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Are Distributional Variables Useful for Forecasting With the Phillips Curve?

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Abstract

Does information on the distribution of wealth and income help us forecast aggregate macroeconomic variables? In this thesis, we study how adding such distributional variables to a standard forecasting model affects the forecast accuracy, in the context of inflation forecasting. Using the simulated inflation forecasting approach of Atkeson and Ohanian (2001), we perform a horse race between a textbook NAIRU Phillips curve to an extension augmented with variables from the wealth and income distributions. These are evaluated against a naive martingale model by comparing the root mean square errors (RMSE). Our initial results find that the top 1% wealth share slightly improves the RMSE:s compared to both the textbook and naive models. However, these results are not robust across different inflation measures. We also find that information on the income distribution does not improve the forecasts. In general, our results indicate no definitive improvements across all distributional variables. Lastly, our results are similar to those of Atkeson and Ohanian (2001), as we did not find the textbook NAIRU Phillips curve to have been helpful in predicting inflation over the past decade compared to the naive model.

Keywords: Aggregates, Distributional Variables, Heterogeneous Agents, Inflation, Phillips curve, Inequality, Wealth, Income
JEL: E12, E17, E21, E24, E31

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1 Introduction

"Of the tendencies that are harmful to sound economics, the most seductive, and in my opinion the most poisonous, is to focus on questions of distribution" - Robert Lucas[1]

"Macroeconomy is a distribution" - Benjamin Moll[2]

In 2016, Janet Yellen, at that time chair of the Federal Reserve, delivered a speech concerning the aftermath of the financial crisis. Yellen discussed the need for a more nuanced understanding of the forces shaping macroeconomic behavior, particularly highlighting the role of heterogeneity among different agents in the economy. Additionally, she mentioned the necessity of better comprehending inflation dynamics (Yellen, 2016), illustrating that we need a deeper understanding of both heterogeneity as well as inflation.

In recent decades, wealth and income inequality has risen significantly (Saez and Zucman, 2016), leading to increased attention on the subject. This includes, for example, the integration of inequality concerns into the Sustainable Development Goals (Osakwe and Solleder, 2023). Moreover, the ongoing global inflationary episode presents a major challenge at both national and individual levels. Periods of heightened inflation exert pressure on households and firms, and, due to global interconnectedness, these effects extend to the international stage as well.

The central theme of this thesis is the link between inequality and inflation and, more precisely, if inequality has an impact on inflation dynamics. Our thesis is primarily inspired by a recent upsurge of a long-standing debate in economics regarding if heterogeneity can influence the aggregate macroeconomy. For example, it is one matter to discuss how fluctuations in aggregate economic variables can influence the wealth and income distributions. However, the converse notion that these distributional factors themselves impact aggregate outcomes is the part that is particularly contested. In a blog post this summer, the renowned economist John Cochrane commented on some fairly new models on this subject, called *Heterogeneous Agent New Keynesian* (HANK) models. These heterogeneous agent models propose precisely that the relationship *does* go both ways: not only does the aggregate economy affect inequality, but inequality also influences the aggregate economy (Ahn et al, 2018). However, Cochrane (2023b) emphasized that the evidence from these models for a direct link on how heterogeneity affects aggregates remains unclear to him. While much of this HANK research has focused on how inequality impacts aggregate demand, recent working papers have additionally started exploring the effects of inequality on inflation (Kwicklis 2023, Kaplan et al, 2023b) - a development of particular interest to our thesis.

These two recent working papers illustrate the channels through which wealth and income inequality affect inflation. Kwicklis (2023) finds that in the short run after transfer payments, inflation rises, as low income households spend a higher proportion of the payment, due to their higher marginal propensity to consume (MPC) - where MPC is the proportion of increased

[1]Robert Lucas wrote for the 2003 Annual Report of the Federal Reserve Bank of Minneapolis.
[2]Benjamin Moll stated at the Asian Meeting of the Econometric Society in 2018

income that gets spent. Kaplan et al. (2023b) also find that in heterogeneous agent models, inflation is higher when transfers go to low wealth households, where a feature of these households is their high MPC. This implies that allocating payments to households with low income and wealth leads to greater economic expansion and higher inflation compared to when payments are received by households with high income and wealth.

Furthermore, in the context of this thesis and drawing from the broader HANK literature, we have identified three distinct types of households based on their place in the wealth and income distributions. First, we have the left tail, which is comprised of households with high MPC and low wealth. Second, is the middle segment which overlaps the average wealth, and finally, we have the right tail which has low MPC and high wealth (Violante, 2021). When examining the tails of the wealth and income distributions, households in the lower end (left tail) seem to increase inflationary pressures, while those in the upper end (right tail) seem to reduce it. This is due to their differing MPC. To capture these different segments in the distribution, we have identified the following groups in our data for both wealth and income: top 0.1%, top 1%, top 10%, decile 50-90, bottom 90% and bottom 50%. How they are related specifically to the wealth and income distributions will be discussed in section 4.

In this thesis, we conduct a simple empirical exercise on U.S. data to examine if incorporating this information on the wealth and income distributions, such as top wealth and income shares, improve inflation forecasting. In particular using the Phillips curve, a key component in HANK models. We extend on a simulated forecasting method as outlined in Atkeson and Ohanian (2001) to assess whether adding these distributional variables improves predictions of the textbook NAIRU Phillips curve. We emphasize that the purpose of this thesis is not to establish a causal relationship, but simply examine if there is information contained in these distributional measures that is helpful for forecasting inflation.

Our data comprises of time series data for the inflation rate, unemployment rate and inequality variables. Using a 70/30 split for our data, where 70% is treated as pure training data and the remaining 30% as training and testing data, we establish a forecasting period from the fourth quarter of 2012 to the first quarter of 2023. The method then follows directly on Atkeson and Ohanian (2001) in that it uses OLS regressions to estimate the parameters and forecast the models. The distributional variables are included as both control and interaction variables to measure their respective impacts. Additionally, iterations are added controlling for secular trends in these inequality variables through first differencing. The different iterations of the distributional forecasts are then benchmarked against the textbook Phillips curve, as well as a naive martingale model, through comparing the root mean squared errors (RMSE:s) of the models to the naive model's. This naive model posits that the best guess of the inflation rate one year from now is equal to the inflation rate for the corresponding quarter this year. This comparison allows us to not only compare the textbook and distributional Phillips forecasts, but also compare their respective performances to a very simple model. As Atkeson and Ohanian (2001) put it, "any inflation forecasting model based on some hypothesized economic relationship cannot be considered a useful guide for policy if its forecasts are no more accurate than such a simple atheoretical forecast."

Our results present mixed findings. Our baseline forecasts follow Atkeson and Ohanian (2001) in initially using the GDP deflator as the measure of inflation. Using this measure, we observe that incorporating the top 1% wealth share yields marginally more accurate results across all our forecasting specifications compared to both the naive model and the textbook Phillips model. However, robustness checks using alternative measures of inflation (CPI, core CPI and PCE deflator) show varying performance, indicating that the model does not consistently predict inflation better. Additionally, our findings suggest that information on the income distribution does not improve forecast accuracy, across all specifications, seeing as they generally underperform both the textbook and naive models. In general, our results indicate no definitive improvements across the distributional variables. We note that the forecast RMSE:s across both the wealth and income distributions are all very close to the naive model's, which indicates that there is not a clear difference between them. This in turn indicates there may not be a large effect of inequality on inflation through this channel. However, we restate that we do not perform a causality analysis. One other possible explanation is that the variables are slow-moving, which could imply that there is not much information when using the de-trended variables. Further, our results could also just be noise from the variables or related to concerns regarding the validity of the Phillips curve. Finally, our results make a further contribution in affirming the Atkeson and Ohanian (2001) conclusions, but for a more recent time period, that the textbook Phillips curve has not been useful for forecasting inflation.

The paper is structured as follows: In section 2, we provide an empirical background relating to inequality, inflation and unemployment. Section 3 provides an overview of the literature surrounding heterogeneous agent models and inflation forecasting. In section 4, we outline the purpose of the thesis, its delimitations, our contribution and research question. Section 5 provides the empirical forecasting methodology and section 6 describes the data used. In section 7 we present our results and section 8 concludes.

2 Empirical Background

To demonstrate the practical significance of inequality and inflation, we will present a concise overview of key facts related to these variables. Our discussion starts by focusing on the growing concern over rising inequality. Following this, we will provide some context regarding inflation and unemployment, which are key variables in standard models used for forecasting inflation.

2.1 Inequality

Wealth inequality has increased remarkably over the past few decades, seen for example in the development of the top 0.1% wealth share in the U.S. in Figure 1, indicating a significant

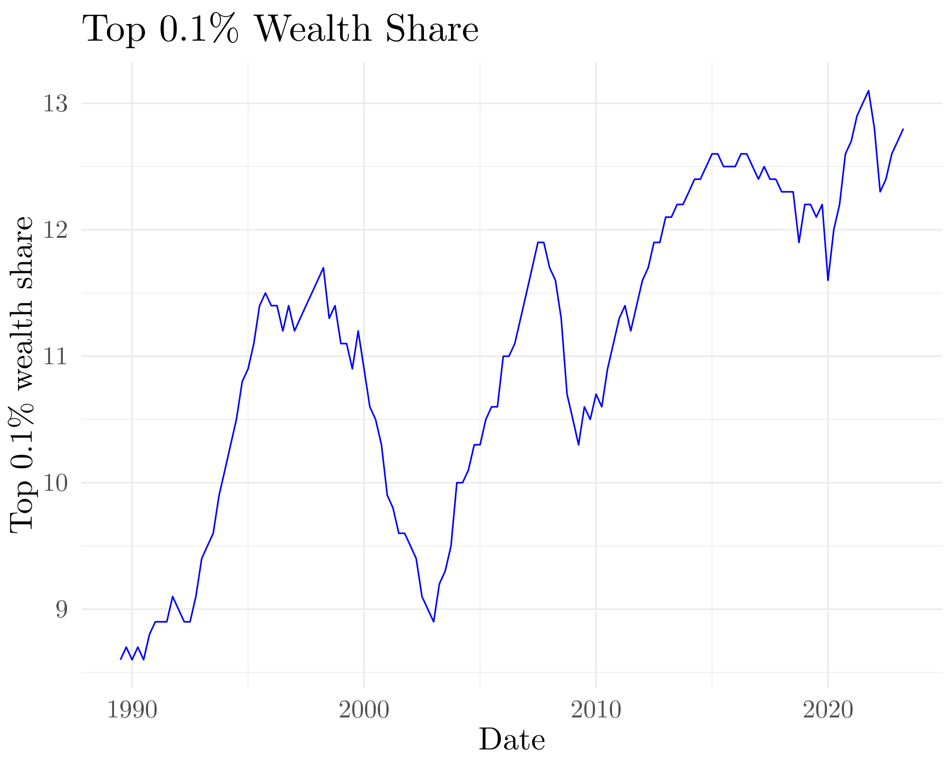

Figure 1: Top 0.1% Wealth Share, United States
Data source: FRED, 1989-2023

change in the wealth distribution. Saez and Zucman's (2016) paper, *Wealth Inequality in the United States since 1913*, illustrated that rising income inequality also fuels wealth inequality, as the highest income households tend to save at higher rates, further concentrating wealth at the top. This trend not only escalates wealth inequality but also leads to increased capital income concentration, which in turn exacerbates wealth inequality (Saez and Zucman, 2016). The combination of higher savings rates among wealthier households and increased incomes for the top earners is one key driver behind the increase in wealth inequality.

The consequences of this escalating inequality have garnered significant attention. For instance, a United Nations working paper has highlighted the growing focus on inequality since its inclusion as one of the Sustainable Development Goals (Osakwe and Solleder, 2023). This attention coincides with the widely accepted view that economic growth is not benefiting all households equally. The paper also explores the negative impacts of inequality, such as hindering growth, impeding poverty alleviation, exacerbating political and social divisions, and fueling conflicts.

2.2 Inflation and Unemployment

2.2.1 Inflation

Many countries are currently struggling with inflation, which has emerged as a central concern due to the interconnectedness of the global economy. The decisions and actions taken by nations

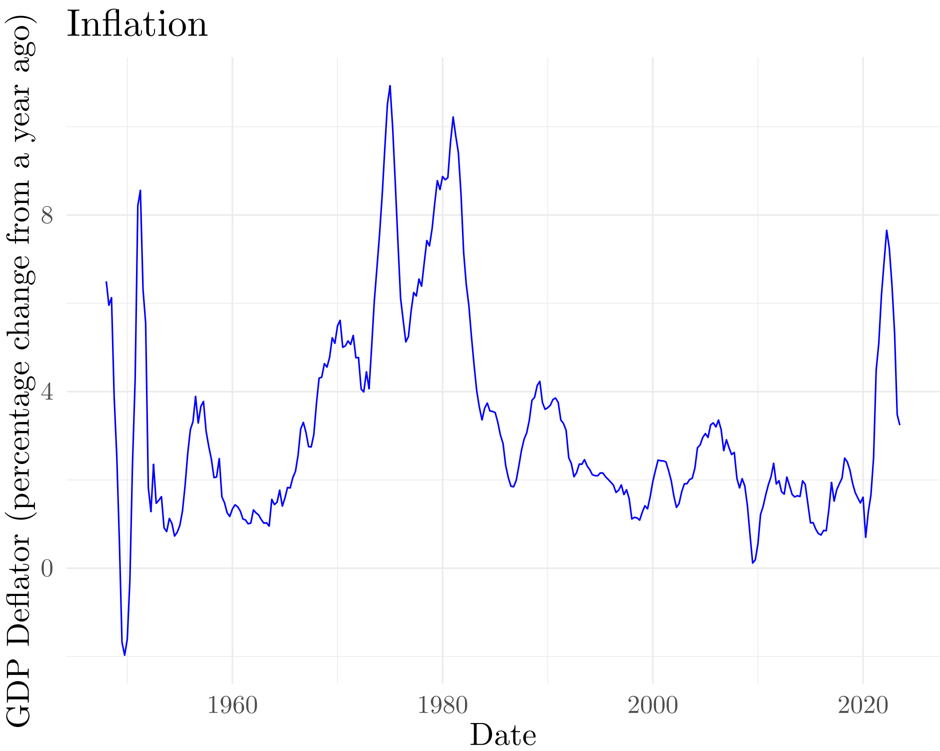

Figure 2: Inflation, United States
Data source: FRED, 1948-2023

to curb inflation, for example through monetary policy, have significant effects on each other (Bonatti et al, 2022). The Swedish Minister of Finance recently noted that while there have been instances of reduced inflation, the core inflation rate remains too high. This persistently high inflation continues to put a strain on both households and businesses (Gillström, 2023).

In the U.S., there appears to be two distinct eras of price behavior. The first era, up to World War I, was characterized by prices fluctuating around a stable average. The second era, following World War II, has seen a steady increase in prices, with the intervening period being more challenging to categorize (Martin, 2017). During this second era, there were two major periods of significant inflation. The first occurred immediately post-war, driven primarily by the substantial government debt accumulated during the war. The second was in the 1970s, marked by the oil crisis and a period of stagflation (a combination of increased inflation and rising unemployment) (Martin, 2017). The most recent inflationary period in the U.S. was triggered by the Covid-19 pandemic. Before the pandemic, inflation had been relatively low, but the pandemic's market disruptions led to increased prices for goods and services (Hernandez, 2023). It is also noteworthy that the war in Ukraine has not dramatically impacted U.S. inflation as it has in Europe, given the U.S.'s lesser dependence on Russia and Ukraine (Kammer et al, 2022). The Covid fiscal stimulus has also been argued as another source of inflation in the U.S. and other countries (de Soyres et al, 2022).

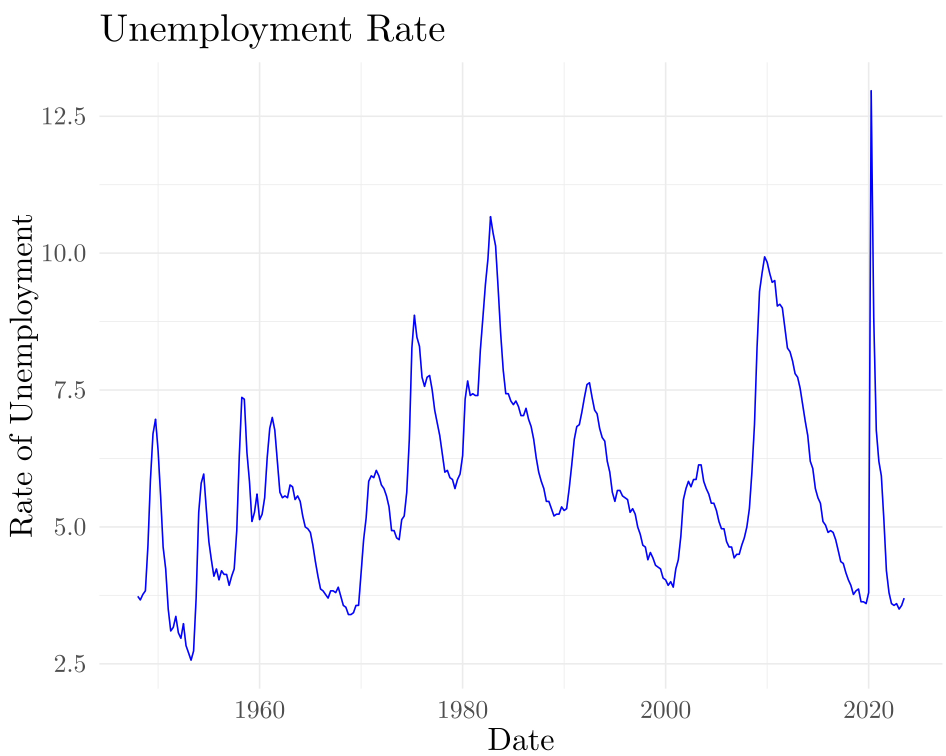

Figure 3: Unemployment Rate, United States
Data source: FRED, 1948-2023

2.2.2 Unemployment

Most individuals in the workforce will experience a period of unemployment at some point in their lives. Within the population, there is the labor force, which encompasses both employed and unemployed individuals. The unemployed segment consists of people who are currently without a job, are actively seeking employment, and are available to work (BLS, 2015).

Unemployment is a challenge faced by countries worldwide. Since the Great Depression, the most severe global unemployment crisis occurred during the Financial Crisis. During this period, global unemployment reached its highest ever recorded level, with 7% of the global workforce in search of employment (Öner, 2010). The most recent instance of high unemployment in the U.S. was a result of the Covid-19 pandemic, which brought an end to a period of economic expansion where unemployment levels were relatively low. In 2020, U.S. employment decreased by over 8.8 million, and the highest unemployment rate recorded during this period was 13% (BLS, 2021). During recessions and economic downturns, policy makers and households pay more attention to the unemployment rate (Card, 2011).

3 Theoretical Background

In this section, we provide an overview of the theoretical background on heterogeneous agent models and inflation forecasting that form the foundations for our analysis. We begin, however, by briefly explaining the representative agent models, in order to be able to contrast them with the heterogeneous agent models. We will also illustrate some key points in the debate on representative versus heterogeneous agent models.

3.1 Representative Agent Models

These models are based on the macroeconomic theory that in complete markets, allowing for perfect risk transfer, a single consumer can effectively represent the entire population in question (Krusell and Smith, 1998). They have been used to analyse the impact of macroeconomic variables under the assumption that there is one homogeneous agent that can represent all households. To achieve this, the average of the macroeconomic variable is taken. Representative agent models have been widely used in economic analysis due to their technical simplicity, in contrast to heterogeneous agent models, where the analysis tends to be more technically demanding (Anderson et al., 2016).

3.2 The Ex-Ante Heterogeneity Debate

If these representative agents are indeed preferred to heterogeneous agents has been debated for a long time.[3] However, we delineate the discussion to the late 1990:s and forwards, beginning with the seminal paper *Income and Wealth Heterogeneity in the Macroeconomy* by Krusell and Smith (1998). Krusell and Smith argued that there is limited evidence supporting the significance of heterogeneity in the macroeconomic context of income and wealth. The main finding of their paper was, "in the stationary stochastic equilibrium, the behavior of the macroeconomic aggregates can be almost perfectly described using only the mean of the wealth distribution." Their benchmark economy, using a heterogeneous agent model, exhibited behavior almost identical to that of an economy with a representative agent model. This result led to the notion that approximate aggregation is sufficient. Krusell and Smith's influential work contributed to a belief among many macroeconomists that "models that incorporate realistic heterogeneity are unnecessarily complicated because they generate only limited additional explanatory power for the aggregate phenomena" (Ahn et al, 2018).

In recent years, however, the discussion has begun to shift. Kaplan et al (2018) argue that in the realm of monetary policy, the differences between heterogeneous agent models and representative agent models are significant. Ahn et al (2018) further discovered that a "quantitatively plausible heterogeneous agent economy such as ours can be useful in understanding the distributional consequences of aggregate shocks, thus paving the way for a complete analysis of the transmission of shocks to inequality." This finding suggests that the representative agent

[3] One of the early macroeconomists who focused on distributional variables was Alan Blinder, former Vice Chairman of the Board of Governors of the Federal Reserve System. In 1975, Blinder sought to determine whether the distribution of income had an impact on the fraction of income that is consumed. His work significantly contributed to the understanding of how the income distribution can influence macroeconomic outcomes. He discovered that consumption behaviors varied depending on which segment of the income distribution was being examined (Blinder 1975).

economy misses a part of the puzzle when it fails to account for distributional impacts. Additionally, they challenge the idea of approximate aggregation proposed by Krusell and Smith (1998), arguing that it is not sufficiently supported (Ahn et al, 2018).

3.3 Recent Contributions: HANK Models

Recent models underlying the new surge in this debate, in particular, the Heterogeneous Agent New Keynesian (HANK) models, highlight the significance of distributional variables in determining aggregate outcomes. We will start by briefly explaining these models and then comparing them to their representative agent model counterpart - the Representative Agent New Keynesian (RANK) models. Thereafter, we will explore the heterogeneous agent models in more detail.

3.3.1 Heterogeneous Agent New Keynesian Models (HANK)

These models are "born from the fusion of two workhorses of macroeconomic theory: (i) the New Keynesian approach to the study of business cycles and stabilization policies, and (ii) the incomplete-market approach to the study of the distribution of income and wealth" (Violante, 2021). Within the framework of heterogeneous agent models, it is noted that "households are heterogeneous ex-ante and ex-post" (Violante, 2021). Integrating this concept with the incompleteness in financial markets of economies reveals varying effects on macroeconomic variables. HANK models operate under the incomplete market approach, where perfect risk transfer is not possible (Baron, 1979). These models encompass factors like uninsurable idiosyncratic risk, an endogenous wealth distribution, and a precautionary savings motive (Kaplan and Violante, 2022).

3.3.2 RANK Compared to HANK

The RANK and HANK models can both be encapsulated by three fundamental equations: "(i) the Phillips curve which specifies a relation between inflation and output dynamics; (ii) the Taylor rule which summarizes how the monetary authority operates its main instrument, the nominal interest rate; (iii) and the Fisher equation which links the real interest rate, the policy rate, and expected inflation" (Violante, 2021). The key distinction between RANK and HANK lies in the substitution of the representative agent. This stems from market imperfections leading to household heterogeneity, both ex-ante and ex-post, and from the inability of households to fully insure themselves against idiosyncratic labor income risk (Violante, 2021).

Two main arguments explain macroeconomists' common reliance on representative agent models over heterogeneous agent models. The first argument is their relative computational simplicity. The second argument relates to the belief that models with heterogeneous agents offer only marginal improvements in terms of explanatory power of aggregate variables. However, recent research in the field challenges the strength of these arguments. As Ahn et al. (2018) discovered, these justifications may not be as robust as initially thought. Furthermore, as Cochrane (2023b) notes, "there is a representative agent, but it cares about distributions".

One can observe that related literature has not extensively explored allowing for heterogeneity, as noted by Krusell (2017). However, despite HANK models being "still in its infancy, it's catching on quite a bit" (Coy, 2023). Our findings indicate a significant amount of research on ex post heterogeneity, such as how aggregate variables like consumption affect distributional variables, such as the income distribution. Yet, there appears to be limited research on the influence of distributional variables on aggregate variables. Cochrane (2023b) emphasizes that the implications of this would address a fundamentally different question. An example further illustrating this is the observation that "the empirical literature assessing directly the relationship between aggregate levels of consumption and the personal distribution of income at the macroeconomic level is surprisingly limited" (Crespo Cuaresma et al, 2018).

Although heterogeneous agent models and the significance of distributions in aggregate analysis are gaining traction, the use of representative agent models is still predominately used in policy analysis and related fields. This trend results in missing out on the distributional effects when evaluating different policies and macroeconomic variables (Ahn et al, 2018). Ignoring the inherent heterogeneity in the economy can decrease the accuracy of responses to critical macroeconomic questions (Storesletten et al, 2009). Moreover, even under identical assumptions, answers to relevant macroeconomic questions can vary (Gallen, 2021).

This literature is large, developing quickly and is sometimes highly technical. Comprehending most of these technical intricacies is currently beyond our grasp and consequently beyond the scope of this paper. However, we will outline some main features of the more recent related models on inequality and inflation in the upcoming section and how this theory will inform our analysis.

3.4 Inequality and Inflation

We now turn our focus to the direct connections between inequality and inflation, an area where research has made significant contributions recently. In this discussion, we will outline the aspects most relevant to our thesis. Additionally, recognizing the technical complexity of these models, we intend to distill their findings into a more accessible form, while acknowledging that this approach may gloss over some of the more nuanced details of the papers.

3.4.1 Heterogeneous Agent Fiscal Theory Models (HAFT)

Very recent research on inequality and inflation has introduced, what John Cochrane (2023a) calls, the "Heterogeneous Agent Fiscal Theory (HAFT)" models; models combining heterogeneous agents with the fiscal theory of the price level (FTPL).[4] A notable work employing HANK models within these models is the working paper titled *Transfer Payments, Sacrifice Ratios, and Inflation in a Fiscal Theory HANK* by Kwicklis (2023). This paper synergizes HANK models, characterized by incomplete markets, with the fiscal theory of the price level (FTPL), which suggests that inflation can be influenced by government deficits financed through nominal bonds. Kwicklis's findings indicate that in the short run, immediately following transfer payments, inflation tends to increase due to heightened spending by lower-income households. He observes that distributing funds to lower-income groups with higher consumption propensities leads to a more pronounced economic expansion than allocating the same to wealthier, high-income households. Kwicklis also points out that integrating the Phillips curve with HANK models reveals the significance of heterogeneity in MPC for understanding inflation dynamics.

Kwicklis findings can for example be related to the Covid-19 stimulus checks, and interpreted in the model as the "fiscal helicopter drops". Transfer payments are however, in general, an integral part of the US economy, with 3,964 billion dollars spent for quarter three of this year (FRED). This highlights the importance of comprehending the impact of transfer payments in general on inflation, a key economic question. Notedly, Kwicklis remarks that in the long run (over 30 quarters), the inflationary impact is dependent on the value and size of the transfer payments rather than the recipients. However, for real economic variables like output and employment, the recipients of these transfers play a crucial role in determining their effect.

Another recent HAFT model, by Kaplan et al. (2023b), presents an additional perspective on the link between inequality and inflation in their updated working paper from this year named *Price Level and Inflation Dynamics in Heterogeneous Agent Economies.* This study combines heterogeneous agent theory with fiscal theory of the price level to analyze inflation dynamics. The authors demonstrate that fiscal shocks, such as deficit expansions and relaxed monetary policy, lead to an amplified increase in the price level. This increase is amplified by factors like redistribution effects and precautionary savings. The paper underscores the helpfulness of heterogeneous agent models with flexible prices and incomplete markets in understanding inflation dynamics.

Kaplan et al. find that in the long run, real interest rates decrease in response to growing primary deficits, which in turn perpetuates higher inflation in heterogeneous agent models. They examine price level dynamics in an economic framework where "(i) a fiscal authority issues nominal debt to finance committed real expenditures and transfers to households; (ii) a monetary authority sets the short-term nominal rate on government debt; (iii) financial markets are incomplete, so households have a precautionary motive to accumulate savings in order to self-insure against idiosyncratic income risk".

When considering the aspect of inequality, the study reveals that under heterogeneous agent

[4] Note that we cannot delve too deeply here into the FTPL more specifically, but interested readers are suggested to look into, for example, John Cochrane's work on the subject.

models, inflation tends to be higher, especially when transfers are made to low-wealth individuals. This contrasts with representative agent models, where the price level increase is less pronounced when transfers target those with lower wealth. This distinction underscores the importance of accounting for heterogeneity in analyzing economic policies and their impact on different segments of society.

3.5 Important Groups in HANK

3.5.1 Important Groups in the Income and Wealth Distributions in HANK

Given the scope of our thesis, it is impractical to delve into the impact of all possible macroeconomic variables on macroeconomic aggregates across all segments of the distribution. Nonetheless, we will focus on the impact of different segments from the wealth and income distributions on inflation and we will highlight some key groups within the distributions. Within the HANK literature, we highlight three distinct household groups. The first group comprises of individuals with low wealth and high MPC deriving their income primarily from wages and government transfers, representing the left tail of the distribution. The second group consists of those driven by a strong precautionary savings motive to minimize dependence on borrowing constraints, with their income largely sourced from labor. The third group includes those with high net worth and low MPC, for whom the precautionary savings motive is negligible (Violante, 2021), representing the right tail of the distribution. Until recently, representative agent models asserted one MPC for the entire population. However, the emergence of heterogeneous agent models, particularly in the world of incomplete markets, has facilitated the recognition of varying MPCs across different segments of the population, which can be dispersed (Kaplan and Violante, 2022).

3.5.2 Three Broad Household Groups in HANK, Inflation and Inequality

By integrating the concepts behind HANK models in relation to both inflation and inequality, we can clarify the effects of inequality on inflation within the HANK framework, acknowledging that this is a simplification which does not include all the technicalities of the theories. This effect is exemplified by considering scenarios where the left and right tails of the distribution experience increases in wealth and income. Note that this simplification suggests only one of the possible causal links. However, this concept is founded on the notion that if the wealth and income distributions act as state variables—essentially indicators of the state of the economy — one could anticipate their utility in improving the forecasting of inflation.

Households in the left tail of the distribution, characterized by high MPC, will likely drive inflation upwards if their wealth or income increases. This is because these households tend to spend a large portion of each additional dollar they receive (Violante, 2021), thus generating inflationary pressures in the economy. Conversely, households in the right tail, that possess high wealth and low MPC, are expected to exert a dampening effect on inflation. When these wealthier households experience an increase in wealth or income, they are less likely to significantly boost their consumption as they spend a low proportion of each additional dollar they receive (Violante, 2021). As a result, the inflationary pressures are not as pronounced as those caused by the high MPC households receiving similar increases in wealth or income.

3.6 Other Research on Inequality and Inflation

Although our thesis primarily focuses on the theory of the heterogeneous agent models, we would also like to recognize a connection between inequality and inflation from a political economy perspective. Various studies have established a positive correlation and causal relationship between income/wealth inequality and inflation, particularly in democratic countries. In these settings, increased inequality often results in heightened inflation.

The dynamic unfolds as follows: in a democratic country experiencing rising inequality, government debt tends to be financed by a relatively small segment of the population. This scenario frequently leads to the election of political parties that represent the interests of the less affluent. Thus it "elects a political party that represents the interests of poor people. Such a party has more of an incentive to levy inflation taxes and erode the real value of debt service, because this hurts the rich more than the poor" (Beetsma et al, 1996). Consequently, this triggers inflation within the economy.

It is important to note that the interplay between these variables is often mediated through inequality influencing the use of monetary policy. Governments may increasingly resort to monetary policy for redistributive purposes or opt to print more money to fund such policies. These actions, in turn, lead to inflation (Dolmas et al, 2000). This perspective sheds light on the complex socio-political dimensions underpinning the relationship between economic inequality and inflation, highlighting how fiscal and monetary policies are intertwined with broader socio-economic structures.

3.7 Inflation Forecasting

As this thesis aims to survey the link between inequality and inflation through the lens of inflation forecasting, we will now provide a brief overview of inflation forecasting and with it, the Phillips curve.

For a long time, there have been academic discussions regarding whether inflation can be forecasted and to what extent. This forecasting is integral for policymakers and central banks in their efforts to anticipate inflation trends. While inflation is measured in the present or retrospectively, forecasting is necessary when looking ahead. Almost all economic agents, including households and firms, pay attention to inflation and anticipate potential changes, their magnitudes, and the timing of these changes (Meyer and Pasaogullari, 2010). Accurately predicting inflation is needed for these agents to make informed decisions.

Policymakers and central banks, in particular, need to forecast inflation not only to track its trajectory but also to implement corrective measures in the economy's inflationary trends if necessary. Svensson (1997) notes that inflation forecasts incorporate all available information, including the preferences of different agents like policymakers, and views on how the economy operates. These forecasts are essential as they help various agents determine the best course of action in an ever-evolving society.

In particular, the Phillips curve and its extensions is a well-known model widely used for inflation forecasting by various agencies, including the Federal Reserve. According to a paper from the European Central Bank, the Phillips curve is one of the most common models employed for this purpose (Llaudes, 2005). The other most common method involves tracking price indices, such as the Consumer Price Index or the Personal Consumption Expenditures Price Index (Gavin and Mandal, 2002).

Using the Phillips curve, it is observed that to maintain inflation stability in the face of economic shocks, inflation expectations should be well-anchored. Recent findings suggest that they indeed have been well-anchored (Adrian, 2023). Central banks can improve this anchoring by closely monitoring expected inflation and implementing methods that align with these expectations (Lansing and Nucera, 2023). This illustrates how the Phillips curve has been used and how its relationship has been exploited by central banks to meet their targets and improve the accuracy of their inflation forecasts.

3.7.1 The Phillips Curve

We will first briefly delve into the Phillips curve's historical background and then explore the arguments that both support and challenge this model.

It all originated with I. Fisher, who identified unemployment as a potential indicator of future inflation (Atkeson and Ohanian, 2001). Later, in 1958, A. W. Phillips published a seminal paper demonstrating the relationship between changes in money wages in the United Kingdom and inflation. Phillips observed that the "rate of change of money wage rates can be explained by the level of unemployment and the rate of change of unemployment" (Phillips, 1958). Subsequently, renowned economists like Solow and Samuelson also found evidence supporting this inverse relationship between inflation and unemployment (Dorn, 2020).

The Phillips curve is based on the idea that if inflation remains constant, the economy is at its baseline rate of unemployment. Deviations from this baseline level of unemployment lead to changes in inflation. For instance, if the unemployment rate is above the baseline level, inflation tends to decrease. This baseline unemployment rate is known as the NAIRU, or the non-accelerating inflation rate of unemployment, forming the basis of the NAIRU Phillips curve

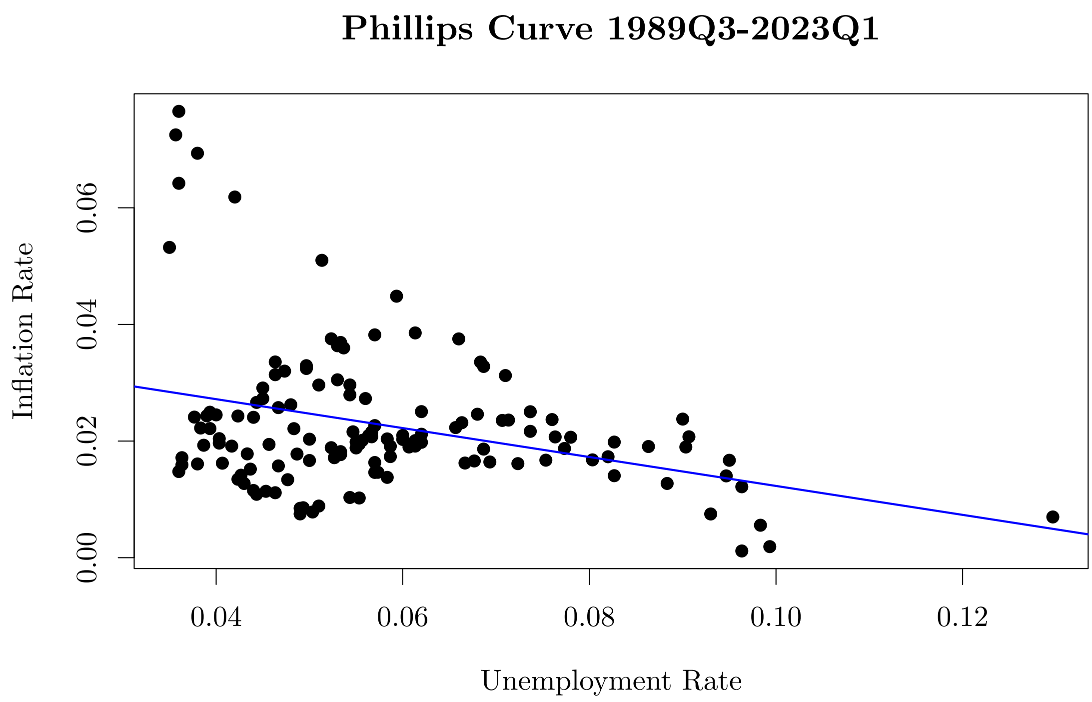

Figure 4: Phillips Curve, United States
Data source: FRED, 1989-2023

(Atkeson and Ohanian, 2001). The Phillips curve has provided a framework for analyzing the impacts of various monetary policies and illustrating the trade-offs involved. For example, the central bank could implement expansionary monetary policy to reduce unemployment, but this comes with the trade-off of higher inflation (Sargent and Hall, 2017).

3.7.2 The Phillips Curve: Support and Criticism

Throughout the years, the Phillips curve has been subject to varying opinions regarding its validity. Despite these differing views, the Phillips curve continues to be a fundamental concept taught to economics students and is widely employed by macroeconomists. The debate on the usefulness of the Phillips curve in forecasting inflation primarily revolves around the question "of whether the statistical relationship between unemployment and inflation documented in these early empirical studies should be expected to remain stable over time" (Atkeson and Ohanian, 2001).

The Phillips curve continues to face criticism to this day. Cochrane (2023a) recently remarked in a blog post that "the Phillips curve still seems like the biggest rotten timber in the ship to me." Economists such as Friedman, Lucas, and Taylor have argued that the relationship depicted by the Phillips curve is too unstable across different economic environments to reliably forecast inflation when these environments change (Atkeson and Ohanian, 2001). Friedman contended that while the Phillips curve suggests a trade-off between inflation and unemployment, this is only a temporary phenomenon, arising from unanticipated inflation, and thus there is no long-term trade-off between the two.

On the other hand, as previously mentioned, economists like Solow and Samuelson have supported the findings of the Phillips curve (Atkeson and Ohanian, 2001). Alan Blinder, former Vice Chairman of the Federal Reserve, stated that the "empirical Phillips curve has worked amazingly well for decades." He concluded, based on this empirical success, that the Phillips curve should occupy a "prominent place in the core model" used for macroeconomic policy-making (Atkeson and Ohanian, 2001). Moreover, recent research by the National Bureau of Economic Research (NBER) posits that "evidence that the price Phillips curve has been dormant for the past several decades does not necessarily mean that it is dead... it could be hibernating, and there is a risk of the Phillips curve waking up, with inflationary pressures rising in the face of an overheating labor market" (Hooper et al, 2019).

Data from the 1950s and 1960s support the theory behind the Phillips curve, demonstrating a pronounced negative slope (Hooper et al, 2019). However, since the 1980s, there have been instances where unemployment and inflation have occurred simultaneously, defying the expected inverse relationship (Clark and Laxton, 1997), and the relationship has weakened with the slope becoming flatter (Hooper et al, 2019). The flattening of the Phillips curve during this period has been extensively researched by the Federal Reserve and macroeconomists. A commonly cited explanation is that "inflation expectations have both become more important (than lagged inflation) as a determinant of current inflation and have become more firmly anchored as the Fed has more clearly committed to achieving a now stated inflation objective" (Hooper et al, 2019).

However, recent research from this year indicates a significant steepening of the Phillips curve during the post-Covid-19 pandemic recovery periods (Miles et al, 2023; Ari et al, 2023). This is in contrast to the pre-pandemic period, where the Phillips curve was notably flatter. The steepening is driven by reductions in unemployment corresponding to larger increases in inflation rates during the post-pandemic recovery, compared to the period before the pandemic (Miles et al, 2023). Therefore, it is of interest to see whether this steeper Phillips curve will persist, or if we will revert to periods characterized by a flatter Phillips curve.

In summary, the reception of the Phillips curve is varied, with both support and criticism evident. Despite concerns regarding its applicability, the Phillips curve continues to be a tool for forecasting, taught to economics students, and a topic of widespread discussion in economic literature. This ongoing engagement with the Phillips curve demonstrates an enduring relevance in the field of economics.

3.8 Unemployment and Wealth Inequality

Since the Phillips curve is an integral part of HANK models and a feature introduced in HAFT models, we will additionally briefly review the relationship between inequality and unemployment. The linkages between unemployment and inequality have been extensively explored in the literature. In the U.S., it was found over almost five decades that "increases in structural unemployment have a substantial aggravating impact on income inequality" (Mocan, 1999). Similar conclusions were reached in Sweden, where increased unemployment was found to lead to increased inequality, resulting in a more unequal income distribution (Björklund, 1991). In an earlier study, Blinder and Esaki (1978) discovered that a one percentage point increase in the unemployment rate "takes about 0.269-0.30% of the national income away from the lowest 40% of the income distribution and gives it to the richest 20%." The positive correlations between the unemployment rate and inequality, measured through the Gini coefficient, have been attributed to job search frictions in the market (Cysne and Turchick, 2012).

4 Research Question

4.1 Purpose

As indicated by the theoretical overview, the intersection of inequality and inflation encompasses a vast body of literature, with its components being actively debated and the field constantly evolving, as evidenced by several recent working papers. Consequently, this thesis will not attempt to draw definitive conclusions regarding causality. Instead, we aim to contribute a piece to the puzzle by applying some fundamental concepts from these models through an empirical simulated forecasting exercise.

In light of the heterogeneous agent models' emphasis on the tails of the income and wealth distributions, we are particularly interested in exploring whether incorporating these distributional variables into standard economic models can improve the accuracy of forecasting aggregates. Due to the limited scope of this thesis, we have chosen to concentrate on a stylized economic model: the textbook NAIRU Phillips curve, which we will augment with distributional variables from the income and wealth distributions.

Our focus on the Phillips curve is motivated by three main reasons. First, as previously discussed, it is one of the three primary equations in HANK models and has appeared in the HAFT models. Second, the Phillips curve is often one of the first models taught to undergraduate economics students, highlighting its significance in shaping economists' understanding of the economy. Finally, both inflation and unemployment are currently highly relevant and widely discussed topics, not only within the field of economics but also in broader societal contexts.

We will perform a simple empirical exercise which will use a simulated forecasting approach similar to Atkeson and Ohanian (2001) to examine whether including variables from the income and wealth distributions improves forecasts of inflation. This will be benchmarked against both the textbook NAIRU Phillips curve and a naive martingale model. The latter stipulates that the optimal forecast for inflation a year from now is the current quarter's level of inflation. This double comparison serves a dual purpose to not only compare the distributional Phillips to the textbook Phillips, but additionally, to compare the models' explanatory accuracy overall by comparing them to a very simple model. As Atkeson and Ohanian (2001) put it, when discussing the comparison of the textbook Phillips curve to this simple martingale model, "any inflation forecasting model based on some hypothesized economic relationship cannot be considered a useful guide for policy if its forecasts are no more accurate than such a simple atheoretical forecast."

In the following sections, we will start by delving into the concept of forecasting and its potential usefulness in this context. Following that, we will elaborate on some delimitations necessary for conducting this empirical exercise. We will conclude by outlining our contribution to the field and articulating the research question that guides our investigation.

4.1.1 Notes on Forecasting

The use of forecasting is particularly relevant in economics, as a key aspect of the discipline involves attempting to predict the future direction of the economy. Economists and economic theories often use simplifying assumptions about the world to facilitate these predictions. A notable analogy used by economists compares this approach to the London Tube map: "laying out tube lines in a simplified way makes planning your route much easier, even though the map is very unrealistic compared to a geographically accurate map" (Moll and Rickard, 2021). This analogy succintly demonstrates how economic models, through simplifying assumptions, aim to focus on key elements of interest to enable predictions, whilst making simplifying assumptions about the rest.

Forecasting is particularly beneficial to our thesis as it allows us to directly compare predictions made with and without considering heterogeneity. This straightforward approach contrasts with the complexity involved in establishing a causal link, as evident in the intricacies of heterogeneous agent models. Going back to the simplified tube map analogy: although it relies on basic assumptions, it remains interesting and valuable to determine whether adding inequality enables us to better navigate from point A to point B.

4.2 Linearity Assumption

One primary assumption underlying our forecasts is the assumption of linearity, due to directly following the methodology of Atkeson and Ohanian (2001). However, both the linear and non-linear Phillips curves are commonly used in research for forecasting inflation. This is something to investigate in future research.

4.3 Distributions and Distributional Groups

In incorporating distributional variables related to inequality, we will employ various measures relating to both the wealth and income distributions. While wealth and income are distinct yet interrelated concepts, the distinction between the two is important. The International Encyclopedia of the Social & Behavioral Sciences provides a concise description: "wealth represents a stock of accumulated assets; income represents a flow of current output" (Wolff, 2001). Consequently, to enhance the robustness of our analysis, we have opted to use different inequality measures for both wealth and income. This approach will allow us to determine whether either set of measures contributes to improving the accuracy of our forecasts. By distinguishing between wealth and income inequality, we aim to provide a more nuanced understanding of their respective impacts on forecasting accuracy.

In our analysis, we will integrate various segments of the wealth and income distributions into the inflation forecasts to evaluate their impact on forecasting accuracy. We are particularly interested in the effects of both tails of the distribution, as they hold different importance (a topic extensively explored in the HANK literature). By examining the distinct contributions of the lower and upper tails of the wealth and income distributions, we aim to gain insights into how these segments influence inflation forecasting and the broader economic dynamics they represent. Below, we will repeat the main attributes of these tails that we will incorporate into these forecasts and how they are represented in our data.

We will summarise these theories against the backdrop of the three aforementioned income and wealth distribution groups, acknowledging that this is a simplification which does not include all the technicalities of the theories. By integrating the concepts behind HANK models in relation to both inflation and inequality, we can clarify some of the possible effects of inequality on inflation. This effect is exemplified by considering scenarios where the left and right tails of the distribution experience increases in wealth and income.

4.3.1 Left Tail

This tail contains households with low wealth and high MPC deriving their income primarily from wages and government transfers (Violante, 2021). Research has found that the MPC of those in the bottom 50% of the wealth distribution is greater than those in the top 50% of the wealth distribution (Di Maggio, 2018). This is due to these households not being able to participate in consumption smoothing, leading to increased vulnerability and them facing differing credit constraints (Ribas Palomo et al, 2022). Additionally, Ribas Palomo et al (2022) found in Brazil that the middle 40% of the wealth distribution is not statistically different from the bottom 50%, concluding that the bottom 90% of the wealth distribution have relatively similar MPC. Two of the explanations for this is due to these two groups having similar behavioral patterns and due to the significantly high concentration of of income the right tail of the distribution in Brazil (Ribas Palomo et al, 2022). As income is also more concentrated in the right tail in the U.S., as in Brazil, we find it of interest to add the wealth shares of the bottom 50% as well as the bottom 90% to our forecasts to see if either of these help improve the accuracy of our inflation predictions. The implication on inflation is that households in the left tail of the distribution, characterized by high MPC, will likely drive inflation upwards when they experience an increase in wealth or income. This is because these households tend to spend a large portion of each additional dollar they receive (Violante, 2021), thus generating inflationary pressures in the economy.

4.3.2 Right Tail

Households in the right tail, that possess high wealth and low MPC, are expected to exert a dampening effect on inflation when these wealthier households experience an increase in wealth or income. They are less likely to significantly boost their consumption as they spend a low proportion of each additional dollar they receive (Violante, 2021). As a result, the inflationary pressures are not as pronounced as those caused by the high MPC households receiving similar increases in wealth or income.

4.3.3 Distribution Delineations: Tails

Here we present the different segments from the wealth and income distributions that capture the different tails, as well as the overlapping middle segment, the former being two of our outlined important groups within the HANK literature. We can visualise these three groups in the wealth and income distributions using our household-level data. These are delineations that persist over time in the data sets. For the wealth distribution, this delineation implies that the right tail consists of the top 0.1% and top 1%. The middle is overlapped with the top 10% and the left tail is comprised of the 50-90 deciles and bottom 50%. For the income distribution, this is slightly different. Here, the right tail consists of the top 0.1%, top 1% and top 10% . The middle is overlapped by the 50-90 deciles and the left tail is comprised of the bottom 50%. This demonstrates a relatively more equal distribution of income in contrast to wealth (Bricker et al, 2020).[5]

To capture these groups, we will add the following segments of the wealth and income distribution, as well as three measures that capture ratios between segments, to our forecasts:

Top 0.1%
Top 1%
Top 10%
Decile 50-90
Bottom 90%
Bottom 50%
Ratio 90/50[6]
Ratio 50/90[7]
Ratio 90/90[8]

[5] For graphs illustrating the distributions, see the Appendix.
[6] top 10/bottom 50
[7] bottom 50/top 10
[8] top 10/bottom 90

4.3.4 Limitations

One concern with inequality variables is that they are slow moving and that a lack of variation in these variables would thus limit their contribution to forecasting accuracy. We consider it a part of our study to examine the extent of this.

4.4 Contribution

In conducting our research, we have not come across any studies that have incorporated variables from the wealth and income distributions in this manner into simulated inflation forecasts using this textbook NAIRU Phillips curve. Furthermore, the data sets we are using for wealth and income — the Distributional Financial Accounts (DFA) and Realtime Inequality which we detail in section 6 — are relatively new and include data up to and including the current year. Given the novelty of these data products and the approach we are taking, we believe that our work contributes with its perspective and topical methodology to the ongoing discussion in this field.

4.5 Research Question

Do variables from the wealth and income distributions improve simulated forecasts with the textbook Phillips curve?

5 Empirical Methodology

Our paper closely follows the methodology outlined in the seminal paper by Atkeson and Ohanian (2001), titled *Are Phillips Curves Useful for Forecasting Inflation?*. In their paper, Atkeson and Ohanian compare inflation forecasts derived from various iterations of the Phillips curve — including a textbook model and models similar to Stock and Watson's versions — alongside the Federal Reserve's Greenbook forecasts, to a naive martingale model.[9] The Atkeson and Ohanian findings indicate that for the approximately 15 years leading up to the turn of the millennium, the Phillips curve models did not perform better than the naive model in forecasting inflation. We plan to follow a similar methodological approach in our analysis, applying this framework to our investigation of wealth and income distribution variables in the context of the Phillips curve.

The main basis of the Atkeson and Ohanian (2001) approach centers around a *simulated forecasting* exercise. In this method, "a simulated series is constructed of the forecasts of inflation that a model would have produced had it been used historically to generate forecasts of inflation." This involves estimating in-sample parameters through Ordinary Least Squares (OLS)

[9] Martingales are a mathematical concept stating that the expected value of the next observation should be the value of the current observation (Alchian, 1974)

regressions using an expanding window of training data which are then applied to forecast future values - *one-step-ahead forecasts.* This technique allows for the assessment of a model's historical forecasting performance by recreating what its predictions would have been in the past, using the data available at each point in time.

The effectiveness of the forecasts is evaluated by comparing the Root Mean Square Error (RMSE) metric of the Phillips curve model to the naive model (as detailed in the RMSE equation provided further down). The RMSE:s summarise the forecasting models' standard deviations, i.e. how much the predictions deviate from the actual data. Following the approach of Atkeson and Ohanian (2001), we will present our results in tables that compare the RMSE of our model to that of the naive model. However, it is important to acknowledge a limitation of this method: while it allows us to determine whether our model performs better or worse than the naive model in terms of RMSE, it does not provide information about the statistical significance of this difference.[10] This means that while we can identify which model has a lower RMSE, we cannot conclusively determine the significance of this improvement or deterioration in forecast accuracy.

The contribution of this paper is extending the textbook model to include distributional variables; more specifically, different variables from the income and wealth distributions. The method directly extends on Atkeson and Ohanian (2001) by adding distributional variables in OLS regressions. Our datasets are not completely overlapping, which means that we unfortunately cannot re-do the analysis with the distributional variables for the same time period. However, the length of our data is approximately the same. One note is that Atkeson and Ohanian (2001) use a rough 50/50 split in the initial training and forecast data. However, we will deviate from their methodology and use the more common 70/30 split for when the simulated forecasts start. This, in order to get more training data observations to use in the forecasts. All forecasts are done for four quarters ahead.

5.1 The Atkeson and Ohanian Forecasting

5.1.1 Naive Model

The method begins with a baseline naive model where inflation (π_t) is treated as a martingale. This model posits that the best guess of the inflation rate one year from now is equal to the inflation rate for the corresponding quarter this year. As Atkeson and Ohanian (2001) state: "at any date inflation will be the same over the next year as it has been over the last year". In practical terms, this implies that if the inflation rate in the first quarter of 2030 is 2%, then the expected inflation rate for the first quarter of 2031 is also projected to be 2%.

$$E_t(\pi_{t+4}) = \pi_t \qquad \text{(Naive)}$$

[10] A critical aspect of concluding whether or not these forecast models improve would be to compute confidence intervals for these RMSE:s. This is something that Atkeson and Ohanian do not do. However, computing standard errors for the RMSE:s is a non-trivial task beyond the scope of this thesis.

5.1.2 Textbook NAIRU Phillips Curve

Next, the textbook NAIRU Phillips curve is introduced. This model incorporates the difference between the current unemployment rate u_t and the natural rate of unemployment $\overline{u}$, with this difference being multiplied by a coefficient, beta β. Essentially, this means that the inflation forecast for four quarters ahead is predicted to be a function of the current quarter's inflation rate and the excess unemployment for the same quarter.

OLS regressions are employed to estimate the parameters β and $\overline{u}$. This estimation process begins with the first quarter of the dataset and continues up to the current forecast quarter. Following the Atkeson and Ohanian (2001) methodology, the unobserved $\overline{u}$ is given directly from the regressions and is therefore not calculated outside the model.

$$E_t(\pi_{t+4}) = \pi_t + \beta(u_t - \overline{u}) \qquad \text{(TB Phillips)}$$

$$E_t(\pi_{t+4}) - \pi_t = \alpha + \beta u_t \qquad \text{(Regression)}$$

$$\Rightarrow \alpha = -\beta\overline{u} \qquad \text{(Intercept)}$$

5.1.3 RMSE Evaluation

Lastly, the RMSE is calculated for the models across all the simulated forecasts. A perfect model (a hypothetical model that would always predict the correct value) would have an RMSE value of 0.

$$RMSE = \left(\frac{1}{T}\sum_{i=1}^{T}\left\{[\pi_{i+4} - E_i(\pi_{i+4})]^2\right\}\right)^{\frac{1}{2}} \qquad \text{(RMSE)}$$

The models are then compared in the same manner as in Atkeson and Ohanian (2001), using an RMSE ratio with the naive model's RMSE in the denominator. A ratio above 1 indicates that forecasts using the textbook NAIRU Phillips curve underperform compared to the naive model.

5.2 Inequality Extension

We now proceed by adding the variables from the wealth and income distributions. In the regression, we initially incorporate the inequality measure I_t as a control variable, and subsequently include an interaction term between the unemployment rate and inequality. The objective is to assess whether merely controlling for inequality or additionally considering its interaction with the unemployment rate improves the forecasts. These steps represent typical extensions in progressing from Simple Linear Regression (SLR) to Multiple Linear Regression (MLR) and thus building directly upon the Atkeson and Ohanian (2001) methodology of OLS regressions. Consequently, the model is expanded so that the forecast of inflation four quarters ahead also depends on this quarter's inequality measure. The parameters β and $\overline{u}$ are also here estimated through the regressions.

5.2.1 Control Extension

First, we consider a forecasting model where the distributional variables are included as control variables.

$$E_t(\pi_{t+4}) = \pi_t + \beta_1(u_t - \overline{u}) + \beta_2 I_t \tag{C.Model}$$

$$\Rightarrow$$

$$E_t(\pi_{t+4}) - \pi_t = \alpha + \beta_1 u_t + \beta_2 I_t \tag{C.Regression}$$

$$\Rightarrow \alpha = -\beta_1 \overline{u} \tag{Intercept}$$

5.2.2 Interaction Extension

Next, we add interactions between the distributional variables and the unemployment rate.

$$E_t(\pi_{t+4}) = \pi_t + \beta_1(u_t - \overline{u}) + \beta_2 I_t + \beta_3 u_t I_t \tag{I.Model}$$

$$\Rightarrow$$

$$E_t(\pi_{t+4}) - \pi_t = \alpha + \beta_1 u_t + \beta_2 I_t + \beta_3 u_t I_t \tag{I.Regression}$$

$$\Rightarrow \alpha = -\beta_1 \overline{u} \tag{Intercept}$$

5.2.3 First Differencing

Our initial analysis uses level wealth and income data. However, the presence of secular trends in the data was evident. To address this, we aim to account for these trends to gain a clearer understanding of the variables' impacts, a common practice in time series analysis (Chan et al, 1977). We do not anticipate look-ahead bias, as our forecasts begin in 2012Q4, a period following several decades of a clear secular trend. Nonetheless, employing the first-differencing method requires the assumption that this trend will persist. Consequently, we applied first-differencing to all the inequality time series, where the value of the current quarter is subtracted by the value of the preceding quarter, calculated as follows:

$$I_t^{FD} = I_t - I_{t-1} \tag{FD Inequality}$$

6 Data

In this section, we discuss the data we use in more detail.

6.1 Inflation, Unemployment and Wealth Data

The majority of our data is sourced from the FRED database, *Federal Reserve Economic Data*, maintained by the Federal Bank of St. Louis. FRED offers a comprehensive collection of U.S. economic time series data across various frequencies, encompassing metrics like inflation, unemployment, and inequality. The database compiles economic data from numerous sources, predominantly U.S. government agencies (FRED). Due to the quality and reliability of the Federal Reserve's data, we have chosen it for our analysis. Our data includes the *GDP Implicit Price Deflator*, the *Unemployment Rate*, and distributional wealth data from the *Distributional Financial Accounts*. Further details on these data sources are provided below.

6.1.1 Inflation Rate, GDPDEF

The Gross Domestic Product using the implicit price deflator (GDP deflator) data is sourced from the FRED database and is provided by the U.S. Bureau of Economic Analysis. This data is available on a quarterly basis, is seasonally adjusted (details regarding this can be found below in section 6.1.4), and uses the year 2017 as the base index. We analyze the percentage change from the previous year as our measure of inflation. Atkeson and Ohanian (2001) use the GDP deflator as their measure of inflation in the textbook model.

6.1.2 Unemployment Rate, UNRATE

The unemployment rate represents the proportion of unemployed individuals within the labor force, defined as those aged 16 years or older, residing in the District of Columbia or one of the 50 states, not on active duty in the Armed Forces, and do not reside in institutions. This data is obtained from the FRED database, originating from the U.S. Bureau of Labor Statistics. Although the unemployment data is provided on a monthly basis, we require quarterly data for our analysis. Therefore, we have calculated the average for each quarter. This data is seasonally adjusted, a common practice given that unemployment data often exhibits seasonal variations during a year (BLS, 2001). Thus, these adjustments are crucial for providing a clearer view by removing the effects of regular seasonal variations in the data (BLS, 2001).

6.1.3 Wealth Distribution

A distinctive aspect of our dataset is the inclusion of a relatively new dataset from 2020, known as the *Distributional Financial Accounts*, provided by the Federal Reserve. This data, accessed from the FRED database, is published by the Board of Governors of the Federal Reserve System. It offers quarterly data on various segments of inequality. For our analysis, we have used data representing the percentage shares of aggregate wealth across different household wealth brackets, specifically for the top 0.1%, the 99th to 99.99th percentiles (top 99-99.99%), the 90th to 99th percentiles (top 90-99%), the 50th to 90th deciles, and the bottom 50% of the distribution. We have then combined these when necessary to produce the wealth shares used in our analysis.

The authors of the DFA describe its usefulness and purpose: "The DFA complements other sources by generating distributional statistics that are consistent with macro aggregates by providing quarterly data on a timely basis, and by constructing wealth distributions across demographic characteristics. We encourage policymakers, researchers, and other interested parties to use the DFA to better understand issues related to the distribution of U.S. household wealth. [...] This paper introduces the Distributional Financial Accounts (DFA), a new data product that provides quarterly measurement of the distribution of U.S. household wealth from 1989 through the present" (Batty et al, 2022). The DFA effectively integrates the Financial Accounts of the U.S. and the Survey of Consumer Finances (SCF) to present a comprehensive overview of household wealth in the U.S., as noted by Chikhale (2023). It provides detailed data on household assets and liabilities.

Using this quarterly data enables a more nuanced examination of the wealth distribution in the U.S., offering more frequent insights into how wealth evolves over time. This new dataset presents more opportunities to empirically investigate the relationship between distributional variables and macroeconomic aggregates.

6.1.4 Note Regarding Seasonal Adjustments

Both the unemployment rate and GDP deflator data sets are seasonally adjusted. Such adjustments are commonplace for these types of data and are essential for conducting analyses without the obscuring effects of seasonal variations. The process of seasonal adjustment is conducted on a year-to-year basis. (BLS, 2023a).

6.2 Income Data

We have also incorporated data collected by Blanchet, Saez, and Zucman, known as *Real-time Inequality*. This quarterly dataset illustrates the distribution of economic growth in the U.S. across various groups, detailing the allocation of wealth and income benefits among them (Zucman). The methodology employed for determining the income distribution involves a combination of both monthly and quarterly national accounts statistics with high-frequency public data sources. These sources include household surveys focusing on employment and wages, as well as quarterly censuses of wages and employment. Notably, all the data used in their analysis is publicly available, which bolsters the transparency and accessibility of their research. We have, as with the wealth data, used the household-level data on the percentage share of total income. Further, we have chosen to use shares of disposable income (after cash transfers and taxes), in order to capture the redistributions.

6.3 Other Clarifications

The datasets have been harmonized to encompass the same time period, excluding any years that are not common across all datasets. Consequently, the data used in our analysis spans from 1989Q3 to 2023Q1. Furthermore, to maintain consistency, we have used data at the household level for the inequality measures. In alignment with the method of Atkeson and Ohanian (2001), all data measures are on a quarterly basis, facilitating a uniform approach to our time series analysis.

7 Results

In this section, we compare how simulated forecasts of the Phillips curve models perform compared to the naive model, through the aforementioned RMSE ratios. All RMSE ratios are presented as a ratio of the RMSE of the specified model to the RMSE of the naive model. A ratio above 1 indicates that the naive model is performing better, and vice versa. A ratio close to 1 indicates that they are performing approximately the same.

7.1 Textbook Model

Table 1: *Textbook model RMSE-ratio to naive model. Data source: FRED.*

Category	RMSE_Ratio
Textbook	0.9948914

We begin by comparing the results from the textbook Phillips curve for the forecasting period 2012Q4-2023Q1 to the baseline Atkeson and Ohanian (2001) results, using the GDP deflator as the measure of inflation. It is has seemingly improved since the 1990:s, as the ratio was 1.88 in the Atkeson and Ohanian (2001) analysis, compared to 0.99 in our analysis. The ratio of 1.88 indicates that forecasts using the textbook NAIRU Phillips curve underperformed compared to the naive model. The ratio from our results of 0.99 indicates that the model performs relatively the same compared to the naive model, illustrating that the textbook NAIRU Phillips Curve seemingly has improved since Atkeson and Ohanian (2001) studied this. It is, however, still not decidedly better than the naive model, considering that the ratio is close to 1.

Further, robustness checks using other measures of inflation (CPI, core CPI and PCE deflator), result in this ratio being slightly above 1 (see Appendix), showing no improvement over the naive model. Thus, we can conclude that the textbook Phillips curve has not been helpful in forecasting inflation the past decade.

7.2 Wealth Distribution Extension

Table 2: *Right Tail: RMSE Ratios to naive model RMSE, percentages in wealth distribution. Comparison of wealth data for level and first differenced (FD) 2012Q4-2023Q1. Data source: FRED.*

Category	Control	FD Control	Interaction	FD Interaction
Top 0.1%	0.9941112	0.9757323	1.0205527	0.9483008
Top 1%	0.9711900	0.9634750	0.9811321	0.9305357

Table 3: *Middle Overlap: RMSE Ratios to naive model RMSE, percentages in wealth distribution. Comparison of wealth data for level and first differenced (FD) 2012Q4-2023Q1. Data source: FRED.*

Category	Control	FD Control	Interaction	FD Interaction
Top 10%	0.9960761	0.9759506	1.0250293	0.9393868

Table 4: *Left Tail: RMSE Ratios to naive model RMSE, percentages in wealth distribution. Comparison of wealth data for level and first differenced (FD) 2012Q4-2023Q1. Data source: FRED.*

Category	Control	FD Control	Interaction	FD Interaction
Decile 50-90	0.9955058	0.9676951	1.0094236	0.9262535
Bottom 90%	0.9959529	0.9801189	1.0256454	0.9480575
Bottom 50%	1.0014254	0.9933945	1.0609892	1.0201243

Table 5: *RMSE Ratios to naive model RMSE, ratios from wealth distribution. Comparison of wealth data for level and first differenced (FD) 2012Q4-2023Q1. Data source: FRED.*

Category	Control	FD Control	Interaction	FD Interaction
Ratio 90/50	1.0092331	0.9986334	1.1158441	1.0252317
Ratio 50/90	0.9997155	0.9962608	1.0527478	1.0134023
Ratio 90/90	0.9986527	0.9724961	1.0344505	0.9331517

Tables 1 through 4 show the RMSE ratios using different segments of the wealth distribution to forecast inflation, with the simulated forecasts beginning in 2012Q4 and ending 2023Q1 using the GDP deflator as the measure of inflation. We benchmark their performance to the naive model against the performance of the textbook Phillips curve to the naive model.

As we can see, the results vary and they depend on the different specifications. Overall, the results from the different specifications do not align, with the control, fixed control and first differenced interaction variables performing on average better or on par. The first differencing interaction variable with the different segments from the wealth distribution performs the best relative to the textbook Phillips curve. The interaction variable performs on average worse. The top 1% on average performs the best throughout the different specifications, where adding the top 1% improves the inflation forecast the most compared to other segments of the distribution. Further, looking at Table 5, the 90/50 ratio and 50/90 ratio perform worse than the textbook model in all the different specifications, with the bottom 50% performing worse in all except in the first differenced control. A possible explanation for this is that when the bottom 50% is included - both as a share or ratio - the wealth share in this group is so low that it does not contain enough information on how this group affects inflation.

However, given the mixed results, and in many cases only marginal improvement (with RMSE ratios close to 1), it cannot be confidently stated that any of the wealth distribution variables help. For robustness, we have also re-done the analysis using three other inflation measures: CPI, core CPI and PCE Deflator (see Appendix). Again, these provide very mixed results from both the right and left tail with the ratios all being close to 1, and often both being above 1 and above the textbook RMSE ratios. Thus, we cannot decidedly conclude that any of the variables from the wealth distribution have been helpful in forecasting inflation with the inequality-extended Phillips curve.

7.3 Income Distribution Extension

Table 6: *Right Tail: RMSE Ratios to naive model RMSE, percentages from income distribution. Comparison of income data for level and first differenced (FD). Data source: Realtime Inequality and FRED.*

Category	Control	FD Control	Interaction	FD Interaction
Top 0.1%	1.0016065	1.0451862	1.0440803	1.2198298
Top 1%	1.0010913	1.0895757	1.0478266	1.2836277
Top 10%	1.0018241	1.1060862	1.0629509	1.1329425

Table 7: *Middle Overlap: RMSE Ratios to naive model RMSE, percentages from income distribution. Comparison of income data for level and first differenced (FD). Data source: Realtime Inequality and FRED.*

Category	Control	FD Control	Interaction	FD Interaction
Decile 50-90	1.0003182	1.1104084	1.0196403	1.2770557
Bottom 90%	1.0018241	1.1060864	1.0629509	1.1329434

Table 8: *Left Tail: RMSE Ratios to naive model RMSE, percentages from income distribution. Comparison of income data for level and first differenced (FD). Data source: Realtime Inequality and FRED.*

Category	Control	FD Control	Interaction	FD Interaction
Bottom 50%	0.9847781	1.0381029	1.1312103	1.0064055

Table 9: *RMSE Ratios to naive model RMSE, ratios from income distribution. Comparison of income data for level and first differenced (FD). Data source: Realtime Inequality and FRED.*

Category	Control	FD Control	Interaction	FD Interaction
Ratio 90/50	0.9944782	1.0419563	1.0934988	0.9703286
Ratio 50/90	0.9977372	1.0681412	1.1125308	0.9845549
Ratio 90/90	1.0021828	1.0984795	1.0632402	1.1301345

Tables 5 through 8 display the RMSE:s for the entire time period, using various segments of the income distribution to forecast inflation, using the GDP deflator as the measure of inflation. As in previous analyses, the forecasts span from 2012Q4 to 2023Q1. These simulated forecasts are conducted in the same manner as those for the wealth distribution. We also benchmark their performance to the naive model against the performance of the textbook Phillips curve to the naive model.

Overall, compared to the textbook model, we observe few improvements across the various specifications using different segments of the income distribution. They are in general worse than the wealth distribution variables. The bottom 50% still underperforms, indicating that the left tail of the distribution does not enhance forecast accuracy. Additionally, they underperform in comparison to the naive model too, with many ratios being above 1. Seeing as all ratios are close to 1 here as well, consequently, we conclude that incorporating shares from the income distribution into these forecasts has seemingly not been helpful to forecast inflation.

8 Conclusion

In this thesis, we have conducted a simple empirical exercise to determine whether information on the wealth and income distributions, such as top wealth and income shares, can improve forecasts of the textbook Phillips curve. Our findings do not provide clear evidence of improvement over the forecasting period from 2012Q4 to 2023Q1. The models with variables from the top of the wealth distribution (especially the top 1%) tend to marginally outperform both the textbook and naive models when using the GDP deflator as the measure of inflation. However, the results are mixed when conducting robustness checks with different measures of inflation (see Appendix). We note that in general, the forecast RMSE:s across both the wealth and income distribution variables are all very close to the naive model's (i.e. RMSE ratios close to 1), which indicates that there is not a clear difference between them. Seeing the mixed results and that all ratios are close to 1, we cannot definitively state that any wealth and income distribution data included improves forecasting accuracy. Furthermore, our results corroborate with the Atkeson and Ohanian (2001) findings in that the textbook Phillips curve does not consistently outperform the naive model. This is supported by our robustness checks (see Appendix), where all textbook Phillips curve RMSE ratios exceed 1.

Several potential explanations emerge for our results. Firstly, the Phillips curve's slope throughout our data period is almost flat, suggesting a very small effect (see Figure 4). This might explain why the textbook Phillips curve RMSE ratios to the naive model are close to 1, if the unemployment rate variable contributes little to the predictions. Secondly, the distributional variables may also have a negligible impact. This could be due to the reasons mentioned earlier: these variables are slow-moving, and further in that their inclusion in the predictions may not considerably alter outcomes. Thirdly, our results could also be due to noise from the variables or from using the linear Phillips cuvre and not taking into account the possibility of a non-linear Phillips curve. Finally, our results could stem from concerns about the validity of the Phillips curve. Numerous discussions highlight uncertainties about the effectiveness of the Phillips curve in predicting inflation, therefore there is a possibility that the specific nature of the curve itself might be influencing these results.

For future research, several avenues could further contribute to this discussion. Firstly, the current high-inflationary episode's trajectory still remains uncertain, even though inflation seems to be on the decline at the moment. This could have implications for the Phillips curve, which is argued to have steepened these past few years. Secondly, analyzing disaggregated data, especially in a vast and diverse country like the U.S., could yield interesting insights. Examining variations among different states could be particularly informative. Thirdly, exploring household balance sheet heterogeneity is of interest, especially in the context of current debates on indebted demand and wealthy hand-to-mouth consumers. There may be faster-moving variables in this area worth investigating. Fourthly, a different forecasting window could be considered. In the method we followed, inflation is forecasted four quarters ahead. Perhaps a shorter or longer forecast horizon would provide different results. Lastly, it is worth re-considering the argument that the Phillips curve may not be an effective tool for inflation forecasting, despite its continued use in research and central bank forecasts. Comparing the analyses in this thesis with those derived from alternative inflation forecasting models could be revealing.

In this thesis, we have looked at if information on the wealth and income distributions can be helpful for forecasting inflation. It is evident that many questions remain unanswered in this field of research, and much is yet to be learned about the impacts of distributional variables on aggregate macroeconomic variables in general. However, as highlighted in this thesis, caution is warranted in overestimating their potential explanatory effects. It is hoped that ongoing research in this area will yield further insights - or perhaps even more interesting questions to delve into in the future.

9 References

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10 Appendix

10.1 Robustness: Additional Inflation Measures

We have employed additional inflation measures to the wealth distribution to compare the results to when the GDP deflator is used, as specified as the main inflation measure for the textbook model in the Atkeson and Ohanian (2001) paper. These simulated forecasts are performed in the same manner and for the same time period as the main analysis. We use the Consumer Price Index (CPI), core CPI and Personal Consumption Expenditures (PCE), as stipulated in Atkeson and Ohanian (2001) for the Stock and Watson versions, but extend it for the textbook model. We use these for robustness checks for the wealth distribution variables. We only conduct robustness checks for the textbook model and wealth distribution extensions, as we saw marginal improvements in some of the specifications, compared to the income distribution where there was arguably no marginal improvements. We are thus interested in if these findings are robust across different inflation measures (which one could argue should be a reasonable property for an inflation forecast).

The CPI gauges the average change in prices over time that households pay for a representative basket of goods and services. The CPI is a reflection of inflation experienced by households in everyday living expenses. The CPI's are based on prices for fuel, food, clothing, shelter, sales taxes and service fees and have different weights corresponding to the amount that different groups spend on the good or service. The core CPI is the CPI excluding the prices paid by households for food and energy. The PCE measures households' current consumption of goods and services.

10.1.1 Benefits of Different Inflation Measures

There is no one best measure of inflation, as it depends on what the data will be used for (BLS, 2023b). When trying to see the equivalent of a basket of goods and services that households could have purchased in the past, the CPI is thought to be the best measure. It enables for comparison between the periods, allowing households to be able to buy at today's prices, (BLS, 2023b). One of the benefits of using the core CPI is due to the frequent varying in prices of both food and energy. Thus, using the core CPI, which excludes both of these, can be more informative of what else is occurring in the economy (FRED, 2023). One of the main benefits of using PCE is in how it illustrates the fraction of earned income that households are spending, rather than being saved for consumption in the future, with consumption being the main driver of economic growth (BLS, 2023c).

The main difference, aside from the calculation methods, when comparing these three alternative measures to the GDP deflator is that the GDP deflator, the main method employed in Atkeson and Ohanian (2001) for the textbook model, includes more agents. CPI, core CPI and PCE all calculate inflation from a household perspective whereas the GDP deflator calculates inflation to include consumption of goods and services from not only households, but also firms, the government, foreigners and other agents (BLS, 2016). Employing the GDP deflator thus allows for a broad inclusion of different agents on which to calculate inflation.

10.1.2 CPI

Atkeson and Ohanian (2001) also use the CPI as a measure of inflation. The data is downloaded from the FRED database and comes from the U.S. Bureau of Labor Statistics. The frequency of the data is monthly, however, as we are interested in quarterly data, we have downloaded the average for each quarter and it is seasonally adjusted. The index is 1982-1984 and we look at the percentage change from a year ago.

Table 10: RMSE Ratios: Textbook and Wealth Distribution to Naive Model using CPI. Data source: FRED.

Category	Control	FD_Control	Interaction	FD_Interaction
Textbook	1.009924	1.009924	1.009924	1.009924
Top 0.1%	1.011734	0.977367	1.069373	0.996100
Top 1%	0.995692	0.960244	1.028911	0.956747
Top 10%	1.020216	0.982574	1.062136	0.956476
Decile 50-90%	1.016167	0.975247	1.050688	0.956275
Bottom 90%	1.020987	0.994520	1.064192	0.972086
Bottom 50%	1.025887	1.017481	1.118832	1.072744
Ratio 90/50	1.033314	1.023361	1.189377	1.069623
Ratio 50/90	1.024649	1.021357	1.105232	1.053407
Ratio 90/90	1.025031	0.988827	1.077729	0.957353

10.1.3 Core CPI

Another measure of inflation that Atkeson and Ohanian (2001) used is the core CPI. The data is downloaded from the FRED database and comes from the U.S. Bureau of Labor Statistics. The frequency of the data is monthly, however, as we are interested in quarterly data, we have downloaded the average for each quarter and it is seasonally adjusted. The index is 1982-1984 and we look at the percentage change from a year ago.

Table 11: RMSE Ratios: Textbook and Wealth Distribution to Naive Model using Core CPI. Data source: FRED.

Category	Control	FD_Control	Interaction	FD_Interaction
Textbook	1.040500	1.040500	1.040500	1.040500
Top 0.1%	0.997530	1.004496	0.991186	0.981140
Top 1%	0.982634	1.005848	0.943211	0.988608
Top 10%	1.015446	1.018768	0.979486	1.001083
Decile 50-90%	1.001111	1.006716	0.915530	0.989125
Bottom 90%	1.016306	1.022357	0.982210	1.013456
Bottom 50%	1.057917	1.038251	1.096356	1.026682
Ratio 90/50	1.128690	1.038947	1.181355	1.045337
Ratio 50/90	1.050530	1.042181	1.081918	1.032884
Ratio 90/90	1.017345	1.012310	0.973872	0.997542

10.1.4 PCE Deflator

The final measure that Atkeson and Ohanian (2001) use is the PCE, using the implicit price deflator. The data is downloaded from the FRED database and comes from the U.S. Bureau of Economic Analysis. The frequency of the data is quarterly, it is seasonally adjusted, the index is 2017 and we look at the percentage change from a year ago.

Table 12: RMSE Ratios: Textbook and Wealth Distribution to Naive Model using PCE. Data source: FRED.

Category	Control	FD_Control	Interaction	FD_Interaction
Textbook	1.0112474	1.0112474	1.0112474	1.0112474
Top 0.1%	1.0183712	0.9876627	1.0783197	1.0168155
Top 1%	0.9972655	0.9695902	1.0339468	0.9677921
Top 10%	1.0214534	0.9881715	1.0714766	0.9569863
Decile 50-90%	1.0204827	0.9804652	1.0636033	0.9581182
Bottom 90%	1.0221263	0.9973248	1.0734979	0.9674305
Bottom 50%	1.0251909	1.0195703	1.1224423	1.0933090
Ratio 90/50	1.0272456	1.0244124	1.1792488	1.0656984
Ratio 50/90	1.0236850	1.0222151	1.1090070	1.0654134
Ratio 90/90	1.0273678	0.9929516	1.0899440	0.9541912

10.1.5 Results of Different Inflation Measures

When summarising the results for the robustness checks, we see that the results from the main simulated forecasts for the wealth distribution extension of the textbook model using the GDP deflator do not hold up when employing different measures of inflation. The results on average have RMSE:s greater than 1 throughout the different specifications, and the different specifications perform differently depending on which inflation measure is used. This illustrates that the models with variables related to the wealth distribution generally underperform compared to both the textbook and naive models when employing these differing inflation measures. The RMSE ratios are all also, as in the GDP deflator forecasts, close to 1, affirming that we cannot definitively conclude that any of the included variables from the wealth distribution improve the forecasts. Additionally, all textbook Phillips curve RMSE:s are greater than 1. This indicates that the findings in section 7.1 are not robust.

10.2 Covid Period

Seeing as the HAFT models have been rolled out during the current inflationary episode, we believe it is of interest to look at the period from the Covid stimulus checks and forward. Here, we are investigating if isolating the forecasts to a specific inflationary episode improves the forecasts. We note that this measures a slightly different property than our baseline forecasts above. The baseline forecasts compare the models' helpfulness in predicting inflation overall over time. The Covid predictions below specifically look at how quickly these models adapt during this period. Considering the discussions on the Phillips curve steepening in recent years, it is therefore of interest to see what happens to the forecasting errors.

10.2.1 Wealth Distribution: Covid-19 Inflation Episode

Table 13: Table of RMSE Ratios, Textbook and Percentages from Wealth Distribution, Covid. Data source: FRED.

	Category	Control	FD_Control	Interaction	FD_Interaction
1	Textbook	0.9841939	0.9841939	0.9841939	0.9841939
2	Top 0.1%	0.9763309	0.9611655	1.0001412	0.9265149
3	Top 1%	0.9501118	0.9477003	0.9429086	0.9075038
4	Top 10%	0.9748399	0.9605990	0.9540610	0.9165456
5	Decile 50-90%	0.9719094	0.9494038	0.9363368	0.8977377
6	Bottom 90%	0.9747842	0.9635646	0.9541547	0.9243922
7	Bottom 50%	0.9852443	0.9821611	1.0161157	1.0148984

Table 14: Table of RMSE Ratios, Ratios from Wealth Distribution, Covid. Data source: FRED.

	Category	Control	FD_Control	Interaction	FD_Interaction
1	Ratio 90/50	0.9938080	0.9868683	1.0446095	1.0153473
2	Ratio 50/90	0.9835584	0.9849402	1.0081147	1.0062988
3	Ratio 90/90	0.9752675	0.9529482	0.9515349	0.9055913

Tables 13 and 14 show the RMSE:s for the pandemic period, using different segments from the wealth distribution to forecast inflation.

Here we use the same simulated forecasts up until 2023Q1, but start in 2020Q2, when the pandemic stimulus checks started being distributed. The training data still uses all available data, implying that the initial training data window is longer.

When forecasting inflation during the period of the pandemic, we can see improvements in the forecasting capabilities of the Phillips curve with the different specifications. The majority of the specifications with the different inequality measures have improvements in the RMSE:s, where in most cases they perform better than the textbook Phillips curve. The only noticeable exceptions are when using the interaction and first differenced interaction variables, where they perform worse than the textbook model for the bottom 50%, the 90/50 ratio and the 50/90 ratio. As discussed in section 7.2, a possible reason for this is due to the bottom 50% having a such a low wealth share, that their part of the distribution does not contain enough information regarding how they affect inflation. However, these RMSE ratios are still close to 1 and we thus cannot definitively conclude that neither the textbook nor the distributional model improve the forecasts.

10.2.2 Income Distribution: Covid-19 Inflation Episode

Table 15: Table of RMSE Ratios, Textbook and Percentages from Income Distribution, Covid. Data source: Realtime Inequality and FRED.

	Category	Control	FD_Control	Interaction	FD_Interaction
1	Textbook	0.9841939	0.9841939	0.9841939	0.9841939
2	Top 0.1%	0.9851534	1.0382049	1.0060915	1.2277596
3	Top 1%	0.9840442	1.0842389	1.0053455	1.2983394
4	Top 10%	0.9841445	1.1041014	1.0181113	1.1338419
5	Decile 50-90%	0.9798014	1.1063604	0.9663847	1.2908230
6	Bottom 90%	0.9841445	1.1041016	1.0181114	1.1338428
7	Bottom 50%	0.9680701	1.0338746	1.1042653	0.9903783

Table 16: Table of RMSE Ratios, Ratios from Income Distribution, Covid. Data source: Realtime Inequality and FRED.

	Category	Control	FD_Control	Interaction	FD_Interaction
1	Ratio 90/50	0.9773955	1.0360149	1.0538525	0.9493034
2	Ratio 50/90	0.9818307	1.0654427	1.0818929	0.9665303
3	Ratio 90/90	0.9840871	1.0950388	1.0159359	1.1300536

Tables 15 and 16 show the RMSE:s for the pandemic period using different segments from the income distribution to forecast inflation, with the forecasts beginning in 2020Q2, when the pandemic stimulus checks started being distributed. The training data uses all available data, but we restrict the simulated forecasts to the period of the pandemic up until 2023Q1

When forecasting inflation during the pandemic, overall the different specifications do not improve relative to the the textbook model. However, the control specification performs relatively similar to the textbook model. When comparing the bottom 50%, 90/50 ratio and 50/90 ratio, the control and first differencing interaction variables perform better than the textbook whereas the first differencing control and interaction perform worse than the textbook. One can therefore wonder how informative the bottom 50% of the distribution is, due to their varying impacts. Especially when comparing this with the results from section 7.3 where they almost consistently perform worse. Again, these RMSE ratios are still close to 1 and we thus cannot definitively conclude that neither the textbook nor the distributional model improve the forecasts.

10.3 Full Model Specifications

Naive Model

$$E_t(\pi_{t+4}) = \pi_t \tag{Naive}$$

Textbook NAIRU Phillips Curve

$$E_t(\pi_{t+4}) = \pi_t + \beta(u_t - \overline{u}) \tag{Model}$$

$$E_t(\pi_{t+4}) - \pi_t = \alpha + \beta u_t \tag{Regression}$$

$$\Rightarrow \overline{u} = \frac{\alpha}{-\beta} \tag{Ubar}$$

Inequality-Extended Phillips Curve with a Control Term

$$E_t(\pi_{t+4}) = \pi_t + \beta_1(u_t - \overline{u}) + \beta_2 I_t \tag{Model}$$

$$E_t(\pi_{t+4}) - \pi_t = \alpha + \beta_1 u_t + \beta_2 I_t \tag{Regression}$$

$$\Rightarrow \overline{u} = \frac{\alpha}{-\beta_1} \tag{Ubar}$$

Inequality-Extended Phillips Curve with an Interaction Term

$$E_t(\pi_{t+4}) = \pi_t + \beta_1(u_t - \overline{u}) + \beta_2 I_t + \beta_3 u_t I_t \tag{Model}$$

$$E_t(\pi_{t+4}) - \pi_t = \alpha + \beta_1 u_t + \beta_2 I_t + \beta_3 u_t I_t \tag{Regression}$$

$$\Rightarrow \overline{u} = \frac{\alpha}{-\beta_1} \tag{Ubar}$$

10.4 Graphs

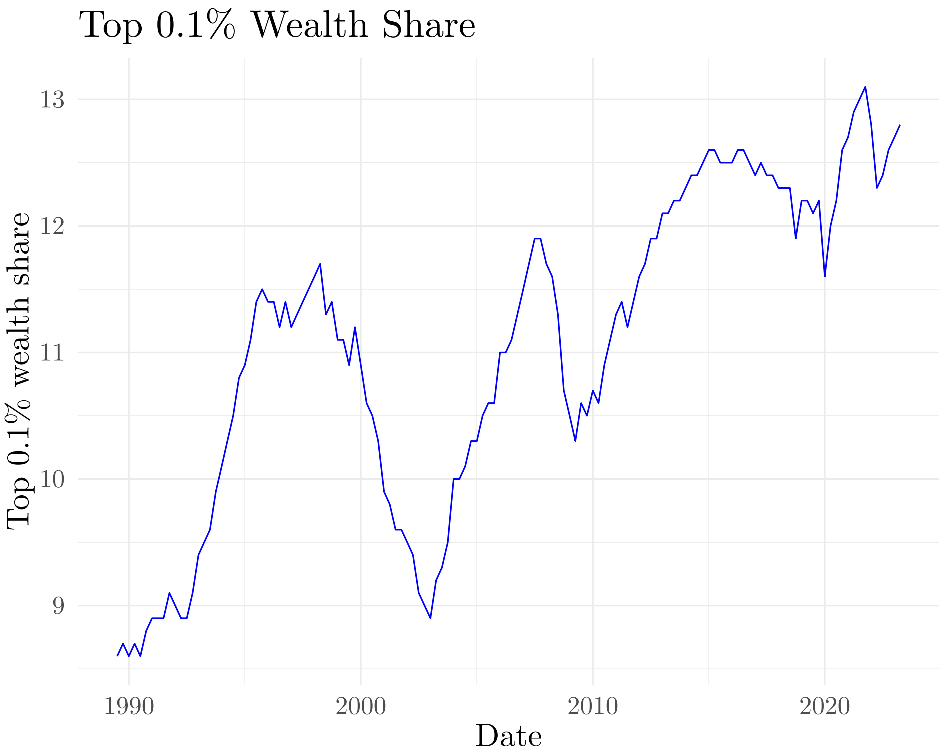

Figure 5: Top 0.1% Wealth Share

Data source: FRED, 1989-2023

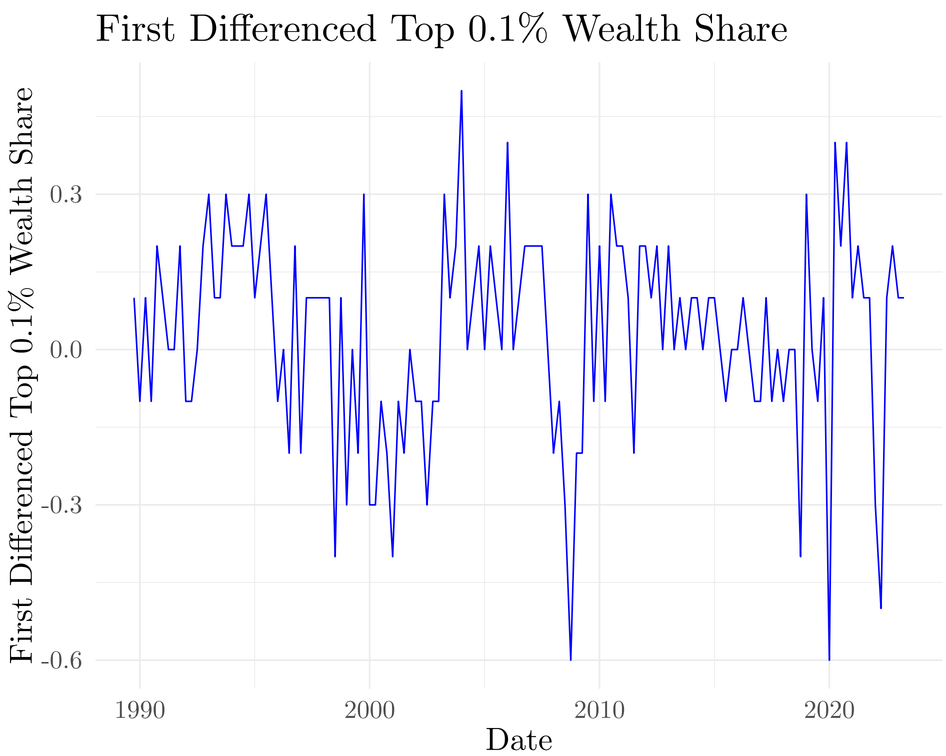

Figure 6: First Differenced Top 0.1% Wealth Share
Data source: FRED, 1989-2023

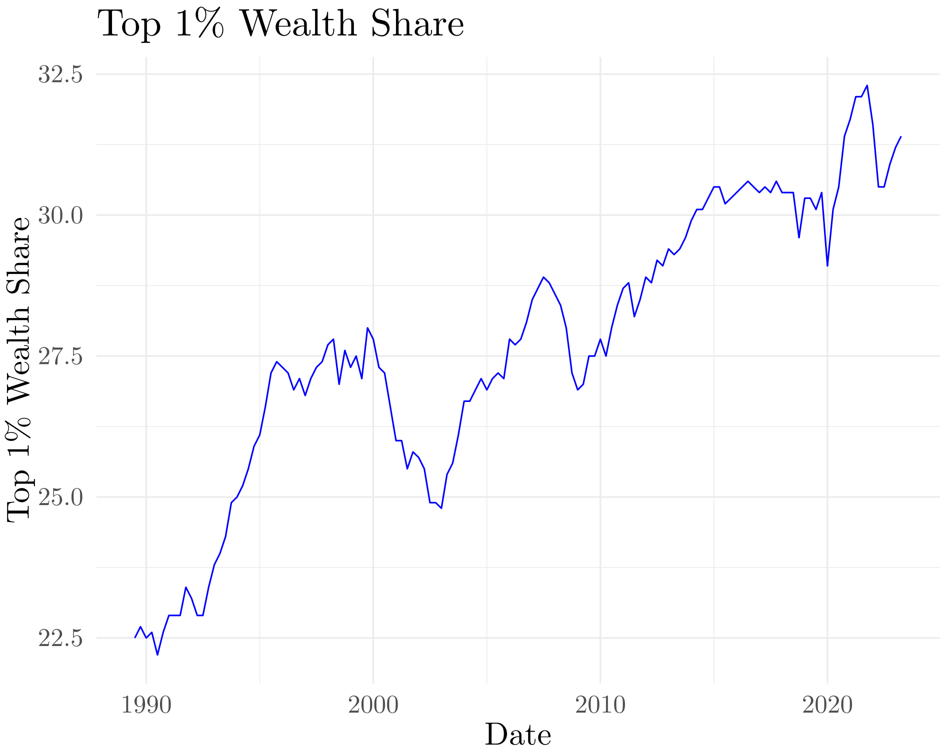

Figure 7: Top 1% Wealth Share
Data source: FRED, 1989-2023

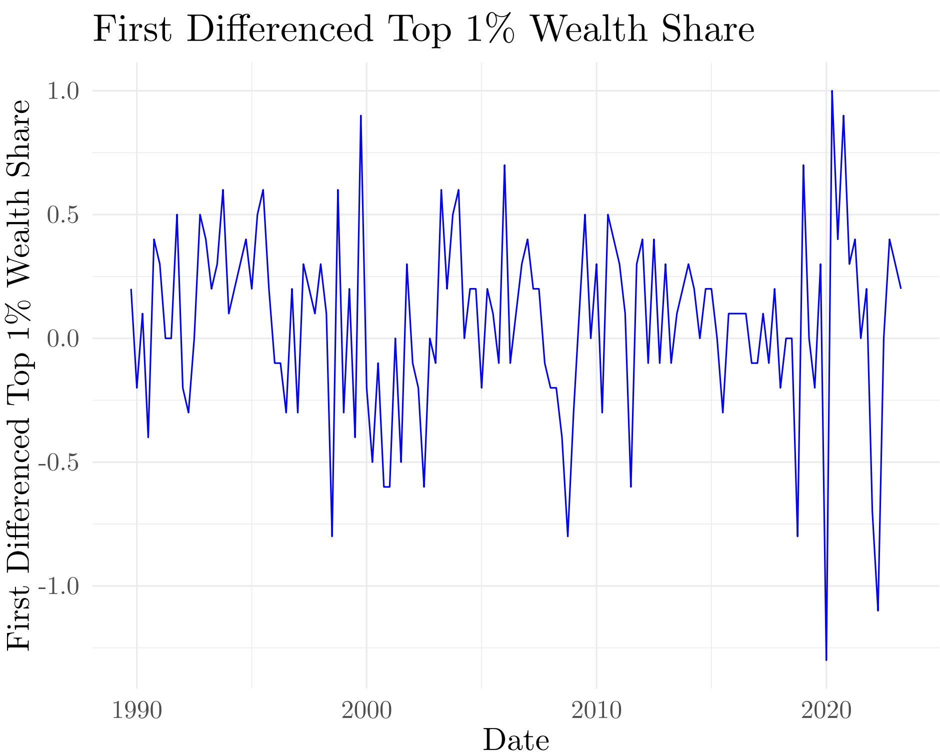

Figure 8: First Differenced Top 1% Wealth Share
Data source: FRED, 1989-2023

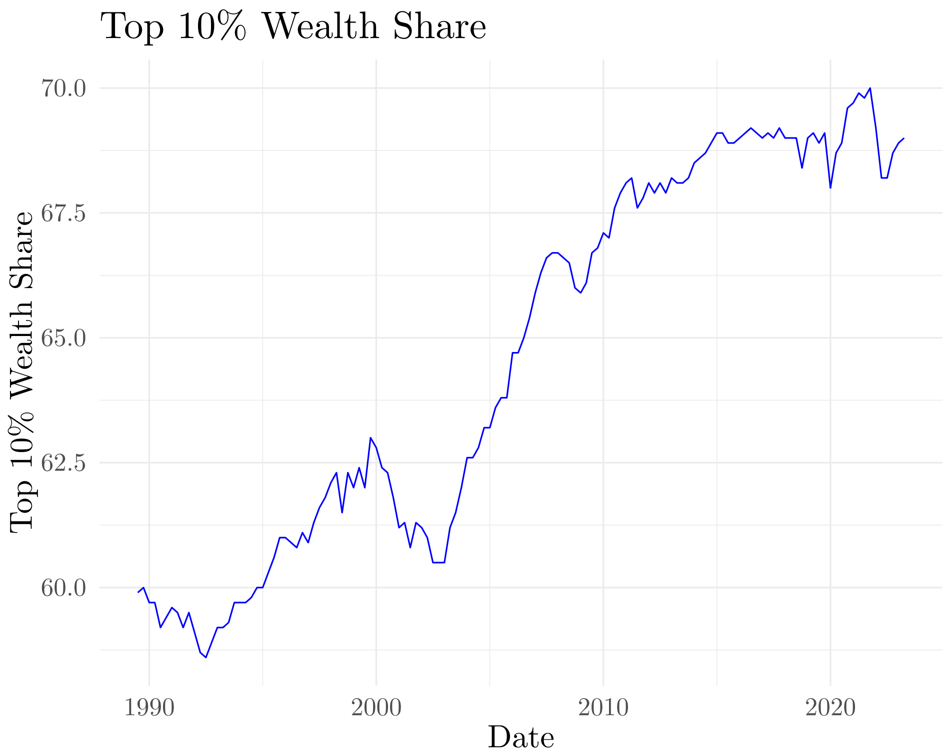

Figure 9: Top 10% Wealth Share
Data source: FRED, 1989-2023

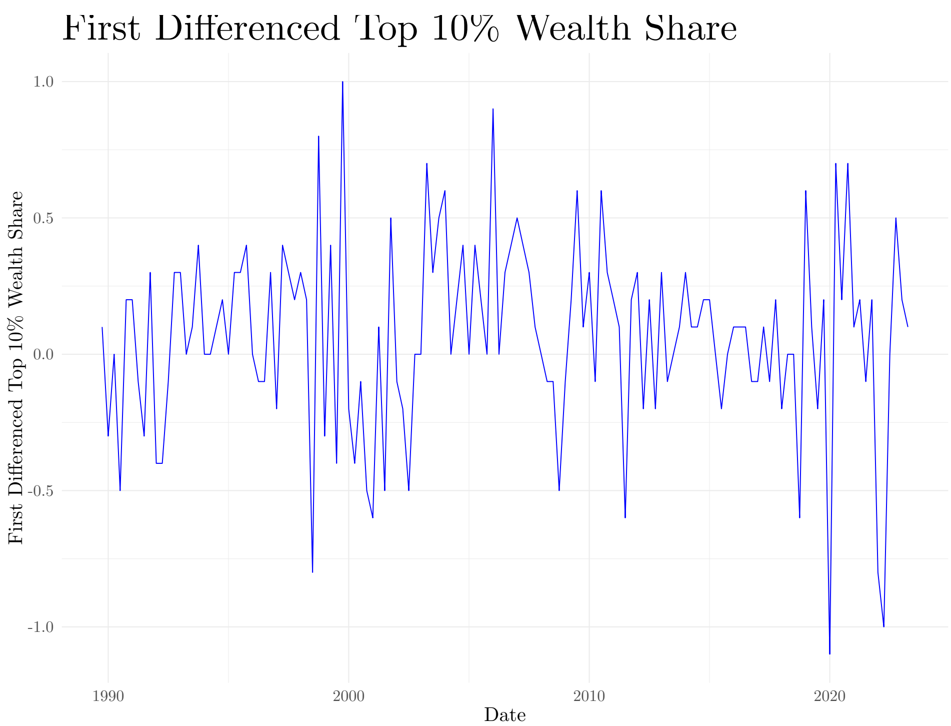

Figure 10: First Differenced Top 10% Wealth Share
Data source: FRED, 1989-2023

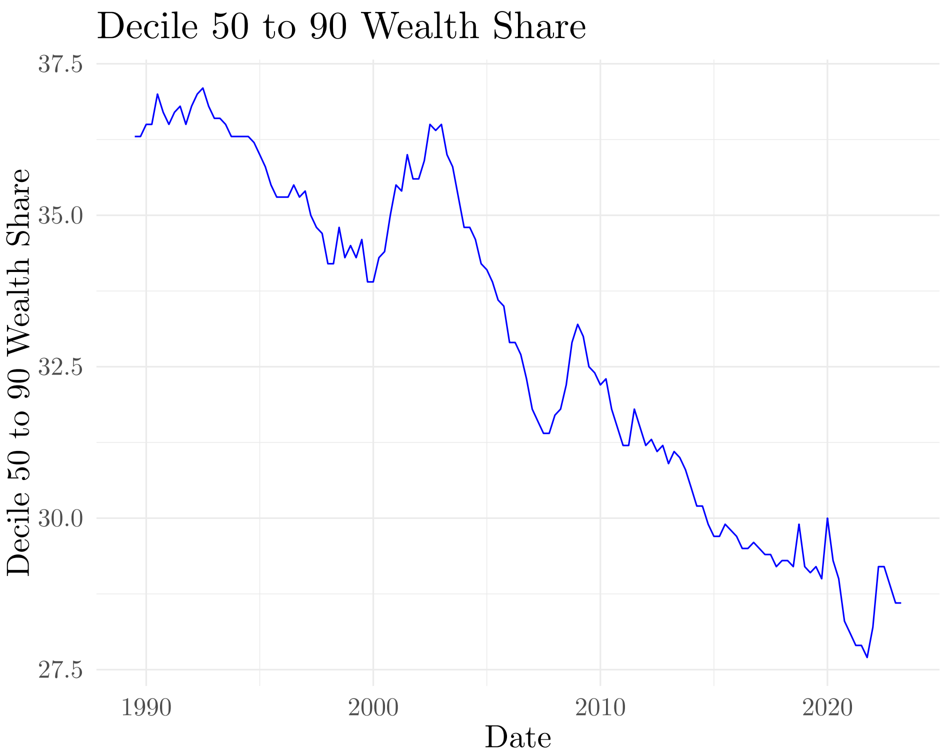

Figure 11: Decile 50-90 Wealth Share
Data source: FRED, 1989-2023

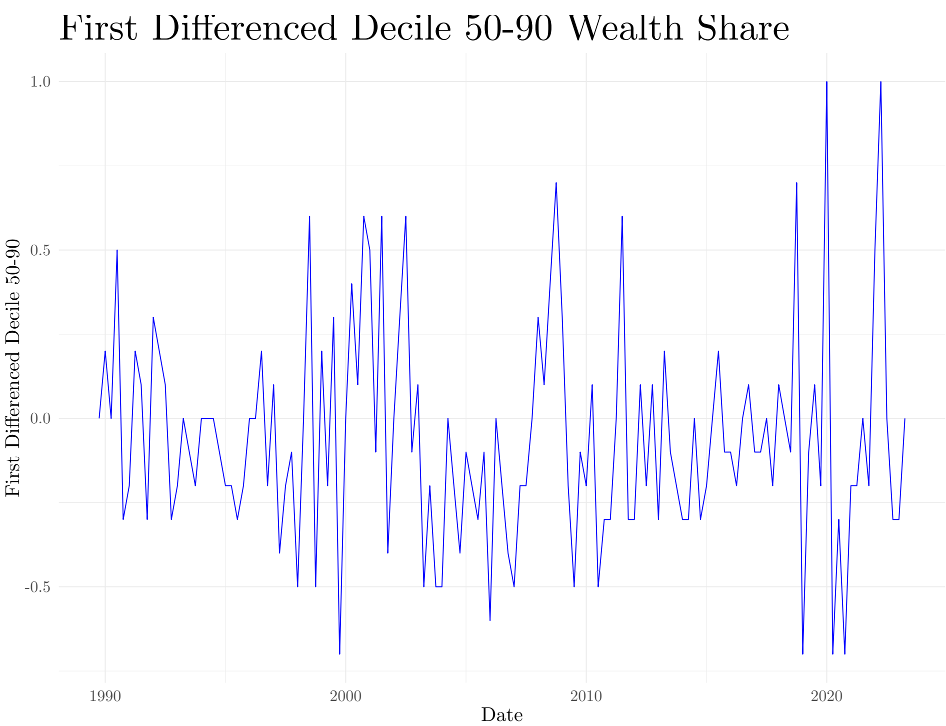

Figure 12: First Differenced Decile 50-90 Wealth Share
Data source: FRED, 1989-2023

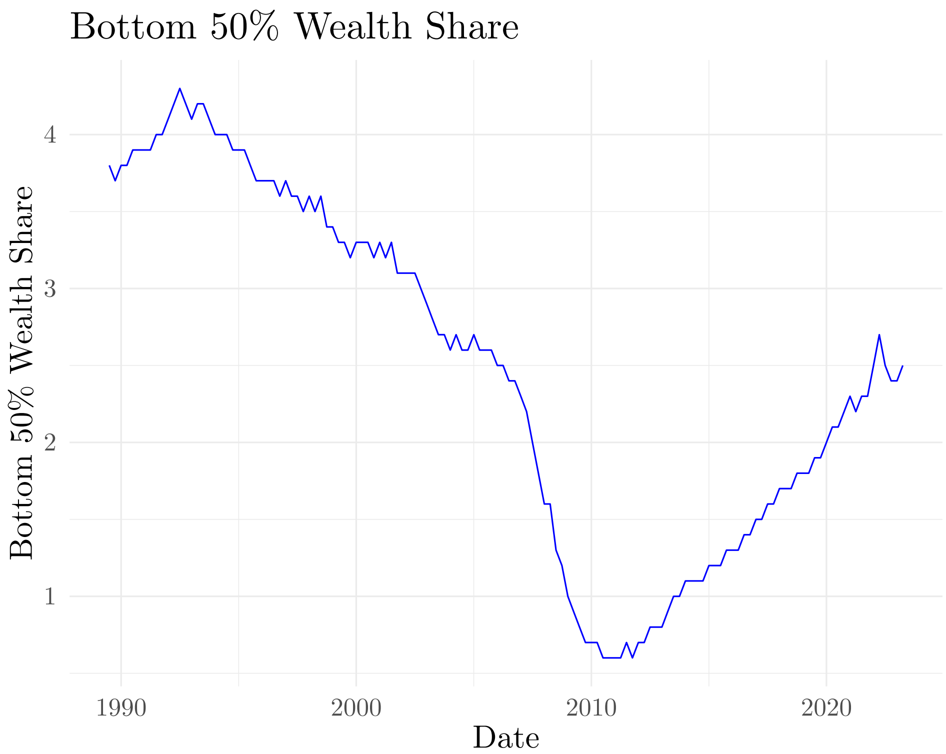

Figure 13: Bottom 50% Wealth Share
Data source: FRED, 1989-2023

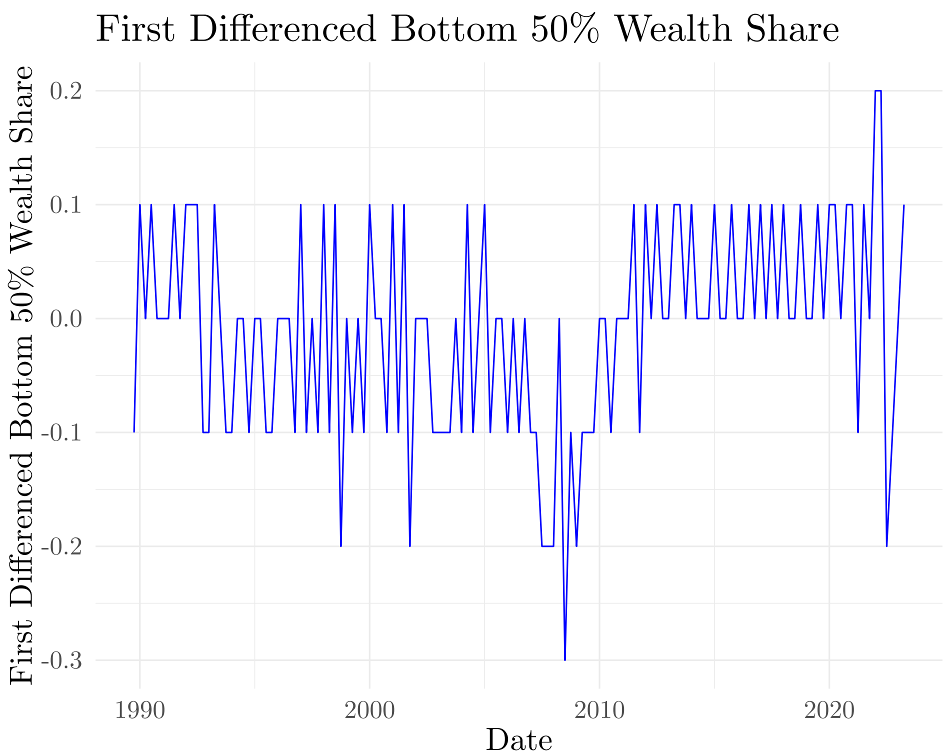

Figure 14: First Differenced Bottom 50% Wealth Share
Data source: FRED, 1989-2023

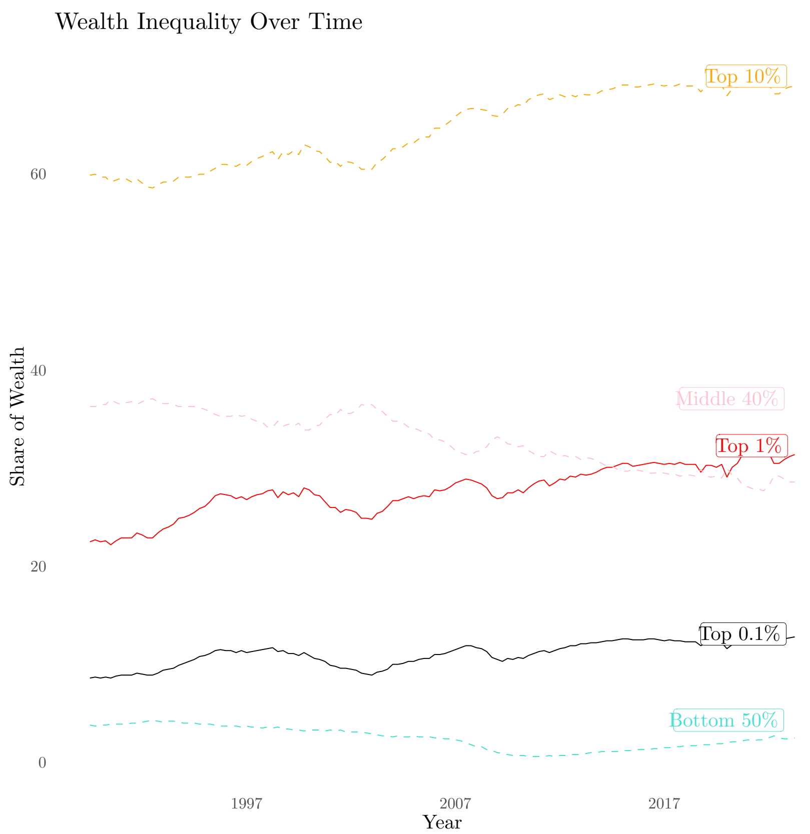

Figure 15: Wealth Inequality
Data source: FRED, 1989-2023

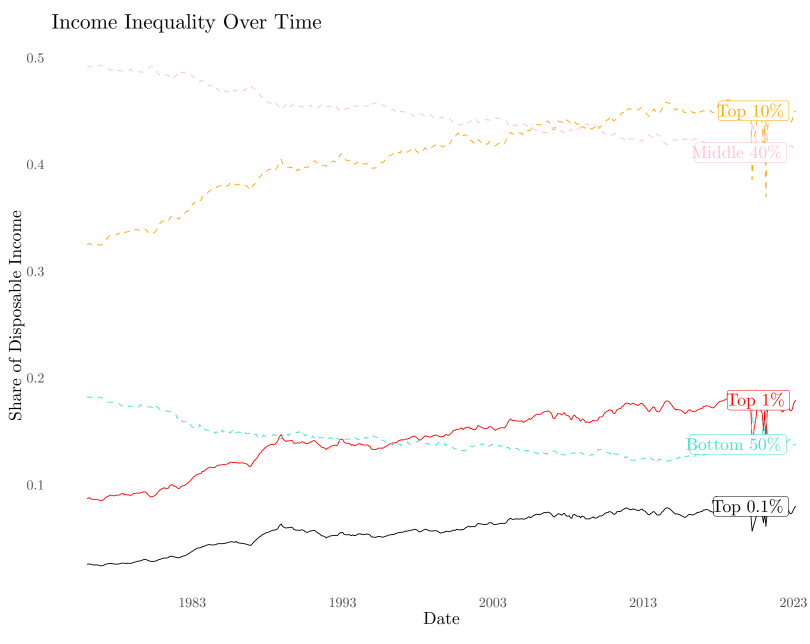

Figure 16: Income Inequality
Data source: Realtime Inequality, 1976-2023