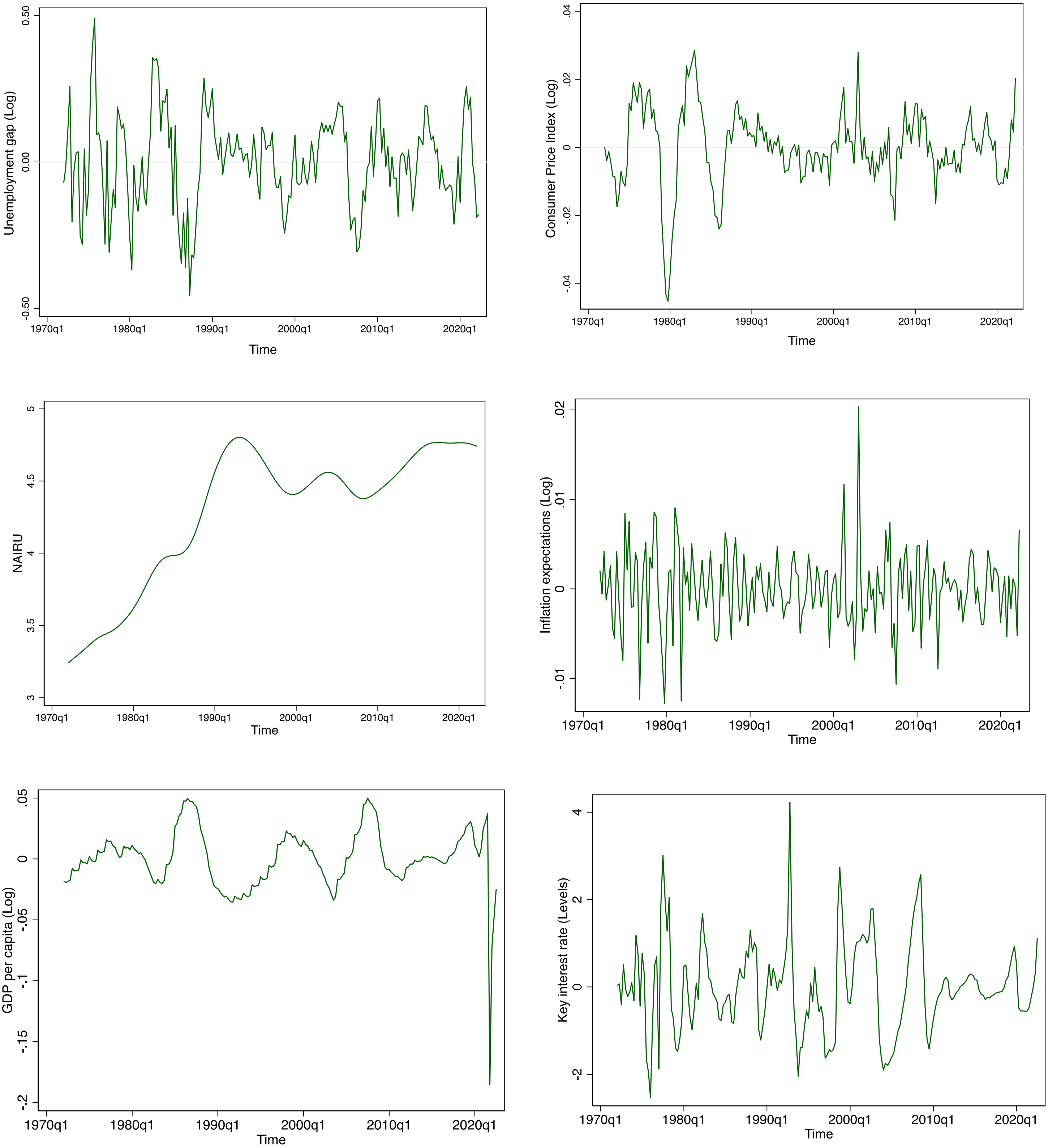
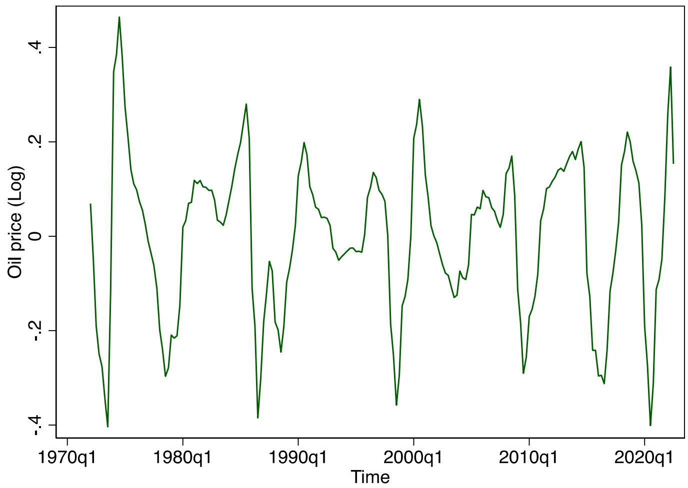
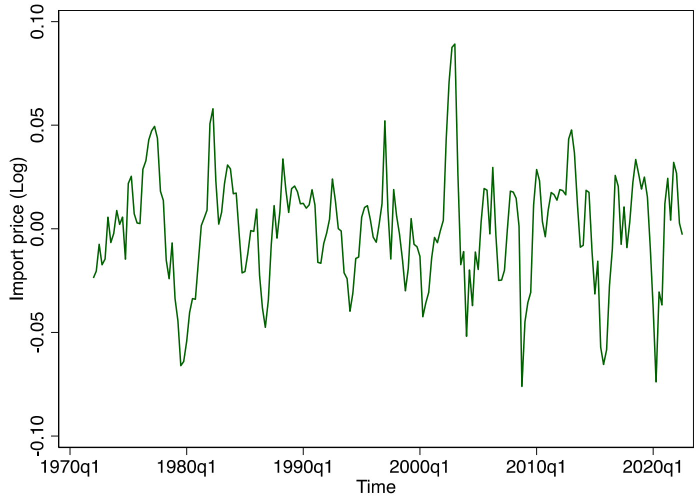
Appendix

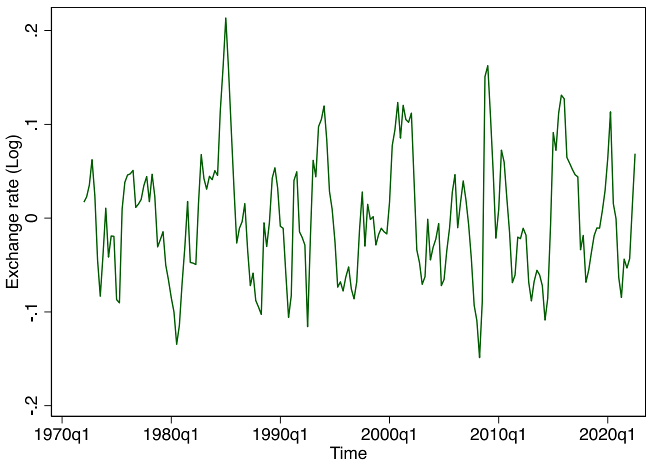
A. Processed and detrended data series

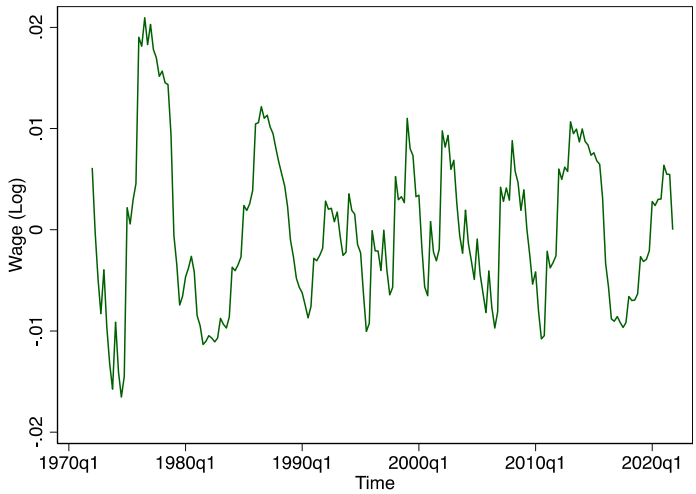
Figure A.1: The detrended data series (All in log except the Key policy rate).

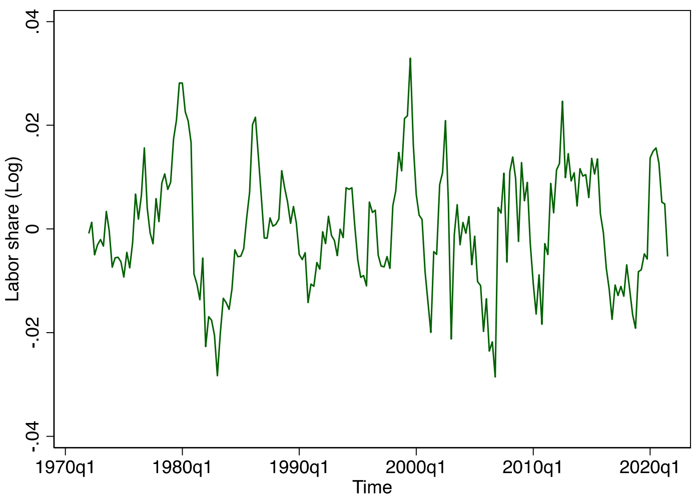


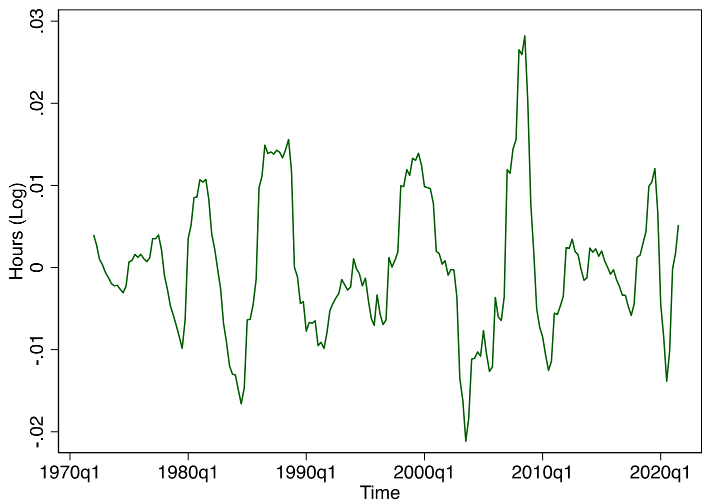

Oil price (Log)
.4
.2
0
-.2
-.4
1970q1
1980q1
1990q1
2000q1
2010q1
2020q1
Time


Import price (Log)
0.10
0.05
0.00
-0.05
-0.10
1970q1
1980q1
1990q1
2000q1
2010q1
2020q1
Time


Exchange rate (Log)
.2
.1
0
-.1
-.2
1970q1
1980q1
1990q1
2000q1
2010q1
2020q1
Time


Wage (Log)
.02
.01
0
-.01
-.02
1970q1
1980q1
1990q1
2000q1
2010q1
2020q1
Time


Labor share (Log)
.04
.02
0
-.02
-.04
1970q1
1980q1
1990q1
2000q1
2010q1
2020q1
Time


Hours (Log)
.03
.02
.01
0
-.01
-.02
1970q1
1980q1
1990q1
2000q1
2010q1
2020q1
Time

B. Model specification tests

B0. Augmented Dickey-fuller test

Table B0.1: ADF Test – The unemployment gap

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-6.927**	**0.0000**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.2: ADF Test – The output gap

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-5.638**	**0.0000**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.3: ADF Test – Inflation

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-4.250**	**0.0005**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.4: ADF Test – Oil price

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-3.504**	**0.0079**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.5: ADF Test – Inflation expectations

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-12.994**	**0.0000**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.6: ADF Test – Exchange rate

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-4.864**	**0.0000**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.7: ADF Test – Key policy rate

		T-Statistic	Probability
Augmented Dickey Fuller Test		**- 5.527**	**0.0000**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.8: ADF Test – Import price index

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-5.378**	**0.0000**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.9: ADF Test – Real Wage

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-7.166**	**0.0000**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.573**	

Table B0.10: ADF Test – Hours

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-2.930**	**0.0420**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.578**	

Table B0.11: ADF Test – Labor share

		T-Statistic	Probability
Augmented Dickey Fuller Test		**-5.042**	**0.0000**
Test critical values	1% level	**-3.476**	
	5% level	**-2.883**	
	10% level	**-2.578**	

B1. Lag-order selection statistics

Table B1.1: Lag-order selection statistics Model 1

Sample: **1972q1 – 2022q3** Number of obs = **198**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**689.468**				**3.3e-06**	**-6.94412**	**-6.93068**	**-6.91091**
1	**852.344**	**325.75***	**4**	**0.000**	**6.6e-07***	**-8.54893***	**-8.5086***	**-8.44929***
2	**853.517**	**2.3454**	**4**	**0.673**	**6.8e-07**	**-8.52037**	**-8.45315**	**-8.3543**
3	**857.367**	**7.701**	**4**	**0.103**	**6.8e-07**	**-8.51886**	**-8.42475**	**-8.28636**
4	**861.774**	**8.8126**	**4**	**0.066**	**6.8e-07**	**-8.52297**	**-8.40197**	**-8.22403**

Table B1.2: Lag-order selection statistics Model 2

Sample: **1973q3 - 2022q2** Number of obs = **196**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**1227.51**				**1.6e-13**	**-12.4644**	**-12.4237**	**-12.364**
1	**1779.65**	**1104.3**	**36**	**0.000**	**8.0e-16**	**-17.7312**	**-17.4468**	**-17.0287***
2	**1850.87**	**142.43**	**36**	**0.000**	**5.6e-16**	**-18.0905**	**-17.5623***	**-16.7859**
3	**1874.72**	**47.707**	**36**	**0.092**	**6.4e-16**	**-17.9665**	**-17.1946**	**-16.0599**
4	**1922.95**	**96.456**	**36**	**0.000**	**5.6e-16**	**-18.0913**	**-17.0756**	**-15.5826**
5	**1979.69**	**113.48**	**36**	**0.000**	**4.6e-16***	**-18.3029***	**-17.0435**	**-15.1921**
6	**2005.25**	**51.117***	**36**	**0.049**	**5.2e-16**	**-18.1964**	**-16.6932**	**-14.4834**

Table B1.3: Lag-order selection statistics Model 3

Sample: **1973q3 – 2021q3** Number of obs = **193**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**2504.23**				**2.3e-19**	**-25.8883**	**-25.8473**	**-25.7869**
1	**3180.34**	**1352.2**	**36**	**0.000**	**3.0e-22**	**-32.5217**	**-32.2342**	**-31.8117***
2	**3241.6**	**122.52**	**36**	**0.000**	**2.3e-22**	**-32.7835**	**-32.2495**	**-31.4649**
3	**3293.97**	**104.72**	**36**	**0.000**	**2.0e-22**	**-32.953**	**-32.1726**	**-31.0258**
4	**3340.94**	**93.938**	**36**	**0.000**	**1.8e-22**	**-33.0667**	**-32.0398**	**-30.5309**
5	**3495.78**	**309.69**	**36**	**0.000**	**5.2e-23***	**-34.2982**	**-33.0249***	**-31.1539**
6	**3532.79**	**74.023***	**36**	**0.000**	**5.2e-23**	**-34.3087***	**-32.7889**	**-30.5558**

B2. Jarque-Bera Normality test

Table B2.1: Jarque-Bera test Model 1 Pre-92

Equation	chi2	df	Prob > chi2
Unemployment	**2.125**	**2**	**0.34559**
CPI	**3.713**	**2**	**0.15625**
ALL	**5.838**	**4**	**0.21160**

Table B2.2: Jarque-Bera test Model 1 Post-92

Equation	chi2	df	Prob > chi2
Unemployment	**0.125**	**2**	**0.93961**
CPI	**4.409**	**2**	**0.11033**
ALL	**4.533**	**4**	**0.33863**

Table B2.3: Jarque-Bera test Model 2 Pre-92

Equation	chi2	df	Prob > chi2
Oil price	**0.039**	**2**	**0.98051**
Unem.	**0.449**	**2**	**0.79879**
GDP per capita	**2.045**	**2**	**0.35977**
CPI	**0.769**	**2**	**0.68082**
Interest rate	**3.456**	**2**	**0.17764**
Exchange rate	**1.429**	**2**	**0.48943**
ALL	**8.187**	**12**	**0.77033**

Table B2.4: Jarque-Bera test Model 2 Post-92

Equation	chi2	df	Prob > chi2
Oil price	**15.938**	**2**	**0.00035**
Unem.	**2.269**	**2**	**0.32161**
GDP per capita	**9.319**	**2**	**0.00947**
CPI	**0.624**	**2**	**0.73215**
Interest rate	**77.553**	**2**	**0.00000**
Exchange rate	**2.148**	**2**	**0.34163**
ALL	**107.851**	**12**	**0.00000**

Table B2.5: Jarque-Bera test Model 3 Pre-92

Equation	chi2	df	Prob > chi2
Wage	**15.748**	**2**	**0.00038**
Hours	**4.434**	**2**	**0.10891**
Labor share	**1.390**	**2**	**0.49910**
Unemployment	**1.596**	**2**	**0.45018**
CPI	**1.644**	**2**	**0.43947**
Interest rate	**3.845**	**2**	**0.14625**
ALL	**28.658**	**12**	**0.00443**

Table B2.6: Jarque-Bera test Model 3 Post-92.

Equation	chi2	df	Prob > chi2
Wage	**0.620**	**2**	**0.73328**
Hours	**4.076**	**2**	**0.13027**
Labor share	**5.147**	**2**	**0.07628**
Unemployment	**0.869**	**2**	**0.64771**
CPI	**0.129**	**2**	**0.93747**
Interest rate	**205.458**	**2**	**0.00000**
ALL	**216.299**	**12**	**0.00000**

B3. Lagrange Multiplier test

Table B3.1: Lagrange-Multiplier test for Model 1 Pre-92 with lag length of one.

lag	chi2	df	Prob > chi2
1	**3.0413**	**4**	**0.55093**
2	**5.0969**	**4**	**0.27750**

Table B3.2: Lagrange-Multiplier test for Model 1 Post-92 with lag length of one.

lag	chi2	df	Prob > chi2
1	**7.8086**	**4**	**0.09885**
2	**13.2964**	**4**	**0.00991**

Table B3.3: Lagrange-Multiplier test for Model 2 Pre-92 with lag length of five.

lag	chi2	df	Prob > chi2
1	**37.6058**	**36**	**0.39555**
2	**39.1602**	**36**	**0.32991**
3	**45.1795**	**36**	**0.14038**
4	**34.0571**	**36**	**0.56128**
5	**37.4598**	**36**	**0.40200**

Table B3.4: Lagrange-Multiplier test for Model 2 Post-92 with lag length of five.

lag	chi2	df	Prob > chi2
1	**39.4999**	**36**	**0.31637**
2	**48.7050**	**36**	**0.07679**
3	**36.7537**	**36**	**0.43379**
4	**38.4985**	**36**	**0.35713**
5	**38.3905**	**36**	**0.36168**

Table B3.5: Lagrange-Multiplier test for Model 3 Pre-92 with lag length of six.

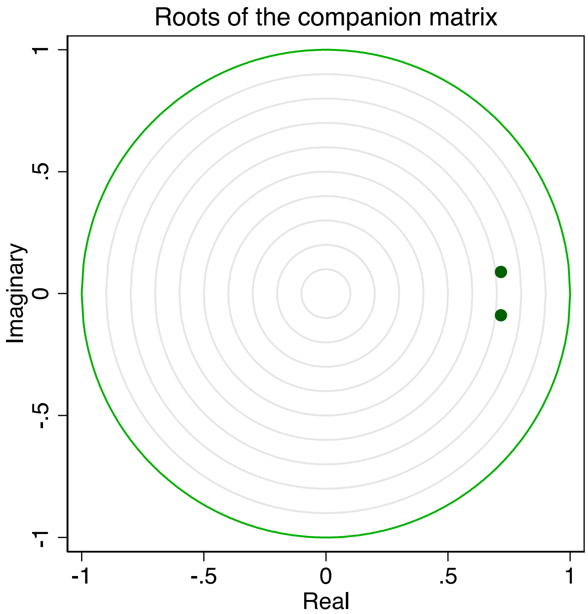
lag	chi2	df	Prob > chi2
1	**41.0007**	**36**	**0.26048**
2	**49.5009**	**36**	**0.06638**
3	**31.4945**	**36**	**0.68274**
4	**47.8524**	**36**	**0.08943**
5	**22.4787**	**36**	**0.96175**
6	**34.7375**	**36**	**0.52857**

Table B3.6: Lagrange-Multiplier test for Model 3 Post-92 with lag length of six.

lag	chi2	df	Prob > chi2
1	**50.5100**	**36**	**0.05491**
2	**30.3023**	**36**	**0.73592**
3	**46.6425**	**36**	**0.11024**
4	**36.8368**	**36**	**0.43000**
5	**40.2119**	**36**	**0.28905**
6	**36.2935**	**36**	**0.45497**

B4. Eigenvalue stability condition

Table B4.1: Eigenvalue Stability Condition test for SVAR Model 1 pre- and post-92.



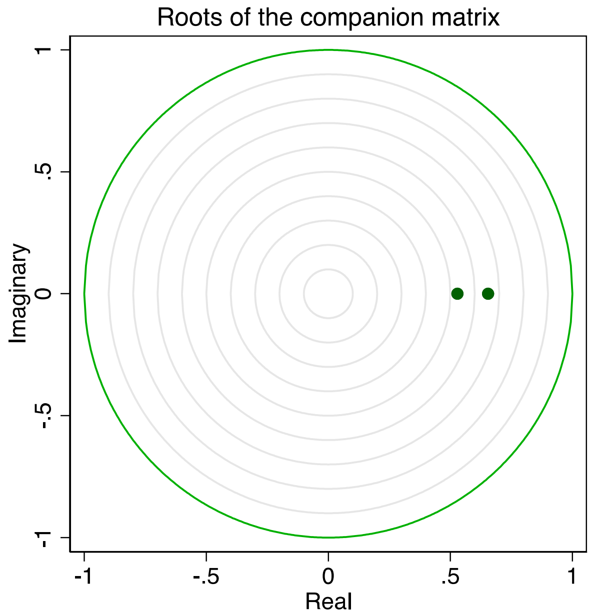
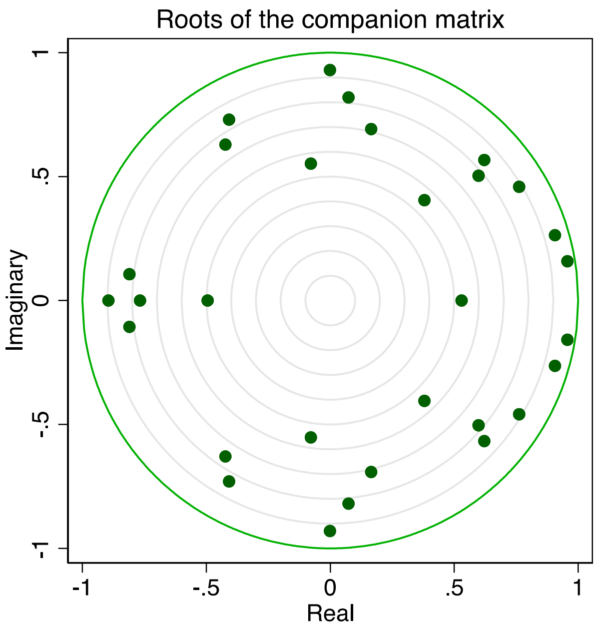


Table B4.2: Eigenvalue Stability Condition test for SVAR Model 2 pre- and post-92.



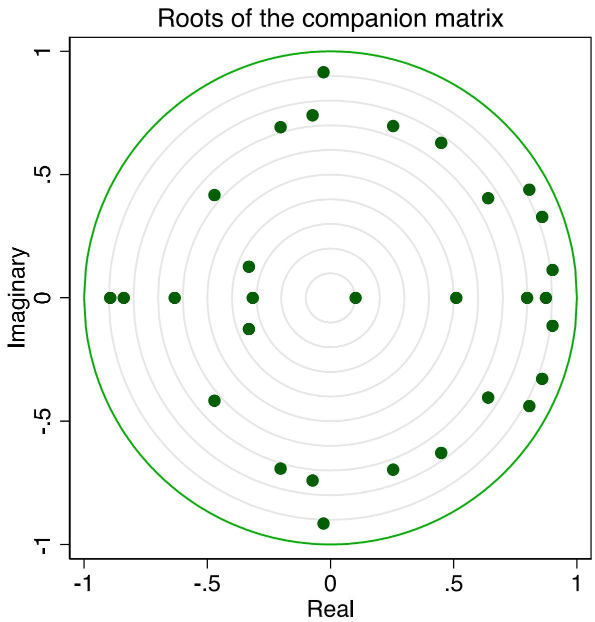
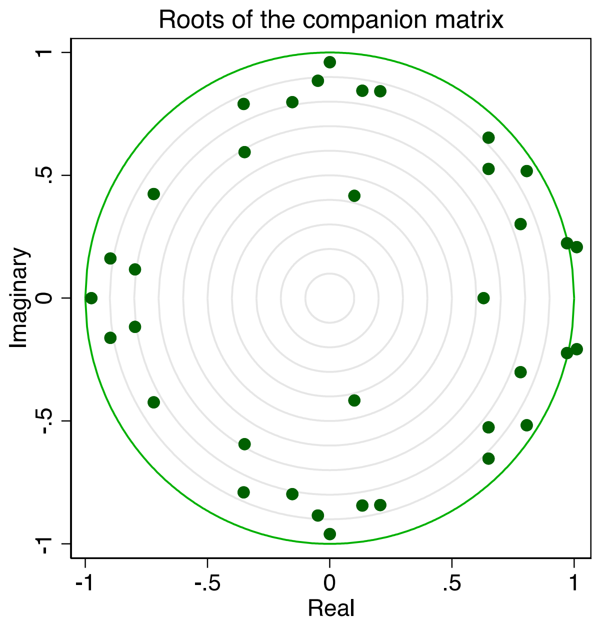
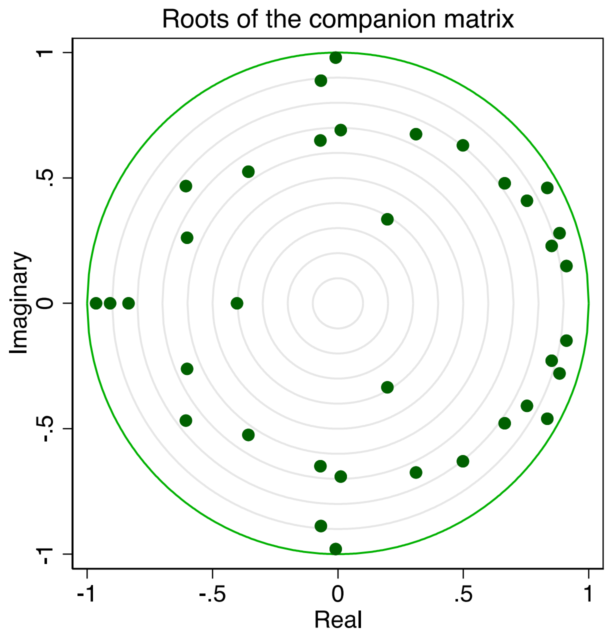


Table B4.3: Eigenvalue Stability Condition test for SVAR Model 3 pre- and post-92.





All the eigenvalues lie inside the unit circle and thus, SVAR Model 1 and SVAR Model 2 satisfies the stability condition. In SVAR Model 3, at least one eigenvalue lies outside the unit circle in the model for the pre-1992 sample. SVAR Model 3 post-1992 satisfies the stability condition.

C. Dummy overview

Table C.1: Dummy overview for SVAR Model 1, SVAR Model 2 and SVAR Model 3.

Year	Dummy	Outlier variable	Model	Economic scope
Pre-92				
1973	D1973Q2	Oil price	M2	OPEC1: The oil price increases from 3.6 US dollar to 15.5 US dollar per barrel.
	D1973Q3	Oil price	M2	
1974	D1974Q1	Oil price	M2	Recession from 1973Q4 – 1974Q4 due to OPEC1, which induces raised production costs and high inflation.
	D1974Q2	Oil price	M2	
	D1974Q3	Oil price	M2	
	D1974Q4	Oil price	M2	
1975	D1975Q4	Policy rate	M2, M3	High GDP growth due to growth in tanker trade.
1976	D1976Q1	Policy rate	M2, M3	After 1975 the recession also hit the Norwegian economy.
	D1976Q3	Wage	M3	
1977	D1977Q1	Policy rate, Wage	M2, M3	Stagflation hit Norway in the late 1970s early 1980s.
	D1977Q2	Policy rate	M2, M3	
	D1977Q3	Policy rate	M2, M3	
	D1977Q4	Policy rate	M2, M3	
1978	D1978Q2	Policy rate	M2	
1979	D1979Q2	CPI	M3	OPEC2: The oil price increases from 16.5 US dollar to 42 US dollar per barrel.
	D1979Q3	CPI	M3	
	D1979Q4	CPI	M3	
1980	D1980Q1	CPI	M3	

1986	D1986Q3	Oil price	M2	Devaluation of the NOK exchange rate leads to imported inflation and increased interest rate.
Post-92				
1992	D1992Q4	Policy rate	M2	Baking crisis 1988 - 1993, due to credit liberalization.
1993	D1993Q4	Policy rate	M3	
1998	D1998Q4	Policy rate	M2	Expansion from 1997Q2 – 1998Q4. High GDP growth due to petroleum production.
2000	D2000Q2 D2000Q3 D2000Q4	Oil price Oil price Oil price	M2 M2 M2	Dotcom bubble. Though limited effect on the Norwegian economy.
2001	D2001Q2	CPI	M1, M2	Inflation target changed from 2% to 2.5%.
2003	D2003Q1	CPI	M1, M2	
2007	D2007Q3 D2007Q4	CPI, GDP GDP	M1, M2 M2	Start of worldwide Financial crisis 2007 - 2010.
2008	D2008Q1 D2008Q2 D2008Q3	Policy rate Policy rate Policy rate	M2 M2 M2	Oslo Stock Exchange falls 64%.

2016	D2016Q3	Oil price	M2	Fall in oil and raw material prices, leads to an economic downturn and increased unemployment.
2020	D2020Q3	Oil price	M2	Covid crisis leads to increased unemployment, decreased GDP growth and increased inflation due to global supply chain constraints.
	D2020Q4	Oil price	M2	
2022	D2022Q2	CPI	M1	The war in Ukraine and sanctions against Russia have induced high energy prices, high inflation, and increased policy rates.

Note: The Outlier variable column in Table C.1 specifies in which davariable the extreme value is found in. The notations «M1», «M2» and «M3» in the Model column specify which SVAR model the dummy variable is included in. SVAR Model 1 = M1, SVAR Model 2 = M2 and SVAR Model 3 = M3. The sources for the economic scope information are Grytten & Hunnes (2016) and Bache (2022).