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Central Banking and Climate Change: How Does Climate Policy Uncertainty Impact Norges Bank's Monetary Policy Mandate? A Google Trends Data Approach

Mariana Barbosa Fernandes

Master in Economics

Supervisor:
Ph.D João António Rodrigues Madeira, Associate Professor with Habilitation, Department of Economics,
Iscte Business School

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Department of Economics

Department of Political Economy

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To intergenerational justice

Acknowledgments

As I complete this dissertation project, I often find myself thinking that I have defied the odds.

The odds of being the first in my immediate family to complete a Master's degree. The odds of originally being from one of the most remote regions of Portugal, my dear Algarve, and having had the opportunity to study and live in Lisbon. The odds of studying abroad, twice. The odds of finding inspiring teachers, counsellors, and colleagues. Even the odds of reaching this very moment of submitting my dissertation.

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This work is not mine alone. It belongs just as much to all those who, in one way or another, have been part of this journey. And what a journey.

Resumo

As alterações climáticas constituem um dos maiores desafios do século XXI, com consequências crescentes não apenas para os ecossistemas e sociedades, mas também para a estabilidade económica e dos sistemas financeiros. Os bancos centrais, embora não sejam diretamente responsáveis pela implementação de políticas climáticas, enfrentam cada vez mais a necessidade de incorporar riscos climáticos nos seus quadros operacionais e de previsão. Este contexto é particularmente relevante para a Noruega, uma pequena economia aberta, altamente dependente das receitas do petróleo e exposta aos desenvolvimentos da política climática global.

Neste sentido, esta dissertação investiga: De que forma a incerteza da política climática afeta a capacidade do Norges Bank cumprir o seu mandato de política monetária? Foram prosseguidos três objetivos de investigação. Em primeiro lugar, foram desenvolvidos novos índices de Incerteza da Política Climática (CPU) para a Noruega e para o mundo, utilizando dados do Google Trends. Em segundo lugar, a trajetória da taxa de juro do Norges Bank foi estimada através de Regras de Taylor, incorporando os novos índices como variáveis explicativas. Em terceiro lugar, as trajetórias estimadas foram comparadas com as revisões passadas da política monetária do Banco.

Os resultados demonstram que a incerteza da política climática molda o processo de tomada de decisão do Norges Bank, salientando que este tipo de risco climático não é negligenciável para as atividades operacionais e de previsão do banco. Os novos índices são consistentes com a literatura e estatisticamente significativos enquanto variáveis explicativas da regra de juro do Norges Bank. Em particular, as medidas domésticas funcionam como determinantes estruturais, enquanto as globais reforçam o poder preditivo ao reduzir os erros de previsão. Os resultados sublinham que os riscos climáticos, embora ainda moderados em magnitude, são cada vez mais relevantes para a política monetária e para o seu horizonte de decisão.

Palavras-chave: Alterações Climáticas; Incerteza da Política Climática; Política Monetária; Regras de Taylor; Norges Bank; Google Trends

Classificação JEL: E52; Q54

Abstract

Climate change is one of the defining challenges of the twenty-first century. Central banks, while not directly responsible for implementing climate policies, increasingly face the need to incorporate climate-related risks into their operational framework. This is particularly important for Norway, as a small open economy highly dependent on petroleum revenues and exposed to global developments.

Hence, this dissertation investigates: How does climate policy uncertainty affect Norges Bank's ability to pursue its monetary policy mandate? Three research objectives were pursued. First, novel Climate Policy Uncertainty (CPU) indexes were developed for Norway and for the world using Google Trends data, based on the assumption that heightened search intensity reflects public uncertainty. Second, Norges Bank's interest rate path was estimated through Taylor-type Rules within a New Keynesian framework, incorporating the new indexes as explanatory variables. Third, the estimated paths were compared with Norges Bank's past monetary policy revisions.

The findings demonstrate that climate policy uncertainty shapes Norges Bank's decision-making process, highlighting that this form of climate risk is not negligible to the bank's operational and forecasting activities. The novel indexes are literature-consistent and statistically significant explanatory variables for Norges Bank's interest rate rule. Particularly, they stand as structural drivers and as predictive enhancers through domestic and global measures, respectively. The results underline that climate risks, although moderate in current magnitude, are increasingly relevant for monetary policy and its pertinent horizon.

Keywords: Climate Change; Climate Policy Uncertainty; Monetary Policy; Taylor Rules; Norges Bank; Google Trends

JEL Classification: E52; Q54

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Introduction

Climate change has become one of the defining challenges of the twenty-first century. Rising global temperatures, more frequent extreme weather events, and accelerating environmental degradation threaten not only ecosystems and societies, but also the stability of economies and financial systems. This threat is expected to intensify and become more palpable in the coming years, as global temperature increases move further away from the objectives set in the Paris Agreement and as political institutions fail to deliver credible plans and commitments to meet them. The costs of a *disorderly transition* are severe and will continue to heighten unless world leaders take plausible actions to avoid a climate catastrophe.

Although central banks are not directly responsible for implementing and designing climate-related policies, the urgency for them to incorporate climate risk concerns into their forecasting frameworks and operational monetary policy strategies cannot be ignored. Climate risks affect the ability to secure prosperity and stability for future generations, exerting considerable influence on key macroeconomic variables, inflationary and deflationary pressures, costly trade-offs, and shaping the transmission mechanisms of monetary policy and the credibility of central banks. Increasingly, these effects are becoming visible in the monetary policy horizon.

Norway, and particularly Norges Bank, should not remain detached from this reality and accompany many other central banks' paths to incorporate climate risk considerations into its operational framework. For Norway, this issue carries specific weight. As a small open economy highly dependent on oil and gas revenues, the country is particularly exposed to global climate policy shifts and the risks associated with a *disorderly transition*. Furthermore, a lagged monetary policy stance has been noted in the literature, raising concerns about how this additional uncertain environment can affect the bank's much-needed credibility in the context of its flexible and forward-looking inflation targeting regime. It is therefore essential to understand how climate policy uncertainty interacts with the Bank's mandate and main tasks.

Hence, this dissertation aims to answer the following research question: How does climate policy uncertainty affect Norges Bank's ability to pursue its monetary policy mandate? To address it, three research objectives are pursued. First, to construct novel Climate Policy Uncertainty (CPU) Indexes for Norway and the world using Google Trends data. Second, to estimate Norges Bank's interest rate path through Taylor-type Rules and a New Keynesian framework, introducing the novel indexes as explanatory variables. Third, to compare the resulting predicted interest rate path with Norges Bank's past monetary policy revisions, assessing whether incorporating climate policy uncertainty enhances the Bank's decision-making framework.

Therefore, this study contributes to the existing literature in several ways. It adds value to the still scarce research on how climate-related risks should be incorporated in monetary policy, and particularly how central banks can effectively address climate policy uncertainty. It also contributes to the growing literature on the usage of Google Trends data to construct novel and meaningful indexes in various academic fields, extending this methodology to the context of a small open economy. Finally, it enriches the empirical analysis of Taylor-type Rules in the Norwegian case, providing further insight into how Norges Bank behaves. The methodology employed to study this relatively new issue of climate risk management in monetary policy, to the best of my knowledge, has not yet been generally employed, neither applied to the Norwegian context.

This dissertation is organised as follows. The Literature Review chapter presents an overview of the state of the art regarding climate change debates and global commitments, the types of climate risks and their macroeconomic impacts, Norges Bank's stance and operational framework, and the theoretical foundations of Taylor Rules and New Keynesian models. The Methodology chapter outlines the motivation, research question and objectives, as well as the steps taken to address them and the studies that serve as a reference. The Results and Discussion chapter presents the empirical findings, critically analyses them, and compares them to the expected outcomes. Finally, the Conclusion synthesises how the research question and objectives have been addressed, and is followed by the Bibliographic References and Annexes.

CHAPTER 1

Literature Review

1.1. Climate Change and Action

2024 was the warmest year on record. It is estimated that the Earth's temperature was on average 1.55 degrees Celsius warmer (with an uncertainty margin of ± 0.13°C) compared to pre-industrial levels, between 1850 and 1900. The last decade has also been registered as the warmest on average (World Meteorological Organization [WMO], 2025).

The Paris Agreement, signed by 196 parties at the 21st Conference of the Parties of the United Nations Framework Convention on Climate Change (COP21), entered into force in 2016. It is a legally binding international treaty with the goal to limit "the increase in the global average temperature to well below 2ºC above pre-industrial levels", while aiming for a maximum increase of 1.5ºC compared to the same period (United Nations [UN], 2015, p. 3). The document sets an ambitious objective, requiring its signatories to commit to its implementation while letting each country define how they should achieve it, with flexible and nationally determined contributions. It does not specify a defined target for global greenhouse gas (GHG) emissions reduction or a date to reach it.

Scientific evidence states that human-induced global warming impacts are already visible in multiple ecosystems, directly affecting organisms, human systems, and well-being. Increased mean and extreme temperatures in both land and sea, heavy precipitation events, increased frequency and magnitude of floods and droughts, as well as more intense and recurrent severe weather events, can be linked to the rise of GHG emissions. Exceeding the 1.5ºC temperature increase threshold compared to pre-industrial levels poses a severe threat to human and natural systems, constituting risks that might be long-lasting or irreversible, including the complete destruction of ecosystems, rising sea levels, species extinction, and lower availability of food and water resources. The impacts are considerably heightened when pondering an increase in global warming of 2ºC on average (Intergovernmental Panel on Climate Change [IPCC], 2018).

Although the average temperature in 2024 was above 1.5ºC when compared to pre-industrial levels, this does not mean that it has become unmanageable to comply with the Paris Agreement, since the document considers a long-term temperature goal (WMO, 2025). However, it is a sign of needed urgency for world leaders to take serious and credible measures to avoid a climate catastrophe, given the increasingly tangible physical impacts of climate change and nature's degradation, coupled with the heightened necessity to transition to a net-zero economy (European Central Bank [ECB], 2024).

Ambitious mitigation policies to limit cumulative emissions of greenhouse gases, such as carbon dioxide (CO_2) and nitrous oxide, are unavoidable to keep global warming well under 2ºC, considering that the IPCC has calculated that these human-made emissions have been the primary cause of world temperature rise during the period between 1951 and 2010 (IPCC, 2015). This requires a global average annual decline of 7% in emissions from 2020 to 2030 to limit the global temperature rise to 1.5ºC (Höhne et al., 2020), or, in other words, reaching net-zero CO_2 emissions within the next 50 to 60 years (IPCC, 2018). As of 2022, the carbon price was around 6 USD per tCO_2, while the estimated necessary value is 140 USD by 2030, 205 USD by 2040, and 250 USD by 2050 to achieve worldwide commitments (Network for Greening the Financial System [NGFS], 2024c).

The climate action path proposed by nations falls short of achieving these goals, since there is a substantial and growing gap between climate-related agreements and palpable political action (Diluiso et al., 2021). Not only have the nation's plans been largely inadequate or unambitious, but their commitments to fulfil their pledges have not been fully proven. Furthermore, in recent political developments, the United States of America has initiated a withdrawal process from the Paris Agreement, which might further compromise the achievement of the treaty's objectives, as it is one of the world's largest emitters of greenhouse gases (Lazarou & Leclerc, 2025). Contrary to what is desirable, the current action pathway is expected to increase GHG emissions slightly by 2030, instead of cutting them by half as positive scenario estimations expected (Höhne et al., 2020).

1.2. Impact on Macroeconomic Variables and Financial Stability

Climate change and the green transition are stated in the literature to have potentially significant impacts on macroeconomic variables and price stability through disruptions in different channels. There are two main types of climate change risks particularly important to central banks: *physical risks* and *transition risks*.

Physical risks are those that directly relate to the impact of climate change. They can be differentiated into *acute physical impacts*, which are associated with the increasing frequency and severity of extreme climate or weather events, such as heatwaves, floods, and extreme precipitation; and *chronic physical impacts*, which are associated with long-term shifts in climate and weather patterns, such as the rise in average temperatures and sea levels. *Acute physical impacts* resemble other types of shocks that occur during the business cycle, constituting a relevant effect for policymakers, while *chronic physical impacts* tend to occur beyond the monetary policy horizon. Either way, the magnitude and overall net effect of *physical risks* highly depends on their nature, intensity, and location, creating a challenge in their macroeconomic modelling for policymakers (NGFS, 2024a).

On the other hand, *transition risks* are those that arise from shifts in policies, technologies, and market preferences during the transition to a low-carbon economy (Batten et al., 2016). Some of the most relevant expected effects on macroeconomic variables are an impact on productivity while transitioning to decarbonised industries, higher short-term costs due to carbon taxation, lower costs associated with green energy in the long-term, increased precautionary savings due to uncertainty around transition policies put into place, and devaluation of carbon-intensive industries with the possibility of leading to stranded assets (NGFS, 2024a).

It is not consensual in the literature whether the green transition will be inflationary or deflationary in the short and medium term, since it is a difficult-to-model context marked by a lot of uncertainty and highly dependent on how carbon taxes are reintroduced into the economy (Andersson et al., 2020). Some authors state that it will be deflationary in the short term since the expected fall in future income due to the implementation of tighter green policies promotes precautionary saving to a point that reduces current aggregate demand (Ferrari & Landi, 2024). But most authors state that it will be inflationary in the short term due to higher carbon and energy costs, and supply-chain and sectoral disruptions, while deflationary in the long term due to increased efficient production and technology, cheaper energy, and productivity rises (NGFS, 2024c).

However, the net effect highly depends on how the transition occurs. To close the action gap between set climate goals and active policies, green policy is likely to tighten over the next few years in line with the established commitments, as carbon taxation is seen as the most efficient way to reduce greenhouse emissions (Matsen, 2019). This fact makes the green transition's macroeconomic impacts more likely to increase at horizons relevant to monetary policy (NGFS, 2024c). Furthermore, it creates the risk of leading to a *disorderly transition*, where the policy pathway is not predictable or expected and where its credibility, feasibility, or continuity might be questioned by the public (Dikau & Volz, 2021).

Literature has found that transition costs seem to be limited when mitigation plans are orderly and credible, namely by gradually rising carbon prices, considering that implementation timings and expectations play a core role in limiting macroeconomic instability. However, when agents have less time to adapt to a new policy framework, the transition costs and the negative effects on key macroeconomic variables are heightened, simultaneously enhancing the financial market's instability (Diluiso et al., 2021). Additionally, the literature states that a sudden and unexpected tightening of carbon emission policies can result in an irregular and unpredictable revaluation of carbon incentive assets, leading to negative supply shocks (Batten et al., 2016).

However, it is important to note that while the transition to a greener economy might give rise to unexpected macroeconomic effects and short-term costly trade-offs, the aggregate effects of a delayed transition or climate inaction will be significantly larger, due to the impacts of more extreme and frequent physical events and damages (NGFS, 2024c). Stern states the benefits of transitioning to a clean-energy economy are so relevant and significant that the economic discussion should circle the benefits and not the costs of such climate mitigation actions and transition policies in place (Stern, 2007), although the perceived costs and benefits, especially in the short term, might have a different balance (Brandstedt, 2018).

1.3. The Role of Central Banks

Although governments are responsible for implementing and designing climate-related policies, there has been a growing discussion on how central banks address sustainable and environmental concerns, incorporate climate risks into forecasting, or even whether they should promote green finance. Although there is no consensus on how this concern should be incorporated into traditional central banks' mandates and operational frameworks, it has become increasingly consensual across nations that the transformations led by climate change cannot be ignored (Dikau & Volz, 2021).

There are many motivations behind this reasoning. For once, out of 135 central banks, 40% of them are mandated to support their governments or community policy priorities while consistent with their main mandate, which generally includes environmental concerns (Dikau & Volz, 2021). Additionally, and most importantly, the impacts of climate change and the green transition are likely to compromise a central bank's ability to meet its monetary and financial stability mandate if not properly pondered (NGFS, 2024c), considering the substantial potential effects on macroeconomic variables and transmission channels mentioned in the previous subchapter. The transition can alter monetary policies' effectiveness and how they work through the economy due to, namely, the decrease in the equilibrium real rate of interest, which shrinks the space where conventional monetary policy instruments function (Schnabel, 2021).

Climate change has been described as the biggest market failure the world has ever experienced (Stern, 2009). So, given that climate risks directly affect a central bank's ability to meet its core responsibilities, "A central bank that does not address climate risks is failing to do its job." (Dikau & Volz, 2021, p. 19).

A growing number of banks have started to incorporate climate-related risks into their macroprudential and forecast modelling framework, which, combined with the establishment of the Sustainable Banking and Finance Network (SBFN) in 2012 and the Network of Central Banks and Supervisors for Greening the Financial System (NGFS) in 2017, has cast new light on the importance of enhancing the role of the financial system to manage new and transforming risks, to be part of an environmentally sustainable context and to share best practices, experiences and knowledge on this relatively new issue. Central banks such as the European Central Bank, the Bank of Canada, and others in countries such as the United Kingdom, Japan, New Zealand, Sweden, and Denmark have signalled publicly that climate-related change is a topic that they are paying great attention to in how it affects their countries' economy (Norges Bank, 2024b).

As an example, the European Central Bank (ECB), coupled with the review of its monetary policy strategy in 2021 (ECB, 2021), formalized its commitment to consider the implications of climate change and the carbon transition within the ECB's mandate, recognising that this phenomenon affects its "primary objective of maintaining price stability due to their impact" on macroeconomic variables and financial stability (ECB, 2022, p. 1). In the ECB's ambitious Climate Plan, the three established strategic objectives regarding climate-related activities are fostering wider action, supporting the green transition, and managing climate-related risks, having improved their analytical tools to adapt macroeconomic projections to environmental changes (ECB, 2024). This concern has also been considered within the scope of its macroprudential and supervision responsibilities.

1.4. The Norwegian Case

Norway is one of the Scandinavian countries and is considered a small open economy that uses its own coin, the Norwegian Krone (NOK). Norway is not part of the European Union but is integrated into the Schengen area. The national oil and gas sector plays a crucial role in the Norwegian economy, financing the welfare state by being the largest industry "measured in terms of value-added, government revenues, investments, and export value" (Norwegian Ministry of Energy & Norwegian Offshore Directorate, 2024). Petroleum activities have contributed over 24,000 billion NOK to Norway's gross domestic product (GDP) since the early 1970s, and, according to macroeconomic indicators, they will account for 21% of its GDP in 2025.

Monetary policy in Norway is conducted by Norges Bank, the national central banking authority. Its mandate, defined in Section 1-2 of the Central Bank Act, is to "maintain monetary stability and to promote the stability of the financial system", while contributing to "high and stable output and employment." (Norges Bank, 2020, Section 1-2, (1) and (2)). It conducts flexible and forward-looking inflation targeting with the operational objective of annual consumer price inflation of close to 2% over time, publishing the interest rate path forecasts to anchor expectations. To estimate underlying inflation, Norges Bank uses as its main indicator the consumer price index adjusted for tax changes and excluding energy products (CPI-ATE), considering that energy prices are highly volatile in Norway (Norges Bank, 2024b).

Although Norges Bank recognises that "climate change and measures to reduce greenhouse gas emissions will increasingly affect the global economy" (Norges Bank, 2024b, p. 46) and that there will be an impact on the monetary policy transition channels, its trade-offs, and even on the neutral interest rate, the bank does not account for climate considerations within its mandate. However, Norges Bank states that it is working to better understand how climate change and the energy transition are affecting the Norwegian economy, having joined the NGFS in 2022.

Nonetheless, it is of growing importance for Norges Bank to accompany the trend of other central banks in incorporating these concerns. Although Norway is in a less vulnerable geographic and financial position regarding physical and transition climate risks, since the literature states that advanced economies in wealthier nations and at higher altitudes are likely to have lower climate-related costs and that colder regions might benefit in the short term from slight average temperature rises and milder winters (Andersson et al., 2020), climate change will nevertheless and most probably conduct to noticeable and unpredictable economic effects that should be considered.

For once, while physical acute or chronic risks are more likely to significantly affect developing economies that are more vulnerable to climate-related disasters due to their geographic location, economic structure, and lower capacity to adapt (NGFS, 2024a), the weather in Norway is still changing. Floods in the country have been more frequent in recent years, which has led to a rise in the annual insurance payouts attributed to climate-related damages. Besides that, "electricity prices vary considerably in Norway depending on the amount of precipitation" (Matsen, 2019, p. 3), a fact that can become more relevant when combining cold winters and dry summers, spiking electricity prices and contributing to inflation volatility.

On the other hand, the climate transition impacts on the Norwegian economy are not consensual among authors. Some literature states that long-term macroeconomic developments and forecasts may change according to climate policy measures, changes in public attitudes and the emergence of new green technologies, with the possibility of diverging forecasts from reality if not accounted for (Matsen, 2019). Other states that consumer prices in the Nordic countries will not be affected by carbon taxation (Kapfhammer, 2023), while it has been found that "fossil-fuel exporters will face a more challenging transition" (NGFS, 2024a, p. 9).

Nevertheless, climate change and the transition to a low-carbon economy have begun to have palpable effects on some business sectors, with the change in customer and employment preferences being the most noticeable characteristic for companies. It has also led to higher intermediate and final costs, which are expected to continue to rise in the following years (Brekke et al., 2023). Simultaneously, these conditions have also attracted new investments, increased the demand for specialised knowledge, and created new business opportunities. As the Norges Bank states, the transition "will be one of the greatest challenges facing Norwegian firms in the years ahead." (Norges Bank, 2021a, para. 2).

Additionally, climate change is a process that does not consider local borders. International external shocks, spillover effects and cross-over impacts are likely to occur as more extreme weather events arise in nations worldwide and as the green transition materialises at different paces (NGFS, 2024a). It becomes increasingly important to rapidly integrate environmental concerns and to model the green transition in macroeconomic projections, recognising the fast-paced and ever-changing technological environment and the potential to shift medium- and long-term trends (Andersson et al., 2020). The impacts on financial instability and the de-anchoring of economic expectations can be heightened if the shocks are not responded to appropriately and promptly, since a delayed monetary policy stance can become a shock in itself when the predictable impact of the forecast error has not been accounted for (Bjørnland et al., 2020).

This reflection should also consider that oil shock fluctuations are of utmost importance for Norway to understand the latest international inflation developments and how they affect the domestic economy, considering the sector's significance in the national GDP (Holvik & Thorsrud, 2024). Oil prices and related shocks are expected to change their patterns and behaviours as the world adapts to a progressively low carbon-based economy, exposing the oil and gas sector in Norway to *transition risk* (Matsen, 2019).

The lagged reaction of Norges Bank to foreign shocks is stated in the literature. Although the bank has improved how it considers international developments in its projections, there is a considerably delayed monetary policy stance by not responding on time to global economic changes, which could be forecasted by incorporating international indicators and developments that lead to interest rate revisions. It has been found that this data is available at the time of the policy revision and of the creation of the forecast, but is currently not used properly (Bjørnland et al., 2020). Similarly, one of the main recommendations made by the Norges Bank Watch in 2024 was for the bank to allocate more space in its "Monetary Policy Reports to exploring alternative assumptions and risk modelling" that may have medium- and long-term changing trends, namely those concerning climate change and the energy transition (Holvik & Thorsrud, 2024, p. 24).

1.5. New Keynesian Models and Taylor-type Rules

Alan S. Blinder famously stated, "Having looked at monetary policy from both sides now, I can testify that central banking in practice is as much art as science. Nonetheless, while practising this dark art, I always found the science quite useful." (Blinder, 1997, p. 17). Indeed, despite the complexities and uncertainties that still surround monetary policy – from the evolution of monetary instruments, the intricacies of the transmission channels and the modelling of uncertainty in an ever-changing world – economic science has made significant developments that provide policymakers with robust theoretical foundations to guide decision-making and improve policy outcomes. This dissertation employs the framework of New Keynesian Models and Taylor-type Rules, whose fundamentals are stated in the current subchapter.

To begin with, monetary policy is stated in the literature as a stable background to the economy by promoting price stability and by having the ability to offset major sources of economic disturbances, reacting to those that arise from non-monetary sources and avoiding creating them by making mistakes (Svensson, 2008). New Keynesian economics frame this mission, building on the classic theoretical framework by incorporating microeconomic fundamentals, nominal rigidities due to price and wage stickiness, imperfect and monopolistic competition, and rational expectations, meaning that future inflation depends on the expectations of future inflation today due to the macroeconomic agents' forward-looking behaviour (Clarida et al., 1999).

Additionally, monetary policy is neutral in the long term and non-neutral in the short term due to price rigidities (Martins, 2000). This means that it can only influence nominal variables, such as the exchange rates, the price level or monetary aggregates, as opposed to real variables, such as unemployment and GDP (Svensson, 2008). Therefore, monetary policy decisions ultimately are rooted in the underlying policy problem: choosing a magnitude and a time path for the monetary policy instrument to target inflation and output, recognising the source of the business cycle shock and its trade-offs between the relevant macroeconomic variables, while subject to behavioural constraints of the transmission mechanisms and the market participants (Clarida et al., 1999).

Currently, inflation targeting is seen as the best practice in monetary policy to achieve the objective of price stability, and more specifically, flexible inflation targeting. This means that the objective is not only to stabilise inflation around a target rate, but also the real economy (Svensson, 2008). This monetary policy framework is employed by Norges Bank, using the short-term interest rate as the chosen instrument and a forward-looking background (Norges Bank, 2024b). Norges Bank was also one of the first central banks to adopt distinctive methods to ground expectations and quantify policy decisions, by publishing its interest rate path predictions and by employing loss functions to assess alternative policy options, respectively (Svensson, 2008).

Modelling the macroeconomy is a challenging endeavour since economists encounter significant uncertainty regarding the intricacies of the economic system, the transcription of real-life constraints and agents' behaviour into econometric models and how shocks propagate through the transmission channels. For instance, modelling representative agents can be misleading, since some social groups within them suffer more than others in recessions (Clarida et al., 1999). Moreover, climate change and the green transition are certainly characterised by substantial uncertainty in macroeconomic modelling, stemming from modeller uncertainties, such as the model's structure choice and the value of its core parameters; and due to uncertainties faced by economic agents, such as how physical impacts affect behaviour, including risk aversion, investment and saving (NGFS, 2024b).

This task is highly dependent on policymakers' knowledge at the time they make decisions, and only by analysing this knowledge and how it evolved can historical economic behaviour be comprehended (Clarida et al., 2000). This is the rationale behind the literature's statement that there is no reverse causation in monetary policy history, since the evolution of monetary policy rules stems from a gradual learning process through research, criticism, observation and central bankers' direct personal experience. Therefore, the correlation between economic policy and economic outcomes goes from "policy to output, not the other way around" (Taylor, 1999, p. 336).

Nonetheless, modelling the reaction of the monetary authority to changes in economic conditions through reaction functions, which summarise how the monetary policy instrument is used, provides valuable assistance for policymakers, since policy rules are better tools than discretion to achieve optimal planning, avoid economic instability and reduce inflation-bias (Hamalainen, 2004). Numerous types of policy rules have been discussed in economic literature, but the most consistent ones are Taylor-type Rules, first introduced by John Taylor in his recognised seminal article in 1993 (Taylor, 1993). The original Taylor Rule stipulates that the monetary authority's instrument reacts to two key goal variables: "deviations of contemporaneous inflation from a pre-set target and deviations of contemporaneous real output from its potential level" (Hamalainen, 2004, p. 1). It can be mathematically described as follows:

$$i = r^* + \pi_t + \alpha(\pi_t - \pi^*) + \beta x_t \quad (1.1)$$

In the equation, all variables are defined in levels. i is the target interest rate proposed by the rule; π_t is the observed average inflation rate over the last four quarters; π^* is the inflation rate target; and x_t is the output gap, defined as the deviation of output from its potential value (Martins, 2000). The coefficients α and β depend on the monetary authority's preferences and the monetary regime in place, defining the extent to which policymakers are willing to accept greater variability in inflation in return for greater output stability (Bernanke, 2015). However, $\alpha > 1$ is a necessary condition for monetary policy not to be accommodative to inflation, so that an increase in the nominal interest rate is enough to raise its real value, since the coefficient determines how aggressively the central bank raises interest rates when inflation exceeds its target (Clarida et al., 1999).

The literature shows that Taylor's Rule is consistent with a set of proposed principles for optimal policy rules and that it estimates fairly consistently the interest rate decisions made by the United States Federal Reserve (FED) during the post-Volcker period, associated with monetary policy decisions that promoted relatively stable output and inflation (Taylor, 1999). The structure of the rule is simple, but it captures well the behaviour of the monetary authority when defining its interest rate path (Hamalainen, 2004). It is labelled as a benchmark for monetary policy, prescribing as well as describing. However, even under an optimal rule, "monetary policy should be systematic, not automatic" (Bernanke, 2015, para. 25), allowing for judgment, flexibility and the analysis of multiple pieces of information not incorporated into the Taylor Rule.

The main criticisms associated with the Taylor Rule regard how the underlying assumptions can substantially change the results derived from the model, such as the determined weight on the stability coefficients and the method used to calculate inflation and estimate unobserved variables, namely the potential output and the equilibrium real interest rate. Therefore, new versions of the original Taylor Rule, named Taylor-type Rules, have been introduced to allow for forward-looking behaviour, price stickiness and interest rate smoothing, in line with New Keynesian foundations (Hamalainen, 2004).

CHAPTER 2

Methodology

2.1. Defining the Research Problem and Objectives

In summary, there are various aspects shaping climate change and the green transition today that are becoming increasingly relevant for central bankers, policymakers and, in particular, for Norges Bank to consider when pursuing its mandate of maintaining monetary stability, promoting high and stable output and employment, and reducing the build-up of financial imbalances (Norges Bank, 2020). These considerations affect Norway in a specific and significant manner, as not only its GDP is highly dependent on the oil and gas sector revenues (Norwegian Ministry of Energy & Norwegian Offshore Directorate, 2024), but also since a lagged reaction in Norges Bank's monetary policy stance to international developments is stated in the literature (Bjørnland et al., 2020).

For instance, the increase in the average global temperature is foreseen to give rise to more frequent and severe extreme weather events, having the potential to substantially impact global value chains and disrupt the economy due to cross-border effects and national interdependencies, affecting key and national macroeconomic variables even if the *physical risk* did not occur in Norway (NGFS, 2024a). These large fluctuations in inflation and output make it challenging to distinguish between temporary and permanent shocks, toughening the job of policymakers, especially if costly trade-offs are involved when the variables are pulled in opposite directions (Norges Bank, 2021b).

Furthermore, to meet the Paris Agreement's targets, green policy is likely to tighten worldwide within the following years, namely through increased carbon taxation, and at a pace that might lead to a *disorderly transition*. This fact heightens the *transition risk*, making its effects relevant in the traditional monetary policy horizon and affecting variables such as investment, inflation and employment (Diluiso et al., 2021). Norway has also set an ambitious target to reduce greenhouse emissions by at least 50% by 2030 in comparison with 1990 levels, a substantial transition that is already taking place with observed and forthcoming significant impacts on enterprise's business activities due to higher selling prices and input costs, changes in customers' choices and preferences, need for diversified expertise, as well as differentiated investment decisions, new business opportunities and altered productivity levels (Norges Bank, 2021b).

In addition, uncertainty surrounding the green transition and climate change can affect the monetary policy transmission mechanisms, since a central bank's credibility depends on how well it understands the effectiveness of the policy instrument. Therefore, as stated by the NGFS as one of the initial takeaways from the growing literature on the topic, "central banks should acknowledge that climate change already is part of their monetary policy contexts" (NGFS, 2020, p. 3).

Indeed, Norges Bank should accompany other central banks' paths and increasingly consensual tendency to incorporate climate risk considerations into its operational monetary policy framework to become more resilient to the fast-changing and unpredictable international environment where it operates, namely by enhancing its forecast practices to include these possible implications regularly. However, the bank is still working to fully integrate various climate-related factors into its analytical framework and to better understand how they affect the Norwegian economy (Norges Bank, 2024a). In the same report, the bank presented the plan to publish, in 2024, a climate stress test to assess how climate change affects risk in Norwegian banks and credit institutions, studying the effect of climate change on the financial system. Yet, past its expected publication date, the report has not been made public.

According to Norges Bank's 2025 Climate Action Plan, its sustainability strategy seems to mainly encompass the management of its investment portfolio in order to reach global net zero emissions within its companies until 2050, by establishing principles, exercising active ownership and investing sustainably (Norges Bank, 2022). However, this course of action is perceived in the literature as more unconventional, and caution is needed when put into practice, as it might give rise to a series of unintended consequences.

On one hand, breaking the long-held principle of market neutrality and applying explicit climate change criteria to a central bank's asset purchase program or to its macroprudential regulatory framework might push banks to diversify less their investment portfolio and potentially create a green market bubble. This decision might even defy the bank's independence and needed credibility. On the other hand, it has been found that a green quantitative easing policy can effectively stimulate the economy in response to an adverse financial shock originating from the fossil sector, but its stabilising properties are not significantly different from those of market-neutral asset purchase programs (Diluiso et al., 2021).

Additionally, Norges Bank also seems invested in reducing emissions associated with its own operations, having earned the Eco-Lighthouse certification scheme and by publicly reporting the carbon footprint of its operational functions (Norges Bank, 2024a). Nonetheless, this act does not address the main concerns regarding climate change in relation to monetary policy and central banking, as outlined in the NGFS Glasgow Declaration: namely, further enriching climate scenarios, deeply integrating climate change considerations, and bridging data gaps when tackling climate-related risks (NGFS, 2021).

Pondering these considerations, this dissertation addresses the following research question: *How does climate policy uncertainty affect Norges Bank's ability to pursue its monetary policy mandate?* More specifically, this study pursues three research objectives: first, to construct novel Climate Policy Uncertainty Indexes using Google Trends data; second, to estimate Norges Bank's interest rate path using Taylor-type Rules, introducing the novel indexes as explanatory variables; and third, to compare the resulting predicted interest rate path with Norges Bank's past monetary policy revisions. The ultimate aim is to assess whether accounting for climate policy uncertainty can enhance the Bank's decision-making framework.

Henceforth, this research contributes to the still scarce literature on how to consider climate-related risks in monetary policy strategy, and, in particular, on *how central banks should account for climate policy uncertainty*, directly following the open key research question prompted by the NGFS (NGFS, 2024a). Therefore, this dissertation builds upon the work of numerous economists, central banks, and formal organisations on how to address this new and pressing matter, thereby filling the existing knowledge gap.

Furthermore, this research contributes to the growing literature on the usage of Google Trends data in Economics and other academic fields. It builds on the studies that developed, using Google Trends, an Uncertainty Index for the United States and Australia, comparing it with traditional uncertainty proxies and unemployment dynamics (Castelnuovo & Tran, 2017), as well as research that created a Climate Change Awareness Index for the United States and linked it to the returns of various industry portfolios (Roque, 2024). Further inspiration comes from the study that constructed a Google Trends-based Environmental Policy Uncertainty Index to examine its impact on macroeconomic performance and the effectiveness of monetary policy (Huang & Punzi, 2024).

Google Trends data has also been successfully adopted in other academic fields, highlighting the growing relevance of developing novel indexes using this type of data. For example, in the area of epidemiology, Ginsberg et al. (2009) predicted influenza epidemics in the United States using Google Trends data. Likewise, D'Amuri & Marcucci (2017) constructed a better-than-the-literature leading indicator for the United States unemployment rate, while Vosen & Schmidt (2011) created a novel index that outperforms survey-based indicators in predicting private consumption.

To the best of my knowledge, introducing Climate Policy Uncertainty Indexes based on Google Trends data as an explanatory variables into Taylor-type Rules, and subsequently analysing its role in enhancing the central banking decision-making framework, has not yet been explored, nor applied to the Norwegian context. Moreover, this dissertation aims to better understand how Google Trends data-based indexes perform in small open economies, as most published academic papers using this source of data have primarily focused on big economies, such as the United States.

Given the complexities of modelling climate change and the diverse methodological approaches required for each research question, this work should be seen as a valuable and incremental contribution rather than a comprehensive solution. It is best comprehended as a stepping stone for gradually incorporating this tool into a broader analytical framework.

2.2. Creating the Climate Policy Uncertainty Indexes

Climate risk is not an observable variable. The most used proxies that attempt to accurately model it are news-based climate risk measures, temperature anomaly statistics, or Climate Change Performance Indexes (CCPI), the latter being commonly produced by non-governmental organisations to track countries' efforts to combat climate change. Indeed, increasingly booming literature uses uncertainty indexes based on news-based measures to quantitatively assess the impact of uncertainty surrounding climate policies on the macroeconomy (Huang & Punzi, 2024).

As an example, a study used tools from the Natural Language Processing (NLP) literature and a dataset of news media coverage, considering the public awareness and discourse related to environmental concerns, to construct country-specific measures of climate change transition risk and related them to commodity currencies in eight countries (Kapfhammer et al., 2020). The country-specific measures were consistent with temperature change observations, one of the most direct and widely used climate change measures. Furthermore, the results showed a persistent depreciation of commodity currencies when climate risk was high, with the correlation in Norway being particularly strong as a primary petroleum exporter.

In another study conducted by Gavriilidis (2021), a Climate Policy Uncertainty (CPU) index for the United States (US) was developed based on news from major newspapers of the country. The resulting measure has been widely used in the literature and is considered to be a reliable indicator for measuring climate policy uncertainty. The index appears to capture major events related to climate policy, and its spikes are associated with a strong negative effect on CO_2 emissions.

This line of research assumes that media functions as an information intermediary between individuals and the state of the world, so that news media coverage can be used as a proxy to measure evolving public perceptions of climate risk, in line with other published and recognised academic papers (Kapfhammer et al., 2020). A similar assumption is used in another set of literature, assuming that economic agents, represented by internet users, search for online information when they are uncertain about a specific future or a doubtful event. The frequency with which they search the topic reflects their level of uncertainty (Castelnuovo & Tran, 2017).

For instance, Castelnuovo & Tran (2017) developed a Google Trends-based Uncertainty Index for the United States and Australia, showing that it is a reliable measure of uncertainty when compared to other existing proxies and that uncertainty shocks are a significant driver of unemployment and prices in the United States. Employing the same framework, Roque (2024) constructed a Climate Change Awareness Index for the United States using Google Trends data, finding that its dynamics significantly explain the returns of several industry portfolios in the country. Similarly, Huang & Punzi (2024) created a Google Trends-based Environmental Policy Uncertainty Index, demonstrating that it closely aligns with other uncertainty measures and corroborates recognised theoretical findings, underlining the importance of monetary policy to alleviate adverse shocks stemming from environmental policy changes.

This dissertation will employ the same assumption framework used by Castelnuovo & Tran (2017), Roque (2024) and Huang & Punzi (2024). Indeed, using Google Trends data to create uncertainty indexes uses the same theoretical approach as the news-based measures, replacing the counting of words reported by the press with the intensity of internet searches (Huang & Punzi, 2024). Therefore, this research project primarily assumes that people search for online information more intensively when confronted with heightened uncertainty about environmental policy, namely when they are uncertain about the occurrence or outcome of a particular event, which induces a greater appetite for knowledge and a more intense usage of internet tools to collect information.

Consequently, to address this study's research question on the impact of climate policy uncertainty on Norges Bank's mandate fulfilment, one of the objectives is to construct country-specific Climate Policy Uncertainty Indexes for Norway based on Google Trends data, and Global Climate Policy Uncertainty Indexes serving as a comparative measure. In this context, the concept of climate policy uncertainty encompasses not only the potential introduction of disruptive or strict environmental legislation, but also doubts regarding the actual implementation of announced policies, the steps required to reach long-term goals and common targets, or eventual changes to existing regulations.

The decision to focus on uncertainty rather than physical risk or general awareness, and particularly on climate policy rather than on a broader definition of climate change, is grounded in three different considerations. First, in this context, uncertainty can be treated as a proxy for risk, since climate risk is not a directly measurable or observable variable. Second, given the Norwegian context, transition risks associated with the shift to greener policies are more pressing than physical risks, which are projected to be relatively mild in the following years. Third, climate policy uncertainty is particularly relevant to Norges Bank's analytical framework, allowing for a more consistent comparative analysis with past monetary policy decisions.

Moving forward with the creation process of the indexes, it is crucial to understand how Google Trends operates. As the most influential internet search engine, Google Trends measures the popularity of indicated search terms on Google, allowing to measure in real time what users are searching for in a specific region and period. It provides estimates of how often a keyword is searched in comparison to the total searches performed on Google, meaning that the data is normalised and scaled between 0 and 100, where 100 represents the peak popularity of a search term.

To construct the Climate Policy Uncertainty Indexes, the process using Google Trends, thoroughly described by Castelnuovo & Tran (2017) and Roque (2024), will be adopted, which involves the following steps. Firstly, a set of keywords related to climate policy uncertainty is identified and selected by analysing the most frequently used terms in Google searches. In the second stage, a benchmark term is chosen to conduct an aggregation process of the keywords, in light of Google Trends' limitation of introducing a maximum of five terms per search group. Finally, the values associated with each keyword's search frequency are delinked from the specific group in which they were searched, allowing Google Trends' internal scaling to be addressed and the values across all groupings to be standardised.

The indexes will cover monthly data from January 2004 to March 2025, the maximum period of data available on Google Trends at the time of their development. To clarify, the indexes to be created are the Norwegian Climate Policy Uncertainty Indexes, henceforth referred to as CPU_N, and the Global Climate Policy Uncertainty Indexes, henceforth referred to as CPU_G. The latter differs solely in the location of the search queries to include all global searches, allowing for a result comparison between national and global behaviour, considering that climate change is a pressing and wide-reaching issue, producing relevant spillover effects across national borders. Additionally, three different versions of each regional index will be created using a different benchmark term in their development, ensuring robustness and comparability of the results.

Following the creation process, a critical analysis of the novel indexes is carried out to assess how the observed uncertainty fluctuations and spikes align with real-world events and political shifts, and to understand how public uncertainty surrounding climate policy has evolved in the last two decades. Only after identifying the most suited version of the indexes compared with the existing literature, will they be studied within the estimated Norges Bank's Taylor-type Rule.

2.2.1. Selecting the Keywords

In the first stage of the indexes' construction, a selection of keywords associated with climate policy uncertainty is needed. Since Google Trends encompasses all languages when a search topic is chosen, translating the keywords to Norwegian (Bokmål or Nynorsk) is unnecessary because it already accurately reflects all the languages used in the region to search for that topic. The only exception made to this regard was in terms heavily used in Norwegian green policy discourse and associated with specific events, legislation or accords.

As employed by Roque (2024), the key search terms will be selected by observing and extracting the related terms to "climate policy" in online Google searches in Norway, as opposed to extracting the keywords from newspaper fonts, directly reflecting the use of the internet as a mechanism to find information about uncertain events. Additionally, the selected keywords were compared to the terms chosen in other academic papers, ensuring consistency with the existing literature and enhancing the validity of the chosen keywords by aligning them with previous successful methodologies. The search intensity of each keyword was also validated on Google Trends to confirm that each term had a sufficient and relevant amount of search volume over time, not constituting an outlier in representing climate policy uncertainty.

Seventy-seven keywords were chosen, as presented in Table 2.1. As an illustrative example of the selection process, one of the initial results when searching for "climate policy" in Norway is Norges Bank's statement on its expectations for its investment portfolio companies regarding climate change. In this document, it is possible to read:

> *Climate change* is one of the defining challenges of the 21st century. As a long-term, diversified, global investor, the fund stands to benefit from an orderly *transition* in line with the goals of the *Paris Agreement*. We expect companies to manage *climate risks* and opportunities in a manner that is meaningful to their business model and situational context. They should set *net zero* and interim *decarbonisation targets*, define strategies to achieve these, and be transparent about their approach (Norges Bank, 2025a, p.3).

In the citation, the highlighted words "climate change", "transition", "Paris Agreement", "climate risks", "net zero", and "decarbonisation targets" are highlighted and compared to other emphasised words in the most relevant Google searches to assess their relative frequency. Moreover, the terms were compared to those used previously in the relevant literature on the topic, and the associated queries and related topics presented by Google Trends were also considered. After this analysis, some initial terms might have been dropped either because they can be substituted by broader or more specific designations, or because their relevance in the context of other possible keywords was not as substantial.

As an example, the initial term “transition” was detailed in two keywords: “transition plan” (keyword n.º76) and “transition risk” (keyword n.º77). On the other hand, the initial term “decarbonisation targets” did not make the final list of selected keywords, but its idea is stated in other terms that were more commonly used and frequently searched, such as “carbon neutral” (keyword n.º7), “decarbonisation” (keyword n.º27), “low carbon” (keyword n.º58) and “net zero” (keyword n.º62).

Table 2.1: List of selected keywords to develop the Climate Policy Uncertainty Indexes.

1. AGW	27. Decarbonisation	53. IPCC report
2. Air pollution	28. Endangered species	54. Klimaforliket
3. Air quality	29. Energy consumption	55. Klimakur
4. Carbon capture	30. Energy efficiency	56. Klimamål
5. Carbon emissions	31. Energy transition	57. Klimaplan
6. Carbon footprint	32. Environment	58. Low carbon
7. Carbon neutral	33. Environmental impact	59. Miljøpolitikk
8. Carbon price	34. Environmental law	60. Natural disasters
9. Carbon storage	35. EU ETS	61. Nature
10. Carbon tax	36. Fossil fuels	62. Net zero
11. Clean energy	37. Gas emissions	63. Offshore drilling
12. Climate	38. Gas industry	64. Oil drilling
13. Climate action	39. GHG emissions	65. Oil industry
14. Climate agreement	40. Global climate change	66. Oil production
15. Climate anxiety	41. Global temperature	67. Ozone layer
16. Climate change	42. Global warming	68. Paris Agreement
17. Climate crisis	43. Green deal	69. Pollution
18. Climate finance	44. Green energy	70. Renewable energy
19. Climate justice	45. Green transition	71. Sea level rise
20. Climate law	46. Greenhouse effect	72. Sustainability
21. Climate policy	47. Greenhouse gas	73. Sustainable
22. Climate risk	48. Greenhouse gas emissions	74. Sustainable development
23. Climate settlement	49. Greta Thunberg	75. Temperature increase
24. Climate strike	50. Hydrogen energy	76. Transition plan
25. Climate warming	51. Ice melting	77. Transition risk
26. CO_2 emissions	52. Inflation reduction act	

As a clarifying note, “AGW” stands for Anthropogenic Global Warming, “EU ETS” for European Union Emissions Trading System, “GHG” for Greenhouse Gas, and “IPCC” for Intergovernmental Panel on Climate Change. Meanwhile, “Klimaforliket” refers to a series of political agreements signed in Norway between 2008 and 2012; “Klimakur” to a comprehensive national climate analysis published in 2010 and commissioned by the Ministry of the Environment; “Klimamål” to Norway’s official climate targets; “Klimaplan” to the set plan to achieve these goals; and “Miljøpolitikk” to the broader concept of environmental policy, also encompassing other climate concepts.

2.2.2. Keywords Aggregation Process

Google Trends data provides the frequency of a particular search term compared to the total search volume. To do so, Google Trends divides each raw data point $R_{i,j,m,r}$ (which is the frequency of a word “i” in a group of searched words “j” in a month “m” in a region “r”) by the total amount of searches “T” in the same month and country. The corresponding formula is the following:

$$S_{i,j,m,r} = \frac{R_{i,j,m,r}}{T_{m,r}} \quad (2.1)$$

The resulting values from the previous formula are scaled to range between 0 and 100, where 100 represents the peak popularity of a search term. When the maximum value “100” is attributed to a search term i, it means that it was the most searched term in group j. Dropping the month and region particularisation for simplicity, the relative frequency of a word i in a group of searched terms j is described by:

$$FI_{i,j} = 100 * \left(\frac{S_{i,j}}{\max(S_{i,j})} \right) \quad (2.2)$$

Due to Google Trends’ limitation of comparing a maximum of five search terms at a time, the keywords were aggregated into several groups of five. In each group, a benchmark term was used, associated with the search frequency $FI^*_{y,m}$, meaning that there was one keyword introduced identically in each group alongside four other keywords selected randomly. Using a benchmark term ensures consistency and comparability across all groups, since Google Trends returns an internally normalised value of the search frequency of each keyword compared to the other terms present in the group.

Once all the keywords were aggregated into groups together with the benchmark term, with the condition that none of them could be repeated, nineteen groups were formed and introduced into Google Trends. In this procedure, the frequency of the benchmark term $FI^{*}_{y,m}$ might change in each j group, due to the fact that the most searched term in each grouping automatically receives the maximum value of 100. The frequency of a word in a given group and month is given by $FI^{x}_{i,j,m}$. By assumption and for consistency, if any $FI^{x}_{i,j,m}$ assumed the value of "<1", it was changed to "0.5".

The final steps to obtain the Climate Policy Uncertainty Indexes aim to delink the frequency of each keyword i from the specific group j with which it was searched. By applying the following formula, the internal scaling imposed by Google Trends is addressed, and the values are standardised across all groupings:

$$FI^{x,*}_{i,m} = FI^{x}_{i,j,m} * \frac{FI^{*}_{y,m}}{FI_{i,j,m}} \quad (2.3)$$

Finally, the Climate Policy Uncertainty Indexes are obtained by summing the monthly frequencies of each keyword as follows:

$$CPU_{m,r} = \sum_{i=1}^{i=77} FI^{x,*}_{i,m} \quad (2.4)$$

In total, this process was repeated six times, since three different benchmark terms were chosen and used respectively in groupings for Norway and the world. The three benchmark terms were "climate change", "pollution" and "sustainable", as these keywords were consistently searched for in the time sample, avoiding the benchmark frequency to be zero, which could compromise the robustness of the indexes. Additionally, these terms are broadly used in the public discourse and have a comprehensive definition regarding climate policy, conceptually overlapping with most of the remaining keywords. Using three different benchmark terms – resulting in six different Climate Policy Uncertainty Indexes - addresses possible nuances in the indexes' values depending on the chosen benchmark term.

Moreover, this approach allows for comparison across the different resulting indexes to understand which one best fits the literature's proxy for climate risk, major political events regarding climate change and environmental law, as well as the estimated Norges Bank's Taylor-type Rules. Specifically, to identify the best suitable version of the Norwegian and the Global Climate Policy Uncertainty Indexes, a Pearson correlation test will be conducted against the Climate Policy Uncertainty (CPU) Index for the United States developed by Gavriilidis (2021). This news-based measure has been widely used in the literature and is considered to be a reliable indicator for measuring climate policy uncertainty, making it a relevant point of comparison for the novel indexes developed in this dissertation.

In order to properly use the created Climate Policy Uncertainty Indexes, tests and transformations will be applied to their original raw version. First of all, the novel CPUs will be transformed from a monthly to a quarterly format by averaging their 3-month values every quarter, to be able to adequately compare and incorporate them into the Taylor-type Rules, which will also use a quarterly format in line with the available Norwegian macroeconomic data. Moreover, the novel CPUs will be tested for stationarity, and modified accordingly using log differences or first differences in case any does not show stable statistical properties over time.

Finally, if deemed necessary and possible, a seasonally adjusted version of the CPUs will be created, using the Holt–Winters seasonal smoothing method (command *tssmooth shwinters* on Stata). This adjustment is important since some of the plotted CPUs displayed signs of seasonality, which could lead to an analysis bias if not properly addressed.

2.3. Estimating the Taylor-type Rules

In order to estimate Norges Bank's interest rate path, Taylor-type Rules will be used and estimated, using the New Keynesian fundamentals described previously. The short-term interest rate is chosen as the monetary policy instrument, as this is the framework employed by Norges Bank (Norges Bank, 2024b). The original Taylor Rule can be written as a linear regression, transforming and simplifying the initial equation in the following way:

$$i = r^* + \pi_t + \alpha(\pi_t - \pi^*) + \beta x_t \quad (1.1)$$
$$i = r^* - \alpha\pi^* + (1+\alpha)\pi_t + \beta x_t$$
$$i = \beta_0 + \beta_1 \pi_t + \beta_2 x_t \quad (2.5)$$

As a reminder, i is the target interest rate proposed by the rule, π_t the observed average inflation rate over the last four quarters and x_t the output gap, defined as the deviation of output from its potential value (Martins, 2000). To achieve the best-fitted model of the estimated Taylor Rule for Norges Bank's policy rate path, described in detail below and in the following Results and Discussion chapter, other variables will also be used and denominated as ur, the unemployment rate and er, the NOK to EUR exchange rate.

In order to estimate the above-mentioned variables, raw data were extracted from official websites. Norges Bank's policy rate path and the exchange rate (NOK/EUR) were extracted from Norges Bank's data warehouse (Norges Bank, n.d.). The consumer price index, the unemployment rate and the gross domestic product were extracted from Statistics Norway (Statistics Norway, n.d.). The Norwegian (CPU_N) and the Global (CPU_G) Climate Policy Uncertainty Indexes are primary data, as explained in the previous subchapter. In this context, Norges Bank's policy rate path (NB_rate) serves as a measure of comparison between the estimated Taylor-type Rules and the verified reality.

The extracted version of the consumer price index is adjusted for tax changes and excludes energy products (CPI-ATE), as well as seasonally adjusted and not harmonised. This is also the measure used by Norges Bank to identify underlying inflation since energy prices in Norway and particularly volatile (Norges Bank, 2024b). On the other hand, the gross domestic product (GDP) uses market values with constant prices and seasonal adjustment, and refers to mainland Norway, excluding offshore petroleum activities and international shipping. Particular weight is given to mainland GDP, which better reflects the domestic economy, since oil prices are business cycles that have little influence on petroleum production, and these are highly volatile and externally driven (Norges Bank, 2024b).

The variables were adjusted in order to be presented in the quarterly format. The monthly interest rate and the CPI-ATE were transformed into quarterly data by using the end-of-quarter value. The monthly GDP, the exchange rate (NOK/EUR) and the Norwegian and Global CPUs were transformed to quarterly data by averaging the 3-month values of the respective quarter. The unemployment rate was already available in the quarterly format.

All data were tested for stationarity by applying the Augmented Dickey-Fuller test (command *dfuller* on Stata) to check for unit roots, transforming them accordingly if needed to ensure stable statistical properties over time. GDP and CPI-ATE were expressed in their natural logarithm format, allowing the series to be more stable over time, equalling to y and p, respectively. The exchange rate was incorporated in the Taylor Rule as its first difference in series ($delta_er$).

Finally, inflation (π) was computed as the quarterly annualised difference of p, and the output gap (x) as the cyclical component of y using the Hodrick-Prescott Filter (command *tsfilter hp* on Stata). Other estimation attempts for the value of the output gap were also attempted, namely by using the growth rate of y and the unemployment rate (ur). However, these calculations did not incorporate the best-fitted models, although their results are presented as annexes.

To estimate Norges Bank's interest rate path, the original Taylor Rule will be modified to account for several aspects. First, instrumental variables will be used to more accurately estimate the effects of the output gap and inflation. Second, interest rate smoothing will be incorporated by including the nominal interest rate level of the previous period in the formula. Third, the NOK to EUR exchange rate will be added to better capture the dynamics that affect a small open economy with its own currency (Hamalainen, 2004).

As presented in the Discussion and Results chapter, the Taylor-type Rules with these characteristics presented themselves as the best fits. However, other variations were also tested, namely using as regressors the GDP growth rate and the unemployment rate as estimates for the output gap instead of the cyclical component of GDP, using forward inflation as an explanatory variable, and by intertwining these combinations and possible characteristics. The resultant estimations are presented as annexes but not thoroughly described in the present dissertation. In Table 2.2 are presented the characteristics and simplified linear formulae of the Taylor-type Rules that achieved the best results when estimating Norges Bank's interest rate path, although the estimation employed non-linear specifications.

Table 2.2: Characteristics and simplified linear formulae of the best-fitted estimated Taylor-type Rules.

Numbering	Characteristics	Formulae
Taylor Rule 1 (TR1)	Use of instrumental variables for inflation and the output gap.	$i_t = \beta_0 + \beta_1 \hat{\pi}_t + \beta_2 \hat{x}_t + u_t$
Taylor Rule 2 (TR2)	Use of instrumental variables for inflation and the output gap and introduction of interest rate smoothing.	$i_t = \beta_0 + \beta_1 \hat{\pi}_t + \beta_2 \hat{x}_t + \rho i_{t-1} + u_t$
Taylor Rule 3 (TR3)	Use of instrumental variables for inflation and the output gap, interest rate smoothing and introduction of the NOK to EUR exchange rate as an explanatory variable.	$i_t = \beta_0 + \beta_1 \hat{\pi}_t + \beta_2 \hat{x}_t + \beta_3 \Delta er_t + \rho i_{t-1} + u_t$

In the original estimation of the simplified Taylor Rule, which uses inflation and the output gap as explanatory variables, Ordinary Least Squares (OLS) was employed as the chosen econometric method. However, for Taylor Rule 1, the estimation method was the IV/GMM model (Generalised Method of Moments with Instrumental Variables). In this framework, both inflation and the output gap are treated as potentially endogenous, meaning that they may be correlated with the error term, so lagged values of these variables are used as instruments. In contrast, for Taylor Rules 2 and 3, the Generalised Method of Moments (GMM) approach was used, allowing for estimation of the non-linear parameters.

In order to verify the robustness of the estimated models, tests were applied to each Taylor Rule variation to analyse whether the needed econometric assumptions hold. The Hausman-type test (command *estat endogenous* on Stata) was used to verify if the explanatory variables were endogenous and if instrumental variables were needed. To test the relevance and strength of the instruments, the command *estat firststage* was applied, which verifies whether the instruments explain a sufficiently large part of the variation in the endogenous regressors. Finally, the Hansen J-test (command *estat overid*) was used to test for overidentifying restrictions, ensuring that all instruments are valid, meaning that they are uncorrelated with the error term. In the GMM estimation method, only the latter test was relevant to apply.

Once the significance of these tests has been ensured, and multiple model specifications and estimation methods have been employed, the best suited version of the estimated Taylor-type Rules is identified by analysing the statistical significance and magnitude of the coefficients, verifying the goodness of fit of the model and its error dimension, and by conducting a critical analysis of the interpretability and alignment of the results with Norges Bank's monetary policy statement and central banking literature. Once this process is completed, the Norwegian and Global Climate Policy Uncertainty Indexes will be introduced as explanatory variables in the formula, in order to understand if they make the estimated Taylor-type Rules a better fit. This identification process is similar to the one described just above, and a critical analysis of the results is conducted.

CHAPTER 3

Results and Discussion

3.1. Analysing the Climate Policy Uncertainty Indexes

After performing the described steps in the methodology chapter to construct the Climate Policy Uncertainty Indexes for Norway (CPU_N) and for the World (CPU_G), we are left with six distinct CPUs, each considering the different benchmark term employed, as shown in Table 3.1:

Table 3.1: Denomination of the Climax Policy Uncertainty Indexes according to the selected benchmark term.

Benchmark term / Region	**Climate change**	**Pollution**	**Sustainable**
Norway (CPU_N)	CPU_{N1}	CPU_{N2}	CPU_{N3}
Global (CPU_G)	CPU_{G1}	CPU_{G2}	CPU_{G3}

Figure 3.1 plots the three Climate Policy Uncertainty Indexes for Norway in a monthly format, as the quarterly format will only be used in the analysis in conjunction with the estimated Taylor-type Rules. As a reminder, each monthly value represents the level of uncertainty regarding climate policy. Higher values indicate increased public attention to climate-related topics and a greater perceived uncertainty or risk regarding climate policy developments.

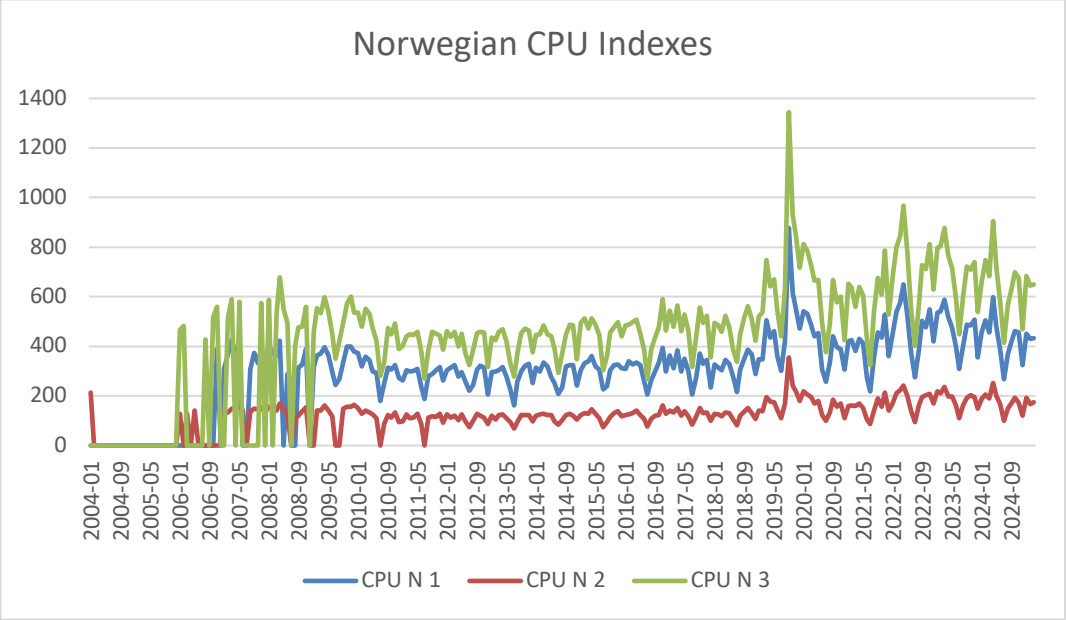


Figure 3.1: Norwegian Climate Policy Uncertainty Indexes (CPU_N) from January 2004 to March 2025.

It is possible to conduct a critical analysis of the plotted graph. As visible in Figure 3.1, the three indexes show quite a similar behaviour in terms of high and low popularity of the searched keywords over time. The main difference among the three CPU indexes is their average value over the sample. In the case of the benchmark term "sustainable", CPU_{N3} has the highest average monthly value, equalling approximately 441.45. It is followed by CPU_{N1}, with a monthly average of approximately 298.77, and only then CPU_{N2}, which differentiates from the other two indexes by having a significantly lower monthly average of approximately 119.51.

It is also important to notice that from January 2004 to January 2006, the large majority of monthly values of the indexes are equal to zero, reflecting a very low relative search interest in climate policy-related topics in that period. This comes to show that there was a reduced public awareness at the time surrounding climate change discourse in Norway, which only started being more heavily discussed and visibly debated after 2006, the time when the indexes' values started being consistently greater than zero.

In Figure 3.2, the contrasting Global Climate Policy Uncertainty Indexes are plotted. Once again, the three indexes show a very similar behaviour over time and, as in the Norwegian case, CPU_{G3}, corresponding to the benchmark term "sustainable", also shows the highest monthly average of approximately 540.61, further distancing itself from the other indexes. However, in the global case, CPU_{G2} is the second index with the highest monthly average of approximately 273.53, closely followed by CPU_{G1}, equalling 224.60.

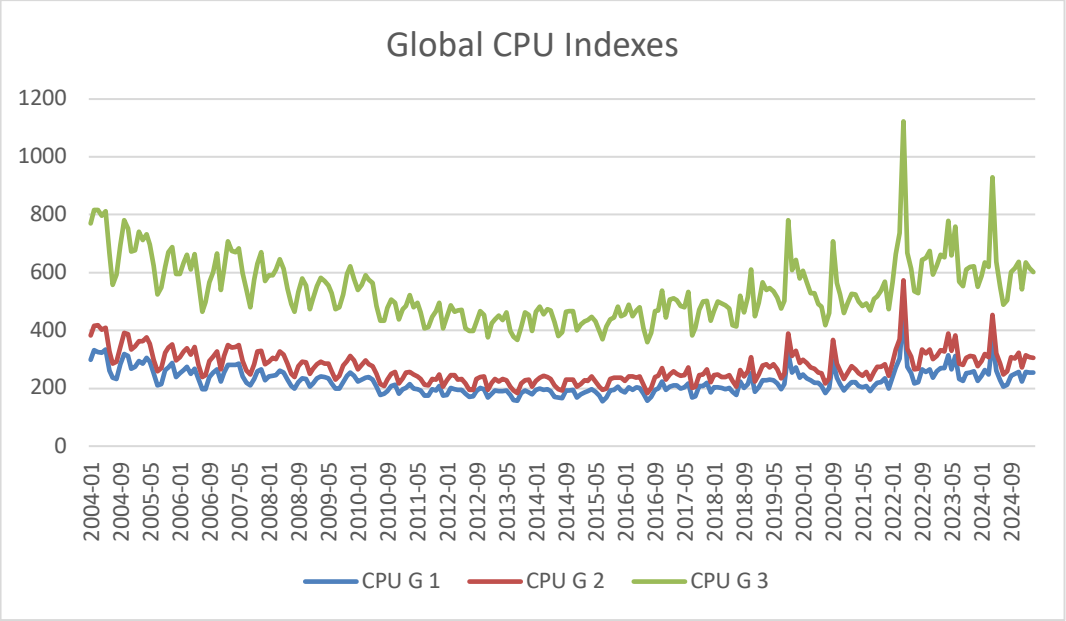


Figure 3.2: Global Climate Policy Uncertainty Indexes (CPU_G) from January 2004 to March 2025.

In the case of the global indexes, there is no period in the sample where the values are consistently equal to zero. This suggests that, when considering worldwide Google searches, public awareness and uncertainty regarding climate policy and climate change-related topics started earlier than in Norway, showing a significant level compared to the total searches conducted at the time. However, looking at the sample monthly average of all the indexes, it is possible to notice that although the Norwegian indexes only show relevant values from 2006 on, the monthly averages are still high and comparable to those of the global indexes, highlighting that public awareness in Norway rapidly grew in the following two decades.

Before starting any other detailed analysis of the novel indexes, the CPUs in their monthly format were tested for stationarity using the Augmented Dickey–Fuller unit-root test (*dfuller* command on Stata), to understand if their statistical properties are stable in the time sample. Indeed, the null hypothesis of the presence of a unit root was rejected at the 1% significance level. The p-values were equal to 0.0000 in all the novel indexes and equal to 0.0002 on the CPU index developed by Gavriilidis (2021) (Annex A), confirming that the series are stationary in levels without needing to be transformed by applying natural logarithms or first differences.

To understand which CPU better relates to the recognised literature, a Pearson Correlation test was applied between the novel indexes and the Climate Policy Uncertainty (CPU) index for the United States developed by Gavriilidis (2021), which is a news-based measure that has been widely used in several academic works and recognised as a reliable indicator for climate policy uncertainty. The correlation test results (*pwcorr* command on Stata) showed that the six novel CPUs have a statistically significant correlation with the literature CPU index at the 1% level, except CPU_{G2}, which is significant at the 5% level (Annex B). This result suggests that the novel indexes using the above-mentioned methodology are robust and empirically validated, being consistent with the performance of the literature index.

The Norwegian indexes have a moderately strong and positive correlation with Gavriilidis' CPU index, ranging from 0.5457 to 0.5739. On the other hand, the global indexes, although still statistically significant, have a weaker positive correlation, ranging from 0.1557 to 0.1687. This difference might arise from the fact that both the literature's CPU for the United States and the novel CPUs for Norway are country-specific measures. At the same time, the global indexes consider a much bigger region of sampling. As such, the former more closely reflects comparable economic and institutional dynamics, since the two countries are developed economies with sustainable policies and public climate change discourse. The broader scope of the latter most likely dilutes the comparability with the country-specific index, reflecting very different manners in which climate policy uncertainty is perceived depending on national factors such as level of development, public commitment to the green transition, and frequency of broadcasted events surrounding climate change.

Both in the Norwegian and in the Global case, the Climate Policy Uncertainty Indexes associated with the benchmark term "climate change" (CPU_{N1} and CPU_{G1}) have the highest correlation level with Gavriilidis' index, at 0.5739 and 0.1687, respectively. As such, these novel indexes seem to best align with the literature benchmark in capturing climate policy uncertainty, as illustrated in Figure 3.3. In light of these findings, a more detailed critical analysis of CPU_{N1} and CPU_{G1} will be conducted.

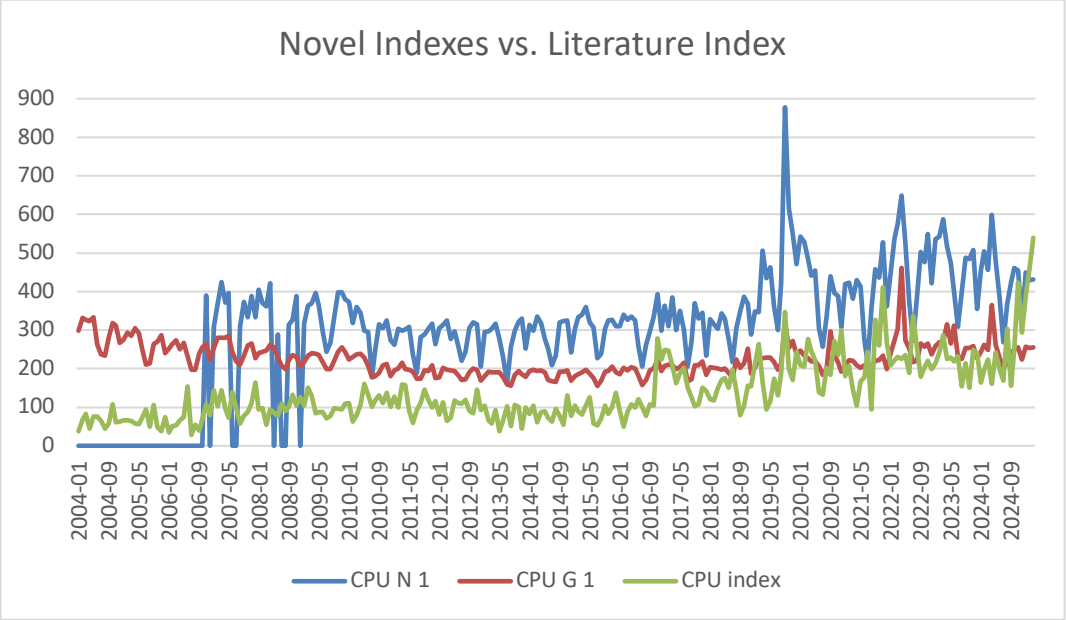


Figure 3.3: Novel CPU_{N1} and CPU_{G1} compared to the literature's CPU Index developed by Gavriilidis (2021).

First of all, when analysing Figure 3.4 that plots the novel Norwegian and Global Climate Policy Uncertainty Indexes associated benchmark term "Climate Change", it is noticeable that both indexes show similar behaviour in capturing climate policy uncertainty over time. Although the overall Pearson correlation between the two indexes is low, equalling a value of 0.0618 (Annex C1), the same analysis made on the first differences of the indexes shows a moderately strong correlation of 0.4920 (Annex C2). This suggests that while there is a weak linear co-movement between the two indexes over the full sample, Norwegian and Global uncertainty tend to move in the same direction and respond similarly to internal climate policy-related events, although not necessarily at the same time or magnitude.

More importantly, in the last decade, there has not only been an increase in average levels of climate policy uncertainty, but also in the indexes' correlation level. Two major climate policy-related events define the last ten years regarding climate change discourse and public awareness: the adoption of the Paris Agreement in December 2015 and the beginning of its forcing in November 2016 (UN, 2015); and the escalation of the Russo-Ukrainian War in February 2022, raising insecurity on topics related to fossil fuel dependency, spiking energy prices and the costs associated with the green transition (Godzimirski, 2024).

These events are portrayed in the indexes' behaviour. Since the beginning of 2015, there has been an increase of approximately 83.13% in the level of climate policy uncertainty portrayed on the Norwegian index, rising from an average of 213.26 between 2004 and 2014, to an average of 390.53 from 2015 until the end of the sample in March 2025. Similarly, since 2022, the increase has been of 68.96% in the Norwegian index and 19.56% in the Global index. Indeed, in the Norwegian case, the year 2022 was the one with the highest relevance for measuring climate policy uncertainty, accounting alone for 7.63% of the total observed uncertainty until 2025.

Additionally, the period between 2015 and 2025 accounts for 62.40% of the total observed uncertainty since 2004, and the period between 2022 and 2025 accounts for 22.03%. These results are indicative of a significant upward shift and rapidly rising concern regarding climate-related topics in recent years, which aligns with the NGFS' concern that climate policy uncertainty will increase in relevance in the following years and become aligned with the monetary policy traditional horizon (NGFS, 2024a).

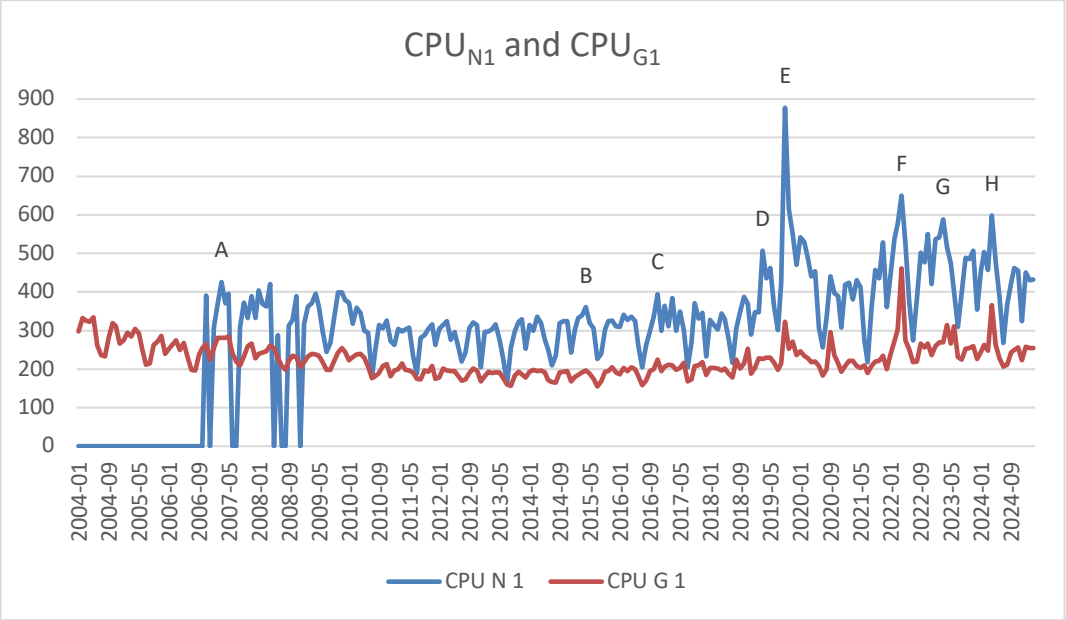


Figure 3.4: Norwegian and Global Climate Policy Uncertainty Indexes associated with the benchmark term "Climate Change", denominated as CPU_{N1} and CPU_{G1}, respectively.

Moreover, the correlation between the indexes has also become much stronger in the last decade (Annexes C3 and C4). Since 2015, the correlation level between CPU^{N1} and CPU_{G1} has risen to 0.8073, and to 0.6513 in the comparative analysis of the first difference version of the variables. Compared to the whole sample, this increase is also noticeable since 2022, having the correlation level risen to 0.7297 and to 0.6308 in level and first differences, respectively. This analysis suggests a growing alignment between Norwegian and global climate policy uncertainty, reflecting the impact of the signing of multilateral agreements and the global energy crisis, where the policy narrative and public discourse are increasingly sensitive and interdependent on global developments, and vice versa.

Granger Causality tests were also applied to verify the lead and lag relation between the two indexes (command *vargranger* on Stata), revealing a dynamic and horizon-dependent behaviour (Annex D). At the short-term 3-month horizon, there is a mutual effect between the indexes, where the leading behaviour of the Global index over the Norwegian index is the most relevant and significant at the 1% level, suggesting that shocks in both indexes are rapidly transmitted to the other. However, over the medium horizon of 6 months, only the Global index is able to predict the Norwegian behaviour at the 5% level, highlighting Norway's reaction to global developments and events. Finally, at a longer horizon of 12 months, the causality effect is reversed, since Norway statistically leads the Global index at the 5% level. This dynamic finding suggests that although the country-specific Norwegian behaviour is mainly influenced by global dynamics in the short- to medium-term, in the long-term it contributes to shaping the global trend. This might be due to Norway's role as a major oil producer and energy exporter, as well as an active participant in international climate policy debates.

The indexes can also be analysed in light of the keywords that affected their behaviour. Both in the Norwegian and in the Global Indexes, the keywords "Nature", "Climate" and "Environment" were the ones which contributed the most to the total calculated climate policy uncertainty over the sample period. Additionally, considering the marked spikes on Figure 3.4, in the Norwegian case, the keyword "Environment" induced spike A, while "Nature" induced spikes B, C and G, "Climate" induced spikes D, F and H, and "Greta Thunberg" induced spike E. On the other hand, in the Global case, the keyword "Nature" induced all the spikes in the graph, except for spikes F and H that were induced by the keyword "Climate".

Each relative spike in climate policy uncertainty can also be examined in the context of major political events, as shown in Table 3.2, which may have driven public online interest in climate policy-related topics. It is important to note that media coverage and public attention may exhibit a lagged effect, meaning that the peaks in search activity do not always perfectly align with the timing of external events. The fact that the spikes successfully match major political events validates the indexes intent to proxy climate policy uncertainty and climate risk with reality.

Table 3.2: Major political events associated with the CPU_{N1} and CPU_{G1} spikes.

Spike	Date	Event
A	03-2007	IPCC released the first part of the Fourth Assessment Report (AR4) in March 2007, and continued publishing other parts in the months that followed. It was the most comprehensive summary of the possible impacts of climate change ever published until that date, having drawn widespread media attention and increased awareness to the topic (IPCC, 2007). At the same time, Norway's government had presented a major climate action plan with ambitious climate targets in 2006 that started to take hold in 2007, intensifying public discussion around carbon taxation, emissions trading caps and the national oil and gas industry (Norwegian Ministry of the Environment, 2007).
B	04-2015	In April 2025, a political scandal unfolded in Norway when the Finance Minister publicly questioned whether climate change was man-induced, conflicting with the country's stance in United Nations climate talks and national targets to reduce carbon emissions (Fox News, 2015).
C	11-2016	The United States presidential election in November 2016 resulted in Donald Trump's first victory to the White House. This outcome likely heightened global perceptions of uncertainty, including those regarding climate policy issues, since Donald Trump had previously expressed scepticism surrounding climate change. Some even described his election as "game over for the climate" (Milman, 2016, para. 2).
D	03-2019	2019 was a year marked by the surge of climate activism led by Greta Thunberg's strikes, and in March of the same year occurred the first widespread school strike in Norway (Bir, 2019). Additionally, early conversations about the UN Climate Change Conference (COP25) that occurred in December of the same year might have surged active search and uncertainty about climate related issues.
E	09-2019	In autumn 2019, climate strikes were a global phenomenon, led by Greta Thunberg's environmental activism and the Fridays for Future movement. It created a shift in youth's climate awareness and the frequency of media coverage on the topic (Taylor et al., 2019). The transition to a sustainable economy and the end to Arctic drilling were also key discussed topics at the time (Hestvik, 2022).

F	04-2022	With the beginning of the Ukrainian War and the banned import of oil and natural gas from Russia, Norway became a major energy supplier to Europe, raising uncertainty among the population on topics related to fossil fuel dependence, spiking energy prices and the costs associated with the green transition (Godzimirski, 2024).
G	03-2023	The energy crisis continued and intensified after the beginning of the Ukrainian War, raising concerns on the dependency of the Norwegian economy to the rest of Europe and on the fossil fuel sector (Godzimirski, 2024). At the same time, the feeling of needed urgency to conduct and plan the green transition led to initial discussions on European Union's Net-Zero Industry Act after the United States announced the Inflation Reduction Act, severely affecting the conduct of climate policy in Europe related to industries and manufacturing (Naujokaitytė, 2023). Additionally, IPCC published the Synthesis Report summarizing the Sixth Assessment Report in March 2023, calling for urgent action to avoid irreversible levels of global warming and global catastrophic impacts (Harvey, 2023).
H	04-2024	2024 was shaped by several high-profile litigation lawsuits imposed on the Norwegian Government for oil drilling in the Arctic, namely by the Worldwide Fund for Nature (WWF), forcing the country to pause the plans to mine the deep sea (McVeigh, 2024). There could also have been public uncertainty regarding climate policies in anticipation to the European Parliament elections, where climate and energy were one of the most debated topics (Wettengel, 2024); and as expectations and discussions on the UN Climate Change Conference (COP29) held in November of the same year grew (WMO, 2024).

3.2. Analysing the Estimated Norwegian Interest Rate Rules

All the variables introduced in the different Taylor-type Rules, to estimate Norges Bank's interest rate path, were tested for endogeneity using the Augmented Dickey-Fuller unit-root test (*dfuller* command on Stata). As presented in Annex E, the results indicate that most series – including inflation, the output gap and most novel climate policy uncertainty indexes in quarterly format – are stationary, with rejection of the unit root hypothesis at the 1% significance level. The unemployment rate and CPU_{N3} are also considered stationary, but only at the 10% significance level. The exchange rate, however, displays clear evidence of non-stationarity, with a p-value of 0.9762, for which the first difference of the variable was used in all estimations to account for this fact.

As outlined in the methodology, multiple alternative specifications of the original Taylor Rule were estimated. Some of these specifications produced relatively weaker fits to Norges Bank's past monetary policy decisions, and are therefore only presented in Annex G. The discussion below focuses on the three specifications that yielded the best alignment with past interest rate decisions, with the corresponding detailed outputs in Annex F.

The first specification, Taylor Rule 1 (TR1), corresponds to the baseline model, where inflation and the output gap are used as explanatory variables for the behaviour of the interest rate rule. Given the possibility of potential endogeneity due to the relation between these regressors and the interest rate, instrumental variables were employed using four lags of each explanatory variable as instruments. However, the Hausman-type test yields a p-value of 0.1421, and the null hypothesis of exogeneity cannot be rejected, implying that there is no evidence that inflation and the output gap are endogenous. Nevertheless, the instruments are still employed for increased robustness.

The validity of the instruments is confirmed in all three main estimated Taylor-type Rules according to the Hansen J-test, with p-values of 0.3168 (TR1), 0.5811 (TR2) and 0.4826 (TR3), indicating that the overidentifying restrictions are not rejected and the instruments are exogenous as a group. In terms of instrument strength, the overidentifying restriction test shows that the instruments explain a reasonable proportion of the variation of the explanatory variables, particularly for the output gap (with a Shea's partial R^2 of 0.4734) and more modestly for inflation (0.2092). Taken together, the results suggest that while the instruments are valid, their strength is limited. This issue of weak instruments is well-documented in the literature (Mavroeidis et al., 2014) and should be considered when interpreting the results.

When analysing Taylor Rule 1 in Figure 3.5 and the corresponding results of the estimation in Annex F1, both explanatory variables' coefficients appear as positive and statistically significant at the 5% level. The inflation coefficient is approximately 0.3196, below the original Taylor's threshold of unity: a necessary condition for monetary policy not to be accommodative to inflation (Clarida et al., 1999). This fact suggests that Norges Bank may not react aggressively to inflation deviations, using other instruments besides interest rate setting to tackle it when employing its credible, flexible and forward-looking inflation targeting regime, namely by publishing the interest rate path forecasts to anchor expectations.

On the other hand, the output gap coefficient is approximately 0.3282, indicating a meaningful reaction to real economic conditions. This result is consistent with the dual objectives of flexible inflation targeting and, specifically stated in Norges Bank's mandate, to "maintain monetary stability and to promote the stability of the financial system", while contributing to "high and stable output and employment." (Norges Bank, 2020, Section 1-2, (1) and (2)). However, the explanatory power of the model is limited (R^2 equals 0.0232), showing that this simplistic estimation captures only a small fraction of the variation in the policy rate and is consistent with the literature that states that the simple contemporaneous Taylor rule is insufficient (Hamalainen, 2004), needing more detailed characteristics that are included in the Taylor-type Rules that follow to be in line with New Keynesian fundamentals.

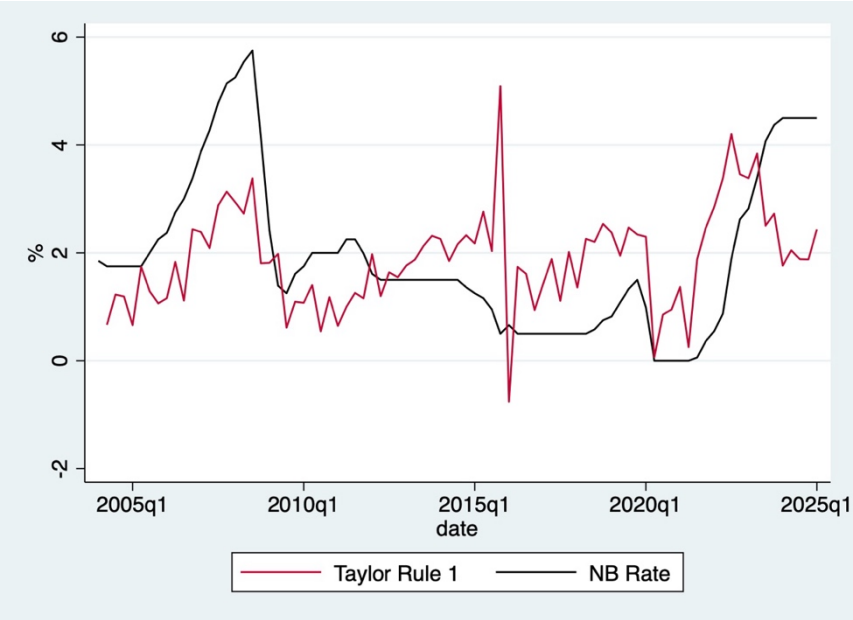


Figure 3.5: Taylor Rule 1 (TR1) - Baseline specification using instrumental variables for inflation and the output gap as explanatory variables.

The second specification, Taylor Rule 2 (TR2), presented in Figure 3.6 and Annex F2, extends the baseline model by allowing for interest rate smoothing through the inclusion of the lagged Norges Bank's policy rate, substantially improving the results verified in Taylor Rule 1. The estimated smoothing coefficient is very high, at approximately 0.7731, and highly significant at the 1% level (p-value < 0.001), indicating that almost four-fifths of the current policy rate is explained by its previous value. This finding reflects Norges Bank's gradualist approach to monetary policy and is consistent with evidence in the literature that central banks' preference for gradualism helps reduce financial market volatility and strengthens the monetary authority's credibility (Woodford, 2003). Indeed, in forward-looking economies, outcomes depend heavily on expected future policy, which, when history-dependent, affects agents' behaviour more effectively.

Additionally, the output gap coefficient rises to approximately 0.6802 and is statistically significant at the 1% level (p-value = 0.002), showing a strong influence on policy decisions and highlighting Norges Bank's concern with real economic activity alongside price stability by paying closer attention to activity and/or output conditions than to inflation in the short term. By contrast, the inflation coefficient becomes smaller, equalling 0.1677, and statistically insignificant (p-value = 0.419). Once again, this is consistent with a regime where the inflation target is credible and expectations are well-anchored, suggesting that deviations in inflation from the target do not necessarily provoke strong monetary policy responses and that real activity is the central driver of the monetary policy decision process. Overall, Taylor Rule 2 substantially improves the fit relative to Taylor Rule 1, since the inclusion of interest rate smoothing drastically improves the explanatory power.

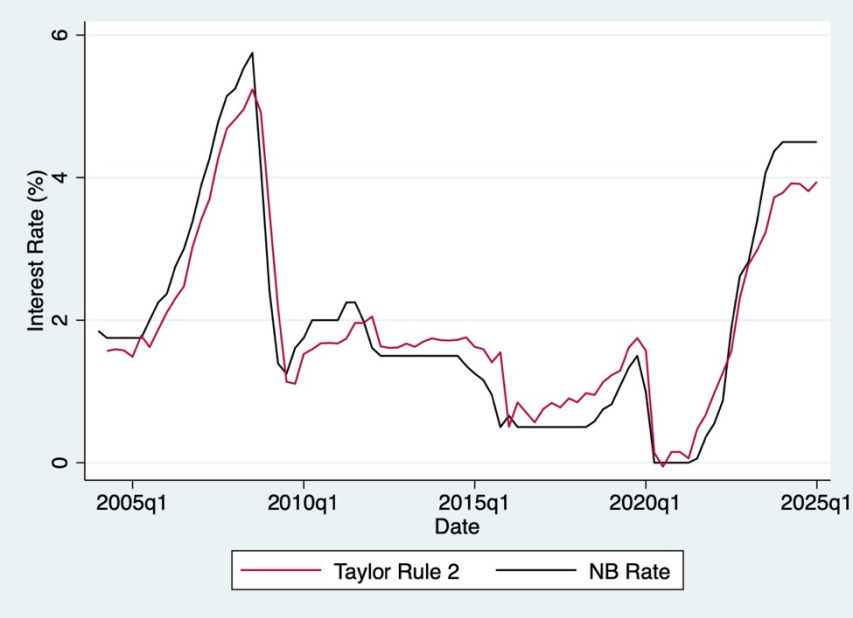


Figure 3.6: Taylor Rule 2 (TR2) - Extends TR1 by incorporating interest rate smoothing through the inclusion of Norges Bank's lagged policy rate.

Finally, the third specification is Taylor Rule 3 (TR3), presented in Figure 3.7 and Annex F3, which incorporates the NOK/EUR exchange rate to reflect Norway's role as a small open economy with its own coin, the Norwegian Krone (NOK). In line with Taylor Rule 2, the evidence of substantial interest rate smoothing is reinforced, with a coefficient of approximately 0.8000, as well as a significant output gap response of approximately 0.6531. Moreover, the inflation coefficient remains small (approximately 0.2675) and statistically insignificant (p-value = 0.378), suggesting that price stability is pursued through expectations anchoring rather than strong contemporaneous policy responses, in line with Norges Bank's usually described monetary policy stance (Norges Bank, 2024b).

Furthermore, the exchange rate coefficient is negative and equal to -0.2433, approximately, which is consistent with theoretical expectations: a depreciation increases import prices and therefore causes inflationary pressures, leading the central bank to tighten the monetary policy in place (Ball, 1999). However, the coefficient is statistically insignificant (p-value = 0.624), suggesting that exchange rate dynamics are not an independent driver of Norges Bank's interest rate decisions once inflation and output are considered. Indeed, the introduction of exchange rates into Taylor-type Rules to better model small open economies, such as Norway, has been studied. However, the results show that they do not explicitly improve the macroeconomic performance of the model, since changes in the exchange rate are already captured through the effect of foreign prices on aggregate demand and production costs, as well as via other domestic variables (Hamalainen, 2004).

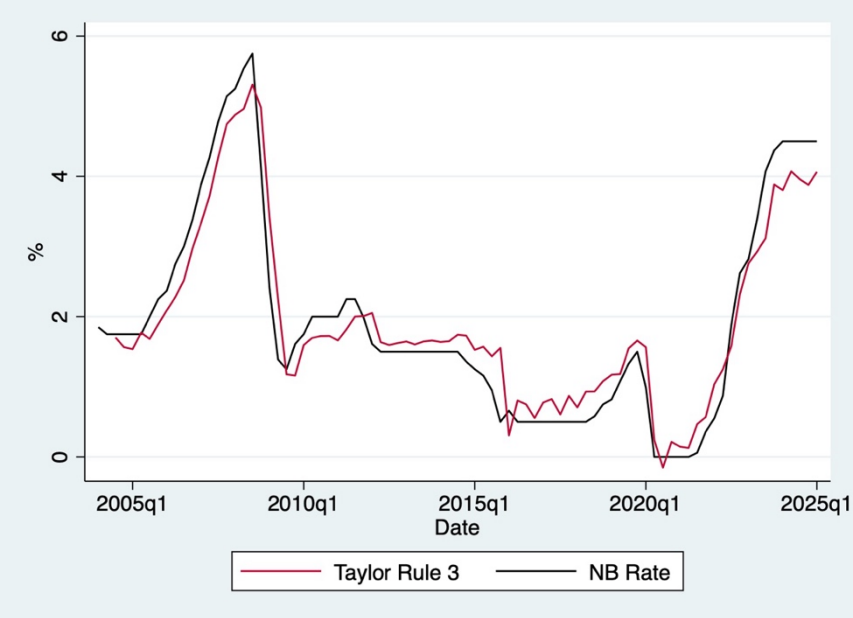


Figure 3.7: Taylor Rule 3 (TR3) – Builds on TR2 by adding the NOK/EUR exchange rate as an explanatory variable.

Overall, the results indicate that Taylor Rule 2 provides the best empirical fit to Norges Bank's past monetary policy decisions, since while the introduction of the NOK/EUR exchange rate as an explanatory variable in Taylor Rule 3 yields the expected negative sign, the coefficient is not statistically significant and does not improve the explanatory power of the model. Consequently, Taylor Rule 2 presents itself as the most appropriate estimation and will be used in the following subchapter when studying the introduction of the novel Climate Policy Uncertainty Indexes as regressors. Regarding Norges Bank's monetary policy behaviour, the Taylor Rule estimations reveal a number of characteristics that are consistent with the literature's findings regarding central banking, but also with the operational framework employed by the Norges Bank.

First, the very high and significant interest rate smoothing parameter (from approximately 0.77 to 0.80) confirms Norges Bank's gradualist approach to monetary policy, in line with its choice to introduce an interest-rate smoothing term in its loss function (Norges Bank, 2024b), and with international evidence solidified in New Keynesian fundamentals that central banks adjust their interest rates cautiously to avoid excessive volatility and to strengthen credibility (Woodford, 2003).

Second, the output gap plays a central role in Norges Bank's decision-making process, with a strong and significant coefficient of around 0.65 to 0.68. This fact highlights the bank's mandate emphasis to not only stabilise inflation within its flexible target, but also to promote the highest output and employment level consistent with price stability over time, working to strike a balance between these dual objectives by placing considerable weight on real economic activity (Norges Bank, 2024b).

Similarly, the inflation response is positive but not statistically significant, suggesting that the bank relies on credibility and expectations anchoring to pursue price stability, and not necessarily on an aggressive contemporaneous interest rate response. Indeed, Norges Bank pursues flexible and forward-looking inflation targeting, with an operational target of consumer price inflation close to 2% over time, using other instruments besides interest rate setting to anchor expectations and reinforce its credibility, such as the publishing of the interest rate forecasts every quarter (Norges Bank, 2024b).

Finally, the NOK/EUR exchange rate does not appear to be an independent policy driver, in line with the literature's belief that its effects in small open economies are absorbed indirectly through domestic variables (Hamalainen, 2004). In 2018, Norges Bank also decided to de-emphasise this variable as a target in itself, recognising that it serves as a shock absorber rather than an explanatory variable to construct monetary policy decisions (Norges Bank, 2024b).

Taken together, the estimated Taylor-type rules reveal that a combination of strong interest rate smoothing, a marked reaction to real economic activity, a softened contemporaneous response to inflation, and no direct targeting of the foreign exchange rate best describes Norges Bank's monetary policy stance. These features are not only consistent with the framework stated by the bank itself, but also with what is found in the state of the art. Indeed, recent research describes Norges Bank behaviour very similarly: a high smoothing coefficient of approximately 0.8, a strong response to the output gap, and a reduced emphasis on inflation as an explanatory variable in recent years due to well-anchored expectations (Lindalen & Maffei-Faccioli, 2025).

This convergence between the Bank's statement, the literature findings and the estimated results obtained in this dissertation reinforces the conclusion that the estimated Taylor Rule 2 provides a robust description of the Norwegian monetary policy framework and behaviour, serving as an adequate baseline to extend the novel by introducing the Climate Policy Uncertainty Indexes.

Another relevant estimation variation to mention is Taylor Rule 4 (Annex G1), which extends Taylor Rule 2 by replacing contemporaneous inflation with forward-looking inflation. Curiously, although it is theoretically expected for forward-looking behaviour to better describe the central bank's decision-making process and the conduct of the economy participants, since New Keynesian fundamentals focus on the importance of inflation expectations (Clarida et al., 1999), the model does not improve TR2's predictions. Indeed, the smoothing and output gap coefficients remain virtually unchanged, and the forward inflation term remains small and statistically insignificant. A plausible explanation for this fact is that inflation expectations are very well-anchored around the 2% target due to Norges Bank's long-established credibility and tools to manage its communication effectively. Once again, it might also reflect the bank's emphasis on real activity to construct and weight its monetary policy decisions.

3.3. Impact of the Index on the Taylor Rule

The last objective of the Results and Discussion chapter is to analyse the impact of introducing the novel Climate Policy Uncertainty Indexes into the best-fitted Taylor-type Rule estimation, which corresponds to Taylor Rule 2. As described earlier, this Taylor-type Rule includes inflation and the output gap as explanatory variables, using as instruments four lags of each variable and accounting for interest rate smoothing. In order to conduct this analysis, the CPUs were transformed to a quarterly format by averaging their 3-month values.

Furthermore, when plotting the Climate Policy Uncertainty Indexes, their behaviour suggested potential signs of seasonality, with peaks often concentrated in March and April. To address this possibility, Holt–Winters exponential smoothing (command *tssmooth shwinters* on Stata) was applied to the series, in order to obtain seasonally adjusted versions of the indexes. Most of the series converged successfully, producing stable weights for level, trend, and seasonal components, thereby confirming the presence of seasonal patterns in most of the CPUs, providing a more reliable representation of the underlying dynamics of climate policy uncertainty based on Google Trends data. However, convergence was not achieved in CPU_{N2}, suggesting that the seasonal component of the series seems to be weak or irregular. Consequently, CPU_{N2} will continue to be used in its original format and no seasonally adjusted version is presented for this index.

The results of the introduction of all CPU variations as explanatory variables into Taylor Rule 2 are presented in Figure 3.8, with detailed results and corresponding graphs in Annex H.

model	cpu	rmse	dRMSEpct	Jp	b4	p_b4	sig_b4
TR2_sa_cpug1	sa_cpug1	0.3724	-0.00	.7755331	.0109587	.01241043	**
TR2_sa_cpug2	sa_cpug2	0.3756	0.85	.77025372	.00840207	.01508633	**
TR2_sa_cpug3	sa_cpug3	0.3794	1.88	.85675436	.00445227	.01135876	**
TR2_cpug2	cpug2	0.4072	9.36	.53270379	.00850871	.09299682	*
TR2_cpug3	cpug3	0.4106	10.26	.6073655	.00454021	.06952389	*
TR2_cpug1	cpug1	0.4246	14.02	.54073453	.01202325	.11254684	
TR2_base		0.4296	15.36	.58109573	.	.	
TR2_sa_cpun2	sa_cpun2	0.4363	17.17	.9245246	.00309106	.078288	*
TR2_cpun2	cpun2	0.4519	21.36	.94131137	.00440516	.04751437	**
TR2_sa_cpun3	sa_cpun3	0.4552	22.24	.87484277	.00108359	.03723642	**
TR2_sa_cpun1	sa_cpun1	0.4559	22.43	.8881391	.00142283	.03467745	**
TR2_cpun3	cpun3	0.4621	24.10	.88043863	.00103405	.0538499	*
TR2_cpun1	cpun1	0.4684	25.78	.95632765	.00169892	.05082928	*

Figure 3.8: Results of the introduction of all CPU variations as explanatory variables into Taylor Rule 2.

First and foremost, it is possible to notice that almost all novel Climate Policy Uncertainty Indexes are statistically significant explanatory variables for Norges Bank's interest rate path, except for CPU_{G1}. All seasonally adjusted versions of the global indexes reached the 5% significance level, as well as the original and the seasonally adjusted versions of CPU_{N1}. The remaining CPUs reached the borderline significance level of 10%. This overall statistical significance is important: it confirms that climate policy uncertainty can be considered a determinant of the monetary policy decisions to set the interest rate. In practical terms, the results support the claim that uncertainty linked to climate policy has entered the range of variables to which Norges Bank may implicitly react when setting its policy rule.

Secondly, the estimated CPU coefficients are consistently positive, meaning that when climate policy uncertainty increases, Norges Bank tends to raise its policy rate. This finding is in line with the theoretical expectation found in the literature, since monetary policy is expected to tighten in response to heightened risk and volatility to counteract inflationary pressures, including when it refers to climate policy uncertainty or, more generally, climate risk (NGFS, 2024b). Nevertheless, the magnitude of the coefficients is relatively small, ranging approximately between 0.0010 to 0.0202 depending on the specification. This suggests that, although climate risk matters in Norges Bank's framework and aligns with the literature, it is not, at least in the current period and data length, a dominant driver of the Taylor Rule and the estimated interest rate path.

Thirdly, it is relevant to analyse the RMSE values, corresponding to the mean squared error that measures forecast accuracy. The results show that all global indexes and their seasonally adjusted versions reduce the RMSE relative to the baseline Taylor Rule 2, thereby improving the predictive performance of the model. In contrast, the country-specific Norwegian indexes slightly increase the RMSE, even when their coefficients are statistically significant.

This is a curious and double-sided outcome: it might suggest that the global measures of climate policy uncertainty, based on Google Trends data, may capture broader external shocks related to climate risk that improve the predictive accuracy of Norges Bank's working framework, while the national indexes seem to capture the bank's structural sensitivity without necessarily enhancing the forecast precision. This distinction could be due to Norway's role as a small open economy, strongly permeable to external shocks that affect its monetary policy stance, but also to international climate developments that spread through physical or transition risks without considering national borders. This fact might make global uncertainty a better predictor of its monetary policy stance, even if domestic climate policy uncertainty remains more statistically significant.

Overall, these results confirm that introducing measures of climate policy uncertainty into Norges Bank's monetary policy framework can add explanatory and predictive value. The CPUs are not only statistically significant regressors but, in the case of the global indexes, also contribute to reducing estimation errors. Indeed, this suggests that the bank could improve the robustness and predictive power of its macroeconomic forecasts and analytical models if it introduced climate risk considerations into its methodological framework.

Henceforth, the findings reinforce one of the few aspects already well-established and consensually recognised in the literature about climate change and central banking: climate risk is not ignorable and should be incorporated into the operational framework of central banks and monetary institutions (NGFS, 2024a). Moreover, transition risk, which includes climate policy uncertainty, is expected to increase in the coming years, as countries tighten green climate policies to meet long-term international targets and the likelihood of a disorderly transition rises (Dikau & Volz, 2021). As climate change and its associated policies become more tangible and noticeable in the traditional monetary policy horizon, the coefficient of the Climate Policy Uncertainty Indexes might tend to increase in magnitude, reflecting stronger monetary policy responses to this type of uncertainty.

Nevertheless, these promising results should be interpreted considering the limitations of this investigation project. First, even when statistically significant, the effects of the CPU variables are economically modest and relatively small. Second, the result of the estimation varies in a significant manner depending on the CPU specification: with different benchmark terms or with incorporated seasonal adjustment. This highlights a lack of long-held robustness and indicates that the explanatory power of the novel indexes is fragile and depends on the methodological choices employed. Taken together, these limitations suggest that while the evidence is encouraging and reinforces the literature's expectation on the growing importance of climate risk considerations and how it influences the central banking system, it should be regarded as exploratory and as a stepping stone for further investigation and validation.

Conclusion

In conclusion and directly addressing the research question: *How does climate policy uncertainty affect Norges Bank's ability to pursue its monetary policy mandate?* This dissertation demonstrates that climate policy uncertainty shapes Norges Bank's decision-making process, highlighting that this form of climate risk is not negligible to the bank's operational and forecasting activities. On the contrary, the novel proxies created in this work demonstrate that, when used as explanatory variables, they can influence the interest rate rule both as structural drivers and as predictive enhancers, particularly through domestic and global measures, respectively.

The monetary policy framework that Norges Bank already employs provides a good starting point to tackle this emerging relevant risk, since flexible inflation targeting naturally allows for a smoother and easier absorption of climate-related shocks. Nevertheless, as climate change becomes more pressing, with recurrent and extreme weather events, the tightening of green policies to meet long-term goals and the possibility of converging to a *disorderly transition*, a more active stance might be necessary. Favourably, the results suggest that monetary policy can play an important and complementary role in mitigating shocks arising from climate-related risks, if these are properly considered and accounted for.

Modelling climate change and the associated physical transition risks indeed remains highly ambiguous and deeply dependent on the assumptions made in this highly uncertain and fast-changing environment. However, this uncertainty only reinforces the relevance of continuing to try to model climate risks and their macroeconomic effects, namely in central banking models. An interdisciplinary approach will be essential to better capture the multiple transmission channels through which climate risks and change materialise.

Therefore, this dissertation should be seen as an incremental contribution rather than a comprehensive solution, offering new insights on how novel tools can be incorporated and contributing to the existing literature in several ways. First, it provides evidence on how climate risks, specifically climate policy uncertainty, can be integrated into the operational framework of a central bank, thereby reinforcing the growing consensus that monetary policy cannot remain oblivious to environmental risks. Second, it enriches the literature on the use novel indexes based on Google Trends data in economics and monetary policy, showing that these novel-type indexes can build robust, useful and literature-consistent proxies, including in small open economies. Third, it provides an applied and successful practical study of Norges Bank's Taylor Rule fit, improving the common understanding of how the institution behaves.

The results should, however, be interpreted with caution and seen as modest given the limitations of this research project. The results of using the novel Climate Policy Uncertainty Indexes, although yielding statistically significant measures, are relatively small and highly dependent on the specification used, such as the chosen keywords and benchmark term employed, which is always a subjective and contextual choice, underlining a lack of broad robustness. Moreover, Google Trends data are only available from 2004 onwards, limiting the time span of the possible analysis.

In future investigations, the robustness of the findings can be analysed as the time sample expands and a wider analysis becomes possible. Besides that, other open questions stem from the developed work. For example, how other Google Trends data-based proxies hold when focusing on other types of climate risks, namely when focused on climate awareness or physical risk perception, and what innovative contributions could be yielded in varying specifications, depending on the employed keywords and benchmark terms. Moreover, different regional and country applications of the indexes could be applied, in order to test if the findings generalise to a broad sample of countries, or if they change according to the way communities use internet tools and Google as a search instrument.

In conclusion, this dissertation demonstrates that while the current magnitude of effects is still moderate, climate policy uncertainty is a significant and increasingly important variable for Norges Bank to consider when setting and achieving its monetary policy mandate, alongside other measures for climate risk. As the importance of climate change grows, and it's devastating impacts become more and more visible, so will the mark of its risks on monetary policy mechanisms. Therefore, this work should be regarded as a stepping stone in a longer journey, towards a more systematic, interdisciplinary and resilient incorporation of climate risks in central banking practices.

Ultimately, this is not a task for economists alone. Although monetary policy can add and should contribute to an effective alleviation of climate-related risks, it is only through a credible and consistent sustainable political stance that the green transition can be actively well-managed, a responsibility primarily carried out by governments and responsible political institutions beyond the mandate of central banks. However, in what concerns us, monetary policy should be guided in a way that benefits the planet, recognising that there will be no forecasts, models or economic studies to produce if there is no planet to live in. Too often, debates have been short-sighted in analysing this topic merely as present cost, in a conversation focused on risk aversion rather than supporting the firms and innovations that can make a real difference and bring a positive outcome.

The cost of inaction is immeasurably higher than the cost of action, commitment and intergenerational justice. Therefore, it is also the role of economists, policymakers and financial institutions to support the green transition and associated costs effectively, not only to reduce the risks today, but especially to ensure the conditions for prosperity tomorrow, and tomorrow, and tomorrow.

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Annexes

Annex A: Augmented Dickey-Fuller stationary tests on the novel Climate Policy Uncertainty Indexes and on Gavriilidis' (2021) Climate Policy Uncertainty (CPU) index for the United States.

```
. dfuller cpun1

Dickey–Fuller test for unit root          Number of obs  = 254
Variable: cpun1                           Number of lags =   0

H0: Random walk without drift, d = 0

                                        Dickey–Fuller
                 Test      ———————— critical value ————————
               statistic           1%           5%          10%
———————————————————————————————————————————————————————————
 Z(t)           -5.427      -3.460       -2.880       -2.570
———————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0000.
```

Annex A1: Stationarity test on CPU_{N1}.

```
. dfuller cpun2

Dickey–Fuller test for unit root          Number of obs  = 254
Variable: cpun2                           Number of lags =   0

H0: Random walk without drift, d = 0

                                        Dickey–Fuller
                 Test      ———————— critical value ————————
               statistic           1%           5%          10%
———————————————————————————————————————————————————————————
 Z(t)           -6.450      -3.460       -2.880       -2.570
———————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0000.
```

Annex A2: Stationarity test on CPU_{N2}.

```
. dfuller cpun3

Dickey–Fuller test for unit root          Number of obs  = 254
Variable: cpun3                           Number of lags =   0

H0: Random walk without drift, d = 0

                                        Dickey–Fuller
                 Test      ———————— critical value ————————
               statistic           1%           5%          10%
———————————————————————————————————————————————————————————
 Z(t)           -6.501      -3.460       -2.880       -2.570
———————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0000.
```

Annex A3: Stationarity test on CPU_{N3}.

```
. dfuller cpug1

Dickey–Fuller test for unit root          Number of obs  = 254
Variable: cpug1                           Number of lags =   0

H0: Random walk without drift, d = 0

                                     Dickey–Fuller
                 Test      ———————— critical value ————————
               statistic           1%           5%          10%
———————————————————————————————————————————————————————————
 Z(t)           -6.287       -3.460       -2.880       -2.570
———————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0000.
```

Annex A4: Stationarity test on CPU_{G1}.

```
. dfuller cpug2

Dickey–Fuller test for unit root          Number of obs  = 254
Variable: cpug2                           Number of lags =   0

H0: Random walk without drift, d = 0

                                     Dickey–Fuller
                 Test      ———————— critical value ————————
               statistic           1%           5%          10%
———————————————————————————————————————————————————————————
 Z(t)           -6.210       -3.460       -2.880       -2.570
———————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0000.
```

Annex A5: Stationarity test on CPU_{G2}.

```
. dfuller cpug3

Dickey–Fuller test for unit root          Number of obs  = 254
Variable: cpug3                           Number of lags =   0

H0: Random walk without drift, d = 0

                                     Dickey–Fuller
                 Test      ———————— critical value ————————
               statistic           1%           5%          10%
———————————————————————————————————————————————————————————
 Z(t)           -6.111       -3.460       -2.880       -2.570
———————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0000.                    ~
```

Annex A6: Stationarity test on CPU_{G3}.

```
. dfuller cpuindex

Dickey–Fuller test for unit root          Number of obs  = 254
Variable: cpuindex                        Number of lags =   0

H0: Random walk without drift, d = 0

                                     Dickey–Fuller
                 Test      ———————— critical value ————————
               statistic           1%           5%          10%
———————————————————————————————————————————————————————————
 Z(t)           -4.551       -3.460       -2.880       -2.570
———————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0002.
```

Annex A7: Stationarity test on Gavriilidis' (2021) CPU.

Annex B: Pairwise correlation between the novel Climate Policy Uncertainty Indexes and Gavriilidis' (2021) Climate Policy Uncertainty (CPU) index for the United States.

```
. pwcorr cpun1 cpun2 cpun3 cpug1 cpug2 cpug3 cpuindex, sig star(0.05)
```

	cpun1	cpun2	cpun3	cpug1	cpug2	cpug3	cpuindex
cpun1	1.0000						
cpun2	0.8836*	1.0000					
	0.0000						
cpun3	0.8855*	0.8167*	1.0000				
	0.0000	0.0000					
cpug1	0.0618	0.1327*	0.0518	1.0000			
	0.3257	0.0341	0.4101				
cpug2	0.0450	0.1202	0.0354	0.9954*	1.0000		
	0.4742	0.0552	0.5739	0.0000			
cpug3	0.0479	0.1200	0.0370	0.9923*	0.9933*	1.0000	
	0.4462	0.0557	0.5569	0.0000	0.0000		
cpuindex	0.5739*	0.5457*	0.5585*	0.1687*	0.1557*	0.1646*	1.0000
	0.0000	0.0000	0.0000	0.0069	0.0128	0.0085	

Annex C: Pearson correlations between CPU_{N1} and CPU_{G1}.

```
. correlate cpun1 cpug1
(obs=255)
```

	cpun1	cpug1
cpun1	1.0000	
cpug1	0.0618	1.0000

Annex C1: Pearson correlation between CPU_{N1} and CPU_{G1} in levels.

```
. correlate d_cpun1 d_cpug1
(obs=254)
```

	d_cpun1	d_cpug1
d_cpun1	**1.0000**	
d_cpug1	**0.4920**	**1.0000**

Annex C2: Pearson correlation between CPU_{N1} and CPU_{G1} in first differences.

```
. correlate cpun1 cpug1 if post2015
(obs=123)
```

	cpun1	cpug1
cpun1	**1.0000**	
cpug1	**0.8073**	**1.0000**

```
. correlate cpun1 cpug1 if post2022
(obs=39)
```

	cpun1	cpug1
cpun1	**1.0000**	
cpug1	**0.7297**	**1.0000**

Annex C3: Pearson correlation between CPUN1 and CPUG1 in levels since 2015 and 2022, respectively.

```
. correlate d_cpun1 d_cpug1 if post2015
(obs=123)
```

	d_cpun1	d_cpug1
d_cpun1	**1.0000**	
d_cpug1	**0.6513**	**1.0000**

```
. correlate d_cpun1 d_cpug1 if post2022
(obs=39)
```

	d_cpun1	d_cpug1
d_cpun1	**1.0000**	
d_cpug1	**0.6385**	**1.0000**

Annex C4: Pearson correlation between CPUN1 and CPUG1 in first differences since 2015 and 2022, respectively.

Annex D: Granger Causality tests between CPU_{N1} and CPU_{G1}.

```
. vargranger
```

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
cpun1	cpug1	**12.009**	**12**	**0.445**
cpun1	ALL	**12.009**	**12**	**0.445**
cpug1	cpun1	**22.018**	**12**	**0.037**
cpug1	ALL	**22.018**	**12**	**0.037**

Annex D1: Granger Causality tests between CPU_{N1} and CPU_{G1} at the 12-month lag horizon.

```
. vargranger
```

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
cpun1	cpug1	**14.575**	**6**	**0.024**
cpun1	ALL	**14.575**	**6**	**0.024**
cpug1	cpun1	**7.3387**	**6**	**0.291**
cpug1	ALL	**7.3387**	**6**	**0.291**

Annex D2: Granger Causality tests between CPUN1 and CPUG1 at the 6-month lag horizon.

```
. vargranger
```

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
cpun1	cpug1	**16.299**	**3**	**0.001**
cpun1	ALL	**16.299**	**3**	**0.001**
cpug1	cpun1	**7.9495**	**3**	**0.047**
cpug1	ALL	**7.9495**	**3**	**0.047**

Annex D3: Granger Causality tests between CPU_{N1} and CPU_{G1} at the 3-month lag horizon.

Annex E: Augmented Dickey-Fuller stationarity tests on the Taylor Rules' explanatory variables.

```
. dfuller infl

Dickey–Fuller test for unit root          Number of obs  = 83
Variable: infl                            Number of lags =  0

H0: Random walk without drift, d = 0

                                     Dickey–Fuller
                 Test          ——————— critical value ———————
               statistic           1%           5%          10%
——————————————————————————————————————————————————————————————
 Z(t)           -8.434        -3.534       -2.904       -2.587
——————————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0000.
```

Annex E1: Stationarity test on inflation.

```
. dfuller outputgap

Dickey–Fuller test for unit root                   Number of obs   =  84
Variable: outputgap                                Number of lags  =   0

H0: Random walk without drift, d = 0

                                      Dickey–Fuller
                     Test          ———————— critical value ————————
                statistic              1%            5%            10%
———————————————————————————————————————————————————————————————————
 Z(t)             -3.551          -3.532        -2.903        -2.586
———————————————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0068.
```

Annex E2: Stationarity test on the output gap.

```
. dfuller er

Dickey–Fuller test for unit root                   Number of obs   =  84
Variable: er                                       Number of lags  =   0

H0: Random walk without drift, d = 0

                                      Dickey–Fuller
                     Test          ———————— critical value ————————
                statistic              1%            5%            10%
———————————————————————————————————————————————————————————————————
 Z(t)              0.275          -3.532        -2.903        -2.586
———————————————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.9762.
```

Annex E3: Stationarity test on the NOK/EUR exchange rate.

```
. dfuller ur

Dickey–Fuller test for unit root                   Number of obs   =  84
Variable: ur                                       Number of lags  =   0

H0: Random walk without drift, d = 0

                                      Dickey–Fuller
                     Test          ———————— critical value ————————
                statistic              1%            5%            10%
———————————————————————————————————————————————————————————————————
 Z(t)             -2.763          -3.532        -2.903        -2.586
———————————————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0638.
```

Annex E4: Stationarity test on the unemployment rate.

```
. dfuller cpun1

Dickey-Fuller test for unit root           Number of obs   =    84
Variable: cpun1                            Number of lags  =     0

H0: Random walk without drift, d = 0

                                        Dickey-Fuller
                     Test            critical value
                statistic          1%           5%          10%
------------------------------------------------------------------------------
 Z(t)             -3.238        -3.532       -2.903       -2.586
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0179.
```

Annex E5: Stationarity test on CPU_{N1} (quarterly version).

```
. dfuller cpun2

Dickey-Fuller test for unit root           Number of obs   =    84
Variable: cpun2                            Number of lags  =     0

H0: Random walk without drift, d = 0

                                        Dickey-Fuller
                     Test            critical value
                statistic          1%           5%          10%
------------------------------------------------------------------------------
 Z(t)             -4.071        -3.532       -2.903       -2.586
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0011.
```

Annex E6: Stationarity test on CPU_{N2} (quarterly version).

```
. dfuller cpun3

Dickey-Fuller test for unit root           Number of obs   =    84
Variable: cpun3                            Number of lags  =     0

H0: Random walk without drift, d = 0

                                        Dickey-Fuller
                     Test            critical value
                statistic          1%           5%          10%
------------------------------------------------------------------------------
 Z(t)             -2.634        -3.532       -2.903       -2.586
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0863.
```

Annex E7: Stationarity test on CPU_{N3} (quarterly version).

```
. dfuller cpug1

Dickey–Fuller test for unit root           Number of obs  = 84
Variable: cpug1                            Number of lags =  0

H0: Random walk without drift, d = 0

                                      Dickey–Fuller
                 Test            ———————— critical value ————————
               statistic              1%           5%           10%
———————————————————————————————————————————————————————————————
 Z(t)           -4.055          -3.532       -2.903       -2.586
———————————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0011.
```

Annex E8: Stationarity test on CPU_{G1} (quarterly version).

```
. dfuller cpug2

Dickey–Fuller test for unit root           Number of obs  = 84
Variable: cpug2                            Number of lags =  0

H0: Random walk without drift, d = 0

                                      Dickey–Fuller
                 Test            ———————— critical value ————————
               statistic              1%           5%           10%
———————————————————————————————————————————————————————————————
 Z(t)           -4.079          -3.532       -2.903       -2.586
———————————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0010.
```

Annex E9: Stationarity test on CPU_{G2} (quarterly version).

```
. dfuller cpug3

Dickey–Fuller test for unit root           Number of obs  = 84
Variable: cpug3                            Number of lags =  0

H0: Random walk without drift, d = 0

                                      Dickey–Fuller
                 Test            ———————— critical value ————————
               statistic              1%           5%           10%
———————————————————————————————————————————————————————————————
 Z(t)           -3.986          -3.532       -2.903       -2.586
———————————————————————————————————————————————————————————————
MacKinnon approximate p–value for Z(t) = 0.0015.
```

Annex E10: Stationarity test on CPU_{G3} (quarterly version).

Annex F: Best-fitted Taylor-type Rule estimations of Chapter 3.2.

Annex F1: Estimation of Taylor Rule 1 and respective robustness tests. TR1 includes inflation and the output gap as explanatory variables, using their lagged values as instruments.

```
. ivregress gmm nb_rate (infl outputgap = infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4)

Instrumental variables GMM regression           Number of obs   =         80
                                                Wald chi2(2)    =      17.61
                                                Prob > chi2     =     0.0001
                                                R-squared       =     0.0232
GMM weight matrix: Robust                       Root MSE        =     1.5001

------------------------------------------------------------------------------
             |               Robust
     nb_rate | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        infl |   .3196017   .1519785     2.10   0.035     .0217294     .617474
   outputgap |   .3282142   .1311833     2.50   0.012     .0710996    .5853289
       _cons |   1.159493   .3523461     3.29   0.001     .4689073    1.850079
------------------------------------------------------------------------------
Endogenous: infl outputgap
Exogenous:  infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3
            outputgap_4

. estat endogenous

  Test of endogeneity (orthogonality conditions)
  H0: Variables are exogenous

  GMM C statistic chi2(2) =  3.90228  (p = 0.1421)

. estat firststage

  Shea's partial R-squared
  ------------------------------------------------------
               |     Shea's             Shea's
      Variable | partial R-sq.   adj. partial R-sq.
  -------------+----------------------------------------
          infl |     0.2092              0.1323
     outputgap |     0.4734              0.4222
  ------------------------------------------------------

. estat overid

  Test of overidentifying restriction:

  Hansen's J chi2(6) =  7.0445 (p = 0.3168)
```

Annex F2: Estimation of Taylor Rule 2 and respective robustness test. TR2 extends TR1 by adding interest rate smoothing

```
. gmm (nb_rate - ({b0} + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap)), instruments (infl_1 infl_2 infl_3 infl_4 outputgap_1 outp
> utgap_2 outputgap_3 outputgap_4)

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .03386113
Iteration 2:  GMM criterion Q(b) =  .02374602
Iteration 3:  GMM criterion Q(b) =  .00996293
Iteration 4:  GMM criterion Q(b) =  .00996293

Step 2
Iteration 0:  GMM criterion Q(b) =  .05139652
Iteration 1:  GMM criterion Q(b) =  .04745977
Iteration 2:  GMM criterion Q(b) =  .04728466
Iteration 3:  GMM criterion Q(b) =  .04728466

GMM estimation

Number of parameters =   4
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust

------------------------------------------------------------------------------
             |               Robust
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         /b0 |   .3694776   .1433028     2.58   0.010     .0886093    .6503459
         /b1 |   .7730853   .0878369     8.80   0.000     .6009281    .9452425
         /b2 |   .1677456    .207634     0.81   0.419    -.2392095    .5747007
         /b3 |   .6802012   .2188561     3.11   0.002     .2512511    1.109151
------------------------------------------------------------------------------
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```

```
. estat overid

  Test of overidentifying restriction:

  Hansen's J chi2(5) = 3.78277 (p = 0.5811)
```

Annex F3: Estimation of Taylor Rule 3 and respective robustness test. TR3 extends TR2 by adding the NOK/EUR exchange rate as an explanatory variable.

```
. gmm (nb_rate - ({b0} + {b1}*L.nb_rate + (1 - {b1})*{b2}*infl + (1 - {b1})*{b3}*outputgap + {b4}*L.delta_er)), instruments(infl_1 infl_2 infl_3 inf
> l_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4)

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .02916027
Iteration 2:  GMM criterion Q(b) =  .01432753
Iteration 3:  GMM criterion Q(b) =  .00983923
Iteration 4:  GMM criterion Q(b) =  .00978046
Iteration 5:  GMM criterion Q(b) =  .00978046

Step 2
Iteration 0:  GMM criterion Q(b) =  .04697134
Iteration 1:  GMM criterion Q(b) =  .04349094
Iteration 2:  GMM criterion Q(b) =  .04336454
Iteration 3:  GMM criterion Q(b) =  .04336454  (backed up)

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	.2926668	.2021647	1.45	0.148	-.1035687	.6889024
/b1	.7989928	.1000492	7.99	0.000	.6028999	.9950857
/b2	.2675464	.3035537	0.88	0.378	-.3274079	.8625006
/b3	.6530824	.2351567	2.78	0.005	.1921837	1.113981
/b4	-.2433002	.4961737	-0.49	0.624	-1.215783	.7291825

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons

. estat overid

  Test of overidentifying restriction:

  Hansen's J chi2(4) = 3.46916 (p = 0.4826)
```

Annex G: Remaining Taylor-type Rule estimations of Chapter 3.2, and respective comparative graphs with Norges Bank's interest rate path.

Annex G1: Estimation of Taylor Rule 4, using forward inflation and the output gap as explanatory variables, with interest rate smoothing.

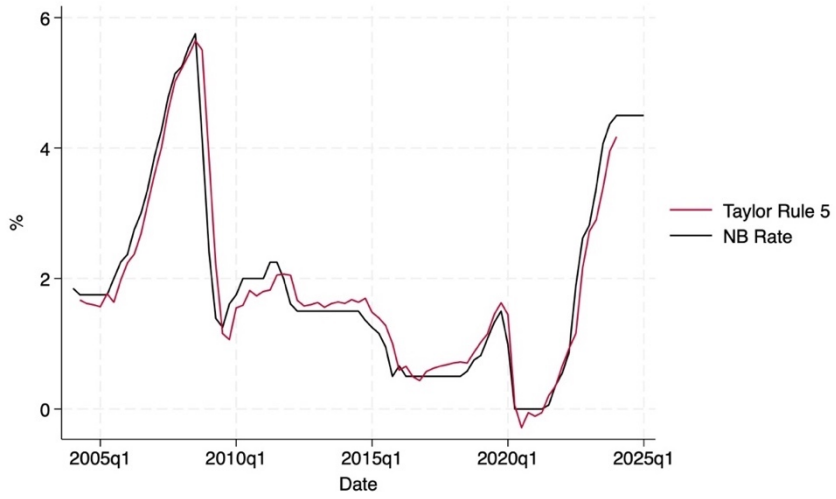
```
. nl (nb_rate = {b0} + {b1}*L.nb_rate + (1-{b1})*{b2}*infl_F4 + (1-{b1})*{b3}*outputgap) if !missing(nb_rate, L.nb_rate, infl_F4, outputgap)

Iteration 0:  Residual SS = 12.88921
Iteration 1:  Residual SS = 9.623782
Iteration 2:  Residual SS = 9.623782
```

Source	SS	df	MS		
Model	147.49922	3	49.1664057	Number of obs =	80
Residual	9.6237818	76	.126628708	R-squared =	0.9388
				Adj R-squared =	0.9363
Total	157.123	79	1.98889872	Root MSE =	.3558493
				Res. dev. =	57.60702

nb_rate	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
/b0	.1525344	.0900319	1.69	0.094	-.0267798	.3318485
/b1	.9245579	.0320821	28.82	0.000	.8606609	.9884548
/b2	.0570974	.2662761	0.21	0.831	-.4732374	.5874321
/b3	1.763524	.6858014	2.57	0.012	.3976325	3.129416

```
Note: Parameter b0 is used as a constant term during estimation.
```

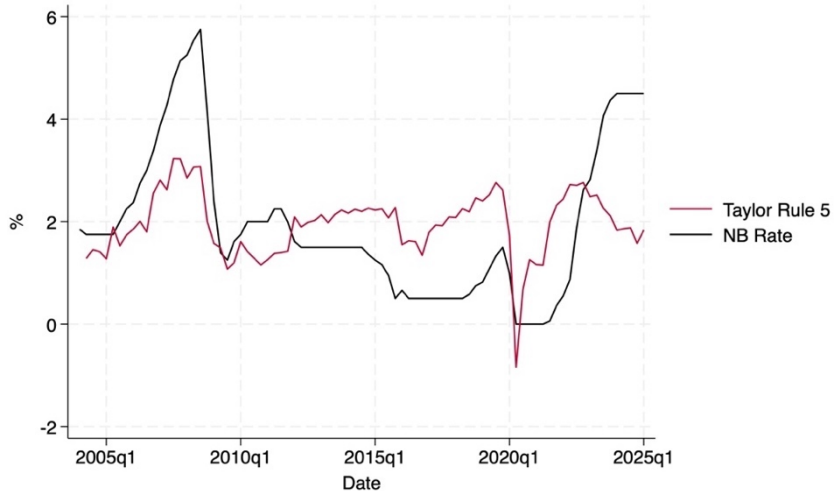


Annex G2: Estimation of Taylor Rule 5, using inflation and the output gap as explanatory variables.

```
. regress nb_rate infl outputgap
```

Source	SS	df	MS	Number of obs	=	84
				F(2, 81)	=	8.61
Model	32.3427118	2	16.1713559	Prob > F	=	0.0004
Residual	152.118844	81	1.87801042	R-squared	=	0.1753
				Adj R-squared	=	0.1550
Total	184.461556	83	2.22242839	Root MSE	=	1.3704

nb_rate	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
infl	.039949	.0693498	0.58	0.566	-.0980354	.1779333
outputgap	.3804175	.0955108	3.98	0.000	.1903809	.5704541
_cons	1.8531	.2165682	8.56	0.000	1.422197	2.284002



Annex G3: Estimation of Taylor Rule 6, using inflation and the output gap as explanatory variables, with interest rate smoothing.

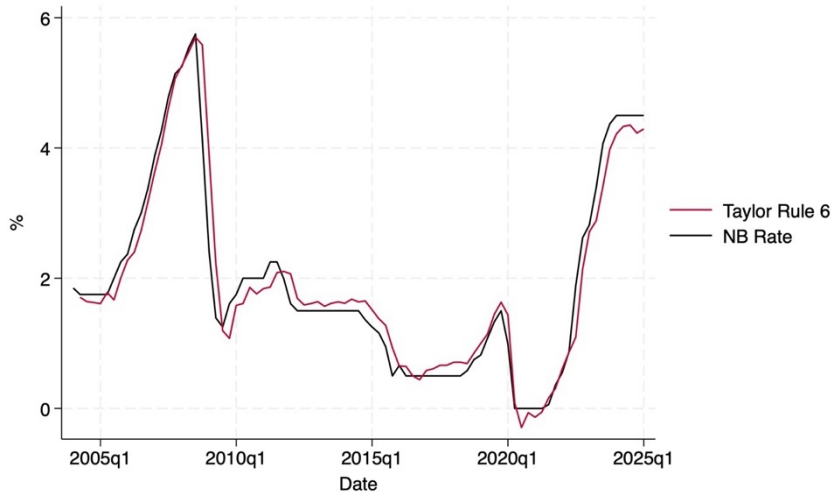
```
. nl (nb_rate = {b0=0} + {b1=0.75}*L.nb_rate  + (1-{b1})*{b2=0.3}*infl   + (1-{b1})*{b3=0.5}*outputgap) if !missing(nb_rate, L.nb_rate, infl, output
> gap), vce(robust)

Iteration 0:  Residual SS = 11.20562
Iteration 1:  Residual SS = 9.808491
Iteration 2:  Residual SS = 9.808491
Iteration 3:  Residual SS = 9.808491

Nonlinear regression                            Number of obs =         84
                                                R-squared     =     0.9468
                                                Adj R-squared =     0.9448
                                                Root MSE      =   .3501516
                                                Res. dev.     =   57.98593
```

nb_rate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/b0	.16033	.0655488	2.45	0.017	.0298837	.2907764
/b1	.9410128	.0454966	20.68	0.000	.8504716	1.031554
/b2	-.1309558	.3788969	-0.35	0.731	-.8849847	.623073
/b3	2.187228	1.439965	1.52	0.133	-.6783929	5.052849

Note: Parameter **b0** is used as a constant term during estimation.



Annex G4: Estimation of Taylor Rule 7, using inflation and the GDP growth rate as explanatory variables.

```
. regress nb_rate infl delta_y
```

Source	SS	df	MS		
Model	2.58924271	2	1.29462135	Number of obs	= 84
Residual	181.872313	81	2.2453372	F(2, 81)	= 0.58
				Prob > F	= 0.5641
Total	184.461556	83	2.22242839	R-squared	= 0.0140
				Adj R-squared	= -0.0103
				Root MSE	= 1.4984

nb_rate	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
infl	.0821106	.0767711	1.07	0.288	-.0706398	.234861
delta_y	.0046931	.0353836	0.13	0.895	-.065709	.0750953
_cons	1.75285	.2613889	6.71	0.000	1.232768	2.272932



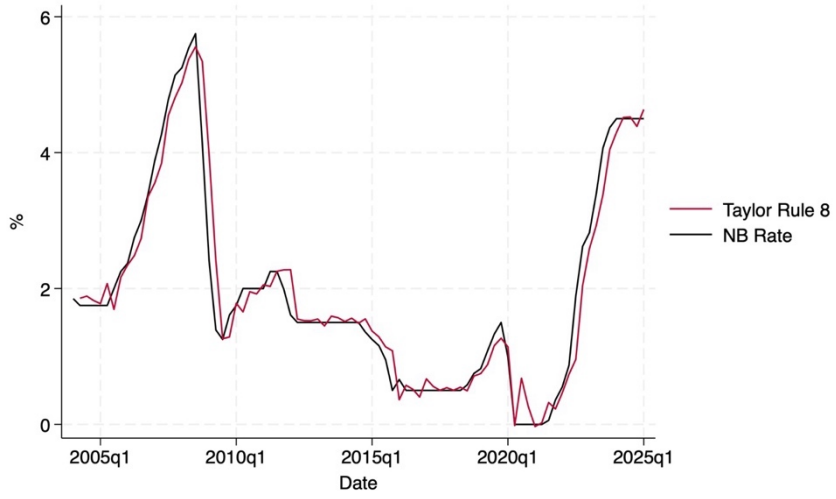
Annex G5: Estimation of Taylor Rule 8, using inflation and the GDP growth rate as explanatory variables, with interest rate smoothing.

```
. nl (nb_rate = {b0=0} + {b1=0.75}*L.nb_rate + (1-{b1})*{b2=0.3}*infl   + (1-{b1})*{b3=0.5}*delta_y) if !missing(nb_rate, L.nb_rate, infl, delta_y),
>  vce(robust)

Iteration 0:  Residual SS =  13.7613
Iteration 1:  Residual SS = 10.22007
Iteration 2:  Residual SS = 10.22005
Iteration 3:  Residual SS = 10.22005

Nonlinear regression                            Number of obs =         84
                                                R-squared     =     0.9446
                                                Adj R-squared =     0.9425
                                                Root MSE      =   .3574223
                                                Res. dev.     =   61.43862

------------------------------------------------------------------------------
             |               Robust
     nb_rate | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         /b0 |  -.0886239   .0450821    -1.97   0.053    -.1783401    .0010924
         /b1 |   .9953966    .036193    27.50   0.000     .9233703    1.067423
         /b2 |   4.256213   31.74978     0.13   0.894    -58.92786    67.44029
         /b3 |   8.525449   65.47504     0.13   0.897     -121.774    138.8249
------------------------------------------------------------------------------
Note: Parameter b0 is used as a constant term during estimation.
```



Annex G6: Estimation of Taylor Rule 9, using inflation and the unemployment rate as explanatory variables.

```
. regress nb_rate infl ur
```

Source	SS	df	MS	Number of obs	=	84
				F(2, 81)	=	20.38
Model	61.7420885	2	30.8710442	Prob > F	=	0.0000
Residual	122.719468	81	1.51505516	R-squared	=	0.3347
				Adj R-squared	=	0.3183
Total	184.461556	83	2.22242839	Root MSE	=	1.2309

nb_rate	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
infl	.0292803	.062163	0.47	0.639	-.0944047	.1529652
ur	-1.246294	.1993894	-6.25	0.000	-1.643017	-.8495721
_cons	6.603548	.7974899	8.28	0.000	5.016793	8.190303



Annex G7: Estimation of Taylor Rule 10, using inflation and the unemployment rate as explanatory variables, with interest rate smoothing.

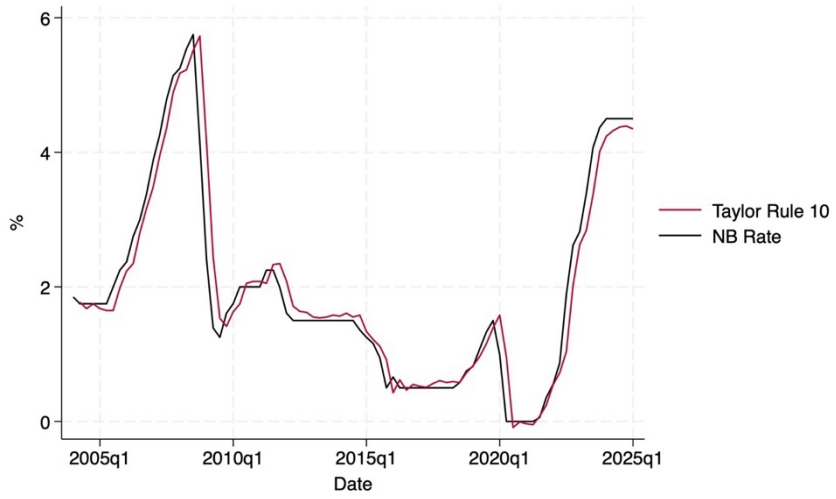
```
. nl (nb_rate = {b0=0} + {b1=0.75}*L.nb_rate + (1-{b1})*{b2=0.3}*infl   + (1-{b1})*{b3=0.5}*ur) if !missing(nb_rate, L.nb_rate, infl, ur), vce(robus
> t)

Iteration 0:  Residual SS = 20.11887
Iteration 1:  Residual SS = 17.00374
Iteration 2:  Residual SS = 14.91172
Iteration 3:  Residual SS = 13.52733
Iteration 4:  Residual SS = 12.42799
Iteration 5:  Residual SS = 12.42799

Nonlinear regression                            Number of obs =         84
                                                R-squared     =     0.9326
                                                Adj R-squared =     0.9301
                                                Root MSE      =   .3941444
                                                Res. dev.     =   77.86894
```

nb_rate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/b0	.6635802	.2330603	2.85	0.006	.1997753	1.127385
/b1	.9460311	.045676	20.71	0.000	.855133	1.036929
/b2	-.0040809	.4232388	-0.01	0.992	-.846353	.8381911
/b3	-2.583008	2.297887	-1.12	0.264	-7.155949	1.989932

Note: Parameter **b0** is used as a constant term during estimation.



Annex G8: Estimation of Taylor Rule 11, using forward inflation and the output gap as explanatory variables.

```
. regress nb_rate infl_F4 outputgap
```

Source	SS	df	MS	Number of obs	=	81
				F(2, 78)	=	14.34
Model	42.2483175	2	21.1241587	Prob > F	=	0.0000
Residual	114.875505	78	1.47276288	R-squared	=	0.2689
				Adj R-squared	=	0.2501
Total	157.123822	80	1.96404778	Root MSE	=	1.2136

nb_rate	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
infl_F4	-.12913	.0646243	-2.00	0.049	-.257787	-.000473
outputgap	.4721764	.0883132	5.35	0.000	.2963583	.6479945
_cons	2.107548	.2006345	10.50	0.000	1.708115	2.50698



Annex H: Taylor-type Rule estimations of Chapter 3.3, and respective comparative graphs with Norges Bank's interest rate path.

Annex H1: Estimation of Taylor Rule 12 as an extension of TR2 by incorporating CPU_{N1} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*cpun1 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outputg
> ap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .02538249
Iteration 2:  GMM criterion Q(b) =  .00080536
Iteration 3:  GMM criterion Q(b) =  .00080536

Step 2
Iteration 0:  GMM criterion Q(b) =  .00869439
Iteration 1:  GMM criterion Q(b) =  .00823679
Iteration 2:  GMM criterion Q(b) =  .00823322
Iteration 3:  GMM criterion Q(b) =  .00823322

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-.0987533	.2649606	-0.37	0.709	-.6180665	.42056
/b1	.8293536	.0938185	8.84	0.000	.6454726	1.013235
/b2	-.1499932	.3921543	-0.38	0.702	-.9186015	.6186152
/b3	.9534305	.4508366	2.11	0.034	.0698071	1.837054
/b4	.0016989	.0008699	1.95	0.051	-6.13e-06	.003404

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H2: Estimation of Taylor Rule 13 as an extension of TR2 by incorporating CPU_{N2} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*cpun2 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outputg
> ap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .01827108
Iteration 2:  GMM criterion Q(b) =  .00082919
Iteration 3:  GMM criterion Q(b) =  .00082919  (backed up)

Step 2
Iteration 0:  GMM criterion Q(b) =  .01000971
Iteration 1:  GMM criterion Q(b) =  .00973534
Iteration 2:  GMM criterion Q(b) =  .00973083
Iteration 3:  GMM criterion Q(b) =  .00973083

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-.079388	.2675168	-0.30	0.767	-.6037114	.4449353
/b1	.8275233	.0914849	9.05	0.000	.6482163	1.00683
/b2	-.1987236	.4372244	-0.45	0.649	-1.055668	.6582205
/b3	.7804177	.3603754	2.17	0.030	.074095	1.48674
/b4	.0044052	.0022229	1.98	0.048	.0000483	.008762

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H3: Estimation of Taylor Rule 14 as an extension of TR2 by incorporating CPU_{N3} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*cpun3 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outputg
> ap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .03464177
Iteration 2:  GMM criterion Q(b) =  .00156191
Iteration 3:  GMM criterion Q(b) =  .00156191  (backed up)

Step 2
Iteration 0:  GMM criterion Q(b) =   .0160997
Iteration 1:  GMM criterion Q(b) =  .01482431
Iteration 2:  GMM criterion Q(b) =  .01482192
Iteration 3:  GMM criterion Q(b) =  .01482192

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-.034279	.2421137	-0.14	0.887	-.5088132	.4402552
/b1	.8373806	.0953535	8.78	0.000	.6504911	1.02427
/b2	-.1984503	.4453863	-0.45	0.656	-1.071391	.6744908
/b3	1.064803	.5746121	1.85	0.064	-.0614166	2.191022
/b4	.0010341	.0005363	1.93	0.054	-.0000171	.0020852

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H4: Estimation of Taylor Rule 15 as an extension of TR2 by incorporating CPU_{G1} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*cpug1 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outputg
> ap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =   .0210021
Iteration 2:  GMM criterion Q(b) =  .00532079
Iteration 3:  GMM criterion Q(b) =  .00532079

Step 2
Iteration 0:  GMM criterion Q(b) =  .04679301
Iteration 1:  GMM criterion Q(b) =   .0388988
Iteration 2:  GMM criterion Q(b) =  .03878784
Iteration 3:  GMM criterion Q(b) =  .03878784

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-2.10257	1.529165	-1.37	0.169	-5.099678	.8945375
/b1	.7872014	.1044364	7.54	0.000	.5825098	.9918929
/b2	-.1760884	.3126399	-0.56	0.573	-.7888515	.4366746
/b3	.5858358	.1951668	3.00	0.003	.2033159	.9683557
/b4	.0120232	.0075768	1.59	0.113	-.002827	.0268735

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H5: Estimation of Taylor Rule 16 as an extension of TR2 by incorporating CPU_{G2} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*cpug2 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outputg
> ap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .01764901
Iteration 2:  GMM criterion Q(b) =  .00495182
Iteration 3:  GMM criterion Q(b) =  .00495182

Step 2
Iteration 0:  GMM criterion Q(b) =  .04739167
Iteration 1:  GMM criterion Q(b) =  .03946335
Iteration 2:  GMM criterion Q(b) =  .03940113
Iteration 3:  GMM criterion Q(b) =  .03940113

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-1.760093	1.240529	-1.42	0.156	-4.191486	.6712999
/b1	.7873581	.1020714	7.71	0.000	.5873019	.9874144
/b2	-.1241829	.2613547	-0.48	0.635	-.6364286	.3880628
/b3	.5879174	.1899283	3.10	0.002	.2156648	.96017
/b4	.0085087	.0050653	1.68	0.093	-.0014191	.0184366

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H6: Estimation of Taylor Rule 17 as an extension of TR2 by incorporating CPU_{G3} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*cpug3 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outputg
> ap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .01917257
Iteration 2:  GMM criterion Q(b) =  .00436442
Iteration 3:  GMM criterion Q(b) =  .00436442

Step 2
Iteration 0:  GMM criterion Q(b) =   .0437447
Iteration 1:  GMM criterion Q(b) =  .03427981
Iteration 2:  GMM criterion Q(b) =  .03388218
Iteration 3:  GMM criterion Q(b) =  .03388218  (backed up)

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-1.876077	1.212985	-1.55	0.122	-4.253484	.5013289
/b1	.7909835	.1018603	7.77	0.000	.591341	.990626
/b2	-.1525654	.2783658	-0.55	0.584	-.6981523	.3930214
/b3	.5778825	.1902743	3.04	0.002	.2049518	.9508132
/b4	.0045402	.0025015	1.82	0.070	-.0003626	.009443

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H7: Estimation of Taylor Rule 18 as an extension of TR2 by incorporating the seasonally adjusted version of CPU_{N1} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*sa_cpun1 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outp
> utgap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .02844961
Iteration 2:  GMM criterion Q(b) =  .00116031
Iteration 3:  GMM criterion Q(b) =  .00116031

Step 2
Iteration 0:  GMM criterion Q(b) =  .01470793
Iteration 1:  GMM criterion Q(b) =  .01423994
Iteration 2:  GMM criterion Q(b) =  .01422951
Iteration 3:  GMM criterion Q(b) =  .01422951

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-.0184997	.2483654	-0.07	0.941	-.505287	.4682876
/b1	.7975336	.0891695	8.94	0.000	.6227645	.9723026
/b2	-.0166758	.2618739	-0.06	0.949	-.5299392	.4965876
/b3	.8720041	.3847707	2.27	0.023	.1178675	1.626141
/b4	.0014228	.0006737	2.11	0.035	.0001025	.0027432

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H8: Estimation of Taylor Rule 19 as an extension of TR2 by incorporating the seasonally adjusted version of CPU_{N2} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*sa_cpun2 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outp
> utgap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =   .0267678
Iteration 2:  GMM criterion Q(b) =  .00097318
Iteration 3:  GMM criterion Q(b) =  .00097318

Step 2
Iteration 0:  GMM criterion Q(b) =  .01261732
Iteration 1:  GMM criterion Q(b) =  .01139256
Iteration 2:  GMM criterion Q(b) =  .01125316
Iteration 3:  GMM criterion Q(b) =  .01125316

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-.0598017	.2517633	-0.24	0.812	-.5532487	.4336453
/b1	.8976259	.1124765	7.98	0.000	.6771761	1.118076
/b2	-.4666844	1.184699	-0.39	0.694	-2.788653	1.855284
/b3	1.295713	1.327684	0.98	0.329	-1.3065	3.897926
/b4	.0030911	.0017556	1.76	0.078	-.0003498	.0065319

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H9: Estimation of Taylor Rule 20 as an extension of TR2 by incorporating the seasonally adjusted version of CPU_{N3} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*sa_cpun3 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outp
> utgap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .03929647
Iteration 2:  GMM criterion Q(b) =  .00135764
Iteration 3:  GMM criterion Q(b) =  .00135764  (backed up)

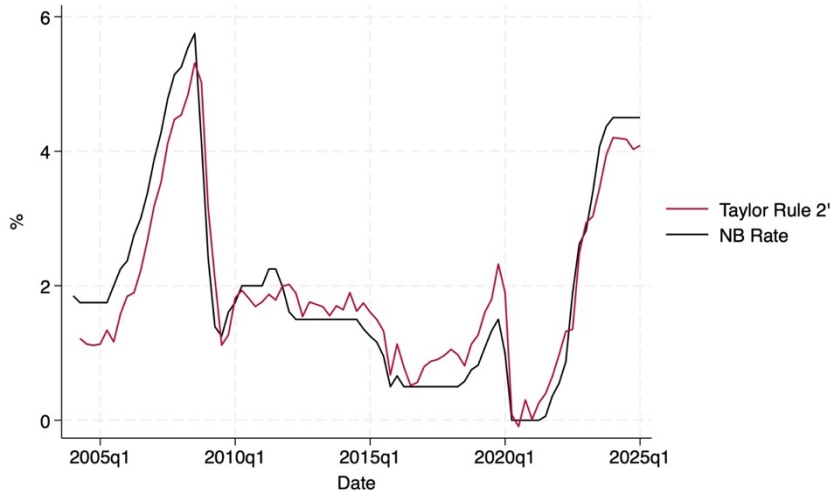
Step 2
Iteration 0:  GMM criterion Q(b) =  .01568768
Iteration 1:  GMM criterion Q(b) =   .0152469
Iteration 2:  GMM criterion Q(b) =  .01524639
Iteration 3:  GMM criterion Q(b) =  .01524639

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-.0088832	.231429	-0.04	0.969	-.4624757	.4447094
/b1	.8228123	.0930769	8.84	0.000	.640385	1.00524
/b2	-.2589364	.4520174	-0.57	0.567	-1.144874	.6270014
/b3	1.152485	.604183	1.91	0.056	-.0316922	2.336662
/b4	.0010836	.0005202	2.08	0.037	.0000641	.0021031

Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons



Annex H10: Estimation of Taylor Rule 21 as an extension of TR2 by incorporating the seasonally adjusted version of CPU_{G1} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*sa_cpug1 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outp
> utgap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .01714166
Iteration 2:  GMM criterion Q(b) =   .0022835
Iteration 3:  GMM criterion Q(b) =   .0022835

Step 2
Iteration 0:  GMM criterion Q(b) =  .02582421
Iteration 1:  GMM criterion Q(b) =  .02234303
Iteration 2:  GMM criterion Q(b) =  .02229147
Iteration 3:  GMM criterion Q(b) =  .02229147

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-1.930365	.8927345	-2.16	0.031	-3.680093	-.1806376
/b1	.8199674	.0946298	8.67	0.000	.6344964	1.005438
/b2	-.1782756	.2817087	-0.63	0.527	-.7304145	.3738634
/b3	.5727515	.236919	2.42	0.016	.1083988	1.037104
/b4	.0109587	.004383	2.50	0.012	.0023681	.0195493

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H11: Estimation of Taylor Rule 22 as an extension of TR2 by incorporating the seasonally adjusted version of CPU_{G2} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*sa_cpug2 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outp
> utgap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .01912239
Iteration 2:  GMM criterion Q(b) =   .0023289
Iteration 3:  GMM criterion Q(b) =   .0023289

Step 2
Iteration 0:  GMM criterion Q(b) =  .02668292
Iteration 1:  GMM criterion Q(b) =  .02269356
Iteration 2:  GMM criterion Q(b) =  .02265222
Iteration 3:  GMM criterion Q(b) =  .02265222

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-1.773543	.8505922	-2.09	0.037	-3.440673	-.1064125
/b1	.8318049	.0949605	8.76	0.000	.6456856	1.017924
/b2	-.2281834	.3330482	-0.69	0.493	-.880946	.4245791
/b3	.5836646	.2545599	2.29	0.022	.0847363	1.082593
/b4	.0084021	.0034572	2.43	0.015	.0016261	.0151781

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```



Annex H12: Estimation of Taylor Rule 22 as an extension of TR2 by incorporating the seasonally adjusted version of CPU_{G3} as an explanatory variable.

```
. gmm ( nb_rate - ( {b0}  + {b1}*L.nb_rate + (1-{b1})*{b2}*infl  + (1-{b1})*{b3}*outputgap + {b4}*sa_cpug3 ) ),  instruments( infl_1 infl_2 infl_3 infl_4 outp
> utgap_1 outputgap_2 outputgap_3 outputgap_4 )

Step 1
Iteration 0:  GMM criterion Q(b) =  4.4992962
Iteration 1:  GMM criterion Q(b) =  .01825498
Iteration 2:  GMM criterion Q(b) =  .00180285
Iteration 3:  GMM criterion Q(b) =  .00180285

Step 2
Iteration 0:  GMM criterion Q(b) =  .01934145
Iteration 1:  GMM criterion Q(b) =  .01661079
Iteration 2:  GMM criterion Q(b) =  .01658925
Iteration 3:  GMM criterion Q(b) =  .01658925

GMM estimation

Number of parameters =   5
Number of moments    =   9
Initial weight matrix: Unadjusted                 Number of obs   =         80
GMM weight matrix:     Robust
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
/b0	-1.861951	.854755	-2.18	0.029	-3.53724	-.1866619
/b1	.8258455	.0953275	8.66	0.000	.6390071	1.012684
/b2	-.2386625	.326563	-0.73	0.465	-.8787142	.4013892
/b3	.5355176	.2407049	2.22	0.026	.0637448	1.00729
/b4	.0044523	.0017588	2.53	0.011	.0010051	.0078994

```
Instruments for equation 1: infl_1 infl_2 infl_3 infl_4 outputgap_1 outputgap_2 outputgap_3 outputgap_4 _cons
```

