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The Trade-Off Between Inflation and Unemployment

A Bayesian Analysis of the New Keynesian Phillips Curve

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Abstract

Using country-level data, I estimate the slope of the New Keynesian Phillips curve (NKPC) for the eleven initial member states of the euro area. The estimation method utilized is a Bayesian implementation of a linear regression model with uninformative priors and a Gaussian error term. As an identification strategy, I rely on variation in macroeconomic variables to mitigate the bias that results from the endogeneity of monetary policy. A posterior mean of 0.04 can be documented for the slope of the PC in a pooled regression and country-specific estimates are in the range of [0.02, 0.19] using unemployment rate, GDP and GDP growth as measures of economic activity. These results imply a mildly steep, yet positively slopped PC. Thus, I fail to conclude that there is a trade-off between inflation and unemployment. Moreover, larger economies in the sample tend to have a smaller slope coefficient than smaller countries. It can therefore be concluded that the common monetary policy seems to have a higher impact on larger economies of the euro area than it has on smaller economies.

JEL Classification: C11, E12, E31, E52

Keywords: New Keynesian Phillips Curve, Bayesian inference, inflation dynamics, monetary policy, euro area

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1 Introduction

"Totgesagte leben länger", which roughly translates to "those declared dead, live longer" is a phrase that describes the discussion in the empirical literature of the Phillips curve (PC) very well. The question if the Phillips curve is dead or alive, i.e., if its slope is flat or steep, is still an ongoing debate even though several studies have provided evidence for its irrelevance in recent decades. Hazell, Herreno, Nakamura, and Steinsson (2022) even go as far as to claim that the slope of the PC has not flattened but has always been flat.

The Phillips curve originated as an attempt to explain inflationary dynamics using variation in unemployment and postulates a negative relation between these two variables. Through some sort of fine tuning of the economy, e.g., via demand management utilizing monetary policy tools, one may trade off lower levels of unemployment with higher levels of inflation, or vice versa, one could have lower levels of inflation but then must accept higher levels of unemployment. For instance, tightening monetary policy, i.e., a rise in the policy rate, dampens aggregate demand and thus reduces inflation. Intuitively, higher unemployment rate leads to a decrease in aggregate income, which in turn reduces aggregate demand. As a corollary, prices fall, resulting in lower inflation rates. On the other hand, a booming economy with excess demand incentives firms to raise prices and workers to bargain for higher wages.

However, there is lack of consensus regarding the empirical validity of the interplay of changes in prices and economic activity. In this thesis, I seek to address the following research questions:

- Can the variation in unemployment explain the variation in inflation?
- Is there a consistent relationship between unemployment and inflation?

Recent studies of the PC (McLeay and Tenreyro, 2020; Hazell, Herreno, Nakamura, and Steinsson, 2022; Eser, Karadi, Lane, Moretti, and Osbat, 2020) hypothesize that monetary policy offset any demand shocks that might help identify the slope of the PC. I address the endogeneity problem of monetary policy by considering a panel of cross-country data. The central bank of a monetary union cannot use a single interest rate to fully counteract regional demand shocks. Country-specific shocks that are not undone by the collective monetary policy can help identify the PC. This makes the euro area a suitable remedy for the inherent endogeneity issues of the PC since it shares a common multi-country monetary authority. Nonetheless, I restrict my sample to the eleven initial member states of the euro area in 1999 since these countries have had an exogenous monetary policy for the whole period since the euro was established. The identification strategy is to exploit country-level variations in macroeconomic variables that are not affected by the aggregate monetary policy. This approach should mitigate the endogeneity bias since the PC is presumed to be more evident in disaggregated panel data than in aggregate data (McLeay and Tenreyro, 2020). Thus, idiosyncratic national shocks of the EA-11 country composition that are not undone by the aggregate monetary policy should make identification possible and result in a more evident Phillips curve.

The econometric specification I employ is an empirical version of the baseline NKPC à la Galí (2007), where I proxy firms' marginal cost with economic activity. This approach results in a model where the underlying time series process is a regression of quarterly changes in inflation rates π_t on changes in forward-looking inflation expectations π_{t+1} and changes in a measure of economic activity x_t. As an estimation method, I utilize a Bayesian implementation of a linear regression with uninformative priors and a Gaussian error term. To the best of my knowledge, this is the first study to apply a Bayesian linear regression to an economic model. In this connection, I provide what I believe is a novel approach to estimate the slope of the NKPC in a limited-information framework, pooling data of the eleven initial member states of the euro area. Limited information is a method that applies only a single equation instead of a system of simultaneous equations to estimate the parameters of a model (Rothenberg, 2018). Subsequently, the results from this Bayesian approach are cross-checked with an ordinary least square estimation.

Following Bobeica and Sokol (2019) and Eser, Karadi, Lane, Moretti, and Osbat (2020), I apply a thick modelling approach to address specification issues. Instead of selecting a single specification, "thick modeling" involves combining the results from multiple econometric models that employ a set of economic variables. This approach is a possibility to reduce model uncertainty regarding the choice of variables to include. Different versions of a NKPC generic function are estimated using three different measures of real economic activity: unemployment rate, GDP and GDP growth. The data consists of 1100 observations at quarterly frequency and with the largest possible sample extending from 1998Q1 to 2022Q4. The data are obtained from ECB's statistical data warehouse, OECD and AMECO.

In a first step, I focus on the overall relationship between inflation and economic activity in the EA-11 country composition rather than the individual country-level effects and assume the same slope coefficient for all countries in a pooled regression. Subsequently, using country-level data across the eleven different economies, I estimate the slope of the NKPC in individual euro area countries.

The overall findings reveal a certain pattern: inflation seems to respond more strongly to changes in real economic activity for smaller economies compared to larger economies in the sample. In all specifications, the range of estimated slope posterior means bearing statistical significance amounts to $[0.02, 0.11]$ for France, Germany, Italy, and Spain, whereas the slope coefficient is relatively steeper vis-à-vis smaller economies like Austria, Belgium, Finland, Ireland, Luxembourg, Netherlands and Portugal with their respective estimates oscillating between 0.03 and 0.19. This observation suggests a stronger relationship between inflation and economic activity in smaller economies in the sample compared to their larger counterparts.

This outcome provides support for the identification strategy: Idiosyncratic national shocks that are unaffected by the common monetary policy should make identification possible and result in a more evident PC. The specific monetary policy tool applied in a certain period reflects the prevailing economic conditions. In a monetary union, it is plausible to assume that the aggregate monetary policy is tailored more towards the economies of the bigger member states compared to smaller economies. Thus, given the pattern of the results, I conclude that idiosyncratic national shocks of bigger economies are more affected by the common monetary policy than those of smaller economies. Consequently, the PC is presumably less evident in larger economies within the euro area than smaller economies since the latter ones are relatively less responsive to monetary policy measures taken on the aggregate level.

Inflation expectations are indicated as strong catalyst for movements in inflation throughout all specifications and across all countries. The posterior densities of the coefficient on inflation expectations imply that the coefficients are statistically highly significant with the theoretically implied sign, i.e., positive, and significantly different from zero. This outcome emphasizes how important is it for a central bank to credibly communicate its commitments to stabilize inflation and cement inflation expectations. Anchored inflation expectations in recent decades might have led to the flattening of the PC[1], which translates into a weaker response of inflationary dynamics to fluctuations in real economic activity. This, in turn, renders the trade-off between inflation and unemployment obsolete.

The applied econometric specifications point to a modestly steep, yet positively sloped PC across all countries, with significant slope coefficients spanning from 0.02 for Spain to 0.19 for Luxembourg. Given that the performed analysis documents a positive relation between inflation and real economic activity, I am cautious to conclude that there is a trade-off between these two macroeconomic variables. Put differently, the outcome of this thesis does not provide empirical evidence for the trade-off between inflation and unemployment (or related measures of real economic activity).

In terms of magnitude as well as significance, the obtained posterior means from the Bayesian inference are consistent with the OLS point estimates across all specifications and countries.

[1] Bank for International Settlements Annual Report (2017), graph I.3, page 11

Furthermore, the goodness-of-fit indicated by the OLS results suggests that a vast amount of the fluctuations in inflation can be explained by the applied covariates.

This thesis contributes to the existing literature by providing new estimates of the NKPC slope for the eleven initial member states of the euro area. It also sheds light on how the size of the fiscal regime possibly influences the impact of the common monetary policy on the economy of the respective country. The bigger the economy, ergo the fiscal regime, the larger the impact of the common monetary policy tends to be.

The thesis is structured as follows: Section 2 reviews related literature on the PC and section 3 elaborates on the underlying economic model of this empirical study. Section 4 deals with the empirical implementation of the NKPC and introduces the methodology and the data used. Section 5 presents the results and a final section concludes.

2 Related Literature

The name bearer of the Phillips curve did not make the link to inflation; instead, the focus was on money wages. In "The Relation between Unemployment and the Rate of Change of Money Wage Rates in the United Kingdom, 1861-1957", Alban W. Phillips (1958) illustrates a trade-off between the growth of nominal wages and unemployment. Given lower unemployment rates, nominal wages exhibit higher growth rates and when unemployment is high, nominal wages tend to grow slower.

Over the past decades, the PC has evolved into a tool for analysing inflationary responses to the state of the real economy, often proxied using the unemployment rate. Nonetheless, the empirical evidence on the PC is inconclusive, sparking an extensive debate in the literature regarding its existence.

Still, the slope of the Phillips curve can be regarded as one of the key aspects of the economy and plays a significant role for central banks. For example, the European Central Bank's (ECB) understanding of the transmission of monetary policy relies heavily on the Phillips curve (Eser, Karadi, Lane, Moretti, and Osbat, 2020), which is part of the empirical tools employed at the ECB to analyse the inflation process (Bobeica and Sokol, 2019).

Eser, Karadi, Lane, Moretti, and Osbat (2020) elaborate on the role of the PC in the process of monetary policy formulation at the ECB and refer to measures taken by the ECB in response to the aftermath of the global financial crisis 2008 and the ensuing outcome of these measures to advocate for the existence of a stable PC. ECB's unconventional monetary policy aimed at easing financial conditions, which subsequently led to positive economic growth, a decline in unemployment, and an increase in inflation. This observation is supported by Bobeica and Sokol (2019) in their empirical assessment of the PC for the euro area, covering the period since the onset of the great financial crisis. In a thick modelling approach, they estimate 550 models of the PC and find the "euro area Phillips curve to be alive."[2] Yet, the estimated magnitudes of the slope indicate that the euro area PC is not very steep.

Ball and Mazumder (2021) utilize the weighted median inflation rate as a measure of core inflation to estimate a textbook Phillips curve in an OLS framework and find that inflationary patterns over the twenty years that the Euro has existed are well captured by a simple PC. In order to find out if their results are specific to Europe, the authors carry out the same estimation using United States data spanning from 1986 to 2018 and obtain results that align closely with those obtained from the European data set.

In contrast to the aforementioned findings of Ball and Mazumder (2021) for the US, Hazell, Herreno, Nakamura, and Steinsson (2022) contend that fluctuations in US inflation rates of the early 1980s stemming from changes in unemployment were relatively modest. This view challenges one of the most prominent pieces of evidence supporting the existence of the PC. The tightening of US monetary policy in the 1980s was successful in achieving its objective and led to an increase in unemployment and a reduction in inflation. In order to counteract endogeneity issues, Hazell et al. utilize regional data to estimate a multi-region PC model of a monetary union where they infer the slope of the aggregate PC from regional estimates. For the full sample period of 1978-2018, they obtain results that are different from zero, albeit with a magnitude that indicates a small slope given an estimate of 0.0062. They conclude that this outcome can be accounted for by anchored inflation expectations in the long-run. In the same vein McLeay and Tenreyro (2020), Hooper, Mishkin, and Sufi (2020) and Mavroeidis, Plagborg-Møller, and Stock (2014) also attribute the flattening of the PC to inflation expectations becoming more anchored in recent decades.

The existing empirical literature evaluating the relation between inflation and unemployment mainly focuses on the global north. Thus, estimates of the PC for other countries other than advanced economies are rather scarce. Zobl and Ertl (2021) fill this gap and estimate the NKPC for four emerging economies of Central and Eastern Europe (CEE). Their findings provide empirical support for the existence of the NKPC utilizing a GMM approach and a Bayesian time-varying parameter estimation.

McLeay and Tenreyro (2020) argue that the Phillips curve is "alive and well in the model"

[2] "Drivers of Underlying Inflation in the Euro Area over Time: A Phillips Curve Perspective", page 95

but not visible in the data due to "endogenous response of optimal monetary policy". As a consequence, identification issues arise when estimating the PC since demand shocks that might help identify the PC are offset by monetary policy. A possible solution to this endogeneity problem would be to estimate the Phillips curve either at the regional level within a country or for countries within a monetary union. If monetary policy is determined on a national level, its effect on idiosyncratic regional demand shocks can be regarded as exogenous. Monetary policy seeks to offset aggregate demand shocks but it does not react to regional deviations from the aggregate. The same goes for the euro area since its member states are subject to a single monetary policy: country-specific demand shocks that are not affected by aggregate measures taken by the ECB should enable the identification of the PC.

As a demonstration of the endogeneity problem, McLeay and Tenreyro (2020) carry out OLS regression analysis using US aggregate data in a first step and then data from 28 US metropolitan areas in a second step for the sample period 1990-2018. The outcome of the former approach, which utilizes the unemployment gap as a proxy for economic slack, suggests a relatively flat PC, although the relationship still exists. Given that policymakers also take similar estimates into account, due to the inherent identifications issues when estimating the PC curve on a national level, they infer that this could lead to unintended conclusions for monetary policy. The consequence is that a flatter PC implies a higher "sacrifice ratio," i.e., the flatter the PC, the higher the unemployment rate required to stabilize inflation dynamics. In the latter estimation where they use city-level data for the US as an identification strategy and the unemployment rate to measure economic activity in a fixed effects model, they obtained a steeper and robust US Phillips curve at the regional level.

The outcome of the two above-mentioned empirical exercises complies with the notion that the PC is more evident on a regional level. Due to the heterogeneous nature of economic development across geographic and administrative areas, idiosyncratic shocks that are not undone by the common monetary policy make identification possible on a regional level. On a national level, however, monetary policy endogenously offsets deviations in aggregate demand, which makes it difficult to identify the slope of the PC, i.e., changes in inflation that stems from changes in economic activity.

Apart from the endogeneity biased resulting from optimal monetary policy discussed above, Mavroeidis, Plagborg-Møller, and Stock (2014) also emphasize the substantial specification uncertainty surrounding the approximation of the NKPC in their extensive review of the empirical literature of the PC covering over one hundred papers. As can also be concluded from the aforementioned papers, the outcome of the empirical assessment of the PC varies across papers and

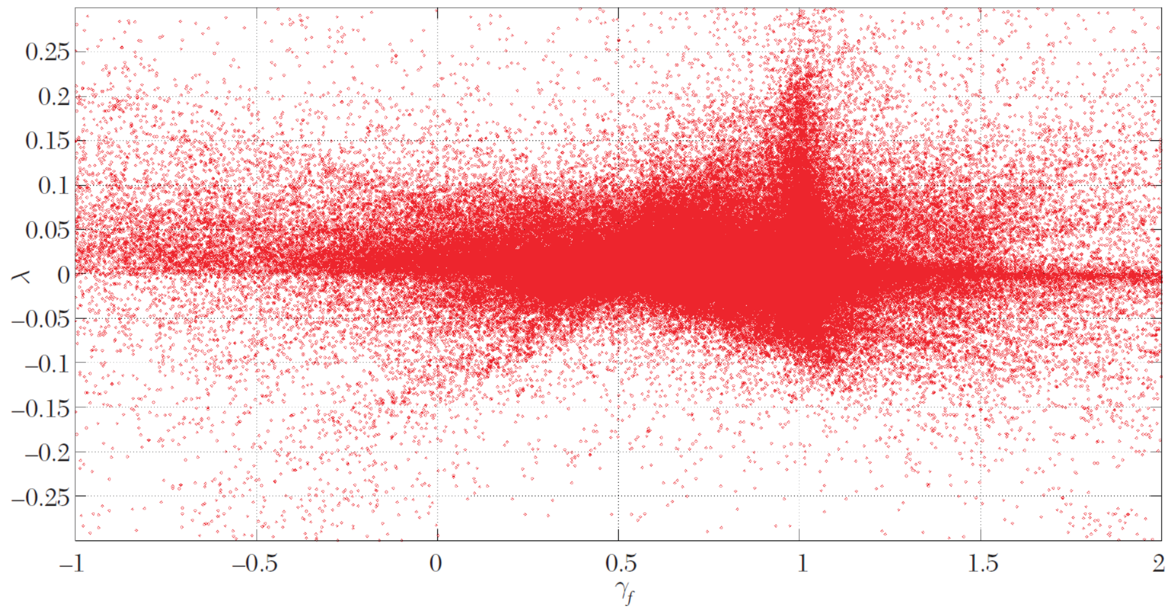

Figure 1: Point estimates of the slope of the NKPC λ and the coefficient on expected inflations γ_f from various specifications using different measures of output gap to proxy economic activity.
Source: Mavroeidis, Plagborg-Møller, and Stock (2014)

exhibit opposing conclusions.

To validate their conclusions from their review of the myriad of papers, Mavroeidis, Plagborg-Møller, and Stock (2014) conduct a comprehensive econometric analysis of the NKPC. They reckon that they "estimated more NKPC specifications than the entire preceding literature combined"[3] and find that the conflicting results obtained for the slope of the NKPC in the empirical literature is due to different identification assumptions, specifications, and estimation methods. Figure 1 illustrates the range of point estimates across different models of the NKPC with various combinations of specification choices and different measures of output gap as a proxy for real economic activity. The plot visually represents the specification uncertainty, showing that the estimates of the slope of the NKPC λ range from -0.3 to 0.3, although they tend to centre around zero. Expected inflation's coefficient is more spread out but are on average around 0.75.

The main take from Mavroeidis et al.'s paper is that, due to the endogeneity of the two components of the pure NKPC, estimates of the slope of the NKPC are overly sensitive to specification and estimation method. Estimates of the NKPC may be affected differently by misspecification of the model. This makes identification rather difficult.

Despite the sensitivity of estimates to choices of specification and econometric strategy and

[3]"Empirical Evidence on Inflation Expectations in the New Keynesian Phillips Curve", page 126

the conflicting results found in the empirical literature, they do not reject the NKPC. Instead, they appeal to both applied and theoretical researchers to develop new sources of identification, such as micro/sectoral data, cross-country models, information from large datasets, and stability restrictions.

3 The New Keynesian 3-equation Model

The underlying theoretical model of this empirical analysis is the NKPC, which, along with the Taylor rule and the dynamic IS curve, constitutes the three-equation New Keynesian model. The NK model is a modification of the general-equilibrium business-cycle model that breaks the assumption of perfect competition and introduces nominal rigidities. Firms are no more price takers but are equipped with market power in a monopolistic competition environment. That is, firms can set prices. Under perfect competition where goods are perfectly substitutable across firms, if firms would set their price above marginal costs, the demand for their goods would shift to their competitors. Consequently, in a competitive equilibrium of a real business cycle model, firms are price takers and cannot set a different price other than the price that equals their marginal costs.

In contrast, monopolistic competition is characterized by a large number of small firms with horizontal differentiated products where each firm is a monopoly in their niché. In other words, firms enjoy market power in their own output market given closely related product varieties, i.e., imperfect substitutes (Heijdra, 2017). This setting allows firms to set their own prices, yet take all other prices as given. The assumption of price-setting firms is necessary to introduce price rigidity in the model. Given imperfect competition, prices are not equal to marginal costs since firms are no longer price takers but have some degree of control over setting a price. Nevertheless, they are restricted in their price setting decision: Calvo price-setting assumes that in each period only a fraction of firms is allowed to adjust their prices. In a Rotenberg set-up, firms are allowed to set their price in any period, but this comes with a cost. So, either firms cannot reset their price in any period they want (Calvo), or they can do so at any point in time they want, but then they have to endure costs of price adjustment (Rotemberg).

In the presence of flexible price adjustment where firms can adjust their prices immediately without any constraints or frictions, monopolistically competitive firms would set their prices at a mark-up over their marginal costs. With sticky prices, their optimal pricing decision becomes dynamic: firms have to take the future price setting behaviour of their competitors into account when setting prices.

Formally, the three key equations describing the equilibrium of the new Keynesian model are defined in their log-linear versions as follows (under the assumption of Calvo pricing).

3.1 The Dynamic IS Curve

Equation 1 represents the dynamic IS curve, which is an intertemporal optimality condition that governs the goods market. It relates the current output gap $\hat{y}_t - \hat{y}_t^{flex}$ with expected future output gap and the real interest rate (= the nominal interest rate i_t adjusted for expected inflation). ε_t^D denotes a demand shock that follows an AR(1) process by assumption.

$$\hat{y}_t - \hat{y}_t^{flex} = E_t(\hat{y}_{t+1} - \hat{y}_{t+1}^{flex}) - \frac{1}{\sigma}(i_t - E_t\hat{\pi}_{t+1}) + \varepsilon_t^D \tag{1}$$

The output gap is the deviation of the actual output of an economy from its potential. Potential output is the level of output that would prevail if prices were fully flexible. If prices are fully flexible, firms can always adjust their prices in response to shocks accordingly to achieve an efficient level of output.

The dynamic IS curve postulates an inverse relationship between current output and the real interest rate. This reflects the notion that a higher interest rate discourages investment, leading to a lower level of output. The equation also implies that consumption decisions are not static but has an intertemporal dimension: The forward-looking component accounts for the assumption that current demand depends not just on the real interest rate but also on expected future income (Sims, 2017).

3.2 The Monetary Policy Schedule

The Monetary Policy schedule, commonly referred to as the Taylor rule, describes the behaviour of the monetary policy authority, i.e., how a central bank adjusts its policy rate in order to manage fluctuations in inflation around its desired target. It relates the nominal interest rate i_t, which is determined by monetary authorities, to the inflation rate and to the output gap, with the parameters ϕ_π and ϕ_{gap} assumed to be positive. ε_t^R is an AR(1) process and constitutes a monetary policy shock.

$$i_t = \underbrace{\phi_\pi\hat{\pi}_t + \phi_{gap}(\hat{y}_t - \hat{y}_t^{flex})}_{\text{feedback to macroeconomy}} + \varepsilon_t^R \tag{2}$$

A central bank's prime objective, at least in high-income economies, is stable prices. Hence most central banks have adopted an inflation targeting regime where they respond endogenously to the level of inflation: if inflation is high, they try to increase the nominal interest rate in an effort to bring inflation down and vice versa.

The first component of the Taylor rate rule describes how the nominal interest rate reacts in feedback to events in the macroeconomy. As can be inferred from the equation, an increase in inflation requires an increase in the policy rate so that the identity still holds. Thus, the central bank raises interest rates when inflation is above target and reduces them when it is below target. Similarly, if the output gap is high, the central bank increases the interest rate.

The central bank's commitment to achieve its objective of stable inflation dynamics via the Taylor rule sets a positive endogenous feedback effects on the state of the macroeconomy in motion. The Taylor principle is the intuition that the policy rate of the central bank needs to respond more than one-to-one to changes in inflation, so that the real interest rate rises when inflation is high. If the coefficient on output gap $\phi_{gap} = 0$, then the nominal interest can only be determined if and only if the coefficient on inflation $\phi_\pi > 1$. Otherwise, the Taylor rule would imply an overheating of the economy given rising inflation rates. The underlying mechanism is as follows:

An increase in inflation necessitates an increase in the nominal interest rate i_t to ensure that the identity of the monetary policy schedule holds. What follows in this case depends on what happens with the real interest rate r_t — this is what economic behaviour depends upon. For simplicity let $E_t(\pi_{t+1}) = \pi_t$ in the Fisher equation so that we have $r_t = i_t - \pi_t$. Given this identity, the real interest rate r_t falls upon an increase in inflation π_t if $\phi_\pi < 1$. Since the

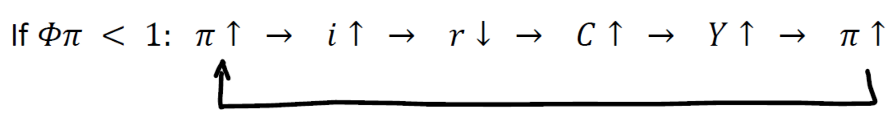

Figure 2: Feedback to the state of the macroeconomy

opportunity cost of consumption — the returns on savings — is naturally negatively related to consumption, a fall in the real interest rate increases consumption. A rise in consumption leads to an increase in aggregate demand, which in turn increases output. The increase in demand further increases inflation, starting the entire process anew — figure 2 provides a sketch of this mechanism.

If the monetary authority does not respond strongly enough, the economy will end up overheating because of an ever-increasing inflation dynamics. A sufficient reaction that would combat the increase in inflation would be to choose a value for the coefficient on the inflation gap in the Taylor rule that is strictly larger than 1, that is $\phi_\pi > 1$. To prevent the economy from overheating, the central bank must respond strongly enough to inflation fluctuations.

Given an adequate value for ϕ_π, an increase in the nominal interest rate raises the real interest rate following a surge in inflation. The corollary of this outcome is a higher opportunity cost of consumption which encourages saving, the flip side of that is less consumption. Consequently, aggregate demand and output decline, triggering a drop in inflation.

Thus, with a more than proportional response to movements in inflation, the central bank manages to contain inflation dynamics, that is, achieving their objective of price stability. In order to have stable inflation dynamics, the coefficient on inflation ϕ_π has to be strictly larger than 1. To phrase it in the spirit of Clarida, Galí, and Gertler (1999), monetary policy boils down to a problem of choosing distinct functions and parameter values for the Taylor Rule. I may also refer to the following quote, which sums up the optimal behaviour of a monetary authority in context of the Taylor rule very well:

> *The policymaker should promise to react aggressively to deviations of inflation from target in conducting monetary policy. The solution to this problem is to set a large coefficient on the inflation gap, technically, $\phi_\pi \to \infty$.*
> (James B. Bullard[4])

Together with the dynamic IS curve, the Taylor rule characterizes the demand side of the macroeconomy in the New Keynesian model.

3.3 The New Keynesian Phillips' Curve

The New Keynesian Philips' curve (NKPC) on the other hand is the supply side of the economy and is characterized by inflation π as a linear function of firms' marginal costs mc_t, forward-looking inflation expectations $E_t\pi_{t+1}$ and an exogenous supply shock ε_t:

$$\pi_t = \lambda mc_t + \beta E_t \pi_{t+1} + \varepsilon_t \tag{3}$$

The relationship is the outcome of firms' intertemporal problem of maximizing lifetime expected discounted profits by choosing the optimal price under sticky prices. The assumption of nominal rigidities warrants the forward-looking component in the NKPC: Given imperfect competition, if firms could set their prices flexibly, they would just set it at a mark-up over their marginal costs. However, since it is either costly for firms to adjust their prices (Rotemberg) or they can only reset it in a certain period of time (Calvo), they set their prices for several periods

[4] Former CEO and president of FED St. Louis. Speech at the ECB Forum on Central Banking, 2018

ahead. So, in the absence of flexible price adjustment, the price setting decision of firms become dynamic as they need to plan forward by considering the future evolution of their costs, markups and the pricing strategies of their competitors (Eser, Karadi, Lane, Moretti, and Osbat, 2020). Put differently, sticky prices forces firms to set their prices for several periods ahead taking the price setting decisions of competitors into account. Thus, nominal rigidities lead to firms accounting for expected inflation in their price setting behaviour.

The more firms that keep their prices unchanged, the less impact the current level of slack has on inflation. In other words, if the fraction of firms that can adjust their prices in each period is relatively small, then economic activity has hardly any impact on inflation. If prices are sticky, then the slope of the NKPC is small since inflation does not react to changes in economic activity. If there are no constraints on flexible price adjustment, the slope of the NKPC is steeper because prices can and do react to changes in real economic activity. The stickier prices are, the flatter is the slope of the PC: if prices are fully sticky, i.e., firms cannot change their prices, then the current level of economic slack has no impact on inflation.

Firms accounting for expected inflation implies that central banks can affect inflation through the management of inflation expectations (Mavroeidis, Plagborg-Møller, and Stock, 2014). Central banks manage inflation expectations inter alia via the Taylor rule. As already outlined above, the Taylor principle requires monetary policy to respond more than proportional to an increase in inflation. By fine tuning its commitment to achieve price stability via the parameters ϕ_π and ϕ_{gap} of the Taylor rule, a central bank can influence the relative volatility of inflation and output. If stabilizing inflation dynamics increases indefinitely ($\phi_\pi \to \infty$), the PC becomes flat (Bullard, 2018).

The larger the parameters of the Taylor rule, the stickier are prices, the bigger will be the effects of nominal shocks, i.e., effects of monetary policy instruments, and the more distorted will be the response of macroeconomic variables to real shocks. Graphically this can be seen by a flatter slope of the NKPC. A successful inflation stabilization translates into anchored inflation expectations and leads to a flat PC. This makes the expectation of future inflation the key endogenous covariate in the NKPC (Mavroeidis, Plagborg-Møller, and Stock, 2014).

The second component of the NKPC also poses an endogeneity problem. The assumption of imperfect competition enables monopolistically competitive firms to set prices as a markup over their nominal marginal costs, which naturally contribute to inflation. It is a common approach in the empirical literature to proxy firms' marginal cost with measures of real economic activity.

However, central banks manage financial conditions through policy rates and other tools and thereby affect consumption and investment decisions. Thus, monetary policy impacts the degree of economic activity, which in turn influences inflation.

Due to the discussed endogeneity problems, estimates of the slope of the NKPC is not independent of the conduct of monetary policy. To measure the causal effect of monetary policy, one needs to control for the variation in macroeconomic variables that the policy endogenously responds to. Identification should be feasible when considering country-specific shocks that are not counteracted by the shared monetary policy (McLeay and Tenreyro, 2020). Hence, Identification is achieved by exploiting country-level variations in economic slack.

4 Empirical Implementation of the NKPC

4.1 Model Specification

The estimation strategy is to use a plain-vanilla linear regression model in a Bayesian framework. Despite, or may be because of the extensive debate in the empirical literature, there is no consensus about the appropriate empirical representation of the NKPC. I opt for a simple bivariate specification and estimate an empirical version of the baseline NKPC à la Galí (2007), (equation 3), where I proxy firms' marginal cost with economic activity. This approach results in a model where the underlying data generating process of inflation π_t is assumed to be a linear combination of forward-looking inflation expectations π_{t+1}, a measure of economic activity x_t and a stochastic term ε, which is often regarded as an unobserved cost-push shock (Poutineau, Sobczak, and Vermandel, 2015, Zobl and Ertl, 2021). Algebraically:

$$\pi_{i,t} = \gamma \pi_{i,\,t+1} + \kappa x_{i,\,t-4} + \varepsilon \tag{4}$$

γ and κ constitute the coefficient for expected inflation and the slope of the NKPC, respectively. i denotes the countries in the sample with $i \in \{$Austria, Belgium, Germany, Finland, France, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain$\}$ and each period t corresponds to a quarter.

It is plausible to assume that the nexus of inflation and economic activity is intertemporal and not contemporaneous. The longer response lags of macroeconomic variables to monetary policy shocks justifies the usage of lagged variables. Thus, following Eser, Karadi, Lane, Moretti, and Osbat (2020), the slack variable is introduced with a lag rather than contemporaneously to allow for a delayed effect on inflation. The transmission mechanism of monetary policy is not instantaneous, it is lagged: It takes some time for monetary policy actions to feed through macroeconomic variables to have an effect on the real economy[5].

Furthermore, the use of lagged variables is in line with the assumption of price rigidity in New Keynesian models. In “Staggered Price and Wage Setting in Macroeconomics”, Taylor (1999) documents an average price duration of one year. Thus, regarding the choice of the number of lags to include, I rely on Taylor’s findings and use four quarters lagged values of economic activity.

It is a common approach in the empirical literature to assume that the marginal costs of firms are proportional to economic slack, proxied by the unemployment gap or the output gap – the deviation of actual output from its potential – which is not directly observable and has to be estimated (with error). A positive output gap implies high demand and a negative output gap indicates weak demand. Theoretically, it follows that, ceteris paribus, if the output gap is positive over time, prices will rise. On the other hand, if actual output falls below potential output over time, inflation will decrease. The concept of unemployment gap is closely associated with the output gap. However, the unemployment gap is inversely related to inflation. Theoretically, other things being equal, a positive unemployment gap is associated with decreasing inflation rates and a negative unemployment gap implies rising prices. Due to lack of data on gap variables and since estimates of the potential level of macroeconomic variables such as GDP and unemployment rate are highly sensitive to the underlying parameters, I refrain from using them and instead use the original data as obtained. This approach is partly motivated by James D. Hamilton’s (2018) stance on applying the Hodrick-Prescott filter to economic data. He advises against using the HP-filter since taking first differences and then applying the smoothing parameter “puts all kinds of patterns into the HP-filtered series that have nothing to do with the original data-generating process and are solely an artefact of having applied the filter.”[6] Following Babb and Detmeister (2017), Kiley (2015), McLeay and Tenreyro (2020), I use observable measures of economic activity such as the unemployment rate as the baseline regression. Nevertheless, I also provide results using two different approaches to estimate gap variables in appendix F.

Acknowledging specification uncertainty, I apply a thick modelling approach where I proxy economic activity with different measures. In other words, instead of selecting a single specification, “thick modeling” involves combining the results of multiple econometric models that utilize different combinations of explanatory variables. This method is a possibility to mitigate model uncertainty regarding the choice of variables to include and thus enhances the

[5] ecb.europa.eu: the transmission mechanism of monetary policy
[6] Why you should never use the Hodrick-Prescott filter | CEPR

robustness of the analysis against measurement uncertainty. Using the above empiric version of the NKPC (equation 4) as a generic function, different adaptions of it are estimated utilizing various measures of economic activity.

To address the potential bias caused by the aforementioned endogeneity problem, I utilize variations in economic activity at the country level within the euro area to estimate the slope of the PC. The euro area has a heterogeneous labour market but shares a common monetary policy. The individual economies within the euro area are affected by the monetary policies of the European Central Bank (ECB), which are determined based on the overall conditions of the entire euro area. When countries within a monetary union are relatively small compared to the overall aggregate, it can be argued that the common monetary policy operates independently of variations at the country level (Eser, Karadi, Lane, Moretti, and Osbat, 2020). This independence allows the estimates to circumvent any bias arising from the endogenous feedback effects of monetary policy. Since EBC's monetary policy responds to changes in aggregate demand of the euro area, using country-level data should account for the endogeneity problem and lessen the bias resulting from it.

In this thesis, I restrict my sample to the EA-11 country composition since these countries have had an exogenous monetary policy for the whole period since the euro was established. In doing so, I hope to mitigate the endogeneity problem of monetary policy, which should then result in a more evident Phillips curve.

4.2 Data

The sample consists of 1100 observations at quarterly frequency and spans the period from 1998Q1 (a year before the euro was established) to 2022Q4 (the most recent period available). Even though the euro was officially launched in 1999, it is reasonable to assume that the involving countries started harmonizing their monetary policy prior to 1999. The data are obtained from ECB's statistical data warehouse, OECD and Annual macro-economic database of the European Commission (AMECO). Inflation and unemployment data are available at monthly frequency. Quarterly values are computed by averaging the original monthly values. Table 1 provides an overview of the data used, along with descriptions and sources. A descriptive statistic of the variables can be found in appendix A.

In this empirical exercise, where the objective is to explain inflationary responses to the state of the real economy, I use underlying inflation as regressand. In doing so, the focus is then on the more persistent factors driving inflation. Core inflation excludes the volatile components of inflation such as energy and food prices. The prices of these commodities tend to be more prone to short-term fluctuations due to circumstances like weather conditions or geopolitical events. I do not explicitly account for supply-side shocks. However, using core inflation instead of headline inflation, to some degree, implicitly controls for cost-push shocks (Mavroeidis, Plagborg-Møller, and Stock, 2014, McLeay and Tenreyro, 2020).

The measurement of expected inflation relies on OECD's inflation forecast indicator. Regarding the measure of economic slack, different versions of equation 4 are estimated taking into account the uncertainty about how to measure economic slack. The specifications iterate across the following three measures of slack: unemployment rate, log(GDP) and GDP growth.

Table 1: Variable Description & Sources

Variable	Description	Source
Core Inflation	HICP - All-items excluding energy and food	ECB Statistical Data Warehouse
Inflation Expectations	HICP Inflation forecast for euro area countries	OECD Inflation forecast
Unemployment Rate	Total, Age 15 to 74	ECB Statistical Data Warehouse
GDP	GDP at market prices, chain linked volume	ECB Statistical Data Warehouse
GDP Growth	GDP at market prices, growth rate, over 1 year	ECB Statistical Data Warehouse

4.3 Estimation Method

4.3.1 Bayes' Theorem: From Prior to Posterior

I employ a Bayesian approach to estimate a linear regression model using uninformative priors and a Gaussian error term. Assuming a normal error yields a normal likelihood of the data. Following the textbook by Lynch (2007), an improper uniform prior over the real line is specified for the regression parameters and an inverse gamma for the error variance parameter. Subsequently, I validate the outcomes of this Bayesian methodology by comparing them with the results obtained through ordinary least squares estimation.

Prior The prior distribution $p(\theta)$ conveys information about the parameters of interest prior to observing the data. It encapsulates the initial uncertainty or prior knowledge about the parameter values.

Likelihood The likelihood function $p(data \mid \theta)$ denotes the probability of the data given the parameter(s) θ of the model. In other words, it measures how likely is it to observe realisations of a random variable — can also be referred to as data — given the parameter(s) θ of the underlying distribution. Since inflation is not predetermined, it can be regarded as a random variable. In line with economic theory, namely the NKPC (equation 3), I specify its likelihood function accordingly.

Posterior In Bayesian estimation, observed data (likelihood) are used to update prior information about an outcome variable of interest. The updated prior is called the posterior, which is then used as basis to perform Bayesian inference. The posterior is proportional to the likelihood multiplied with the prior, formally:

$$p(\theta|data) \propto p(data|\theta) \times p(\theta)$$

Density functions, in order to satisfy the Kolmogorov probability axioms, are equipped with a normalizing constant that ensures their sum (or integral in the continuous case) equals 1. However, in Bayesian inference, this normalizing constant can be disregarded. Hence, the usage of "$\propto$" instead of "$=$".

4.3.2 Derivation of the Posterior Distribution

Let $y = X\beta + \varepsilon$ with $\varepsilon \sim \mathcal{N}(0,\, \sigma_\varepsilon^2 I_n)$ where $y = \pi_{i,t} \in R^{n\times 1},\ \varepsilon \in R^{n\times 1}$,
$X = [\pi_{i,t+1},\, x_{i,t-4}] \in R^{n\times k}$ with $\pi_{i,t+1} \in R^{n\times 1}$ and $x_{i,t-4} \in R^{n\times 1},\quad \beta = (\gamma_t\ \kappa_t)^\top \in R^{k\times 1}$

Given a Gaussian error term, the **likelihood function** of the data y is also a normal distribution (y is just a shift by the constant $X\beta$):

$$p(y\,|\underbrace{\beta,\ \sigma_\varepsilon^2}_{=:\theta}) \sim \mathcal{N}(X\beta,\ \sigma_\varepsilon^2 I_n) \quad \Longrightarrow \quad \begin{aligned} p(y\,|\,\theta) &= \prod_{i=1}^{n} p(y_i\,|\,\theta) \\ &= \prod_{i=1}^{n} (2\pi\sigma_\varepsilon^2)^{-1/2} \exp\left[-\frac{1}{2\sigma_\varepsilon^2}(y_i - X_i^\top\beta)^\top (y_i - X_i^\top\beta)\right] \\ &= (2\pi\sigma_\varepsilon^2)^{-N/2} \exp\left[-\frac{1}{2\sigma_\varepsilon^2}(y - X\beta)^\top (y - X\beta)\right] \end{aligned}$$

Taking an agnostic approach regarding the values of the coefficients on the components of the NKPC, an improper uniform **prior** over the real line is specified for the regression parameter vector β, which results in a non-informative prior. For the error variance parameter σ_ε^2, the common reference prior for the normal distribution model, the inverse gamma, is specified as prior:

$$\sigma_\varepsilon^2 \sim \mathcal{IG}(a,\ b) \implies p(\sigma_\varepsilon^2\,|\,a,\,b) \propto (\sigma_\varepsilon^2)^{-(a+1)} e^{-\beta/\sigma_\varepsilon^2}$$

Now let the hyperparameters a and b of the inverse gamma distribution approach 0 in the limit to obtain a flat prior:

$$\sigma_\varepsilon^2 \sim \mathcal{IG}(0,\ 0) \implies p(\sigma_\varepsilon^2) \propto \frac{1}{\sigma_\varepsilon^2}$$

Under the assumption that β and σ_ε^2 are independent, the joint prior of these parameters is the product of their respective priors:

$$p(\beta,\ \sigma_\varepsilon^2) = p(\beta)p(\sigma_\varepsilon^2) = \frac{1}{\sigma_\varepsilon^2}$$

The resulting **posterior distribution** for β and σ_ε^2 is obtained via Bayes' Theorem:

$$\begin{aligned} p(\beta,\ \sigma_\varepsilon^2 \mid y) \propto p(y \mid \beta,\ \sigma_\varepsilon^2)p(\beta,\ \sigma_\varepsilon^2) & \\ & \propto (\sigma_\varepsilon^2)^{-N/2} \exp\left[-\frac{1}{2\sigma_\varepsilon^2}(y - X\beta)^\top (y - X\beta)\right] \sigma_\varepsilon^{-2} \\ & = \sigma_\varepsilon^{-(N+2)} \exp\left[-\frac{1}{2\sigma_\varepsilon^2}(y - X\beta)^\top (y - X\beta)\right] \end{aligned} \tag{5}$$

The conditional posterior $p(\theta_i \mid \theta_j,\ y)_{i \neq j}$ of a parameter $\theta_i \in \{\beta,\ \sigma_\varepsilon^2\}$ is proportional to the joint posterior (equation 5) evaluated at a particular value for $\theta_j \in \{\beta,\ \sigma_\varepsilon^2\}$, differing only by a normalizing constant: to compute the conditional posterior, any term of the joint posterior that does not include θ_i can be dropped as it is viewed as a proportionality constant with respect to θ_i. For example, let $a = const$ in $e^{a+b} \implies e^{a+b} = e^a \cdot e^b \propto e^b$.

Computing the conditional posterior distribution for the regression parameter vector β requires considering σ_ε^2 as fix and dropping any term that does not involve β:

$$\begin{aligned} p(\beta \mid \sigma_\varepsilon^2,\ y) \propto \exp\left[-\frac{1}{2\sigma_\varepsilon^2} \underbrace{(y - X\beta)^\top (y - X\beta)}_{=\,\mathrm{SSR}}\right] & \\ & = \exp\left\{-\frac{1}{2\sigma_\varepsilon^2}[(y^\top - (X\beta)^\top)(y - X\beta)]\right\} \\ & = \exp\left\{-\frac{1}{2\sigma_\varepsilon^2}[y^\top y - y^\top X\beta - (X\beta)^\top y + \beta^\top X^\top X\beta]\right\} \end{aligned}$$

$y^\top y$ is a constant w.r.t. β and so it can be removed as a multiplicative proportionality constant. $y^\top X\beta$ and $(X\beta)^\top y$ are 1×1, i.e., a scalar, and are identical, one is just a transposed version of the other, thus they can be grouped:

$$= \exp\left\{-\frac{1}{2\sigma_\varepsilon^2}(\beta^\top X^\top X\beta - 2\beta^\top X^\top y)\right\}$$

Following Lynch, the numerator and denominator can be multiplied through by $(X^\top X)^{-1}$

appropriately to obtain

$$= \exp\left\{-\frac{1}{2\sigma_\varepsilon^2(X^\top X)^{-1}}[\beta^\top \underbrace{(X^\top X)^{-1}(X^\top X)}_{=I_n}\beta - 2\beta^\top(X^\top X)^{-1}X^\top y]\right\}$$
$$= \exp\left\{-\frac{1}{2\sigma_\varepsilon^2(X^\top X)^{-1}}[\beta^\top\beta - 2\beta^\top(X^\top X)^{-1}X^\top y]\right\} \tag{6}$$

It can be inferred from equation 6 that the conditional posterior distribution of the regression parameter vector β, given σ_ε^2, is the exponential of a quadratic form in β and hence is a normal distribution with variance $\sigma_\varepsilon^2(X^\top X)^{-1}$. To show that the mean of this distribution is $\hat{\beta} = (X^\top X)^{-1}X^\top y$, it suffices to demonstrate that $\beta^\top\beta - 2\beta^\top(X^\top X)^{-1}X^\top y$ is equal to the quadratic term $[\beta-(X^\top X)^{-1}X^\top y]^\top[\beta-(X^\top X)^{-1}X^\top y]$ up to additive terms that do not depend on β, which correspond to multiplicative constants in the posterior density function, and can therefore be dropped[7]:

$$\begin{aligned}
&[\beta - (X^\top X)^{-1}X^\top y]^\top[\beta - (X^\top X)^{-1}X^\top y] \\
&\qquad = \beta^\top - [(X^\top X)^{-1}X^\top y]^\top[\beta - (X^\top X)^{-1}X^\top y] \\
&= \beta^\top\beta - \beta^\top(X^\top X)^{-1}X^\top y - [(X^\top X)^{-1}X^\top y]^\top\beta + [(X^\top X)^{-1}X^\top y]^\top(X^\top X)^{-1}X^\top y
\end{aligned}$$

The second and third term of the last line are both 1×1 and identical, one is just a transposed version of the other, thus they can be grouped. And the last term is a constant with respect to β, hence it can be dropped:

$$\beta^\top\beta - 2\beta(X^\top X)^{-1}X^\top y + \underbrace{[(X^\top X)^{-1}X^\top y]^\top(X^\top X)^{-1}X^\top y}_{\text{constant w.r.t. } \beta} \propto \beta^\top\beta - 2\beta(X^\top X)^{-1}X^\top y$$

The conditional distribution of the error variance parameter σ_ε^2 is straight-forward to derive from equation 5. Taking β as fixed yields:

$$p(\sigma_\varepsilon^2 \,|\, \beta, y) \propto (\sigma_\varepsilon^2)^{-(n/2+1)}e^{SSR/2\sigma_\varepsilon^2}$$

This corresponds to an inverse gamma distribution with $a = n/2$ and $b = SSR/2$. To wrap it up,

[7]an alternative approach would be to complete the square in β utilizing smart zero:
$a^2 - 2ab = a^2 - 2ab\underbrace{+b^2 - b^2}_{\text{smart zero}} = (a-b)^2 - b^2$

the conditional distributions of the parameters are as follows:

$$p(\beta \,|\, \sigma_\varepsilon^2, Y) \sim \mathcal{N}(\hat{\beta}, \Sigma_n), \text{ with } \hat{\beta} = (X^\top X)^{-1} X^\top Y \text{ and } \Sigma_n = \sigma_\varepsilon^2 (X^\top X)^{-1} \qquad \textit{subsubsectio}$$
$$p(\sigma_\varepsilon^2 \,|\, \beta, Y) \sim \mathcal{IG}(n/2, SSR/2)$$

Estimating coefficients — in fact, distributions thereof — in Bayesian statistics boils down to sampling parameters conditional on having data. Thus, after obtaining the posterior distributions, the parameters are then estimated by means of Markov Chain Monte Carlo (MCMC) sampling. I employ the MCMC method Gibbs sampling, which iterates between the conditional posterior densities. It samples from the conditional distribution for each parameter given the current value of the other parameter and repeatedly cycles through this updating process. The steps of the algorithm are as follows:

1. a value of β is sampled from its conditional posterior distribution using some value for σ_ε^2.

2. then σ_ε^2 is sampled from its conditional posterior distribution using the sampled β (hence SSR) from step 1.

3. and then again, the sampled σ_ε^2 is used to generate another sample of the β regression coefficient.

4. the sampled β from 3. is used to generate another sample of σ_ε^2.

5. the algorithm proceeds by iterating through steps 3. to 4. for $i = 1 \dots M$ to generate M draws from the posterior density and then save the posterior samples.

This process converges to the joint posterior distribution of β and σ_ε^2. To account for the potential influence of the starting values, the first period of n iterations of the algorithm, the so-called "burn-in," are discarded.

5 Results

Bayesian estimation obtain posterior distributions as opposed to point estimates in a frequentist approach. The posterior mean of the density of a parameter can be regarded as the equivalent of a point estimate of the parameter. Therefore, in the following, "estimate" always refer to the respective posterior mean, unless stated otherwise. Uncertainty is quantified in Bayesian inference using credible intervals. They are not quite the equivalent but the Bayesian version of confidence intervals and have a more intuitive interpretation. For example, a 95% credible interval means that there is a 95% probability that the parameter of interest falls within the provided range.

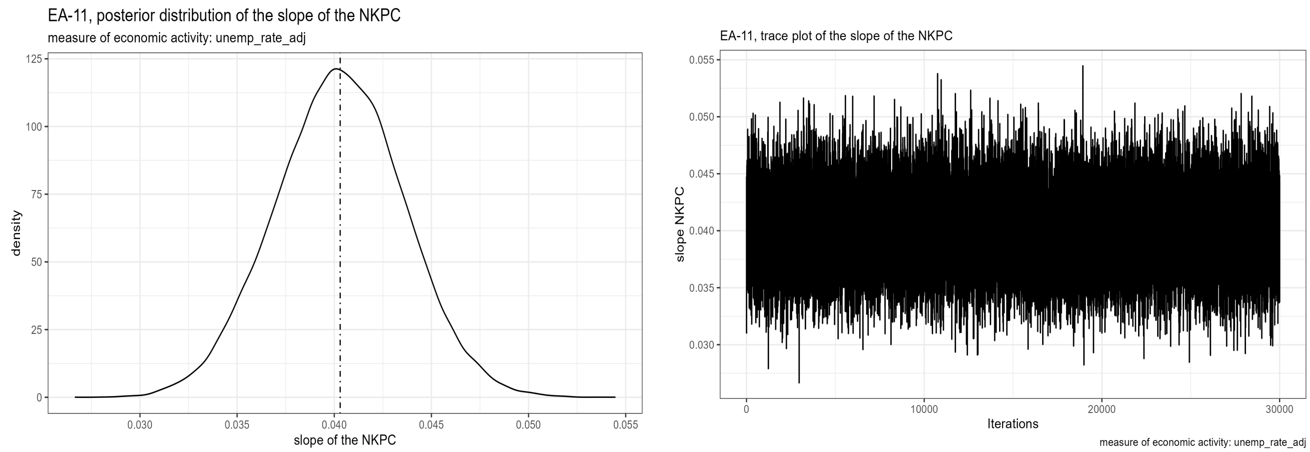

Figure 3: Posterior density (left) and trace plot (right) of the slope of the NKPC from the pooled regression with unemployment rate as a proxy for slack. The dashed line corresponds to the OLS point estimate which coincides with the posterior mean of 0.04.

The regression coefficients on the parameters of the NKPC are estimated by means of Markov Chain Monte Carlo (MCMC) sampling drawing 50,000 samples and a burn-in period of 20,000 samples using the statistical programming software R[8]. Figures 3 and 4 depict the posterior distributions and trace plots from the pooled regression for the unemployment rate specification. Convergence diagnostics indicate efficient MCMC sampling and a good algorithm performance. Asymptotically, the MCMC algorithm should approach a Gaussian distribution. As can be seen in figures 3 and 4, the resulting Markov chain of the algorithm converges to the appropriate density and mixes well throughout the support of the density. The plots from the other specifications as well as country-specific posterior distributions and trace plots can be found in appendix C.

Table 2 summarises the results for the slope of the NKPC for all three measures of economic activity for each country and the pooled regression for the EA-11. The estimates of the regression coefficient on inflation expectations can be found in appendix B. The results are also visualized as a box plot, which compactly summarises the distribution of a coefficient from all three specifications in one diagram. The middle line of each box marks the median, which corresponds to the 50^{th} percentile of the distribution. Figures 5 and 6 display the spread of the distribution for the slope of the NKPC and the coefficient on expected inflation from the

[8]the R code is available at github.com/patrick-jesse/ma_thesis.

pooled regression of the EA-11. See appendix D for box plots from country-specific regressions.

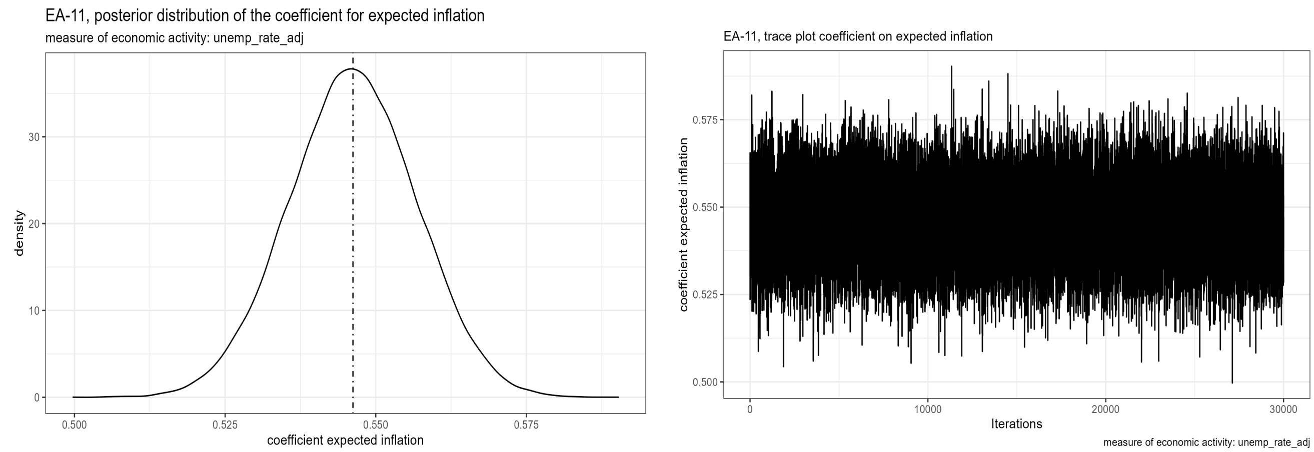

Figure 4: Posterior density (left) and trace plot (right) of the coefficient on expected inflation from the pooled regression with unemployment rate as a proxy for slack. The dashed line corresponds to the OLS point estimate which coincides with the posterior mean of 0.54.

Overall, the order of magnitude of the coefficient estimates found in this thesis — amounts to 36 in total each for the slope coefficient and the coefficient on expected inflation — are consistent with the spread of estimates reported in the empirical literature. The value of the slope coefficients is within the bounds of $[-0.025, 0.187]$, which comply with Mavroeidis et al.'s cloud of point estimates that lie between $[-0.3, 0.3]$ (figure 1).

Inflation expectations are indicated as strong catalyst for movements in inflation throughout all specifications. The estimated impact of expected inflation on realized inflation is statistically highly significant with the theoretically implied sign. Across all specifications and countries in the sample, the posterior densities of the coefficient on inflation expectations indicate that the coefficients are positive and significantly different from zero (appendix B). They determine inflation dynamics strongly with an average posterior mean of the coefficient estimate amounting to 0.51 across countries and a posterior mean of 0.54 from the pooled regression utilizing the unemployment rate as proxy for economic activity (figure 5). The magnitude of the estimates is very similar to the ones typically found in the empirical literature on the PC (Mavroeidis, Plagborg-Møller, and Stock, 2014).

In general, most posterior distributions of the slope of the NKPC exhibit a consistent picture across all three models in terms of magnitude and sign since they all have a density with a large mass around similar values of the respective posterior mean. Phrased differently, the posterior means of the different specifications do not differ substantially within a country and the large mass surrounding the posterior means strongly indicates statistical significance. Likewise, the

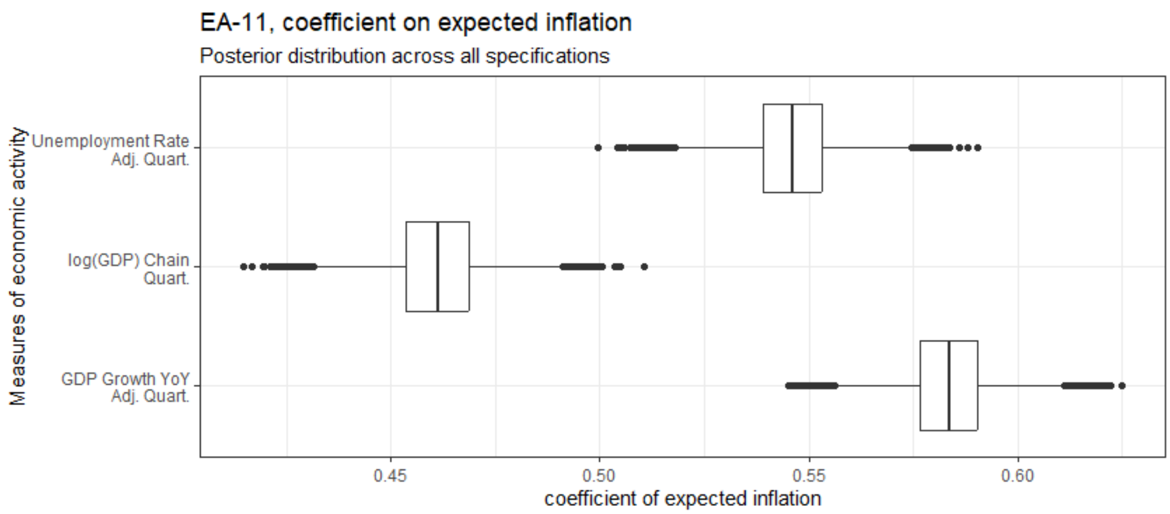

Figure 5

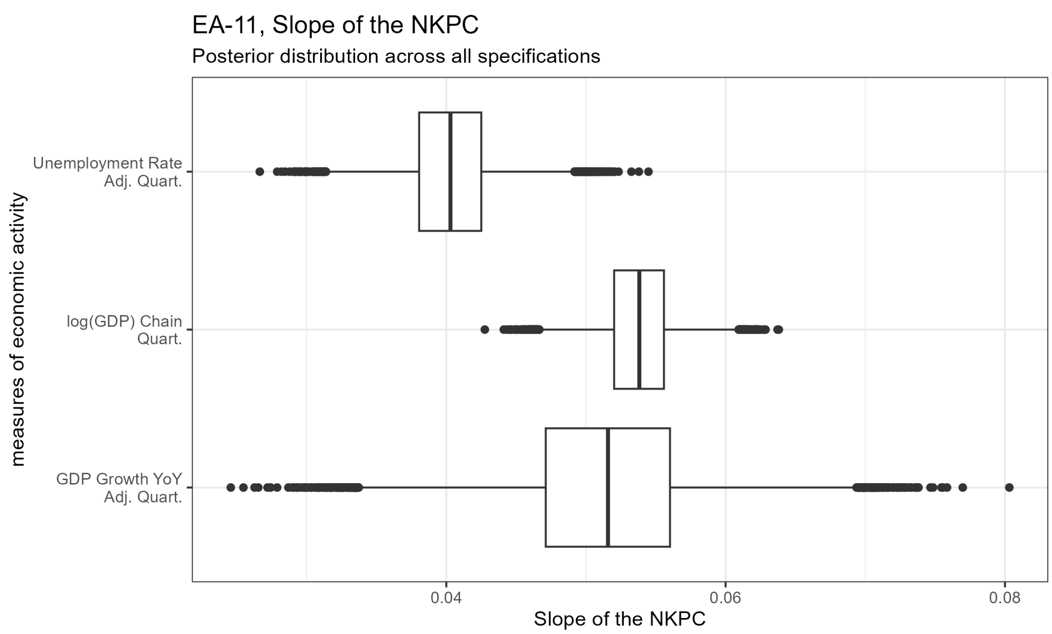

Figure 6

sign and magnitude order of most of the estimates are insensitive to alternative measures of economic activity. The considerable mass of greater than zero of most of the posterior distributions across and within countries provide evidence for a positively sloped PC in the EA-11 country composition. Thus, the empirical findings regarding the sign of the slope of the NKPC is the opposite direction from what one would expect from the conventional interpretation of the PC.

Furthermore, considering the countercyclical stylized fact of unemployment, one would expect opposing outcomes regarding the effect of output indicators and unemployment on inflation. As already outlined in section 4.1, theoretically, output is positively related to inflation whereas the opposite holds for unemployment and price dynamics. Thus, it is puzzling that the estimates bear the same sign across all specifications. Nonetheless, the outcome of a positive slope coefficient and a strong coefficient on expected inflation is in line with the findings of Mavroeidis, Plagborg-Møller, and Stock (2014) that highly cited papers report a positive slope coefficient. There are a few exceptions, but generally forward-looking behaviour dominates.

Assuming the same slope coefficient for all countries in a pooled regression, I document a posterior mean of 0.04 for the slope of the PC (table 2) utilizing unemployment rate as a proxy for real economic activity. The estimated credible interval shows that 95% of the sampled values are within the range of [0.034, 0.047] and the posterior standard deviation (0.003) can be considered as highly significant. This outcome is echoed by the other two specifications with an estimated posterior means of 0.054 and 0.052 for the slope coefficient utilizing log(GDP) and GDP growth as measures of economic slack, respectively.

I regard these results as suggestive evidence for a flat PC in the EA-11 country composition. This contrasts the results obtained by Eser, Karadi, Lane, Moretti, and Osbat (2020) using a similar sample period for the euro area employing country-level data in a pooled regression and a fixed effects model. Even though the order of magnitude of their estimates are not notably different from zero, i.e., the slope is generally not very steep, they are significant with the theoretically implied sign, implying an inverse relationship between inflation and economic slack. However, their specification excludes forward-looking inflation expectations.

Since a pooled regression does not account for heterogeneity among the countries in the sample or country-specific effects, the obtained estimates could be diluted. As an alternative, I use GDP-weighted aggregate of the explanatory variables to approximate the NKPC slope, which results in slightly higher coefficient estimates for unemployment rate and GDP. The coefficient on GDP growth becomes statistically not significant.

The next analysis goes beyond a pooled regression and explores country heterogeneity. The obtained results of the country-specific analysis reveal a picture that is consistent across countries and models (table 2 and appendix D). The posterior densities of significant slack parameters are skewed towards positive domain of the distribution, pointing to a positively slopped PC. The only estimates bearing negative signs are those for Ireland (-0.004) with unemployment rate as a proxy and Italy (-0.025) with GDP growth as a proxy (table 2). However, they are both not significant given that their respective standard deviations are either of the same magnitude or even larger than the estimate itself. Otherwise, all other specifications document a positive relation between economic slack and inflation.

The posterior distribution of the coefficient on GDP growth in France is dispersed around zero (table 2), which indicate that the coefficient is not statistically significant. Besides, the insignificance of this coefficient can also be inferred from their standard deviation, since it is larger than the respective posterior mean. The same holds for the posterior density of the estimated impact of unemployment rate on inflation in Ireland since it also bares a large mass around zero.

Moreover, notice that the only specification that renders a significant estimate for Ireland's PC is the one utilizing GDP growth as a proxy, albeit its standard deviation of 0.014 given an estimated slope of the PC of 0.042 implies modest significance. Interestingly, this specification otherwise results in insignificant estimates for most countries in the sample apart from Belgium, Ireland, Luxembourg, Portugal, and Spain.

Concerning signs and magnitudes of the coefficient estimates, the results of the model utilizing unemployment rate to proxy economic activity overall comply with the findings obtained with log(GDP). The economies of Ireland and Portugal are the only ones in the sample where their estimates suggest that unemployment is not a significant driver of inflation, otherwise this specification exhibits a high degree of significance for all other countries in the sample. The results provide suggestive evidence for a positive and statistically significant nexus of unemployment and inflation for the EA-11 excluding Ireland and Portugal. Furthermore, the magnitudes are of reasonable sizes varying between 0.023 for Spain and 0.19 for Luxembourg.

When specifying the NKPC instrumenting GDP as a measure of real economic activity, it yields results similar to, though marginally different from, the aforementioned specification. The estimated slack coefficients from the GDP-specification that are statistically significant only decrease slightly compared to the model using the unemployment rate to gauge economic activity. Ireland and Portugal's role of not complying with the other countries in the sample in terms of order of magnitude and significance of their estimates does not change. Ireland's estimate for the slope of the PC remains insignificant when economic activity is represented by log(GDP). Portugal's coefficient estimate (0.03), on the other hand, increases and gains statistical significance, albeit at a moderate degree (sd = 0.01). The estimates of the PC slope for the other countries are deemed highly significant with magnitudes in the range of 0.04 and 0.13 for France and Luxembourg, respectively.

In summary, inflation appears to respond more strongly to changes in real economic activity for smaller economies compared to their larger counterparts in the sample. Throughout

Table 2: Posterior Statistics of the Slope of the NKPC

	posterior_mean	posterior_sd	credible_interval_[95%]
Austria			
unemployment rate	0.164	0.015	[0.134, 0.194]
log(GDP)	0.080	0.007	[0.067, 0.093]
GDP growth	0.018	0.026	[-0.032, 0.068]
Belgium			
unemployment rate	0.138	0.011	[0.117, 0.159]
log(GDP)	0.102	0.006	[0.089, 0.114]
GDP growth	0.092	0.037	[0.02, 0.163]
Finland			
unemployment rate	0.074	0.009	[0.056, 0.092]
log(GDP)	0.059	0.008	[0.044, 0.074]
GDP growth	0.011	0.022	[-0.032, 0.054]
France			
unemployment rate	0.043	0.008	[0.028, 0.059]
log(GDP)	0.037	0.006	[0.026, 0.048]
GDP growth	0.005	0.018	[-0.03, 0.04]
Germany			
unemployment rate	0.050	0.011	[0.028, 0.072]
log(GDP)	0.045	0.006	[0.034, 0.056]
GDP growth	0.035	0.025	[-0.014, 0.084]
Ireland			
unemployment rate	-0.004	0.011	[-0.026, 0.019]
log(GDP)	0.013	0.011	[-0.008, 0.033]
GDP growth	0.042	0.014	[0.015, 0.068]
Italy			
unemployment rate	0.072	0.008	[0.055, 0.088]
log(GDP)	0.066	0.006	[0.054, 0.078]
GDP growth	-0.025	0.025	[-0.073, 0.024]
Luxembourg			
unemployment rate	0.187	0.021	[0.147, 0.228]
log(GDP)	0.129	0.010	[0.11, 0.147]
GDP growth	0.092	0.024	[0.045, 0.141]
Netherlands			
unemployment rate	0.094	0.016	[0.063, 0.127]
log(GDP)	0.064	0.008	[0.048, 0.08]
GDP growth	0.029	0.036	[-0.042, 0.1]
Portugal			
unemployment rate	0.011	0.009	[-0.008, 0.029]
log(GDP)	0.031	0.010	[0.011, 0.051]
GDP growth	0.053	0.023	[0.009, 0.098]
Spain			
unemployment rate	0.023	0.007	[0.01, 0.036]
log(GDP)	0.057	0.009	[0.039, 0.075]
GDP growth	0.109	0.019	[0.072, 0.145]
EA-11 pooled			
unemployment rate	0.040	0.003	[0.034, 0.047]
log(GDP)	0.054	0.003	[0.049, 0.059]
GDP growth	0.052	0.007	[0.039, 0.064]
EA-11 aggregate			
unemployment rate	0.078	0.007	[0.065, 0.091]
log(GDP)	0.064	0.005	[0.055, 0.074]
GDP growth	0.036	0.022	[-0.008, 0.079]

all specifications, the range of estimated slope posterior means holding statistical significance amounts to $[0.02, 0.11]$ for France, Germany, Italy, and Spain, whereas the slope coefficient is relatively steeper vis-à-vis smaller economies like Austria, Belgium, Finland, Ireland, Luxembourg, Netherlands, and Portugal with estimates oscillating between 0.03 and 0.19. This observation suggests a stronger relationship between inflation and economic activity in smaller economies in the sample compared to their larger counterparts. However, Italy and Spain step out of line in the group of the big four with a relatively steeper coefficient estimates for the slope of the NKPC.

I cross-check the results from the Bayesian linear regression model with an OLS regression. The outcome, reported in appendix E, confirms the analysis of the Bayesian inference in terms of magnitude as well as significance and provide further information regarding the goodness of fit. On average, the obtained R^2 imply that the covariates of the applied specifications can explain around 90% of the fluctuations in inflation, indicating a good fit of the applied models to the data. Additionally, the significance level of most estimates suggest that I can reject the null hypothesis of the regressors having no effect on the regressand. Across all specifications, the OLS point estimates are in line with the obtained posterior means.

A note on specification uncertainty: the findings of Mavroeidis, Plagborg-Møller, and Stock (2014), that the NKPC exhibits a high degree of inference sensitivity to econometric specifications does not fully apply to the outcome of this thesis. Although the estimates obtained are sensitive to the specific measure of real economic activity since their order of magnitude do vary with the choice of specification, these variations are deemed as negligible given that they are hardly distinguishable from zero in most cases. Nevertheless, it should be stated that the three specifications applied in this thesis are just a mere fraction of the battery of specifications applied by Mavrodeidis et al. in their extensive empirical analysis of the NKPC. Thus, even though high specification uncertainty of NKPC finds weak support in this thesis, it should be emphasized that Mavroeidis et al. employed considerably more specifications.

6 Conclusion

This thesis analyses the empirical relation between inflation and unemployment (or related measures of real economic activity) over the past 25 years by using country-level data of the EA-11 country composition. The estimates are obtained via Bayesian inference in a linear regression set-up and are comparable in magnitude to results typically found in the empirical literature (figure 1).

With respect to the posterior means of the slope of the NKPC, one can observe a certain pattern in the overall results: the effect of economic activity on inflation varies with the size of the fiscal regime and tends to be larger for smaller economies than for bigger economies in the sample.

This outcome provides support for the identification strategy which relies on cross-country variation in macroeconomic variables to mitigate the bias that results from the endogeneity of monetary policy. The idea elaborated in section 3.3 can be summarised as follows: In its commitment to stabilize prices, monetary policy attempts to counteract any demand shocks that might help identify the PC. So, the specific monetary policy tool applied in a certain period reflects the prevailing economic conditions (represented by ϕ_{gap} and ϕ_{π} in equation 2). This endogeneity makes it difficult to identify the slope of the PC, which describes changes in inflation that stems from unemployment. If a country within a monetary union is relatively small compared to the overall aggregate, it can be argued that the common monetary policy operates independently of variations at the country level. Therefore, idiosyncratic national shocks that are unaffected by the common monetary policy should make identification possible and result in a more evident PC. In light of the obtained results, one can argue that the common monetary policy has a relatively larger impact on bigger economies in the monetary union compared to smaller member states. It is plausible to assume that the aggregate monetary policy tends to be tailored more towards the needs of the bigger economies.

So, overall, one can conclude that the estimated coefficients to some degree reflect the size of the economies in the sample. The bigger the economy, the less evident the PC tends to be. Presumably, the PC is less evident in larger economies within the euro area than smaller economies since the latter ones are relatively less responsive to aggregate monetary policy measures.

Not surprisingly, the coefficients on expected inflation exhibit a high degree of statistical significance and are of reasonable sizes. An outcome common to the vast majority of specifications of the NKPC in the empirical literature. Moreover, the higher the estimated role of expected inflation, the lower the PC slope coefficients tends to be. This emphasizes how important is it for a central bank to credibly communicate its commitments to stabilize inflation and anchor inflation expectations. Anchored inflation expectations in recent decades might have led to the flattening of the PC[9], which translates into a weaker response of inflationary dynamics to the level of real economic activity. This, in turn, renders the trade-off between inflation and unemployment obsolete

Regarding the implied strength of the estimated impact of the covariates of the NKPC, the applied econometric specifications point to a mildly steep, yet positively sloped PC across all countries, with significant slope coefficients varying between 0.02 (Spain) and 0.19 (Luxembourg). This reflects the widely accepted notion that inflation expectations have been anchored in the last decades and caused a flattening of the PC. If we assume that anchored inflation expectations translate into sticky prices, then this outcome complies with the New Keynesian

[9] Bank for International Settlements Annual Report (2017), graph I.3, page 11

theory of the PC being modestly steep under sticky prices.

According to Mavroeidis et al. (2014), the idea of a trade-off between inflation and unemployment is wildly accepted among economists and central banks. Thus, it remains unclear why the results of this thesis, contrary to conventional wisdom but in line with all highly cited papers, imply a positive relation between inflation and unemployment.

Furthermore, considering the countercyclical stylized fact of unemployment, one would expect opposing outcomes regarding the effect of output indicators and unemployment on inflation. Thus, it is puzzling that the estimates bear the same sign across all specifications. Nonetheless, the outcome of a positive slope coefficient and a strong coefficient on expected inflation is in line with the findings of Mavroeidis, Plagborg-Møller, and Stock (2014) that highly cited papers report a positive slope coefficient. There are a few exceptions, but generally forward-looking behaviour dominates.

The outcome of this thesis makes me reluctant to conclude that there is a trade-off between these two macroeconomic variables given that the performed analysis documents that a positive relation holds between inflation and real economic activity. Hence, the outcome of this thesis does not provide empirical evidence for a trade-off between inflation and unemployment in the EA-11 country composition.

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Appendices

A Summary Statistics

EA-11, Summary Statistics

1056 rows x 5 cols

COLUMN	PLOT OVERVIEW	MISSING	MEAN	MEDIAN	SD
hicpX	-2.9 7.1	0.0%	1.6	1.5	1.1
exp_infl	-3 14	0.0%	2.1	1.9	1.9
unemp_rate_adj	2 26	0.0%	8.2	7.8	3.9
log_gdp_chain	8.9 13.6	0.0%	11.7	11.5	1.2
gdp_growth_yoy_adj	-22 26	0.0%	2.0	1.9	3.8

B Posterior Statistics: Coefficient on Expected Inflation

Table 3

	posterior_mean	posterior_sd	credible_interval_[95%]
Austria			
unemployment rate	0.461	0.030	[0.402, 0.521]
log(GDP)	0.456	0.028	[0.401, 0.51]
GDP growth	0.711	0.032	[0.649, 0.773]
Belgium			
unemployment rate	0.241	0.026	[0.188, 0.292]
log(GDP)	0.205	0.024	[0.158, 0.252]
GDP growth	0.430	0.038	[0.356, 0.505]
Finland			
unemployment rate	0.447	0.032	[0.384, 0.511]
log(GDP)	0.440	0.035	[0.371, 0.509]
GDP growth	0.633	0.033	[0.568, 0.698]
France			
unemployment rate	0.474	0.036	[0.404, 0.544]
log(GDP)	0.434	0.036	[0.363, 0.505]
GDP growth	0.617	0.029	[0.559, 0.675]
Germany			
unemployment rate	0.448	0.032	[0.386, 0.51]
log(GDP)	0.362	0.030	[0.304, 0.421]
GDP growth	0.521	0.030	[0.462, 0.578]
Ireland			
unemployment rate	0.768	0.033	[0.704, 0.832]
log(GDP)	0.735	0.038	[0.66, 0.81]
GDP growth	0.688	0.038	[0.614, 0.762]
Italy			
unemployment rate	0.422	0.030	[0.363, 0.481]
log(GDP)	0.364	0.029	[0.308, 0.42]
GDP growth	0.608	0.032	[0.544, 0.671]
Luxembourg			
unemployment rate	0.357	0.033	[0.292, 0.422]
log(GDP)	0.263	0.029	[0.205, 0.32]
GDP growth	0.479	0.039	[0.403, 0.555]
Netherlands			
unemployment rate	0.487	0.029	[0.43, 0.545]
log(GDP)	0.421	0.030	[0.362, 0.48]
GDP growth	0.569	0.036	[0.499, 0.639]
Portugal			
unemployment rate	0.723	0.034	[0.656, 0.788]
log(GDP)	0.660	0.038	[0.584, 0.735]
GDP growth	0.712	0.030	[0.653, 0.772]
Spain			
unemployment rate	0.539	0.036	[0.468, 0.608]
log(GDP)	0.441	0.038	[0.367, 0.515]
GDP growth	0.545	0.028	[0.49, 0.6]
EA-11 pooled			
unemployment rate	0.546	0.011	[0.525, 0.567]
log(GDP)	0.461	0.011	[0.439, 0.483]
GDP growth	0.584	0.010	[0.564, 0.604]
EA-11 aggregate			
unemployment rate	0.391	0.021	[0.351, 0.431]
log(GDP)	0.602	0.028	[0.546, 0.658]
GDP growth	0.358	0.022	[0.314, 0.401]

C Posterior Distributions and Trace plots

Given over 132 posterior densities and trace plots for both components of the NKPC, here I only report the plots for the EA-11 pooled regression due to limited space. Country specific plots are available upon request Additionally, one may refer to the box plots in appendix D.

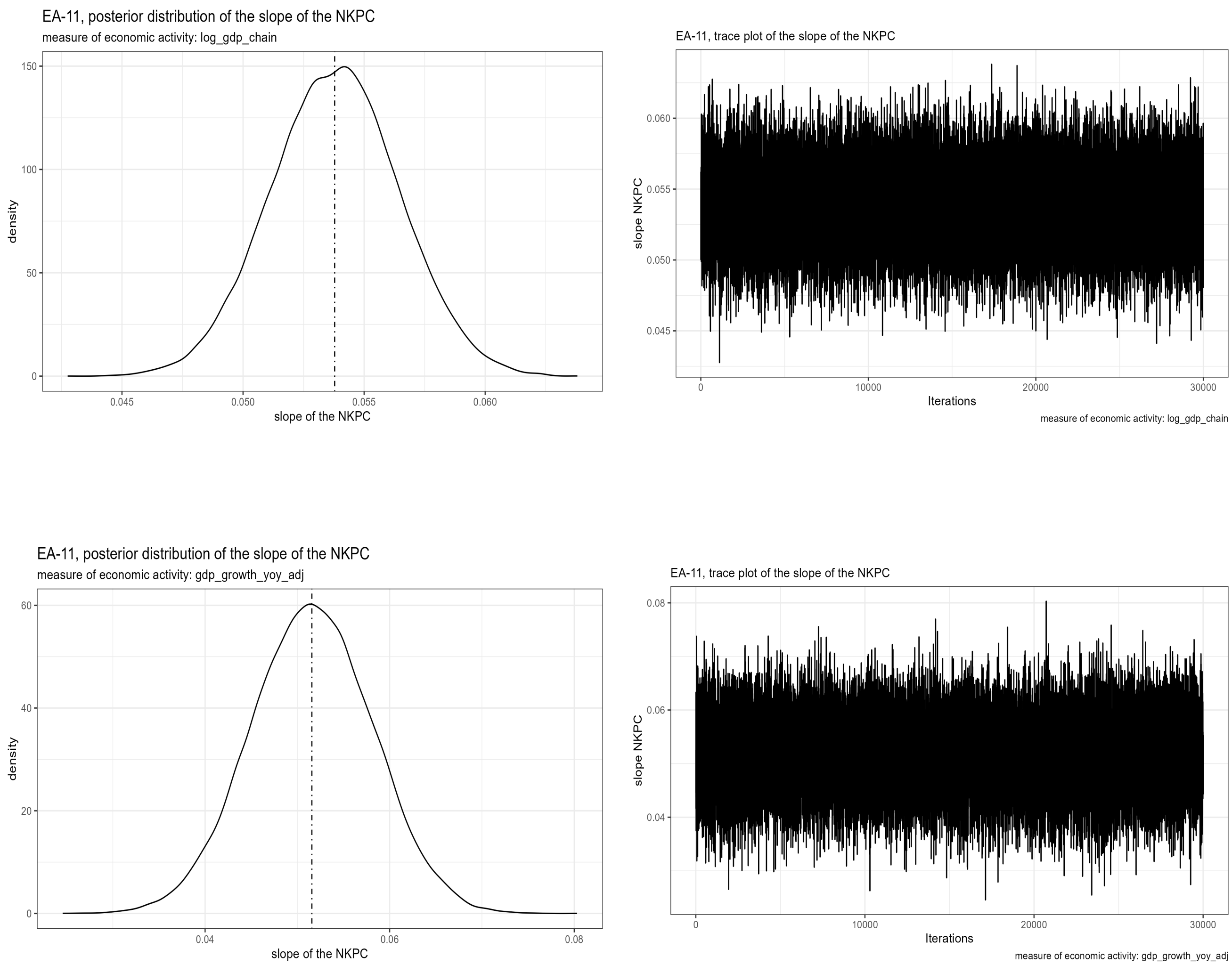
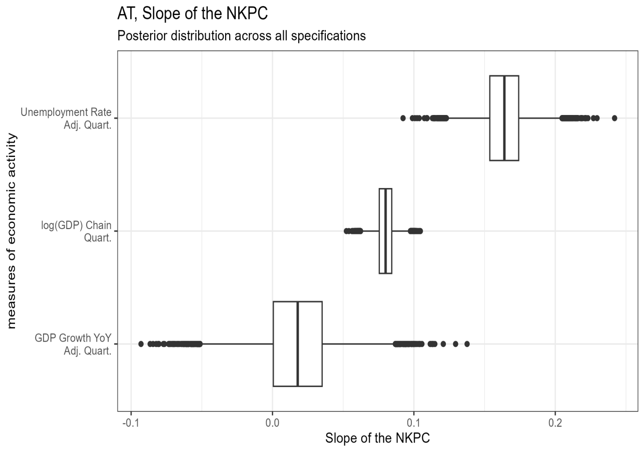
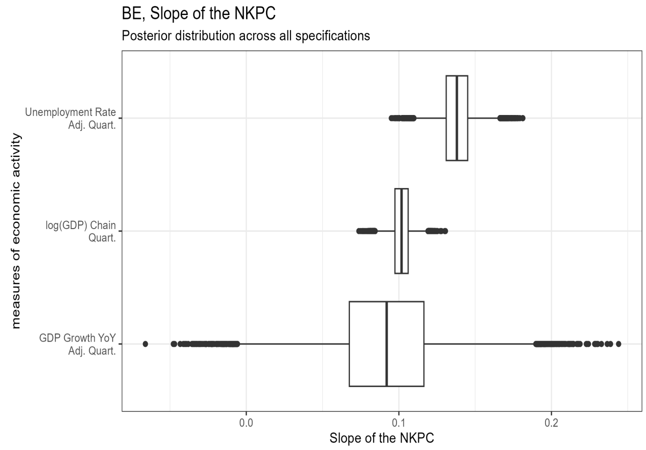
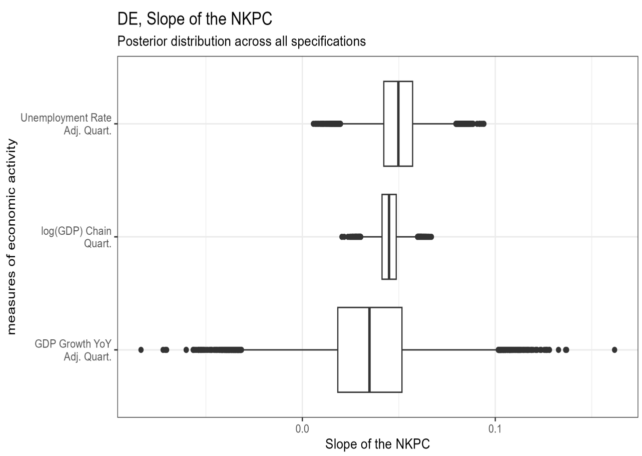


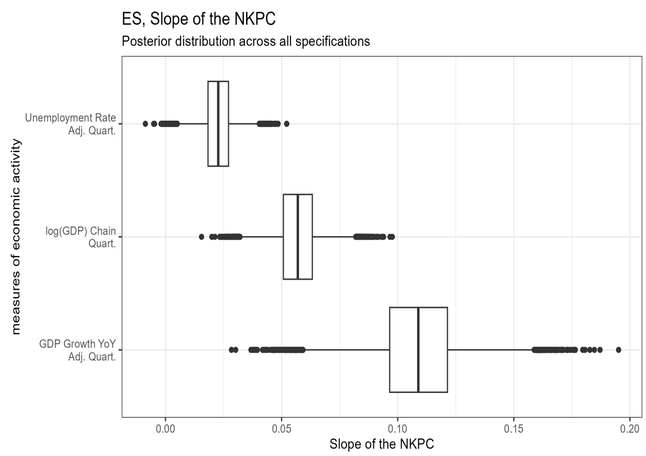
Figure 7: Posterior densities (left) and trace plots (right) of the slope of the NKPC. Proxy for economic activity: log(GDP) (upper panel) and GDP growth (lower panel). The dashed lines correspond to the OLS point estimates.

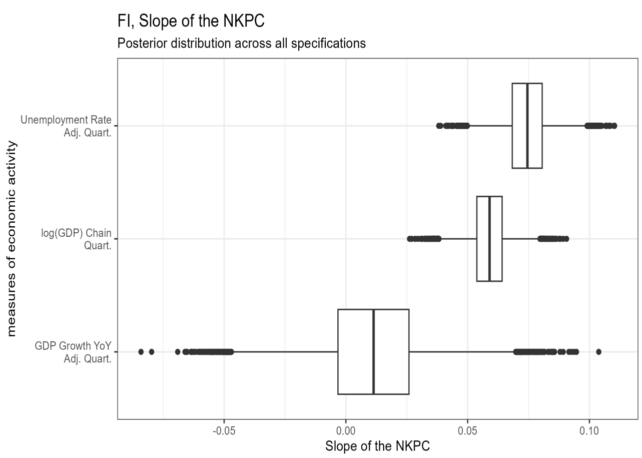
D Box plots

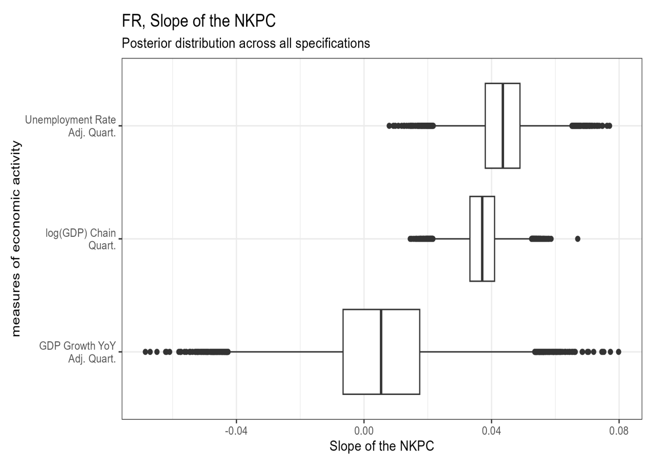

AT, Slope of the NKPC
Posterior distribution across all specifications
Unemployment Rate Adj. Quart.
log(GDP) Chain Quart.
GDP Growth YoY Adj. Quart.
measures of economic activity
-0.1
0.0
0.1
0.2
Slope of the NKPC

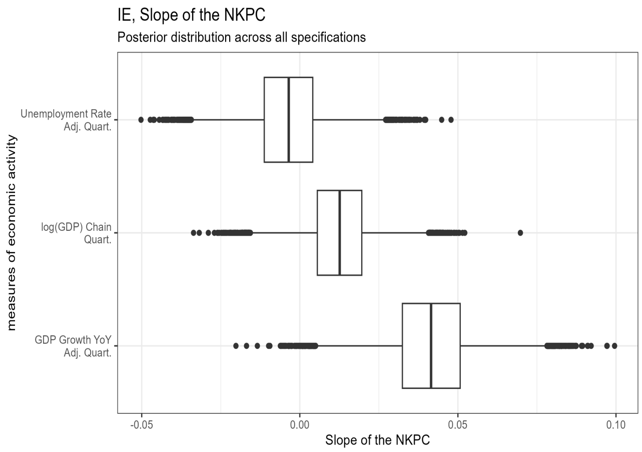

BE, Slope of the NKPC
Posterior distribution across all specifications
Unemployment Rate Adj. Quart.
log(GDP) Chain Quart.
GDP Growth YoY Adj. Quart.
measures of economic activity
0.0
0.1
0.2
Slope of the NKPC

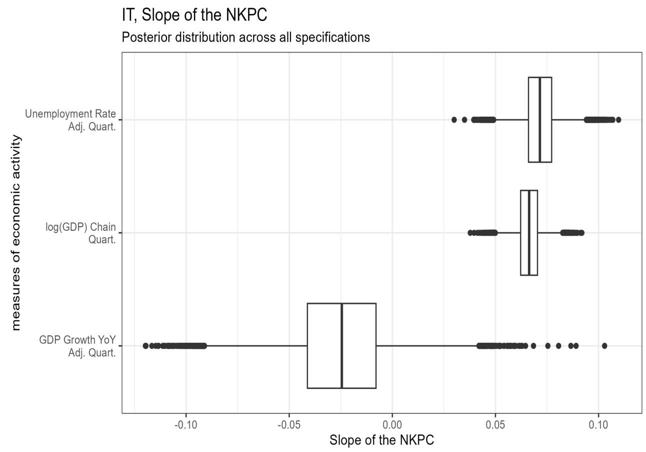

DE, Slope of the NKPC
Posterior distribution across all specifications
Unemployment Rate Adj. Quart.
log(GDP) Chain Quart.
GDP Growth YoY Adj. Quart.
measures of economic activity
0.0
0.1
Slope of the NKPC

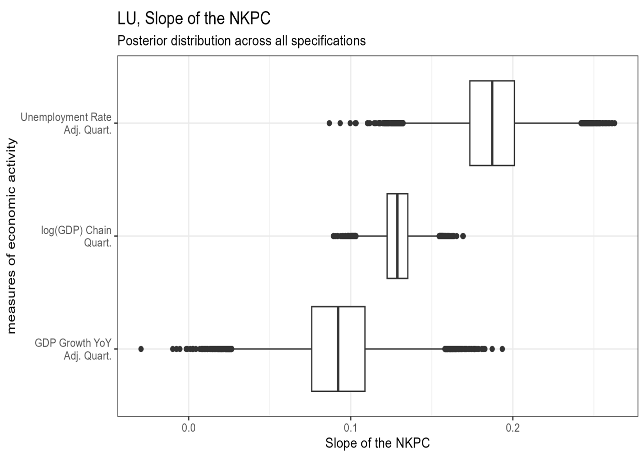

ES, Slope of the NKPC
Posterior distribution across all specifications
Unemployment Rate Adj. Quart.
log(GDP) Chain Quart.
GDP Growth YoY Adj. Quart.
measures of economic activity
0.00
0.05
0.10
0.15
0.20
Slope of the NKPC

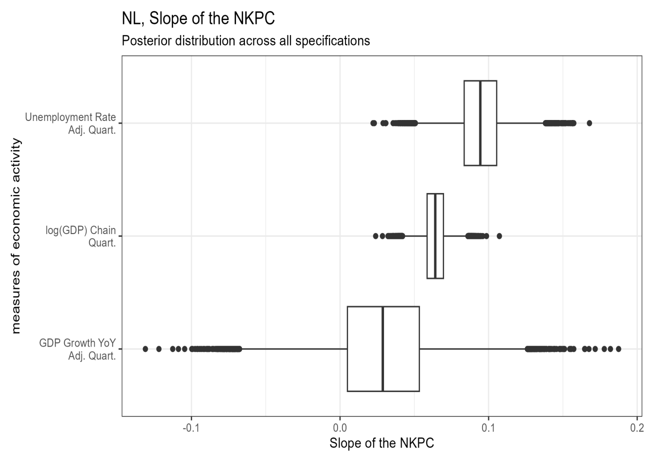

FI, Slope of the NKPC
Posterior distribution across all specifications
Unemployment Rate Adj. Quart.
log(GDP) Chain Quart.
GDP Growth YoY Adj. Quart.
measures of economic activity
-0.05
0.00
0.05
0.10
Slope of the NKPC

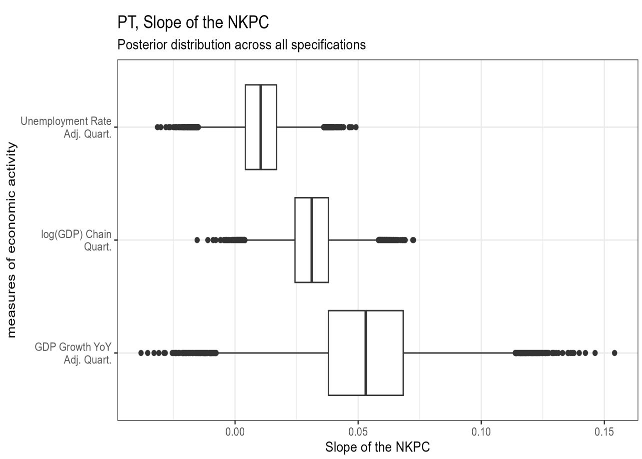

FR, Slope of the NKPC
Posterior distribution across all specifications
Unemployment Rate Adj. Quart.
log(GDP) Chain Quart.
GDP Growth YoY Adj. Quart.
measures of economic activity
-0.04
0.00
0.04
0.08
Slope of the NKPC











E Ordinary Least Squares Estimates

Table 4: EA-11, pooled, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.546***	0.461***	0.584***
	(0.010)	(0.011)	(0.010)
unemployment rate	0.040***		
	(0.003)		
log(GDP)		0.054***	
		(0.003)	
GDP growth			0.052***
			(0.007)
Observations	1,056	1,056	1,056
R^2	0.845	0.873	0.833
Adjusted R^2	0.845	0.873	0.832
Residual Std. Error (df = 1054)	0.763	0.692	0.794
F Statistic (df = 2; 1054)	2,877.906***	3,618.294***	2,619.804***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: AT, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.462***	0.456***	0.711***
	(0.030)	(0.027)	(0.031)
unemployment rate	0.164***		
	(0.015)		
log(GDP)		0.080***	
		(0.007)	
GDP growth			0.018
			(0.025)
Observations	96	96	96
R^2	0.950	0.956	0.886
Adjusted R^2	0.949	0.955	0.883
Residual Std. Error (df = 94)	0.468	0.438	0.705
F Statistic (df = 2; 94)	885.234***	1,017.881***	364.388***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: BE, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.241***	0.205***	0.429***
	(0.026)	(0.024)	(0.037)
unemployment rate	0.138***		
	(0.010)		
log(GDP)		0.102***	
		(0.006)	
GDP growth			0.093**
			(0.036)
Observations	96	96	96
R^2	0.905	0.926	0.745
Adjusted R^2	0.903	0.925	0.739
Residual Std. Error (df = 94)	0.546	0.481	0.895
F Statistic (df = 2; 94)	447.714***	590.729***	137.260***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: DE, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.448***	0.363***	0.520***
	(0.031)	(0.030)	(0.029)
unemployment rate	0.050***		
	(0.011)		
log(GDP)		0.045***	
		(0.005)	
GDP growth			0.035
			(0.025)
Observations	96	96	96
R^2	0.847	0.892	0.818
Adjusted R^2	0.844	0.889	0.814
Residual Std. Error (df = 94)	0.589	0.496	0.642
F Statistic (df = 2; 94)	260.404***	386.695***	211.556***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: ES, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.539***	0.441***	0.545***
	(0.035)	(0.037)	(0.028)
unemployment rate	0.023***		
	(0.007)		
log(GDP)		0.057***	
		(0.009)	
GDP growth			0.109***
			(0.018)
Observations	96	96	96
R^2	0.845	0.876	0.872
Adjusted R^2	0.841	0.873	0.869
Residual Std. Error (df = 94)	0.828	0.742	0.752
F Statistic (df = 2; 94)	255.786***	330.774***	320.428***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: FI, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.447***	0.440***	0.633***
	(0.032)	(0.034)	(0.033)
unemployment rate	0.074***		
	(0.009)		
log(GDP)		0.059***	
		(0.008)	
GDP growth			0.011
			(0.022)
Observations	96	96	96
R^2	0.909	0.905	0.845
Adjusted R^2	0.907	0.903	0.841
Residual Std. Error (df = 94)	0.515	0.527	0.672
F Statistic (df = 2; 94)	469.332***	446.140***	255.662***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: FR, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.475***	0.434***	0.617***
	(0.035)	(0.036)	(0.029)
unemployment rate	0.043***		
	(0.008)		
log(GDP)		0.037***	
		(0.006)	
GDP growth			0.005
			(0.018)
Observations	96	96	96
R^2	0.896	0.906	0.864
Adjusted R^2	0.893	0.904	0.861
Residual Std. Error (df = 94)	0.458	0.435	0.524
F Statistic (df = 2; 94)	403.304***	453.322***	297.729***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 11: IE, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.768***	0.735***	0.688***
	(0.033)	(0.038)	(0.037)
unemployment rate	−0.004		
	(0.011)		
log(GDP)		0.013	
		(0.010)	
GDP growth			0.042***
			(0.013)
Observations	96	96	96
R^2	0.877	0.879	0.888
Adjusted R^2	0.874	0.876	0.886
Residual Std. Error (df = 94)	0.868	0.861	0.827
F Statistic (df = 2; 94)	335.426***	340.951***	374.021***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: IT, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.422***	0.364***	0.608***
	(0.030)	(0.029)	(0.031)
unemployment rate	0.072***		
	(0.008)		
log(GDP)		0.066***	
		(0.006)	
GDP growth			−0.024
			(0.024)
Observations	96	96	96
R^2	0.897	0.919	0.817
Adjusted R^2	0.894	0.918	0.813
Residual Std. Error (df = 94)	0.584	0.516	0.777
F Statistic (df = 2; 94)	407.228***	535.650***	209.884***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 13: LU, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.357***	0.263***	0.479***
	(0.033)	(0.029)	(0.038)
unemployment rate	0.187***		
	(0.021)		
log(GDP)		0.129***	
		(0.009)	
GDP growth			0.092***
			(0.024)
Observations	96	96	96
R^2	0.887	0.929	0.816
Adjusted R^2	0.885	0.927	0.812
Residual Std. Error (df = 94)	0.671	0.535	0.858
F Statistic (df = 2; 94)	370.740***	610.363***	208.026***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 14: NL, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.487***	0.421***	0.569***
	(0.029)	(0.030)	(0.035)
unemployment rate	0.095***		
	(0.016)		
log(GDP)		0.064***	
		(0.008)	
GDP growth			0.029
			(0.036)
Observations	96	96	96
R^2	0.877	0.899	0.834
Adjusted R^2	0.874	0.897	0.830
Residual Std. Error (df = 94)	0.747	0.675	0.868
F Statistic (df = 2; 94)	335.187***	420.456***	235.836***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 15: PT, OLS Results

	Dependent variable:		
	core inflation		
	(1)	(2)	(3)
expected inflation	0.723***	0.660***	0.712***
	(0.034)	(0.038)	(0.030)
unemployment rate	0.011		
	(0.009)		
log(GDP)		0.031***	
		(0.010)	
GDP growth			0.053**
			(0.022)
Observations	96	96	96
R^2	0.888	0.897	0.893
Adjusted R^2	0.886	0.895	0.891
Residual Std. Error (df = 94)	0.759	0.728	0.742
F Statistic (df = 2; 94)	372.957***	409.815***	392.404***
Note:			*p<0.1; **p<0.05; ***p<0.01

F NKPC Slope Estimates Using Unobservable Variables

The output gap describes how far away current output is from its potential and constitutes a measure for economic slack. It is a theoretical concept that cannot be measured directly and has to be estimated. Different statistical techniques yield different estimates.

For instance, gap variables can be estimated via the Hodrick-Prescott filter, which computes the trend component of a time series by taking fourth-differences of the original data and then taking smoothed, weighted average of past and future values of those differences. In view of the critique of the HP filter outlined in section 4.1, I also utilize a model based approximation of potential output following Müller and Watson (2008). This approach involves calculating the low-frequency trend of the time series and utilizing it to gauge the deviation of the time series from its low-frequency trend.

The results of the gap specifications (table 16) are largely theory consistent and point to a steeper PC compared to the results obtained with the original data in section 5. However, most of the estimates lack significance and the empirical evidence is rather mixed with no clear pattern. Only 17 out of 48 estimates are statistically significant and the order of magnitude for GDP specifications are rather too high compared with the usual estimates in the empirical literature. Spain is the only country in the sample with statistically significant coefficients for GDP gap estimates with an estimated slope of 11.4 and 10.7 for the Hodrick-Prescott (HP) and Müller-Watson (MW) gap measures, respectively. It is also the only member state with statistically significant estimates across all gap measures.

Statistically significant estimates of specifications utilising unemployment gap measures range from -0.7 for Belgium to -0.2 for Spain. Astonishingly, German's slope coefficient estimate on remains among the lowest estimates when using unemployment gap variables to approximate the slope of the NKPC. One could argue that this reflects Germany's dominance in the ECB since the relative small estimate could point to the notion that the common monetary policy of the euro area has a relatively larger impact on Germany's economy compared to the other economies in the sample.

A possible explanation for the overall mixed and inconclusive empirical evidence of the gap specifications could be the global output gap hypothesis, according to which the global output gap might have an impact on domestic inflation due to globalization (Calza, 2009).

All in all, contrary to the results obtained with the original data, the estimates obtained with the gap variables imply a trade-off between unemployment and inflation. However, given that gap variable estimates depend highly on the underlying parameters, the meaningfulness of these results with regard to policy implications is to be doubted.

Table 16: Posterior Statistics of the Slope of the NKPC

	posterior_mean	posterior_sd	credible_interval_[95%]
Austria			
unemployment gap, HP	-0.463	0.133	[-0.725, -0.206]
unemployment gap, MW	-0.453	0.170	[-0.787, -0.118]
GDP gap, HP	6.157	3.541	[-0.799, 13.07]
GDP gap, MW	6.648	4.411	[-2.033, 15.336]
Belgium			
unemployment gap, HP	-0.518	0.150	[-0.812, -0.227]
unemployment gap, MW	-0.742	0.246	[-1.224, -0.259]
GDP gap, HP	9.233	5.431	[-1.269, 19.802]
GDP gap, MW	6.696	6.080	[-5.256, 18.577]
Finland			
unemployment gap, HP	-0.235	0.123	[-0.477, 0.008]
unemployment gap, MW	-0.277	0.184	[-0.641, 0.083]
GDP gap, HP	-2.475	3.577	[-9.523, 4.504]
GDP gap, MW	-1.017	4.769	[-10.419, 8.345]
France			
unemployment gap, HP	-0.471	0.121	[-0.71, -0.233]
unemployment gap, MW	-0.605	0.178	[-0.952, -0.254]
GDP gap, HP	2.126	2.517	[-2.747, 7.104]
GDP gap, MW	1.889	2.942	[-3.998, 7.62]
Germany			
unemployment gap, HP	-0.283	0.137	[-0.554, -0.013]
unemployment gap, MW	-0.363	0.318	[-0.979, 0.264]
GDP gap, HP	6.838	3.516	[-0.126, 13.748]
GDP gap, MW	5.220	4.638	[-3.968, 14.275]
Ireland			
unemployment gap, HP	-0.276	0.079	[-0.429, -0.121]
unemployment gap, MW	-0.312	0.164	[-0.633, 0.014]
GDP gap, HP	-0.357	2.686	[-5.667, 4.931]
GDP gap, MW	0.040	3.460	[-6.791, 6.911]
Italy			
unemployment gap, HP	-0.117	0.154	[-0.417, 0.184]
unemployment gap, MW	-0.466	0.212	[-0.883, -0.048]
GDP gap, HP	2.790	3.405	[-3.839, 9.471]
GDP gap, MW	2.887	4.282	[-5.473, 11.264]
Luxembourg			
unemployment gap, HP	-0.269	0.155	[-0.573, 0.038]
unemployment gap, MW	-0.081	0.217	[-0.508, 0.347]
GDP gap, HP	5.936	4.538	[-2.988, 14.801]
GDP gap, MW	2.130	5.629	[-8.937, 13.12]
Netherlands			
unemployment gap, HP	-0.416	0.130	[-0.672, -0.164]
unemployment gap, MW	-0.762	0.361	[-1.474, -0.059]
GDP gap, HP	8.672	5.074	[-1.103, 18.699]
GDP gap, MW	5.890	7.013	[-7.914, 19.651]
Portugal			
unemployment gap, HP	-0.105	0.088	[-0.28, 0.067]
unemployment gap, MW	-0.159	0.154	[-0.465, 0.144]
GDP gap, HP	4.141	3.124	[-1.95, 10.293]
GDP gap, MW	2.993	3.855	[-4.562, 10.516]
Spain			
unemployment gap, HP	-0.190	0.064	[-0.316, -0.065]
unemployment gap, MW	-0.421	0.122	[-0.659, -0.183]
GDP gap, HP	11.407	2.991	[5.483, 17.278]
GDP gap, MW	10.707	3.873	[3.088, 18.28]
EA-11 aggregate			
unemployment gap, HP	-0.331	0.126	[-0.579, -0.083]
unemployment gap, MW	-0.610	0.214	[-1.029, -0.195]
GDP gap, HP	5.325	3.075	[-0.689, 11.337]
GDP gap, MW	4.618	3.852	[-2.833, 12.125]