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Navn:	Synne Voldsund og Marita Sekse

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The Effect of Monetary Policy on Income-specific Inflation Rates in Norway

Master of Science in Business, Major in Economics.

Supervisor: Maria Olsson

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Abstract

The goal of this master thesis has been to find out whether monetary policy has heterogeneous effects across the income distribution through the inflation channel in Norway. We find that the households at the bottom 5 percent of the income distribution face less frequent price changes relative to the middle 40-60 percent and top 1 percent income groups. When analyzing the volatility of price changes, our results are divided depending on the level of aggregation of consumption categories. We use a structural vector autoregressive (VAR) model to investigate the effect of monetary policy on income-specific inflation rates. The impulse response functions of the households at the top 1 percent of the income distribution react the most to a monetary policy shock, while the bottom 5 percent react the least. Hence, the magnitude of the responses is increasing with income. All in all, the results of our study indicates that monetary policy might affect income-specific inflation rates heterogeneously.

(Some of) the data applied in the analysis in this publication are based on "Consumer Expenditure Survey, 2012". The data are provided by Statistics Norway, and prepared and made available by NSD - Norwegian Center for Research Data. Neither Statistics Norway nor NSD are responsible for the analysis/interpretation of the data presented here.

Acknowledgement

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Table of Contents

1. Introduction

The landscape for monetary policy and central banks has changed fundamentally since the Great Recession – much as a consequence of interest rates hitting the zero-lower bound, resulting in an extensive use of unconventional monetary policy tools. It was quickly observed that the increasing use of unconventional tools was associated with rising inequality, which led to a perception of an unjust monetary system that disproportionately benefits those in the higher ranks of the wealth distribution (Schnabel, 2021). This raised discussions on how monetary policy is potentially affecting inequality and whether central banks should extend their objectives beyond simply meeting inflation and employment targets.

Traditionally, it has primarily been the government's mandate to alleviate uneven market outcomes and pursue redistributive measures through the use of fiscal policy. The monetary policy mandate in Norway is simply to maintain monetary stability by keeping inflation low and stable. It is the Norwegian central bank, Norges Bank, who is responsible for the implementation of this. Their operational target has since 2001 been annual consumer price inflation close to two percent over time. Inflation targeting intends to be forward-looking and flexible in order to contribute to high and stable output and employment, in addition to diminishing the build-up of financial imbalances (Norges Bank, 2021). However, there are several channels through which monetary policy might affect inequality. Are agents saving or borrowing? Are they active in financial market transactions? How much currency do they hold? What does their income composition look like? What do they consume, and does it affect they inflation they are facing? To which extent monetary policy affects income and wealth inequality depends on the answers to these questions. If there is clear evidence that monetary policy leads to increased inequality, the central bank may need to adjust its mandate. Numerous studies on the topic have been published, however results remain ambiguous.

Turning to the development of inequality in Norway, average income has gradually increased, but so has the *pre-tax* national income share accruing to the richest 10 percent (World Inequality Database, 2021). Based on data from World Inequality Database (2021), the share of pre-tax income accrued by the top 10 percent has increased from 27.2 percent in 1980 to 31.9 percent in 2018. On the other hand, for the bottom 50 percent, the share has decreased from 25.1 to 23.8 percent over the same time span. This is illustrated in figure 1. The fact that the statistics are *pre-tax* means they are interpreted before redistributive policies are implemented. Turning to *post-tax* statistics, it is clear that redistributive policies have a strong impact on the level of inequality. As can be seen from figure 2, the bottom 50 percent then accounts for a larger share of total income compared to the top 10 percent. However, the share of total income, and hence the difference between top 10 percent and bottom 50 percent of the income distribution, has been more or less constant since the latter half of the 90s. It is also worth mentioning that the income and wealth gap might be even larger than the statistics show as company owners have had incentives to withdraw a smaller share of dividends, which are not accounted as personal income in official statistics, after the introduction of dividend tax in 2006. (Aaberge et al., 2020). A relevant question to ask is therefore whether or not monetary policy can, and should, ease fiscal policy or close the gap further.

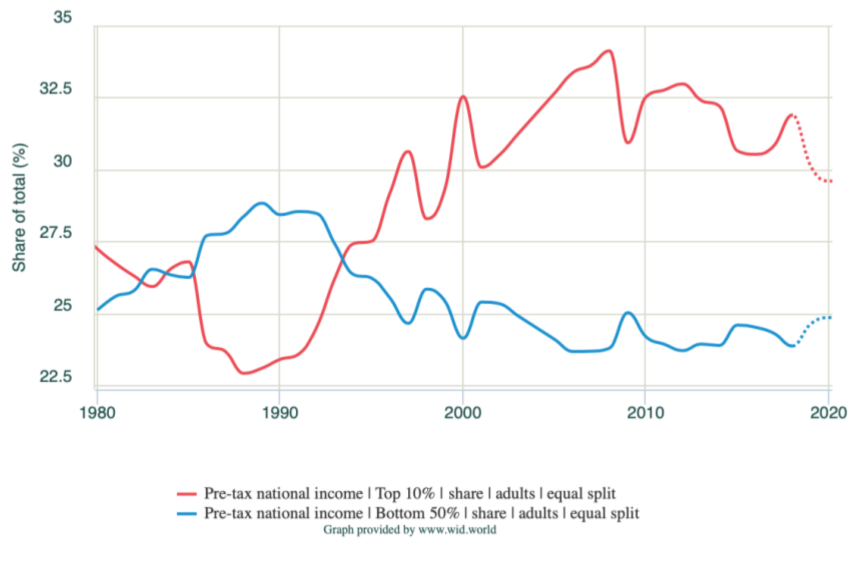

Figure 1: *Income inequality in Norway from 1980 to 2020, based on pre-tax national income (World Inequality Database, 2021).*

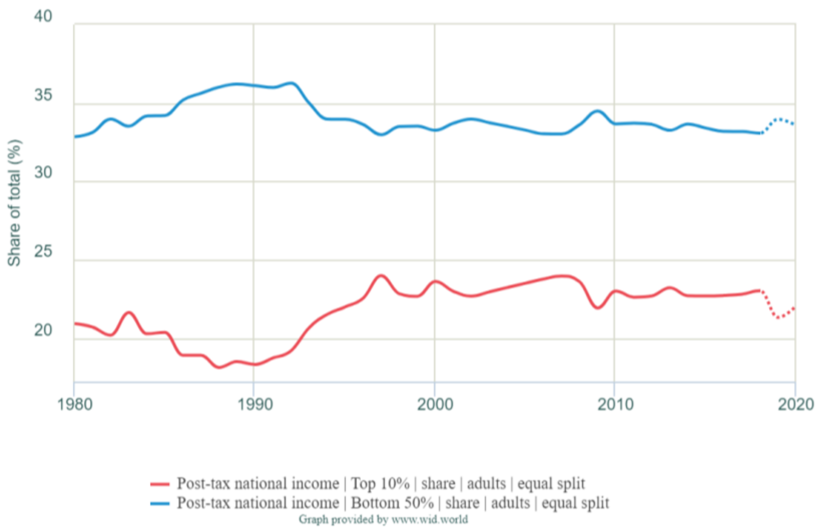

Figure 2: *Income inequality in Norway from 1980 to 2020 based on post-tax national income (World Inequality Database, 2021).*

The expenditure pattern and lifestyle of wealthy and poor are usually quite different. Different households along the income distribution tend to consume different commodities and services, ergo consumption baskets and the weight given to various goods also differ. This indicates that the households also might face heterogeneous inflation rates, as the effects of monetary policy on prices are heterogeneous across different types of commodities and services. Hence, monetary policy may have distributional effects by impacting real income differently through the inflation channel, while nominal income increases at the same rate across households.

Expenditure shares and heterogeneous inflation rates have been studied for several countries by different authors, for instance in the US by Cravino et al. (2020), North Macedonia by Jovanovic and Josimovski (2021), Pakistan by Cheema and Malik (1986) and Germany by Mehrhoff and Breuer (2010). The former two have in fact been of great inspiration for our thesis. As far as we know, we are the first to study this transmission mechanism for the case of Norway. This leads us to the following research question:

How does a monetary policy shock affect income-specific inflation rates in Norway?

To answer the research question, our research will generally be conducted in two parts. The first consists of a detailed analysis of consumption expenditure shares and inflation rates faced by households at different points on the income distribution. This includes a thorough investigation of price volatility and price frequencies. In the second part, we will estimate a structural vector autoregressive (VAR) model to identify a monetary policy shock and study the effect on the income-specific inflation rates calculated in the first part. The analysis from both parts will then be discussed in light of each other to form the basis for a conclusion. The overall goal is to see whether income-specific inflation rates respond heterogeneously to a monetary policy shock.

The rest of our thesis is organized as follows. Section two presents the literature review. Section three describes the data we will be using, both for part one in our consumption and price analysis, and for part two in our structural VAR analysis. The methodology we are using for both parts is presented in section four. Section five presents some stylized facts from our consumption analysis and how this affects the prices in which the different households face, while our empirical results from the structural VAR model is presented in section six. Our findings from section five and six are discussed and compared in section seven. Section eight concludes.

2. Literature review

The distributional effect of monetary policy is heavily discussed among researchers and the literature on the topic is extensive. The transmission mechanisms of monetary policy are complicated, and inequality can emerge through several different channels. It has therefore been proven difficult to draw inferences on the inequality consequences of monetary policy. In this section, we give a brief overview of the most relevant literature for our question of research. We first review the main research papers which our thesis is based on. Then, we proceed by summarizing some key findings on how the burden of inflation may be heterogeneously distributed along the income distribution. Towards the end of this section, we look into some empirical findings on the distributional effects of monetary policy with particular focus on Norway.

2.1 The effect of Monetary Policy on Income-specific Inflation Rates

To contribute to the literature, we have decided to focus our thesis on a novel transmission channel, first studied by Cravino et al. (2020). The channel investigates how consumption baskets differ across the income distribution and how this gives rise to monetary policy having distributional effects by affecting inflation differently. Thus, our thesis draws on two strands of literature: heterogeneous consumption baskets and distributional effects of monetary policy. Since their working paper was first published in 2018, more and more researchers have replicated their study for other countries. In the following, we will present what we find to be the most important findings on the channel to this date.

Cravino et al. (2020) study how US households in different percentiles along the income distribution are affected differently by a monetary policy shock. The effect of monetary policy is transmitted through an inflation channel, where it is assumed that households have different consumption baskets in which the CPI is based on (see section 3.1.2 for further details on the CPI). A consumption basket is simply a constant basket of goods and services representing private household's consumption; however, the weighting and the products differ across income groups. To document the effect on prices, they start off by finding the percentile income of households at different places on the income distribution which they use to create income groups. They then compute each group's expenditure shares. The expenditure shares are combined with item-level price indices at the finest publicly available level of disaggregation to create income-specific consumer price indices (CPIs). The income-specific expenditure shares are then used to study patterns in consumption of different income quantiles, and further, to understand the volatility and frequency of the prices that the households are facing. By doing a comparative analysis of the consumption baskets and the prices to which households are exposed, they find that the households in the lower and upper tail of the income distribution consume goods and services with more sticky prices. In comparison, households with income around the median are exposed to a higher mean frequency of price adjustment, or in other words, more flexible prices. They find a similar inverted u-shaped pattern when it comes to price volatility, i.e., that the middle-income households face prices with higher variation than those at the tails. The findings on prices have implications when they look into the effect of monetary policy, suggesting that a monetary policy shock can have distributional consequences.

To study how a monetary policy shock affects the households in different income percentiles, they apply an empirical factor-augmented vector autoregressive (FAVAR) model. They apply monthly data for the sample period 1969-2008. Distributional effects are studied through the income-specific CPIs and identifying impulse response functions for each CPI rate. In response to a 100-basis-point increase in the policy rate, they find that the CPI of the households at the top of the income distribution reacts substantially less to a monetary policy shock compared to those in the middle of the income distribution. Furthermore, the difference between the income-specific CPI rates increases over time. Although the response of inflation to a monetary policy shock in itself is not statistically significant, they find that the zero impact of the *difference* between the income-specific responses can be rejected. Specifically, they find that the difference in the CPI response of the top 1 percent and the middle 40-60 percent is statistically significant, concluding that monetary policy has distributional consequences.

Another paper which looks into the same transmission channel, is one by Jovanovic and Josimovski (2021). They study the effect of monetary policy on income-specific inflation rates, only for the case of North Macedonia. The greatest difference from Cravino et al. (2020) is that they divide income groups into deciles instead of percentiles as a result of their limited access to micro-data, which ends up having implications for their results. Jovanovic and Josimovski (2021) do not find the same inverted u-shaped relationship between income groups and price flexibility as Cravino et al. (2020). Instead, they find a negative correlation between the size of income and price frequency and price volatility, meaning that those in the lower income range consume products with more volatile and high-frequently changing prices. As a result, their FAVAR model implies that the inflationary effects of a monetary policy shock are quantitatively larger for the low and middle-income groups, compared to the richer households. However, the difference in the responses of income-specific inflation rates is minor. They justify these results as a shortcoming of using deciles, which gives more aggregated and less economically meaningful income groups, masking some important results (Jovanovic & Josimovski, 2021).

2.2 Inflation Inequality

Cheema and Malik (1986) look into the cost-of-living effects of inflation for households in different income brackets in different areas in Pakistan. Their results do not indicate that there are substantial differences in the pattern of inflation across households. Households in the lower income brackets seemed to face lower inflation rates in periods when prices of food rose at lower rates than those of non-food items. When food prices rose sharply these differences disappeared, resulting in a higher inflation rate for the lower income brackets compared to the higher income brackets. However, the numerical magnitude of these differences was not very large. Mehrhoff and Breuer (2010) aim at quantifying the differences in distribution of the inflation burden among households in Germany. They analyze data on household income and expenditure at the lowest level of aggregation publicly available in order to argue whether or not inflation is heterogeneously distributed among income groups. They do find some variation in price indices and weighting schemes across households. However, the general inflation trend seems to be constant, irrespective of the household's net income. In another paper, Jaravel (2021) discusses recent findings on the measurement of inflation inequality. He states that earlier research on inflation inequality suggests that there are modest differences in inflation rates across households. However, recent work has shown that substantial differences across households arise when more detailed data are used, as this helps to ease aggregation bias. In the United States, inflation rates have been shown to decline with income when micro-level data have been used, in contrast to when product categories were coarser. Hence, data on micro-level have been proven necessary to measure inflation inequality to its full extent.

2.3 Monetary policy and Distributional Effects in Norway

There are reasons to believe that the distributional effects of monetary policy differ across countries. Turning to research conducted on Norway, Mimir et al. (2021) quantifies the short-term effect of conventional systematic and non-systematic monetary policy on income and wealth distribution in Norway. They find that an unexpected reduction in the interest rate disproportionately benefits young people and households with middle to lower income and wealth, thereby reducing inequality in disposable income and wealth. The mechanism is as follows; a lower interest rate leads to higher inflation, decreasing the real interest rate, which raises both stock and house prices. Only the very rich benefit from higher stock prices, while most Norwegian households gain from higher house prices due to the high rate of home ownership in Norway. However, the middle and lower part of the distribution gain relatively more since they are more indebted. In addition to studying the effect of monetary policy shocks, they look into systematic monetary policy. Their results suggest that systematic monetary policy tends to dampen income and wealth inequality, in addition to stabilizing output and inflation. This indicates that central bankers' direct responsibility regarding inequality is of less concern but is still important to be aware of as distributional effects may affect the transmission mechanism of monetary policy. Holm et al. (2021) has also studied the transmission of monetary policy in Norway. More specifically they look into the transmission of monetary policy on household consumption. Households are put in order according to their liquid asset positions, before estimating impulse responses at a fine segment along the distribution. The consumption response to a monetary tightening is stronger for the households at the bottom of the distribution than for those at the median. The latter group initially saves less or borrow more when their disposable income falls, while the households at the bottom reduce their consumption. Households at the top of the liquid asset distribution initially increase their consumption as a result of a rise in the interest income. Based on their results they conclude that indirect effects of monetary policy play a significant role in transferring changes to consumption, by simply affecting the disposable income of households.

Hafemann et al. (2018) compare how different income inequality measures respond to a monetary policy shock across three different advanced economies: Norway, Canada, and the US. The countries vary in their level of income inequality and government intervention, which is the motivation behind their objects of study. To narrow down their research, they decide to focus specifically on two distribution channels of monetary policy: *the income composition channel* and *the employment channel*. The income composition channel considers the heterogeneity of household's different income sources and how this can lead to redistributive effects. In general, households at the lower tail of the income distribution tend to rely more on different forms of transfer, while households at the median rely mainly on salaries. The households at the upper tail of the distribution receive relatively more business and capital income. Income inequality occurs when capital income increases disproportionately to labor income. The employment channel, on the other hand, is more focused on the effect of monetary policy on the labor market. By applying a structural VAR model with sign restrictions, they analyze the effect of an expansionary monetary policy shock on the number of employed people and on different income sources, more specifically, on labor income, capital income and the capital-wage ratio. Overall, they find that an expansionary monetary policy shock leads to inequality, mainly through the income composition channel. However, for Norway the effect is dampened as they only find a minor increase in the capital-wage ratio. The effect is also not statistically significant. An explanation is that governmental redistribution through taxes and transfers, which is more present in Norway, mitigates the redistributive effects of monetary policy. They therefore conclude that there is no need for the central banks to incorporate a pure inequality-related target in their objective function.

In the literature, it has been proven difficult to draw inference on whether monetary policy leads to inequality or not. One of the reasons is that inequality can originate from several different sources, along with being hard to identify. Based on our review, there seems to be some evidence that monetary policy affects the distribution of income, wealth, and consumption. Still, there is a need for more evidence before advising central banks to take distributional effects into account when formulating their monetary policy. Both cross-country and within-country studies are needed. Due to limited evidence on the distributional effects of monetary policy in Norway, this is our motivation to look into this case specifically.

3. Data

In this section we will present the data we are going to make use of in our thesis. We start off by giving an insight to the data relevant for our consumption analysis and the calculation of income-specific expenditure shares and measures of price stickiness and volatility. Thereafter, we introduce and elaborate on the data relevant for part two of our thesis, i.e., the data we will utilize when estimating our baseline model. We will also justify our chosen sample period.

3.1 Part 1: Consumption and Price Analysis

In this first part we will generally rely on secondary data, which refers to data that were originally collected by another research team. This is because large-scale and nationally representative data, which is what we will be needing, requires extensive resources to collect. Such high-quality datasets are for that reason often made available by organizations, to allow researchers to conduct independent research (Statistics Solutions, 2021).

3.1.1 Data on Consumption and Income

For the first part of our thesis, we use household-level micro-data from the Household Budget Survey (HBS), which provides a detailed overview of Norwegian household's annual consumption of various goods and services. These data are distributed by the "Norwegian Center for Research Data" (NSD), which is a national center and archive for research data (Norwegian Centre for Research Data, 2022). However, the data is collected by Statistics Norway (SSB). Information about the survey is gathered in a detailed documentation note by Holmøy and Lillegård (2014), which is our source for the rest of this section.

The HBS was carried out yearly between 1974-2009 but is now carried out as larger periodic surveys at different intervals. The first of these was done in 2012, and at this point this is also the most recent. For these reasons, this dataset is the one we are using in our research. Hence, we assume that the consumption baskets we find are constant over time. Ideally, we would prefer to compare the expenditure structure we obtain from this survey with another survey done a few years earlier to make sure it is reliable. However, due to the significant changes to the survey, this would be too time-consuming for a master thesis.

A sample of 7,000 households was drawn to participate, stratified by district and type of household, and randomly drawn within each stratum. The participants were drawn from a population of private households where at least one person in the household is below 85 years old. In the end, a total number of 3,363 households completed the survey. The data was collected by a questionnaire, diary (on paper or electronically), and receipts. An introductory interview was carried out to begin with, before the households kept track of their expenses for 14 days. After the tracking period, another interview was done. The purpose of this latter interview was to measure the expenditures of large or durable goods and services that the households buy less frequently, like for instance housing expenses, cars, appliances, luxury clothes, and vacations. The entire process of data collection lasted for 15 months, however the tracking of expenses lasted from January 1st to December 31st in 2012. This corresponds to 26 tracking periods, with equally many households randomly assigned to each period, to ensure coverage of all months of the year. Biases in the sample, as a result of households shifting their tracking period, are adjusted for through post-stratification.

In order to make the interview shorter and increase the usefulness of the information collected, information about education is retrieved from the education sector and information about income, fortune, employer and social security and benefits is obtained from the tax authorities and the Norwegian Labor and Welfare Administration (NAV).

3.1.2 CPI

To quantify the differences in the burden of inflation across income groups, we construct income-specific inflation rates using data on the CPI in addition to the consumption data described above. The CPI data is provided by SSB and measures the development in prices of private household's consumption basket, where the consumption basket consists of a certain composition of products and services. The weights are based on the private household's expenses on each category, which are reviewed and incorporated into the index every year. The goods and services are classified into categories after the "Classification of Individual Consumption According to Purpose" (COICOP)[1], which is the international reference classification of household expenditure (Fløttum, 1999). Appendix A provides an overview of the structure of the CPI and how it can be decomposed into a representative level of products. In general, the purpose of the

[1] Food, beverages and tobacco, clothing and footwear, housing, household equipment, health, transportation, communications, recreation and culture, education, restaurants and hotels, and miscellaneous.

CPI is to measure how the costs-of-living of private households evolve over time and it is used by many monetary authorities as an approximation of the inflation rate (Statistics Norway, 2001).

The CPI measures the costs of the consumption basket in one year relative to a reference base (year) where the prices are set equal to 100. The reference year as of 2022 is set to 2015 (2015 = 100). Technically, the CPI is based on thousands of weighted micro indices of each representative item. The micro indices are further aggregated to consumption groups and total CPI (Statistics Norway, 2001). To be able to calculate the index, Statistics Norway collects data on both prices and expenditure shares. The expenditure shares were earlier based on yearly data from the HBS but have since 2011 been based on numbers from the Norwegian national accounts. The reason for the shift in sources of data was primarily to make the budget weights more relevant and qualitatively better, as data from the national accounts are published more frequently and are based on a larger and more representative sample of Norwegian households (Langer & Johannessen, 2010). The data on prices are collected monthly based on a sample of companies who report prices on some representative goods, where the sample is drawn based on geographical location, business code, and turnover. To make the representative goods relevant, the goods are continuously evaluated, and each company is a part of the survey for a period of six years (Statistics Norway, 2001). Overall, the CPI is an important measure of consumer price development, it is easy to work with, as well as being published at a high frequency. We therefore use it extensively in our thesis. SSB provides different types of CPIs and at various levels of aggregation, whereas the most important measure of cost-of-living is the total CPI. To create the income-specific CPIs we weight monthly sub-indices at a lower level of aggregation for each group of households. These will further be summed up to measures of total income-specific CPIs. The methodology behind these rates is discussed more in detail in section 4.1.2.

3.1.3 Measures of Price Frequencies

To analyze differences in frequency of price changes across households we use reported measures of price stickiness constructed by Wulfsberg (2016). These can be interpreted as the probability that prices change in a particular month, for different groups of products and services classified after COICOP. Based on around 14 million monthly price observations of 1,124 goods and services from Norwegian firms, Wulfsberg (2016) documents price adjustments in time periods with both high and low inflation. We have chosen to use the frequencies from the low-inflation period, 1990-2004, as this is the period which matches the rest of the data in our estimated model the best. Average monthly frequency of price changes for each item each year, f_{it}, is computed as the fraction of the total number of price changes. This is decomposed into mean frequency of price increases and price decreases, computed by weighting the items by their current CPI-weight. Hence, we can sum the price increases, f_{it}^{+}, and the price decreases, f_{it}^{-} reported by Wulfsberg (2016) to find the frequency of price changes for each consumption category that we want to use for our analysis (see appendix D.1). Wulfsberg (2016) generally reports a lot of variation in the frequencies across items in Norwegian data. Vegetables, fruits, energy and petroleum are examples of goods that experience frequent price changes, while various services experience less frequent price changes. The main finding of his research is on what components of price adjustment, i.e., size or frequency of price change, that best explain the variation in inflation. The short-term and long-term variability in the inflation rate is mostly explained by the frequency of price change. However, when separating periods, he finds that low and stable inflation is explained by both the frequency and magnitude of price change, but the size of price change seems to contribute the most.

3.2 Part 2: Structural VAR

After having analyzed the income-specific expenditure shares and identified income-specific CPIs using the data presented in section 3.1, we study the impulse response functions of these indices by estimating a structural VAR model. The data we use for this section is presented in the following. We generally rely on quarterly time-series data collected from various sources. By looking at any single year, inflation inequality is minor. Therefore, in order to assess to what extent differences in inflation rates faced by different households affect inequality, we need to look into the long-term trend in inflation inequality.

3.2.1 Sample Period

We choose the sample period 1994-2019. The starting point of the sample is a choice that is mainly based on data availability, as most of the relevant datasets were not published until the early 1990s. Furthermore, we also want to avoid *structural breaks*, defined as unexpected jumps in economic time series due to structural changes, for instance changes in monetary policy regimes. If such breaks lead to changes in the correlation between the economic variables in the model, it may cause misleading estimation (Bjørnland & Thorsrud, 2015, p. 70). The monetary policy regime of Norway experienced significant changes during the 1990s. The fixed exchange rate regime was abandoned in 1992 and replaced by a managed float of the exchange rate. The central bank did not adopt an inflation target until 2001, however, this specific change in regime did not lead to any significant changes in the conduct of monetary policy, probably as a result of the tight connection between inflation and exchange rate (Bjørnland, 2009; Olivei, 2002). Hence, the period after 1992 can be seen as a period of relatively stable monetary policy regime, and we therefore do not worry about structural breaks in our sample. Based on the reasoning above, using 1994 as a starting point seems reasonable.

The chosen endpoint is also based on data availability, as some of the data were not available after 2019. However, the most important reason is to avoid the significant changes in consumption caused by the recent COVID-19 recession. The outbreak of the virus in late 2019, led to shutdowns in many sectors, impacting global supply chains massively. In addition to the negative supply shock, the demand-side of the economy was also impacted negatively, leading to both precautionary saving and reduced consumption. Moreover, theorists argue that the spillover effects from special supply shocks, such as the COVID-19 recession, can in some circumstances cause shortfalls in aggregate demand larger than the initial supply shock itself (Guerrieri et al., 2022). Since a substantial part of our thesis is to analyze consumption among households, and we assume consumption expenditure shares are constant, such a significant change in behavior could cause misleading results. Another implication following the COVID-19 lockdown was the computation of the CPI, in which SSB had to adjust. In accordance with international guidelines, SSB adjusted the CPI by assuming that consumption in certain sectors dropped completely, implicitly redistributing the weightings in the CPI (Johannessen, 2020). Since we use the CPI extensively in our thesis and we want to look into prices and consumption under normal circumstances, this is yet another reason why we choose to limit our sample period to 2019.

3.2.2 Variables

The main focus of our analysis is to capture the effect of monetary policy on inequality through the inflation channel. To create a baseline model with appropriate interaction between monetary policy and shocks of important economic variables, the choice of variables should reflect the theoretical set-up of a New Keynesian small open economy model (Bjørnland, 2009). In the model, we therefore include the most important economic variables representing a small open economy: *output gap, inflation, the policy rate,* and *the exchange rate*. We use income-specific inflation rates instead of total inflation in order to capture potential differences in responses to a monetary policy shock. A complete overview of the data and its sources can be found in appendix B.

Output gap

The output gap is based on nominal gross domestic product (GDP), collected and reported by SSB. We choose seasonally adjusted GDP of mainland Norway, i.e., value creation sourcing from domestic production activity, except foreign shipping and the oil and gas industry (Statistics Norway, 2014). This is to avoid unnecessary volatility as the production in these industries can vary widely (Wålen, 2021).

We use output gap as a measure of the state of the economy. The choice is motivated by the output gap being a key variable for central banks, especially for central banks operating with a flexible inflation target (Furlanetto et al., 2020). Output gap is defined as the deviation of GDP from its potential, where potential output is the maximum level of output that is sustainable with full employment and capital utilization. This is also the level that is consistent with stable inflation (Bjørnland et al., 2005). When output gap is positive, the economy is utilizing more resources than what is sustainable, thereby creating inflationary pressure, in which case the central bank will respond by increasing the interest rate. A negative output gap indicates that the economy is underutilizing resources, and the central bank may want to decrease the interest rate to stimulate the economy and prevent inflation from falling below target. Since potential output is a theoretical construct and therefore is impossible to observe accurately, it needs to be estimated. Furlanetto et al. (2020) find evidence that an average of different measures is more reliable and respond better to ex-post data revisions and inflation forecasting. However, because of limited time and resources, we decide to use a two-sided HP-filter instead, which is a simple and widely used statistical filter to separate the trend from the cycle (Bjørnland et al., 2005).

Inflation

The income-specific inflation rates are constructed in part one of our thesis and are based on CPI data from SSB, as described in section 3.1.2 Since the income-specific CPIs are computed at a monthly frequency and we have a quarterly structural VAR model, we convert the series to a quarterly series by averaging over the quarter. Inflation has both positive and negative sides to it, however in theory we assume that frequent and volatile changes in prices are perceived as negative by the households. This is because inflation creates unpredictability and uncertainty among consumers. To maximize utility, the life-cycle theory of consumption assumes that households seek to smooth consumption over their lifetime by borrowing when their income is low and saving in periods where their income is high (Modigliani & Brumberg, 1954). When prices are changing frequently, it makes it difficult for households to compare prices across periods and make intertemporal decisions on consumption. Therefore, we assume that households that experience high price frequency and volatility are generally worse off. If we observe large differences in the inflationary responses across income groups, we can conclude that monetary policy creates distributional effects. High inflation also makes the consumption basket more costly, which decreases the purchasing power of consumers, if we assume income is held constant.

Policy Rate

To capture a monetary policy shock, we use the policy rate. We use data on the policy rate provided by Norges Bank. They provide a series with monthly averages, which we further average to a quarterly series. The policy rate is the main instrument used by the Norwegian central bank to stabilize inflation and output in the economy, which makes it the best measure of monetary policy (Norges Bank, 2022). What type of interest rate the central bank uses as its policy rate can differ across countries. In Norway, the policy rate is the rate that banks get on their overnight deposits held at the central bank, up to a specific quota (Norges Bank, 2022). In general, by setting the policy rate at an appropriate level, the central bank is able to impact overall financial conditions and thereby stimulate or restrain overall demand for goods and services. The transmission of monetary policy happens through different channels. Usually, banks and financial institutions will not borrow or lend money at an interest rate significantly different from that of the central bank, and they therefore follow the change in policy rate by changing its own short-term interest rates charged to households and firms. Long-term interest rates are usually impacted through agent's expectations, using tools such as communication and forward guidance about the policy rate. Furthermore, monetary policy also affects other economic variables, like asset prices and the exchange rate. The overall effect working through all of these different channels, is a change in overall demand for goods and services, leading to an increase or decrease in prices (The Federal Reserve, 2021). When the interest rate is lowered, we refer to it as expansionary monetary policy, while an increase of the interest rate is called contractionary monetary policy. As long as monetary policy is conducted optimally, the effects on demand will make inflation move back to the target set by the central bank.

Exchange rate

The exchange rate is an important transmission channel in open economies (Bjørnland, 2009). Since Norway can be categorized as a small open economy, we include the real broad effective exchange rate (REER) provided by the Bank for International Settlements (BIS). The series are only provided at a monthly frequency, and we therefore average over the quarter to create a quarterly series. The REER is a weighted average of the bilateral exchange rates between Norway and its trading partners, adjusted by relative consumer prices (Bank for International Settlements, 2022). Since the REER considers price and cost developments, it can be seen as an indicator of a country's competitiveness. If the REER increases, exports become expensive relative to imports, and the country loses trade competitiveness.

4. Methodology

In this section we will present our methodology. We start off by explaining how we calculate the income-specific expenditure shares and inflation rates based on the data from the HBS and the CPI, as well as how we calculate our income-specific frequencies of price changes and measure of price volatility for each income group. Thereafter, we present in detail and argue for our chosen estimation model, including the empirical framework, model specifications and limitations.

4.1 Part 1: Consumption and Price Analysis

The goal of this part of our thesis is to identify and analyze heterogeneities in consumption between different households along the income distribution. This is done by creating income-specific expenditure shares, as well as measuring volatility and frequencies of price changes. The methodology behind this is presented in the following.

4.1.1 Income-specific Expenditure Shares

To compute our income-specific expenditure shares, we start off by dividing the households in the HBS into percentiles based on their income level, using STATA. The income variables in the survey represent the entire household in question and not only the main income earner. We divided the income groups based on the household's *annual income before tax*, which allows us to split the households according to their actual earnings before intervention from any authorities in terms of taxes and transfers. Fiscal policy should not be strong enough to shift households from one income group to another, so dividing the households based on *post tax income* should give the same result. The income variables in the dataset are categorized exactly as in the income and wealth statistics for households classified by SSB, which can be found in appendix C.1. A variable for income before tax is created by summing the following variables: *wages and salaries, net-income from self-employment, property income, taxable transfers,* and *tax-free transfers*. The income groups are then created by aggregating households into percentile groups, based on annual income before tax. More specifically, we find the 5th, 40th, 60th, 96th, and 99th percentile of the household's income, which enables us to create six income groups. The lower-and upper-income cutoffs can be found in appendix C.2. The percentile groups are named based on where they belong on the income distribution: bottom 5 percent, lower-middle 5-40th percentile, middle 40-60th percentile, upper-middle 60-96th percentile, high-income 96-99th percentile and top 1 percent.

Since we are working with percentiles, it gives us six groups of unequal sizes, which can be both beneficial and problematic. The benefit of having groups divided by percentiles instead of for instance deciles, is that it is informative. Income groups based on percentiles are less disaggregated and give us the opportunity to study more interesting cases, for instance we are able to analyze the behavior of the bottom 5 percent or the top 1 percent of the income distribution. This gives more informative results compared to studying ten equal-sized groups. The downside is that some groups can become very small and do not necessarily represent the target population. An example is the top 1 percent group who only consists of 33 observations (see appendix C.2). Also, both the median and mean of income for this group of households lies around 1.8 million NOK, while the maximum value is 2.3 million NOK. This reinforces the assumption that our top 1 percent income group does not represent the actual top 1 percent of the income distribution in Norwegian society.

After having identified our income groups, we are able to create expenditure shares for each of these. The consumption variables from HBS are reported at the five-digit level based on the structure in appendix A. We therefore aggregate them into larger consumption groups in order to make them easier to work with, and also match the CPI data and price frequencies. First, we gather the consumption variables from the questionnaires, diaries, and the interviews, into 12 main categories of goods and services following COICOP. We remove negative and extreme values which seemed unrealistic and impacted our results in spurious ways. Then, we sort the income groups in ascending order and calculate each individual household's total consumption, as well as the household's expenditures of each of the 12 goods and services. The expenditure shares are created by dividing the household's expenditures of each consumption category k by total consumption of goods and services:

$$X_{i,k}^{h} = \frac{c_{i,k}^{h}}{\sum_{k=1}^{K} c_{i,k}^{h}} \tag{1}$$

where c is the household's expenditures on consumption good k and the sum of these, the denominator, equals total consumption expenditures. We create in total 12 expenditure shares for each household i in income group h. Then, to create the income-specific expenditure shares, we take the average of the household's expenditure shares for each income group. The calculation of income-specific expenditure shares can be summarized by the following formula:

$$\omega_{k}^{h} = \frac{1}{N}\sum_{i=1}^{N} X_{i,k}^{h} \tag{2}$$

where ω is the expenditure share of product category k for income group h, while N is the number of households in the income group. The resulting average expenditure shares can be found in appendix C.3 and are an essential part of our analysis. In the following, the expenditure shares will be used to compute income-specific inflation rates and measures of price volatility and price stickiness.

4.1.2 Income-Specific CPI Rates

In order to compute the income-specific inflation rates, we multiply the CPIs for each of the 12 consumption categories with our self-constructed expenditure shares. This gives us the income-specific CPIs:

$$P_{t}^{h} = \sum_{k=1}^{K} \omega_{k}^{h} p_{k,t} \tag{3}$$

where $p_{k,t}$ is the CPI for a given product category k in a given month t, and ω_{k}^{h} is the expenditure share for the same product category for income-group h. By summing $\omega_{k}^{h} p_{k,t}$ we get the total income-specific CPI, P_{t}^{h}.

4.1.3 Price Volatility and Price Frequency

To understand whether the volatility and frequency of prices is heterogeneous across the different consumption baskets is important when analyzing distributional effects through the inflation channel. Larger variation in prices for one group compared to another, both in terms of size and frequency, may imply higher uncertainty and affect the total cost of their consumption basket. The volatility of our income-specific inflation rates is found by first calculating the 12-month log-difference of the income-specific inflation rates described in the previous section, before calculating the standard deviation of these. Then, to analyze whether income groups face products with different degrees of price frequency, we compute income-specific measures based on numbers from Wulfsberg (2016). We use the following formula to compute weighted mean frequency of price changes for each income group:

$$\theta^h = \sum_{k=1}^{K} \omega_k^h \theta_k \tag{4}$$

where $\boldsymbol{\theta_k}$ is a measure of product-specific price frequency from Wulfsberg (2016) and $\boldsymbol{\omega_k^h}$ is the same weights that we have used throughout this whole section.

4.2 Part 2: Structural VAR

In part two of our research, the goal is to investigate whether or not the income specific inflation rates from part one reacts heterogeneously to a monetary policy shock. If there are significant differences in the responses, it signals that monetary policy has distributional effects through the inflation channel. The model we use in this context is a structural VAR model, which is built in a way that enables us to identify a monetary policy shock and estimate the corresponding impulse response functions of income-specific inflation. In the following section, we will present the general structural VAR framework and how we have decided to specify the model.

The econometric theory in this section is based on Bjørnland and Thorsrud (2015) unless otherwise explicitly cited.

4.2.1 Econometric Framework

Motivation and the VAR framework

VAR models are commonly used to study and analyze the dynamic relationship between economic variables in a multivariate framework and has become an increasingly popular way to construct and identify structural monetary policy shocks. We start off by describing the general VAR framework.

The VAR model represented in reduced form can be expressed as following:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + e_t \tag{5}$$

where A is a (KxK) vector with coefficients and e_t is a $(Kx1)$ error term. K represents the number of variables. The error term is assumed to be Gaussian white noise, i.e., independent and identically distributed random variables with a normal distribution:

$$e_t \sim N(0, \Sigma_e) \tag{6}$$

The model is a multivariate extension of a simple AR-model where the dependent variables in y_t are related to past values of itself, y_{t-1}. However, because of the vector-structure, the k'th variable in y_t does not only depend on past versions of itself but also on past values of all the other K variables represented in the system. This makes it extremely useful in a context where we want to study the causality and correlation between several variables. For instance, the VAR model enables us to construct impulse response functions (IRFs), where we can look into how a given shock in one variable affects the other variables over time. The variables in the system are chosen based on the purpose of the study. If the goal is to do a structural causal analysis, the variables of interest are chosen *a priori*, usually based on economic theory. As mentioned earlier, the variables we will use specifically in our model seek to represent a New-Keynesian open economy.

As long as the errors are normally distributed and we know the true data generating process (DGP), the VAR model can be estimated consistently by employing ordinary least squares (OLS) regression on each equation. However, since we never fully know the true DGP there will always be some uncertainty regarding lag length and which variables to include. To avoid a misspecified model, we apply different tests and methods to make sure we choose the correct model specification. The specifications we make are described in further detail in section 4.2.3.

The Structural VAR

The VAR model can be used to identify structural shocks. However, the problem with doing a structural analysis is that all the variables in the model tend to move simultaneously and depend endogenously on each other, making them correlated with the error term. If this is the case, it is not possible to apply OLS, since estimators then will become inconsistent, i.e., not converge to their true value. Another problem is that it will make the errors in the model correlated with each other. We will observe this in the variance-covariance matrix, which OLS will give us an estimated version of. The variance-covariance matrix consists of estimated variance of the errors on the diagonal, while the upper and lower triangle contains the covariance between the different shocks. In the structural VAR model, a key assumption is that all the covariances are equal to zero. However, if simultaneous causality occurs, the variance-covariance matrix will in general not be a diagonal matrix with zeros off the diagonal. If both issues are present, we would not be able to identify the effect of monetary policy on income-specific inflation rates. To solve the simultaneous causality issue, we must transform the structural VAR model to a reduced form VAR model and then employ structural identification methods to make the shocks uncorrelated and be able to apply OLS.

Our structural VAR model can be expressed like this:

$$\psi y_t = \Phi y_{t-1} + \cdots + \Phi y_{t-p} + \varepsilon_t \tag{7}$$

where Ψ is a $(6x6)$ matrix of structural parameters that allow for contemporaneous relationship between the six variables and the matrix Φ_p consist of $(6x6)$ coefficients describing the relationship between the lagged variables on the dependent variables. The y_t vector consists of the chosen variables of interest and y_{t-1} is a vector of the lagged variables of order p. In our case, the vector y_t looks like this:

$$y_t = \begin{bmatrix} og_t \\ p_t^1 \\ p_t^3 \\ p_t^6 \\ i_t \\ x_t \end{bmatrix} \qquad (8)$$

where og_t is the output gap, i_t is the policy rate, x_t is the exchange rate, and p_t^1, $p_t^3$and p_t^6 is the income-specific CPI rates of bottom 5 percent, middle 40-60 percent, and top 1 percent, respectively. That is, we choose to proceed with three of the six groups created in part one. The reason for this is that these are the groups we find to give the most diverse picture of the income distribution and may also represent the most interesting cases. The middle-income household represents the "average man in the street", while bottom 5 percent and top 1 percent illustrate the most extreme cases. Last in the structural VAR equation, we have the structural error term which is a $(6x1)$ vector consisting of the error, or shocks, of each variable. The errors are assumed be uncorrelated and therefore have the following properties: $\varepsilon_t \sim i.i.d. N(0, \Omega)$, where the variance-covariance matrix Ω is equal to the identity matrix *I* with ones on the diagonal and zeros off the diagonal.

As mentioned, OLS is not applicable to estimate the structural VAR model. To estimate the model, we therefore need to turn the model into a reduced form VAR. We start off by multiplying both sides of the equation with Ψ^{-1}, which yields[2]:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + e_t \qquad (9)$$

where $A_p = \Psi^{-1}\Phi$ and $e_t = \Psi^{-1}\varepsilon_t$. This is exactly equal to equation 5 above. As one can observe, the reduced form errors are linear combinations of the structural errors with variance-covariance matrix:

$$E(e_t, e_t') = \psi^{-1}E(\varepsilon_t, \varepsilon_t')(\psi^{-1})' = \psi^{-1}\Omega(\psi^{-1})' = \psi^{-1}\mathrm{I}(\psi^{-1})' = \Sigma_e \qquad (10)$$

[2] The computation is shown in detail in Bjørnland and Thorsrud (2015)

As mentioned, without any restrictions in place, the covariance matrix will not be a matrix with zeros off the diagonal, and hence, the shocks will be correlated. In this case, the structural parameters in equation 6 will not be consistently identified. There exist several identification approaches, but the one we will be using is a Cholesky decomposition, which will be described in further details in section 4.2.3. Before using the Cholesky decomposition, it is convenient to transform the reduced form VAR to a moving average (MA) representation. This is done by taking all the variables, except for the error term, over to the left-hand side, and express it in terms of a lag-polynomial:

$$y_t - A_1 y_{t-1} - \cdots - A_p y_{t-p} = e_t$$

$$A(L) y_t = e_t \tag{11}$$

Then, we can multiply each side with $A(L)^{-1}$ to get the MA-representation:

$$y_t = A(L)^{-1} e_t \tag{12}$$

where $A(L)^{-1}$= B(L).

4.2.2 Cholesky Decomposition

To avoid a shock in one variable to be accompanied by a shock in another variable we need to make the shocks uncorrelated. To put it another way, the analyses must be performed in terms of a MA representation where the residuals are orthogonal. The most popular and simplest way to do so is through the Cholesky decomposition, which is a form of short-run restriction, i.e., we impose restrictions on the model in the short run.

Any positive definite symmetric matrix can be written as the product Σ_e = PP'. P is the Cholesky decomposition, a lower triangular matrix with positive diagonal elements, of the matrix Σ_e , while P' is its conjugate transpose. This recursive ordering prevents the first variable in the system to react contemporaneously to any shock in the remaining variables, but the other variables will be able to react to shocks in the first variable. By using this, we can rewrite the reduced form VAR:

$$y_t = \sum_{i=1}^{\infty} B_i P P^{-1} e_{t-i} \tag{13}$$

where $P^{-1}e_t = v_t$

We assume the following: monetary policy does not affect growth and income-specific inflation rates contemporaneously but will do so with a lag. Hence, the policy rate needs to be placed after the output gap and the income-specific inflation rates. Output gap is placed on top as all remaining variables react to it contemporaneously. The exchange rate is an asset price which responds contemporaneously to all the variables and will therefore be placed last.

$$\mathrm{Y}_t = \begin{pmatrix} P_{11} & 0 & 0 & 0 & 0 & 0 \\ P_{21} & P_{22} & 0 & 0 & 0 & 0 \\ P_{31} & P_{32} & P_{33} & 0 & 0 & 0 \\ P_{41} & P_{42} & P_{43} & P_{44} & 0 & 0 \\ P_{51} & P_{52} & P_{53} & P_{54} & P_{55} & 0 \\ P_{61} & P_{62} & P_{63} & P_{64} & P_{65} & P_{66} \end{pmatrix} \begin{pmatrix} v_{1,t} \\ v_{2,t} \\ v_{3,t} \\ v_{4,t} \\ v_{5,t} \\ v_{6,t} \end{pmatrix} + \sum_{i=1}^{6} B_i P v_{t-i} \tag{14}$$

From this equation we can see that the Cholesky identification implies that the second shock, the shock to CPI for bottom 5 percent ($v_{2,t}$) does not affect output gap contemporaneously. Further, the third shock ($v_{3,t}$) does not affect the two first variables, output gap and CPI for bottom 5 percent, and so forth. However, all shocks can affect the exchange rate, which is the last variable, contemporaneously. In later periods all shocks can affect all variables as no further restrictions are in place.

4.2.3 Model Specification

All variables, except from the policy rate, are measured in natural logarithms (log-levels), so that a unit change can be interpreted as a percentage change (Bjørnland, 2009). The policy rate is already measured as a ratio. A full overview of the transformation is found in appendix B. Most time series in macroeconomics are usually non-stationary, i.e., they have a unit root and are integrated of order one or more, which we can see visualized by plotting the data (see appendix E.1). To be certain, we statistically test for non-stationarity using a hypothesis test called the Augmented Dickey-Fuller (ADF). See appendix E.3 for results and more details on how the test works. Our test finds that the GDP, the CPIs and the REER are non-stationary. On the other hand, the policy rate has been trending downwards since the Great Recession and our test finds it to be trend-stationary at certain lags. GDP is transformed to output gap using HP-filter and we therefore do an ADF-test for output gap as well (see appendix E.4). One solution to remove unit roots from the CPIs is to take the first difference of the data, but the downside of doing so is that you lose important level-information and impulse responses can be hard to interpret. We choose not to take the difference of any of the time series but rather fit the VAR to the data directly, keeping the VAR in levels and testing for stability in the entire model instead of for each variable. According to Sims et al. (1990), by using structural VAR in levels as a modeling strategy one avoids the danger of inconsistency in the parameters caused by imposing incorrect cointegrating restrictions. Potential cointegration between variables will be implicitly determined in the model (Hamilton, 1994). However, the downside is reduced efficiency (Sims et al., 1990). In order to recover the moving average form of the model and perform a structural analysis without differentiating first, our estimated model needs to be stable. To determine whether our estimated model is stable or covariance-stationary, we determine the eigenvalues of the companion form matrix. These must be less than one in absolute value for the shocks to eventually die out. Our maximum eigenvalue is 0.9837.

As mentioned in section 3.2.2, we have chosen to include output gap as our variable for output in our estimated model. To obtain the output gap we have used the Hodrick-Prescott (HP) filter, proposed by Hodrick and Prescott (1997). This is the most popular way to extract business cycles. The HP-filter emphasizes the true business cycle frequencies and downplay the other frequencies on the grounds that these represent noise rather than business cycles. The smoothing parameter, λ, determines the smoothness of the filtered series. Hence, the cycle of the data will be sensitive to the value of λ, so a justification for the choice of its value must be made. $\lambda = 1{,}600$ is argued to be a reasonable choice for quarterly data given the characteristics of the US economy. The Norwegian economy is however small and open, implying more cyclical volatility. We therefore decide to go with $\lambda = 160{,}000$, which seems to fit our data. A representation of the output gap with different values of λ can be found in appendix E.2. It is important not to forget that there are several concerns related to the HP-filter, one of them being the end-of-sample problem. At the beginning and at the end of the sample the HP-filter produces cyclical series which are close to the observed data. The optimal trend will be more responsive to a transitory shock at the end of the sample as the filter is not able to lower the trend after the shock due to the data ending.

We also need to take a stand on the appropriate lag length of our structural VAR model. By including too few lags we might omit valuable information, and the residuals might become autocorrelated as everything not included as independent regressors end up in the residual. On the other hand, by including too many lags, additional estimation errors might be introduced into our model and our parameter estimates become more uncertain. Alternative methods for determining lag length in time series data are often based on minimizing an information criterion. Two popular functions for doing so are the Akaike and the Bayes information criterion, referred to as AIC and BIC. They evaluate the trade-off between increased model fit and increased parameter uncertainty as we include more lags. Which criterion one should use will differ depending on the question being asked and the application. The BIC criterion delivers more parsimonious models, which may be desirable when forecasting, while one might be better off using the AIC criterion for fitting models, which we are, as it will not penalize the size of the model as much as the BIC. In our case, AIC suggests eight lags while BIC suggests two lags (see appendix E.5). Including eight lags led to spurious impulse responses due to the variables being underfitted. This might be because we work with a relatively small sample. The estimated model with 8 lags is shown in appendix G.3. When including two lags, as BIC suggests, we obtain autocorrelation in the output gap and the policy rate. By including three lags we are able to remove most of this autocorrelation (see appendix E.7). All of the autocorrelation is removed when including six lags, however we obtain more fluctuations in the IRFs which we want to avoid. We decided to include three lags in our estimated model as this seems to fit our model the best.

4.2.4 Limitations

Structural VAR models have been much criticized. However, the criticism usually refers to particular applications and interpretations of empirical results. One limitation of the VAR approach is that it must be estimated to low order systems, which may lead to large distortions in the impulse responses as all effects of omitted variables will be in the residual. This makes the impulse responses of little use for structural interpretations. Another thing which makes interpretations of impulse responses difficult is measurement errors and misspecifications of the model, which also induce unexplained information in the error term. This emphasizes that a careful empirical analysis should be applied when specifying a VAR model. One should therefore be careful not to over-interpret the evidence from the model. Another issue is the choice of lag length. As data sets are finite, one must limit the number of lags to estimate finite VAR models. In that way, one will commit a specification error by implying a bias in the estimated parameters. However, extensive research indicates that though the results may be somewhat distorted, it should not be a major concern as the distortions will not be too large.

5. Stylized Facts on Consumption Baskets

In this section we present and discuss our empirical findings for the first part of our analysis. We look at differences in consumption baskets across the income groups, as well as price frequency and price volatility along the distribution. We start off by presenting some stylized facts regarding the income groups, and thereafter discuss some characteristics of their expenditure shares and the following dynamics of their income-specific inflation rates.

5.1 Income and Consumption

To get a better understanding of our income groups, we have taken a closer look at their income sources. Figure 3 illustrates the income sources for each quantile, and it clearly shows that wages contribute the most to total income for most of the groups. The exception is for the bottom 5 percent of the income distribution, where taxable transfers, i.e., pensions from the National Insurance Scheme, occupational pensions, disability pensions, unemployment benefits and received contributions, accounts for the largest share. See appendix C.1 for further description of income statistics. Capital income accounts for a significantly higher share of total income for the top 1 percent compared to the rest, while the share of tax-free transfers, including child benefits, housing allowance, scholarships, and social assistance, decreases with income.

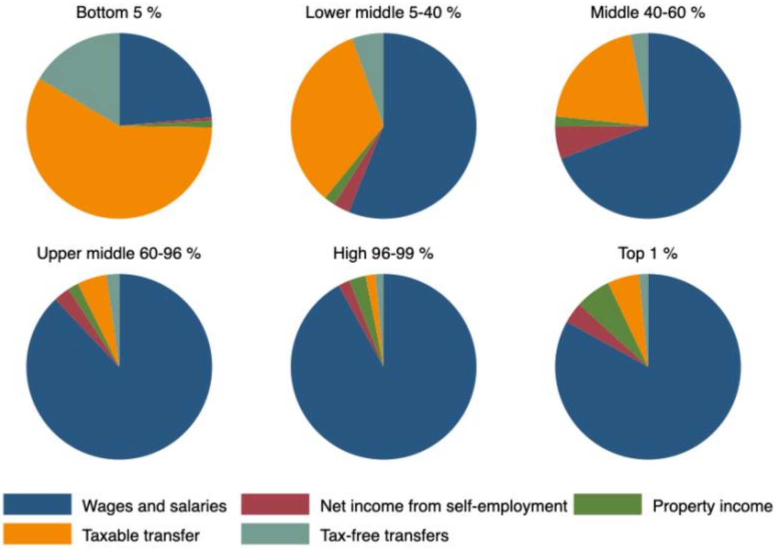

Figure 3*: Sources of income for each income group*

Figure 4 shows average consumption for each income group, varying from NOK 235,520 for the bottom 5 percent to NOK 1,339,664 for the top 1 percent households. More detailed statistics can be found in appendix C.4. The level of consumption increases with income, which is not surprising. As discussed previously, our top 1 percent might not be representative of the actual top 1 percent in Norwegian society in terms of the level of income and consumption. However, we still get a good indication of the consumption pattern of Norwegian households across the income distribution.

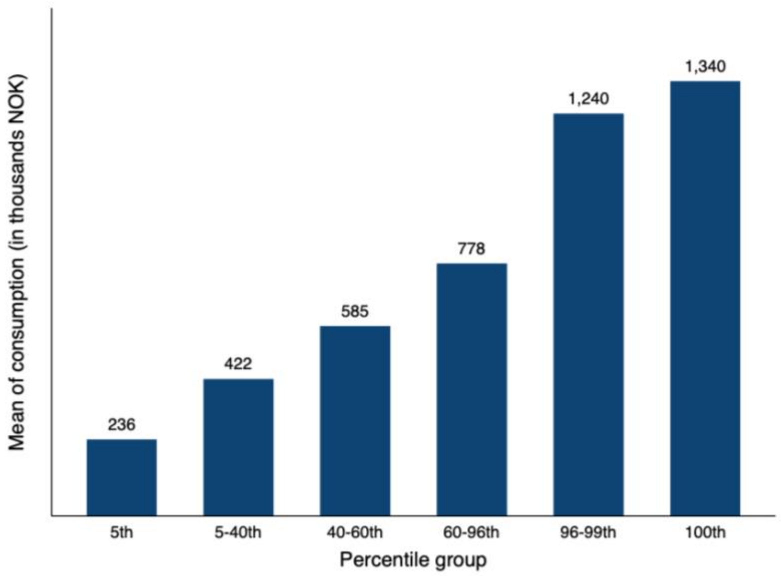

Figure 4 : *Mean of total consumption for each income group in terms of 1,000 NOK.*

If we look more detailed into the consumption baskets of income groups, we find significant differences in consumption along the income distribution. Figure 5 illustrates the resulting consumption expenditure shares of households located at different places on the income distribution and is evidence that household's consumption baskets are heterogeneous. Detailed statistics for each category across income groups can be found in appendix C.4.

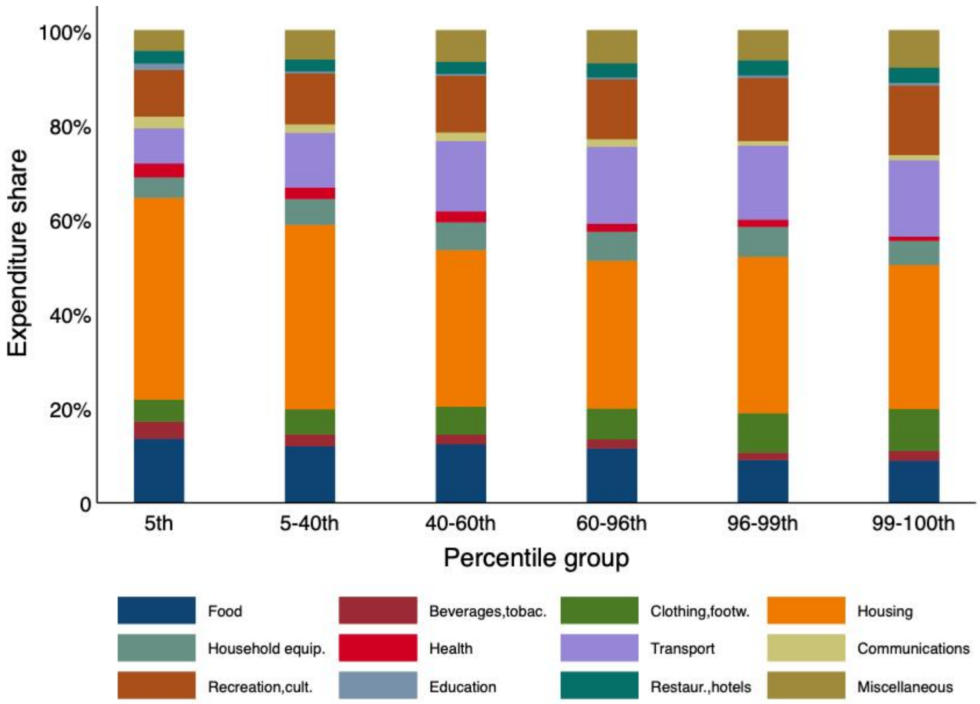

Figure 5: *Expenditure shares for each income group. The expenditure shares are expressed as a percentage of total consumption.*

We find that the expenditure share on *Food* declines as income rises, which is in line with results from the case of North Macedonia (Jovanovic & Josimovski, 2021). This result seems reasonable since food is a necessary good which households consume regardless of their income. The high-income households might however consume more expensive products, for instance locally produced vegetables and meat instead of low-cost products from First Price, but due to the significantly higher income, this will not have a large effect on the average expenditure share. An important thing to notice when looking at the summary statistics in appendix C.4 is that there exist some extreme values which might affect the mean, e.g., the food expenditure share is zero in some of the income groups. However, we observe that the median gives the same consumption pattern, i.e., expenditures on *Food* decrease with income. Some expenditures may also be underreported by households, for instance alcohol and sugar, which might impact our results. Further, we find that consumption of other necessity goods and services, such as *Communication*, *Health*, *Education*, and *Housing*, constitutes a larger share of total expenditure for the households in the lower range of the income distribution. In general, *Education* makes up a relatively small share of the consumption expenditures for all households in our sample, ranging between 0.3 to 1 percent of total expenditures. This is not a surprising finding, as Norway has the highest public share of education measured in GDP, in international comparisons between OECD countries (Statistics Norway, 2021). The high public coverage of education is therefore unique for Norway and enables us to justify the low expenditure shares. However, the expenditure share is larger for the bottom 5 percent. From the median value, these results are most likely driven by some observed extreme values in the data set.

The division named *Housing* consists of expenditures related to rentals, electricity and gas, water supply, and other services for the maintenance of the dwelling. This division can be considered as the most expensive necessities that the households demand and it is therefore not surprising that the bottom 5 percent spends on average 42.70 percent of total consumption on housing, where most of their expenses go to rent and electricity. Rentals for housing is the category which is most disproportionately consumed by the bottom 5 percent relative to the top 1 percent. In fact, as much as 18.10 percentage points more are spent on rents for these households (see appendix, tables F.3). In the rest of the income groups, most households seem to own their own dwelling, which after all is very common in Norway. However, expenditures on electricity, gas, and other fuels constitute a larger share of total expenditures for the low and middle-income households, while the top 1 percent spend relatively more on maintenance and repairing of their dwelling. This is illustrated in the relative tables in appendix F. An important thing to note is that the costs related to owning a dwelling are stated as the estimated market price for renting that exact dwelling, which means that the costs related to *Housing* can be inaccurate. Mortgage loans are not included, which in Norway can be considered as the channel which gives monetary policy the largest potential to affect inequality. Although we are focusing on distributional effects of monetary policy through the inflation channel, and not how it affects loans and the entire wealth of households, this is a weakness.

We find evidence that the mean expenditure shares of *Transport*, *Clothing*, *Recreation and Culture*, *Restaurants and Hotels*, and *Miscellaneous* increase with income. This can be justified by the fact that a fraction of these categories are luxury goods and services, which high-income households demand more of. For instance, high-income households spend more money on major durable goods for *Recreation* and *Culture*, which includes boats, horses, airplanes, and musical instruments. Considering the *Transport* division, both the middle-class and the richest households spend relatively more on goods and services for the operation of cars, like gasoline, maintenance and other services related. Other categories that are dominating in the top of the income distribution are package holidays, insurance, and transport services, which includes transport services by road, air, and sea.

5.2 Frequency and Volatility of Income-specific Inflation Rates

Analyzing the prices faced by different households along the income distribution can help us understand how the groups are heterogeneously impacted by the burden of inflation. From figure 6, which plots the income-specific inflation rates for the three income groups of interest, we see that the rates are positively correlated. However, they do differ slightly in some periods, especially in the high-inflation periods; the inflation rate of the bottom 5 percent income group tends to increase more than for the other groups.

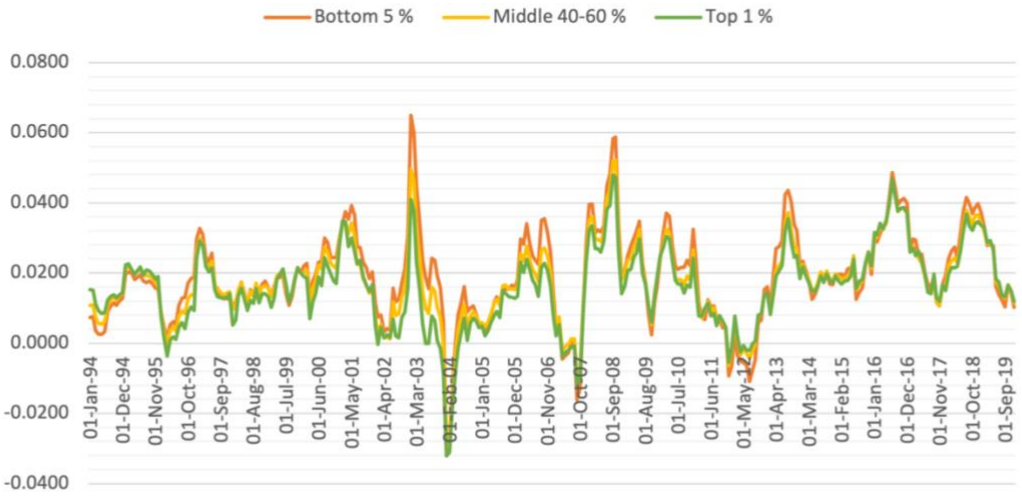

Figure 6: *Income-specific inflation rates for the bottom 5 percent, middle 40-60th percentile, and top 1 percent from January 1994 to December 2019.*

Figure 7 illustrates the results obtained by calculating average frequency of price change along the income distribution (see appendix D.2). The solid red line is the local polynomial fit, while the shaded area is the 95 percent confidence interval. The dots represent the frequency of price change for 5 percent of the income distribution. In accordance with Cravino et al. (2020), we assume that frequency of price change is a measure of price stickiness. We observe a slightly inverted u-shaped pattern, i.e., middle-income households seem to consume goods and services with the most flexible prices. However, the average price stickiness of the middle-income households does not differ much from that of high-income households. This can be seen from the regression line flattening out at the top. The most rigid prices can be found at the lower end of the income distribution, which differ from Cravino et al. (2020) who found that the least flexible prices were found at the top of the distribution.

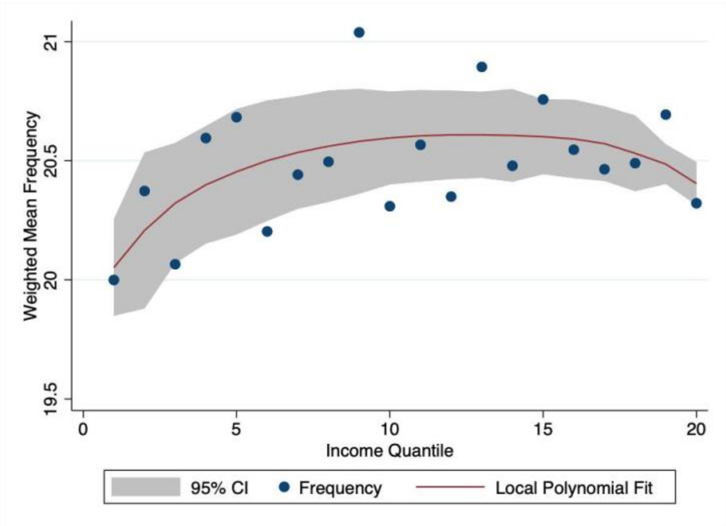

Figure 7: *Plot of the weighted mean frequency of price change along the income distribution, where households are divided into 20 income quantiles. Each observation represents the average price frequency of a quantile group representing 5 percent of the income distribution.*

The hump-shaped relationship we find is not very strong. The lowest weighted mean frequency of price change is 19.99, belonging to the lowest income quantile, while the largest mean frequency belongs to the 9th quantile and counts to 21.04. This gives a range between the lowest and the highest measure of only 1.03 compared to a range of around 3 from Cravino et al. (2020). This can be a result of the fact that we are looking into a low-inflation period. According to Wulfsberg (2016), the frequency of price change is strongly correlated with inflation, i.e. the long-term trend in variation in inflation is primarily explained by variation in the frequency of price changes. We therefore assume that the variation in the inflation rate during the low-inflation period we are considering is explained by a general lower average frequency of price change, and larger size-related price changes. Lower variation in the price frequency of price change overall could mean that we also see less variation in price frequency between households. This signals that, although we find some variation in price frequency among income groups, the heterogeneity is not that strong. It could be interesting to do the same study for a high-inflation period, for instance during the 1970s and 80s or in current years, post-COVID, where we experience that inflation has flared up.

Figure 8 plots the standard deviation of the CPIs for 20 income quantiles. The fitted line is downward sloping and somewhat u-shaped along the income distribution. Prices of goods consumed by low-income households seem to be more volatile than prices of goods consumed by high-income households, while the 14th and 16th quantiles seem to face the lowest price-volatility. However, the range between the lowest and highest standard deviation, 1.08 percent for 16the quantile and 1.36 percent for 2nd quantile, is relatively small. The standard deviation of changes in CPIs observed by Cravino et al. (2020) for the US were higher, had a higher range, and were clearly hump-shaped along the income distribution. That is, our results on differences in price volatility along the income distribution are quite different from the results found by Cravino et al. (2020). They were also quite different from our own results related to frequency of price changes, which we did not expect.

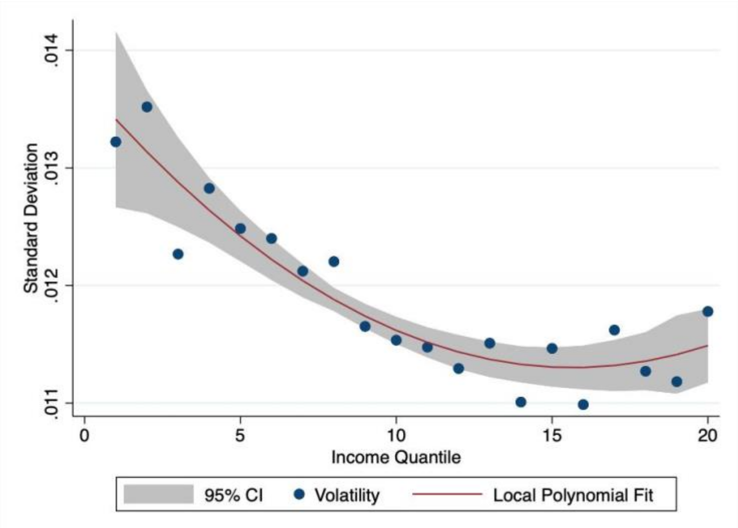

Figure 8: *Plot of standard deviation of the 12-month log difference in CPIs for 20 income quantiles, where each observation represents 5 percent of the income distribution.*

Based on previous literature and economic interpretation we would assume that households which consume goods and services with more frequent price changes also would face the most volatile prices. According to our results, this is not the case. However, the dispersed results might be explained by a combination of reasons. For instance, price frequency and price volatility are not necessarily the same thing as the standard deviation captures both the frequency and the size of the changes in CPIs, whereas the frequency does not capture the magnitude of price changes. As mentioned above, inflation of the bottom 5 percent tends to increase more in magnitude than for the other groups, which will be captured in our standard deviation but not frequency of price changes.

To gain a better understanding of what drives our results, it can be convenient to investigate the top 10 relative goods and services consumed by the three main income groups. An overview of these can be found in appendix F and will be discussed in section 7 where we further explore and discuss why we obtain the results we do above.

6. Empirical Results

In this section, we present and analyze the results from our estimated structural VAR model in order to answer our research question on whether monetary policy affects households heterogeneously through the inflation channel. Monetary policy might have distributional effects through inflation if we find evidence that it heterogeneously affects prices of consumption baskets as a consequence of variation in income. As discussed in the previous section, low-income households seem to face relatively less sticky prices than middle and high-income households, taking our observed measures of price stickiness into consideration. This suggests that monetary policy shocks might have heterogeneous effects across the income distribution, by affecting relative prices of consumption baskets of households differently.

Figure 9 plots the impulse responses of all the variables to a shock in the policy rate, where the monetary policy shock is normalized to a 100-basis-point increase, i.e., we identify a contractionary monetary policy shock. The shock has a temporary negative effect on both output and prices. Output gap increases in the short run before reversing after two quarters, giving a negative hump-shaped effect. Output gap reaches its bottom after 7 quarters, i.e., after almost 2 years. In the long run, the output gap becomes positive. The exchange rate responds a bit puzzling by depreciating, while in theory we would expect it to appreciate as a result of rising domestic interest rates attracting foreign investment. However, the model is robust to omission of the exchange rate which can be seen in appendix G.4.

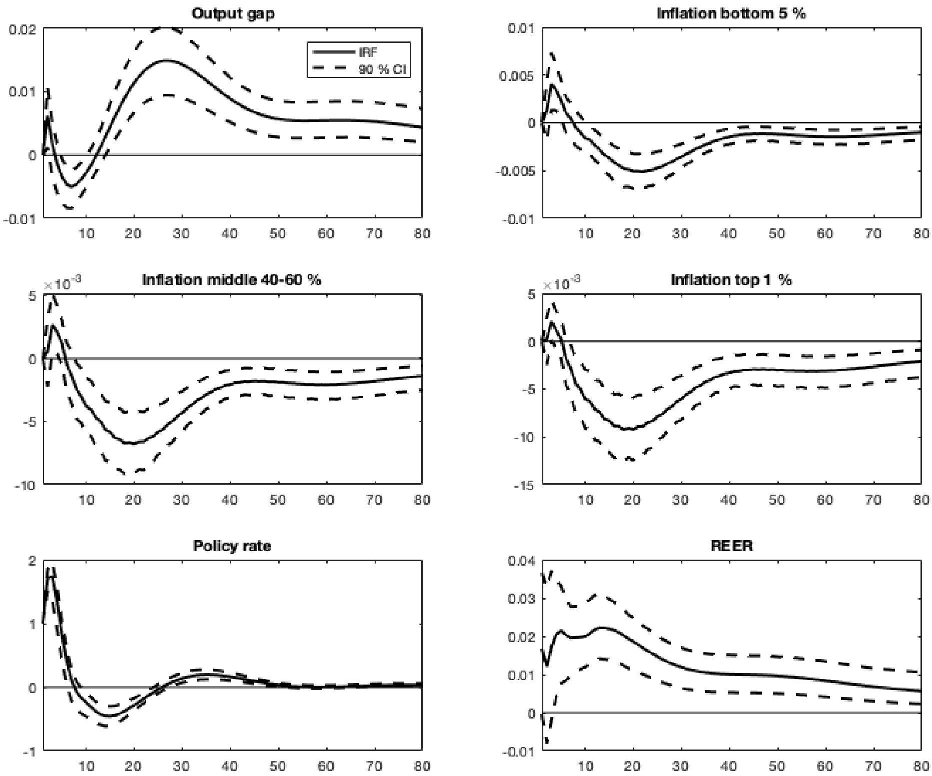

Figure 9: *IRFs of output gap, CPI for the three income groups of interest (bottom 5 percent, middle 40-60 percent, and top 1 percent) and exchange rate in response to a 1 percentage point increase in the policy rate. The y-axis represents the level of the response in terms of percentage points, while the x-axis represents the time horizon in quarters. The dotted lines are 90 percent confidence bands.*

The three CPI rates all react by increasing the first year and then reversing to below zero after 5 quarters. They then continue at a negative rate for about 5 years, before the effect gradually dies out. The fact that prices are increasing in the short run is not what one would expect based on standard economic theory and has in the VAR literature been referred to as the *price puzzle*. The puzzle can be explained by several factors, the cost channel of firms being one of them. That is, when the interest rate increases, borrowing gets more expensive for firms, so in order to compensate for increased marginal costs they start to increase prices

(Ravenna & Walsh, 2006). Others argue that the structural VAR model is missing some forward-looking variables, for instance expected inflation, which we often find in DSGE models. This can lead to omitted variable bias and the impulse response functions not reflecting the real structural relationship. In the real world there are tons of variables, but the VAR model is restricted in that it gets heavily parameterized if we include too many variables (Bjørnland & Thorsrud, 2015). The puzzle can be solved by including forward-looking variables or using a FAVAR model, which is not restricted to a minimum number of variables, as in Cravino et al. (2020) and Jovanovic and Josimovski (2021). Since our goal is to study the differences in magnitude of responses, and not necessarily the given path, this is not of major concern.

To analyze the IRF's of the three CPIs more thoroughly we plot them in the same graph to get them on the same axis and make it easier to observe their differences. This can be seen in figure 10, where the y-axis still shows the level of the responses of the IRF's in percentage points and the x-axis is the time-period in terms of quarters. The blue semi-dotted line represents the CPI for the bottom 5 percent group, the red dotted line represents the CPI for the middle 40-60 percent group, while the yellow line represents the CPI for the top 1 percent group. In the short term, approximately until two years have passed, the CPI of the bottom 5 percent income group reacts the most to a monetary policy shock. Middle-income households' CPI react by 40.57 percent less, while the CPI of the top 1 percent react by 65.82 percent less.

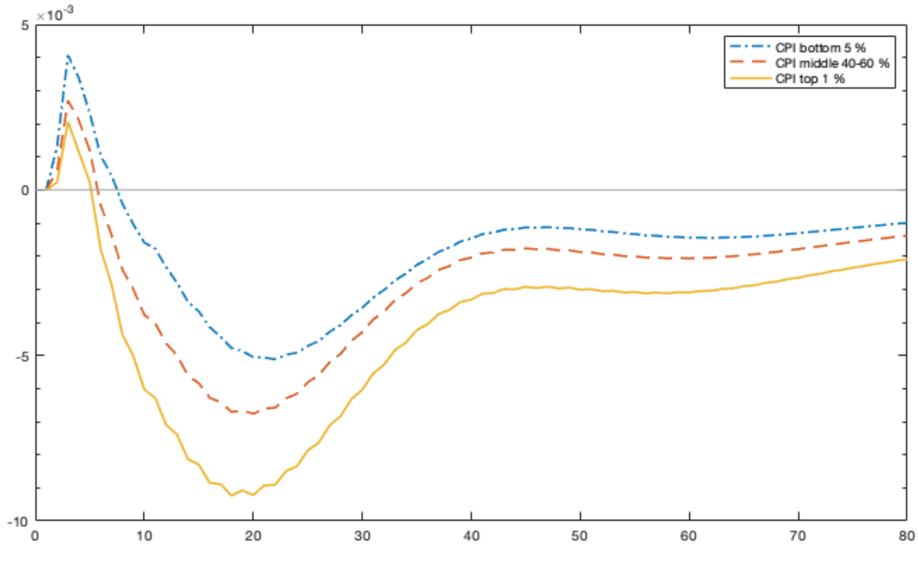

Figure 10: *IRFs of the CPIs for bottom 5 percent, middle 40-60 percent and top 1 percent of the income distribution. The y-axis represents the level of the response in terms of percentage points, while the x-axis represents the time horizon in quarters.*

Looking at the medium and long term the results change. Generally, a contractionary monetary policy shock seems to reduce the inflation rates for all households along the income distribution. The CPI of the top 1 percent households at the income distribution reacts the most to the monetary policy shock. Around 5 years, corresponding to 20 periods, the CPIs reach their bottom point. At this point, the top 1 percent reacts by 58.95 percent more than the households at the bottom 5 percent of the income distribution. Even though the percentage differences between the IRFs are smaller, the gap between them is larger (in terms of percentage points). The total negative response in the medium term is larger than the total positive response in the short run. The order is also reversed at this point; the level of response to the policy shock is increasing with income, i.e., the top 1 percent of the income distribution reacts the most to the shock, while low-income households seem to react the least to the monetary policy shock.

In order to make sure that the results discussed above are more or less robust to changes in the model, we plot six additional models where we change one part holding everything else constant. For instance, in model one we change our measure of output from output gap to GDP, in model four we omit the exchange rate, while in model five we use monthly data instead of quarterly. These models can be found in appendix G. The responses of the three income-specific CPIs of interest are more or less the same as in figure 10 described above.

7. Discussion

The results obtained in section five and six are more dispersed than we expected them to be. According to our analysis of price volatility, the bottom 5 percent of the income distribution face the most volatile prices, which indicates that they may respond the most to an unexpected monetary policy shock. Our analysis of price frequencies, on the other hand, indicates that the bottom 5 percent income group face more sticky prices than the two other groups, which indicate that they may respond the least. The IRF's obtained from our estimated VAR model shows that the response to a monetary policy shock is increasing with income; the top 1 percent of the income distribution reacts relatively more to an unexpected monetary policy shock than the middle 40-60th percentile group, which again reacts more than the bottom 5 percent. The differences in our results might be caused by several factors, which we will elaborate on and discuss in the following.

The differences in price stickiness and price volatility might be masked by the fact that we are dividing consumption groups at the aggregated two-digit level. Ideally, one should look into consumption expenditure shares at the micro-level, i.e., at the six-digit product category level (see appendix A for illustration). For completeness, we have looked into price volatility and price stickiness at the three-digit level. Again, we use measures on price frequency from Wulfsberg (2016) but this time at the three-digit level. They include both the high and the low inflation period, hence they are not directly comparable with earlier results. However, this is the only data we have available at this level. The results are depicted in figure 11 and figure 12.

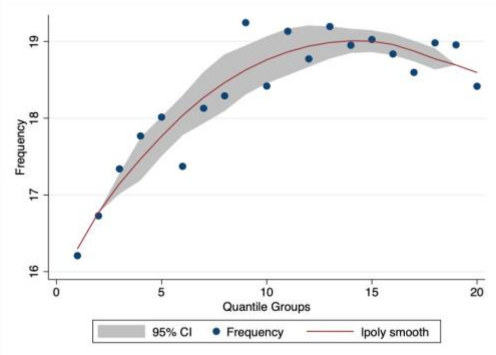

Figure 11: *Frequency of price change along the income distribution. The measures of frequency of price change at the three-digit level are taken from table B5 in the appendix of Wulfsberg (2016)*

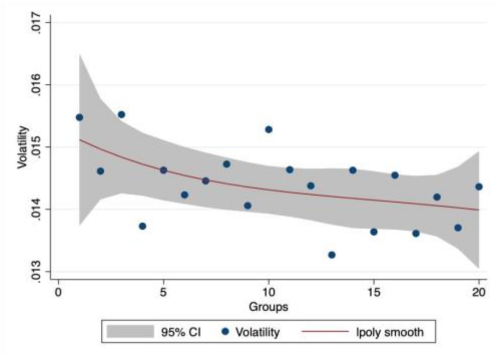

Figure 12: *Price volatility along the income distribution. Volatility is measured as the standard deviation of income-specific inflation weigthed at a lower level of aggregation.*

The relationship between frequency of price change and income becomes stronger, whereas the relationship between price volatility and size of income almost disappears, although we observe that it is still downward sloping. When looking at figure 11, the most notable observation is the range between the average price stickiness of the low-income groups and those above the median of the income distribution. The range between the highest and lowest observation is now 3.04, which is a value twice as high as what we found in our main analysis and closer to what Cravino et al. (2020) found. Furthermore, middle-income and high-income households do not seem to face prices that differ much in frequency.

Looking at the top 10 consumables from a relative standpoint makes it easier to compare what lies behind the differences in price stickiness and price volatility across consumption baskets. An overview of these can be found in appendix F. Since the largest disparities are found between the bottom 5 percent and the middle 40-60 percentile group, it makes most sense to compare these two groups. We therefore focus on the tables in appendix F.1. Based on the top 10 product categories in which these groups consume most disproportionately from each other, the average frequency of price change is 17.2 percent for the middle class compared to 15.4 percent for low-income households. Categories contributing to the higher average frequency for the middle-income households are goods and services such as *Purchase of vehicle, Operation of personal transport equipment,* and *Maintenance and repair of the dwelling.* For instance, the 40-60th percentile consumes the most gasoline, which is also the good in the CPI with the highest average price frequency. On the other hand, the bottom 5 percent consume more price-sticky goods such as *Education, Transport Services,* and *Telephone Services.* These three categories are categorized as services, which generally are found to change prices less frequently (Wulfsberg, 2016). However, the trends in price stickiness between income groups are not universal and we can find both price sticky and price flexible categories among both income groups. The comparison of expenditure shares between the bottom 5 percent and top 1 percent forms the same picture as we have drawn here (see appendix F.3), i.e., that the prices of the bottom 5 percent stand out the most by consuming the least sticky prices.

As mentioned earlier, the prices of the top 10 products and services confirm our results relating to prices; however, the standard deviation of *Electricity, Gas, and Other Fuels* seem to push the average sharply upwards. The households in the low to middle range of the distribution seem to exhibit a larger expenditure share of products and services related to electricity and gas relative to the top 1 percent. When removing this category from the dataset, the distribution of volatility changes significantly while the distribution of frequencies of price changes remains more or less the same. This is shown in figure 13 and 14 below.

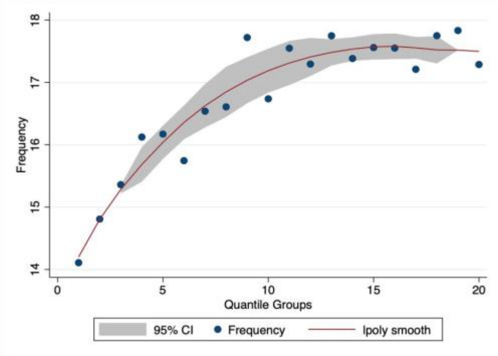

Figure 13: *Frequency of price change along the income distribution when the measure of "Electricity, Gas, and Other Fuels" are removed*

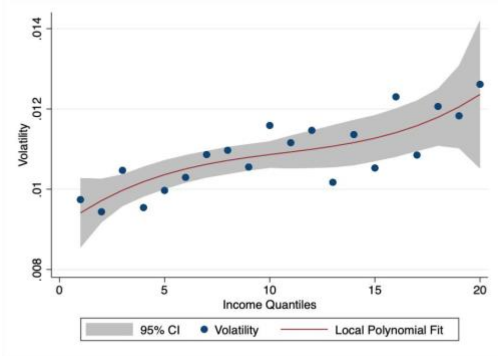

Figure 14: *Price volatility along the income distribution when the category "Electricity, Gas, and Other Fuels" are removed from the CPI*

The differences of price stickiness between middle-income and high-income has now vanished, while the correlation between volatility and income has switched from negative to positive. In other words, our story is still coherent regarding price frequency, but consumption of energy seems to have a significant impact on how the volatility of prices is distributed along the income distribution. By removing energy prices, the results are consistent with what we find in our empirical analysis, i.e., the CPI for the top 1 percent of the income distribution reacts more to a monetary policy shock while the bottom 5 percent reacts the least. As we have evidence that energy prices are volatile and have a high average frequency of price change, we expect the prices to react fast to a monetary policy shock, being a major driver of the CPI in the short run. However, in the medium and long run, most of the flexible and volatile prices of the goods and services in the middle and high-income households' consumption baskets will react, giving a more substantial impact on their income-specific CPIs. We see this from the IRF of the CPI of the top 1 percent income group, which reacts less to begin with before responding more than the others in the long run. Based on the life-cycle theory of consumption, volatile and high-frequent price increases make it harder for households to plan how to intertemporally balance consumption and saving. The volatile and frequent price-changes that the top 1 percent income group experiences over time may therefore be perceived as negative, lowering their utility.

Hafemann et al. (2018) found that the income composition channel was an important explanation on how monetary policy led to rising inequality for different countries. In section 5.1, we found evidence that the composition of income varies between income groups. Although the income distribution channel is not the focus of our study, and we do not consider wealth effects, the conclusion that the redistributive effect of monetary policy is muted for Norway is an important factor to take into consideration in our case too. Taxes are an efficient way to redistribute nominal income that further affect disposable income, which limits how much households can afford to consume. Since the richest households depend more on wages and salaries, while the poorest relies more on tax-free transfers, taxes will have a larger (negative) impact on the former group. However, if contractionary monetary policy leads to lower prices for the richest, it will work against the redistributive effects of fiscal policy. That is, lower prices increase the purchasing power of consumers, giving the opportunity to consume more. If we assume nominal income increases at the same rate in response to the monetary policy shock, real income increases more for the richer households relative to the other groups. Differences in prices may therefore have a cost-of-living effect, changing the distribution of real income to the benefit of the richest top 1 percent. However, if prices decrease vastly with a high frequency they will also tend to increase with a high frequency, captured by the high price frequency and volatility of the top 1 percent. In light of this, the top 1 percent would still be worse off as a matter of the unpredictability related to prices.

The fact that our results on price volatility changes significantly when studying more detailed consumption categories suggests that our results would have been more trustworthy had we used more detailed micro-data. This is in line with what Jaravel (2021) observed and stated in his paper, which we mentioned in our literature review. Generally, there has been found modest differences in inflation rates across households when more aggregated data has been used. Micro-level data has been proven necessary to fully measure inflation inequality. However, this could not be done in our case as we needed our consumption categories to exactly match the division of CPI's available at SSB. Doing a more thorough analysis of micro-level consumption categories and income groups would also have been too time-consuming for our master thesis.

The fact that we need to assume our consumption and income variables to be constant over the entire sample period is a weakness. The composition of consumption baskets is likely to change as prices and economic conditions change, which would have an impact on our IRFs. Also, as mentioned earlier, our top 1 percent of the income distribution is not representative of the actual top 1 percent in Norwegian society as we lack data to accurately explain and analyze their consumption pattern and expenditure shares, and thereby the specific inflation rate which they face. A larger survey which represents all income groups in the society correctly would improve our results substantially. Besides, to get a more thorough analysis, one should also seek to combine studying income inequality and wealth inequality. The reason is that inflation affects the distribution of both income and wealth (Cheema & Malik, 1986). In our thesis we have only looked into the former, but it is recognized that in order to fully understand income inequality it is also necessary to consider the household's composition of assets and liabilities. Our thesis does not consider the effect of monetary policy on debt, which generally is the most important channel to consider when studying distributional effects of monetary policy in Norway.

8. Conclusion

In this master thesis an attempt has been made to find out whether monetary policy heterogeneously affects income-specific inflation rates in Norway. Based on detailed consumption data provided by NSD we divided households into percentiles based on their level of income and studied each group's expenditure comprehensively. After having identified income-specific expenditure shares we were able to calculate income-specific inflation rated based on these and CPI data from SSB. We also studied the volatility of CPIs for all income groups, as well as frequencies of price changes. This is what we refer to as the first part of our thesis. In the second part, we estimate a structural VAR model and analyze the impulse response functions of the CPIs for our three income groups of interest: the bottom 5 percent, the middle 40-60 percent and the top 1 percent. The results from both parts were then compared and discussed in order to come up with a conclusion.

We have found evidence that households along the income distribution consume heterogeneous consumption baskets, giving rise to differences in inflation rates. The variation in inflation is determined by both the weights that households assign to the various goods and services, and the change in the prices of these. There are large differences in the price dynamics of goods and services, and households are more exposed to price changes of the goods they assign higher weights. Our measures of volatility of CPIs shows that the bottom 5 percent income group face the most volatile prices when electricity is taken into consideration. Looking into more detailed consumption categories the result remains the same, but weaker. When removing *Electricity, Gass and Other Fuels*, the pattern changes and the top 1 percent income group suddenly face the most volatile prices. This is more in line with our results regarding frequencies of price changes, and what we expected to find. The bottom 5 percent seem to face the stickiest prices compared to middle 40-60 percent and top 1 percent. These results are in line with the evidence found in our structural VAR model where we find that prices of the top 1 percent react the most to a contractionary monetary policy shock. Hence, our results suggest that monetary policy might have distributional effects through the inflation channel.

Our main results are not in line with the empirical literature on the topic, where the general finding is that the inflation of high-income households is least responsive to a monetary policy shock. However, it is proven that in order to find reliable and significant results, the income-specific inflation rates should be created based on consumption categories at the fines level (six-digit level). Future research on monetary policy through income-specific inflation rates should therefore be based on prices and product categories at a lower level of aggregation. It would also be interesting to do the same study looking into differences across age groups or geographical regions in Norway, as these are other common groups which have been in focus in previous literature regarding other economies. Investigating inequality with respect to gender, race or house size through the inflation channel would also be instructive. As mentioned, wealth inequality is not considered in our study, but is an essential part of an inequality analysis. To draw a thorough conclusion on whether monetary policy has distributional effects, the results from this study should be combined with a study on the effects of monetary policy on wealth inequality.

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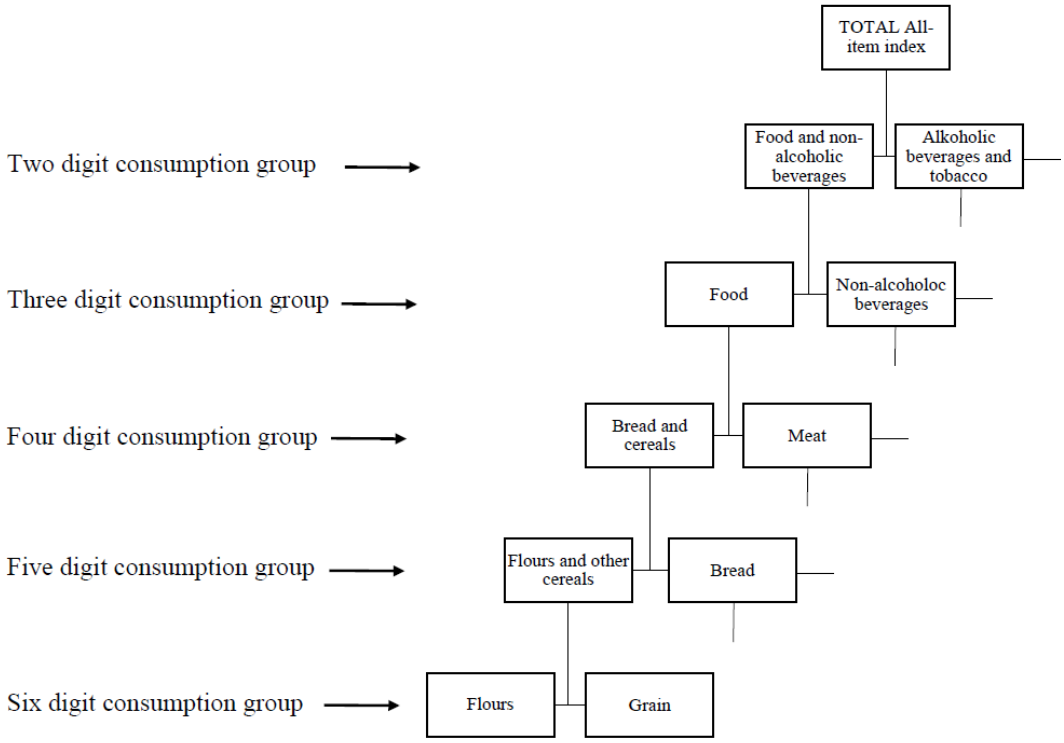
Appendix

Appendix A: COICOP

A.1 Figure: COICOP



The structure of the consumer price index. (Statistics Norway, 2001, p. 19).

Appendix B: Data, Sources and Transformation

Data	Source	Transformation
Consumption	HBS by NSD	
Income	HBS by NSD	
Frequency of Price Change	Wulfsberg (2016)	
Nominal GDP	SSB	Transformed to output gap using HP-filter
CPI	SSB	Log-levels
Policy Rate	SSB	
Exchange Rate	FRED	Log-levels

Appendix C: Consumption and Income

C.1 Table: Income and Wealth Statistics for Households

INCOME FROM WORK
Wages and salaries
Net income from self-employment
PROPERTY INCOME
Interested received
Share dividends received
Realized capital gains
Realized capital losses
Other capital incomes
TAXABLE TRANSFERS
Social security benefits
Old-age pensions
Disability pensions
Work assessment allowance
Service pensions
Contractual pensions
Unemployment benefits
Other taxable transfers
TAX-FREE TRANSFERS
Family allowances
Dwelling support
Scholarships
Social assistance
Basic and attendance benefits
Cash for care
Other tax-free transfers
TOTAL INCOME
Tax
Negative transfers
AFTER TAX INCOME

Source: *Income and wealth statistics for households. (Statistics Norway, 2022)*

C.2 Table: Income Cutoffs, Average Income and Number of Observations

	Cutoffs				
	Lower	**Upper**	**Median**	**Mean**	**N**
Bottom 5 %	-32.000	241.000	195.000	173.536	168
Lower income 5-40 %	242.000	638.000	464.000	458.356	1175
Middle income 40-60 %	640.000	854.000	744.000	746.358	670
Upper income 60-96 %	856.000	1,556,000	1,068,000	1,106,071	1205
High income 96-98 %	1,557,000	1,715,000	1,635,000	1,632,446	101
Top 1 %	1,720,000	2,344,000	1,812,000	1,860,121	33

Note: *the table shows an overview of income cutoffs from selected quantiles of the income distribution. It also reports the median and mean income of each quantile, including the number of observations in each group.*

C.3 Table: Consumption Expenditure Shares

	Income percentiles					
	Bottom 5%	Lower middle 5-40%	Middle 40-60%	Upper middle 60-96%	High 96-99%	Top 1%
Total consumption	235,519.5	421,794.9	585,269.9	778,107.5	1,239,718.0	1,339,664.0
Food	0.1359	0.1198	0.1241	0.1156	0.0910	0.0893
Beverages, tobac.	0.0361	0.0254	0.0204	0.0184	0.0153	0.0207
Clothing, footw.	0.0468	0.0528	0.0590	0.0658	0.0837	0.0883
Housing	0.4270	0.3908	0.3315	0.3127	0.3308	0.3053
Household equip.	0.0429	0.0545	0.0590	0.0615	0.0635	0.0511
Health	0.0294	0.0243	0.0229	0.0165	0.0151	0.0089
Transport	0.0742	0.1160	0.1489	0.1636	0.1570	0.1615
Communications	0.0250	0.0177	0.0182	0.0155	0.0093	0.0106
Recreation, cult.	0.0988	0.1082	0.1201	0.1263	0.1343	0.1474
Education	0.0138	0.0034	0.0034	0.0041	0.0047	0.0054
Restaur., hotels	0.0271	0.0255	0.0255	0.0301	0.0323	0.0322
Miscellaneous	0.0432	0.0617	0.0669	0.0699	0.0631	0.0793

C.4 Detailed Statistics of the Consumption Groups

Total Consumption:

groups	min	max	sd	mean	p50
5th	21253.84	1242231	150334.6	235519.5	198750.1
5-40th	39742.9	3584774	254610.6	421794.9	365882.9
40-60th	194975.6	2065258	252577.2	585270	535945
60-96th	155536.5	4116818	388312.7	778107.5	696803.1
96-99th	354800.3	3830554	652987.1	1239718	1119877
99-100th	383052.5	3057779	616776	1339664	1216094
Total	21253.84	4116818	392443.1	606897.2	519253.8

Food:

groups	min	max	sd	mean	p50
5th	.0053013	.7251649	.095376	.1359271	.119018
5-40th	0	.6261265	.067152	.1197898	.1107998
40-60th	.0091975	.4835127	.0629939	.1240668	.1141424
60-96th	0	.3990656	.0589743	.1156242	.1072124
96-99th	.0058693	.2170475	.0441073	.0909658	.0843037
99-100th	.0199508	.2062834	.0438139	.0892812	.0868853
Total	0	.7251649	.0648638	.1187859	.1094159

Beverages, tobacco:

groups	min	max	sd	mean	p50
5th	0	.2519118	.056976	.0361079	.0107408
5-40th	0	.2447339	.0386584	.0253605	.008871
40-60th	0	.2430906	.0303759	.0204409	.0079918
60-96th	0	.3428074	.0275633	.0184456	.0089636
96-99th	0	.1168686	.0219776	.0153451	.0081034
99-100th	0	.112892	.0234292	.0206784	.0158542
Total	0	.3428074	.0343868	.0220819	.0087923

Clothing, footwear:

groups	min	max	sd	mean	p50
5th	0	.3362638	.0571519	.0467505	.0228969
5-40th	0	.3686094	.0557673	.0528283	.0348609
40-60th	0	.4829128	.0551251	.0590233	.0429315
60-96th	0	.3362862	.0543689	.0657773	.0510335
96-99th	.0007446	.4057403	.0697035	.0837011	.0623953
99-100th	.0061436	.2588483	.0645186	.0882748	.0604035
Total	0	.4829128	.0562979	.0596957	.0434909

Housing:

groups	min	max	sd	mean	p50
5th	0	.7750756	.1688679	.4269614	.418936
5-40th	0	.9321089	.1547414	.3907532	.380071
40-60th	.0622398	.821134	.1303697	.3315072	.3124473
60-96th	.0242669	.891248	.1394438	.3126576	.291619
96-99th	.0489057	.8487983	.1808594	.3308164	.2817352
99-100th	.0891289	.7578674	.16482	.305315	.251611
Total	0	.9321089	.1513452	.3500064	.328085

Household equipment:

groups	min	max	sd	mean	p50
5th	0	.3005171	.051814	.0429252	.0258696
5-40th	0	.7211286	.0605259	.0545397	.0368707
40-60th	0	.4030079	.0580149	.0589971	.0414999
60-96th	0	.4486349	.059988	.0614961	.0440138
96-99th	.0008884	.3058948	.0609587	.0634547	.0456632
99-100th	.0020014	.2459941	.0492675	.0511406	.0431394
Total	0	.7211286	.0594785	.0575849	.0401673

Health:

groups	min	max	sd	mean	p50
5th	0	.3381287	.0586151	.0293532	0
5-40th	0	.734991	.0579346	.0242827	.0054311
40-60th	0	.3230556	.0425787	.0228713	.0070389
60-96th	0	.2509249	.0277085	.0164753	.0062392
96-99th	0	.0949743	.0213119	.0150721	.0037312
99-100th	0	.0467746	.0115924	.0089095	.0045927
Total	0	.734991	.0449184	.0210184	.0059008

Transportation:

groups	min	max	sd	mean	p50
5th	0	.5174673	.0941004	.0741707	.0461701
5-40th	0	.7660648	.1377661	.1159548	.065634
40-60th	0	.6955335	.1490427	.148905	.0884682
60-96th	0	.7268108	.1512325	.1636399	.1030762
96-99th	.001716	.6190343	.1474594	.1569695	.0892684
99-100th	.01624	.5822616	.1602881	.1615308	.0934138
Total	0	.7660648	.1459006	.139274	.0829262

Communications:

groups	min	max	sd	mean	p50
5th	0	.3983076	.0469529	.0249776	.0064827
5-40th	0	.3426918	.0345591	.0177253	.0040446
40-60th	0	.1958755	.0276338	.0181707	.0073877
60-96th	0	.3060281	.0263054	.0154992	.0060748
96-99th	0	.102652	.0163051	.0092897	.0046544
99-100th	0	.0528874	.0155066	.0105618	.0034112
Total	0	.3983076	.0307612	.0170523	.0057134

Recreation, culture:

groups	min	max	sd	mean	p50
5th	0	.6104953	.0968096	.0987985	.0636821
5-40th	0	.6371266	.088521	.1082067	.0895749
40-60th	0	.6548395	.0879903	.1201418	.1019353
60-96th	0	.6752501	.0907275	.1262824	.1059964
96-99th	.0093902	.6087324	.1015784	.1342949	.1050953
99-100th	.0191964	.6047148	.1280033	.1473776	.122067
Total	0	.6752501	.0909611	.1177898	.0978805

Education:

groups	min	max	sd	mean	p50
5th	0	.5029039	.0633966	.0137843	0
5-40th	0	.232119	.0145211	.0034352	0
40-60th	0	.2243515	.0151227	.0034294	0
60-96th	0	.1879691	.0125567	.004061	0
96-99th	0	.1200748	.0153583	.0046905	0
99-100th	0	.0945121	.0166547	.0053707	0
Total	0	.5029039	.0197706	.004234	0

Restaurant, hotels:

groups	min	max	sd	mean	p50
5th	0	.1831296	.0399395	.0270397	.008772
5-40th	0	.4472072	.0384683	.0254648	.011944
40-60th	0	.2424684	.0352178	.0255015	.01364
60-96th	0	.3083391	.0379714	.0300916	.0169556
96-99th	0	.1336484	.0298282	.0322602	.0229039
99-100th	0	.2162715	.0409819	.0322249	.0202352
Total	0	.4472072	.0375743	.027486	.01496

Miscellaneous:

groups	min	max	sd	mean	p50
5th	0	.2832768	.0478326	.0432039	.0288789
5-40th	0	.6522791	.0673763	.0616591	.0416391
40-60th	0	.433939	.0560482	.066945	.0496867
60-96th	0	.3171764	.0505925	.0699499	.0569825
96-99th	.0068538	.284117	.0519385	.0631401	.0453049
99-100th	.0191296	.4272927	.0782071	.0793348	.0572504
Total	0	.6522791	.058564	.0649907	.0484477

Appendix D: Frequency of Price Changes

D.1 Table: Frequencies of Price Changes from Wulfsberg (2016)

		1990 - 2004 (low inflation period)		
		f^+	**f^-**	**Total frequency**
1	**Food and non-alcoholic beverages**	13.4	10.2	23.6
2	**Alcoholic beverages, tobacco and narcotics**	11.0	3.2	14.2
3	**Clothing and footwear**	5.7	8.3	14.0
4	**Housing, water, electricity, gas and other fuels**	13.5	9.6	23.1
5	**Furnishing, household equipment and routine household maintenance**	7.3	5.0	12.3
6	**Health**	7.5	2.0	9.5
7	**Transport**	23.1	11.6	34.7
8	**Communication**	2.6	8.2	10.8
9	**Recreation and culture**	9.2	4.9	14.1
10	**Education**	6.7	0.4	7.1
11	**Restaurants and hotels**	5.9	1.7	7.6
12	**Miscellaneous goods and services**	6.9	2.7	9.6

Note: *f^+ is the rate of price increases and f^- is the rate of price decreases for respective goods, classified according to COICOP. These are taken from Wulfsberg (2016). We sum the price increases and price decreases to find the total frequency of price changes for each consumption category, which we further use to calculate income-specific frequencies of price changes. The income-specific frequencies can be found in appendix D.2.*

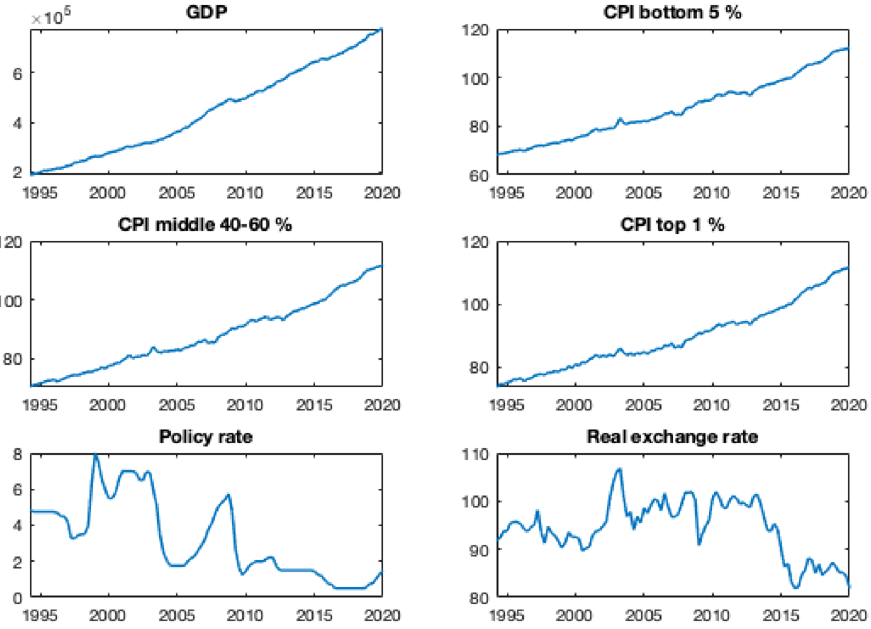
D.2 Table: Income-specific Frequencies of Price Changes

Groups	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Food	3.21	2.74	3.09	2.77	2.84	2.77	2.79	2.79	2.73	2.68	3.15	3.16	3.05	2.91	2.94	2.68	2.63	2.57	2.43	2.14
Beverages, tobac.	0.51	0.34	0.46	0.38	0.30	0.37	0.36	0.31	0.31	0.29	0.29	0.28	0.24	0.28	0.28	0.31	0.24	0.24	0.26	0.24
Clothing, footw.	0.65	0.69	0.74	0.64	0.88	0.70	0.73	0.81	0.71	0.81	0.86	0.93	0.80	0.89	0.81	0.93	0.94	0.94	1.09	1.18
Housing	9.86	10.12	8.88	9.13	8.92	8.93	8.58	8.62	7.95	7.82	7.59	7.27	7.68	6.98	7.66	6.72	7.70	7.12	6.74	7.40
Household equip.	0.53	0.68	0.60	0.55	0.66	0.67	0.71	0.84	0.69	0.71	0.75	0.76	0.71	0.73	0.76	0.75	0.84	0.76	0.74	0.75
Health	0.28	0.21	0.29	0.23	0.24	0.22	0.25	0.18	0.19	0.24	0.22	0.21	0.14	0.17	0.15	0.14	0.20	0.13	0.17	0.12
Transport	2.57	3.27	3.44	4.28	4.52	3.84	4.38	4.46	5.81	4.85	5.04	4.98	5.60	5.59	5.45	5.95	5.22	5.67	6.36	5.45
Communication	0.27	0.26	0.19	0.17	0.17	0.23	0.19	0.14	0.20	0.16	0.21	0.21	0.20	0.18	0.15	0.19	0.15	0.15	0.15	0.11
Recreation, cult.	1.39	1.30	1.50	1.62	1.40	1.64	1.68	1.53	1.67	1.83	1.64	1.63	1.57	1.74	1.64	1.96	1.65	1.97	1.84	2.01
Education	0.10	0.02	0.02	0.03	0.02	0.03	0.02	0.04	0.02	0.03	0.02	0.03	0.03	0.03	0.02	0.04	0.03	0.02	0.03	0.03
Hotel & rest.	0.21	0.19	0.19	0.20	0.22	0.20	0.19	0.18	0.18	0.20	0.18	0.22	0.20	0.22	0.19	0.24	0.22	0.27	0.25	0.25
Other	0.41	0.54	0.67	0.61	0.51	0.63	0.58	0.61	0.59	0.69	0.62	0.67	0.67	0.77	0.70	0.64	0.64	0.65	0.64	0.64
Price Frequency	20.00	20.37	20.07	20.60	20.68	20.20	20.44	20.50	21.04	20.31	20.57	20.35	20.89	20.48	20.76	20.55	20.46	20.49	20.69	20.32

Note: *The expenditure shares from appendix C.3 are multiplied with measures on frequency of price changes, listed in appendix D.1, for each consumption category at the two-digit level according to COICOP (see illustration in figure A.1). The price frequency for each consumption category is then summed up to equal income-specific total weighted average price frequency, as seen in the bottom of the table.*

Appendix E: Structural VAR

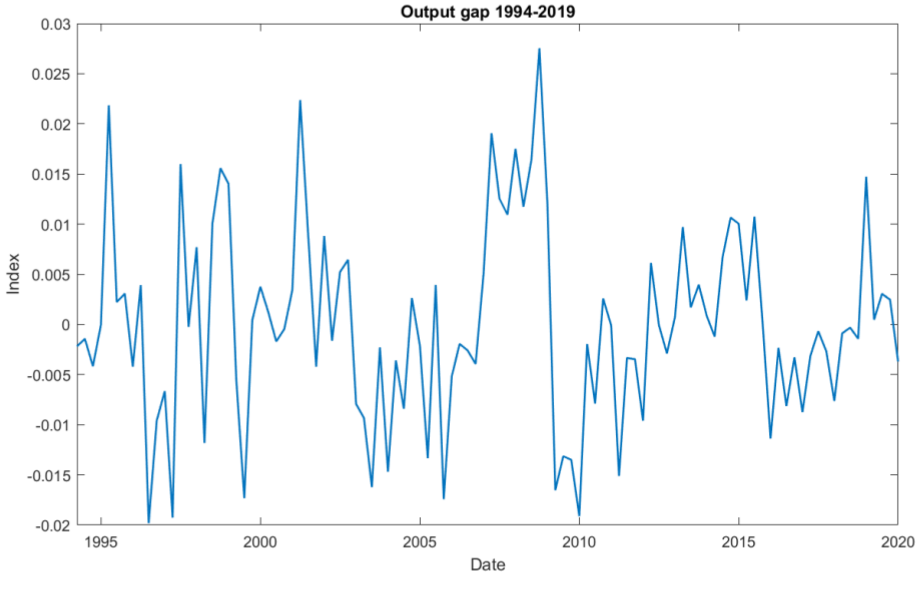
E.1 Figure: Plot of Data



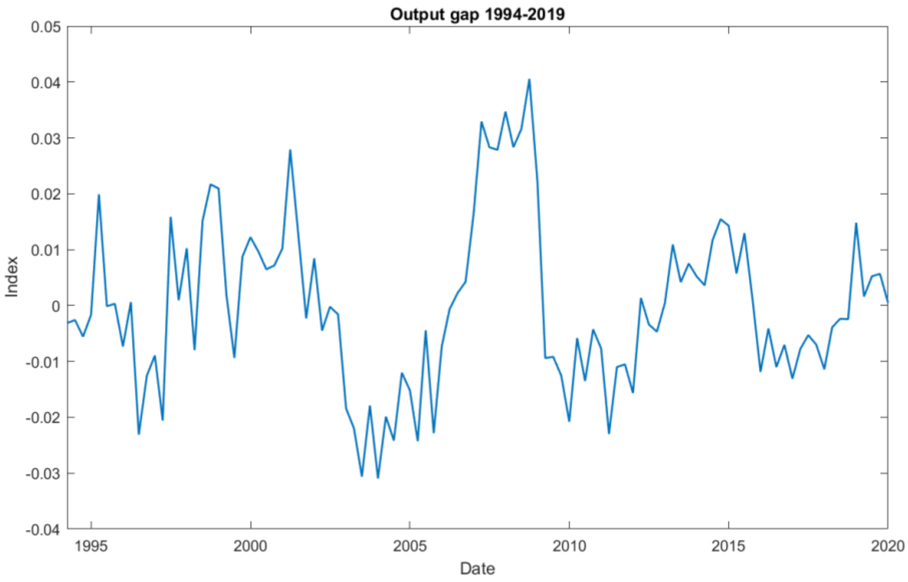
Note: *Plot of the time series before any transformation*

E.2 Figure: HP-filter

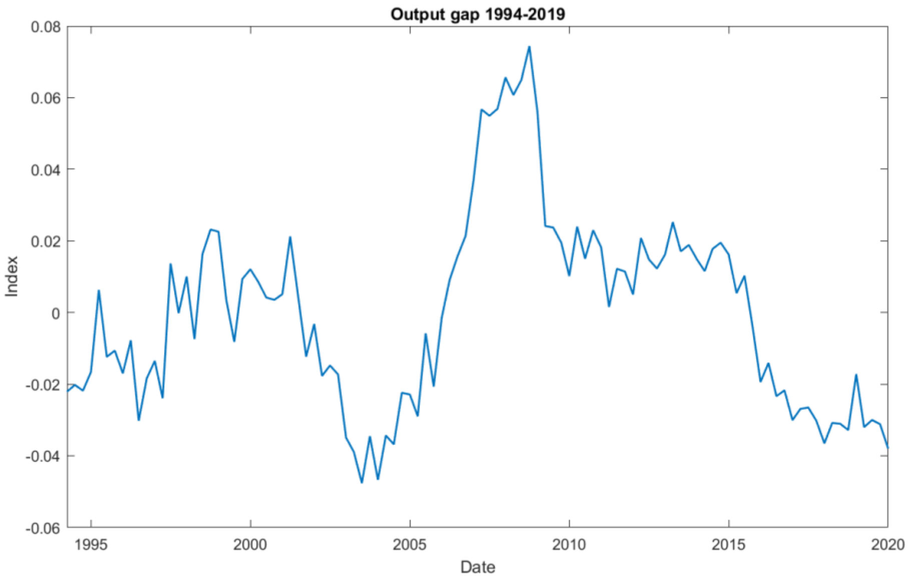
λ = 200:



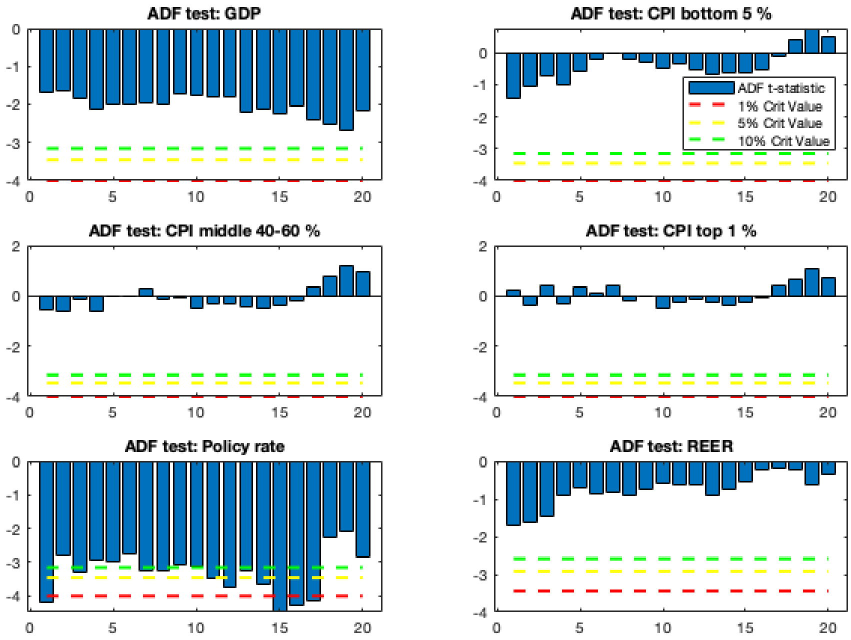
$\lambda = 1{,}600$:



$\lambda = 160{,}000$:



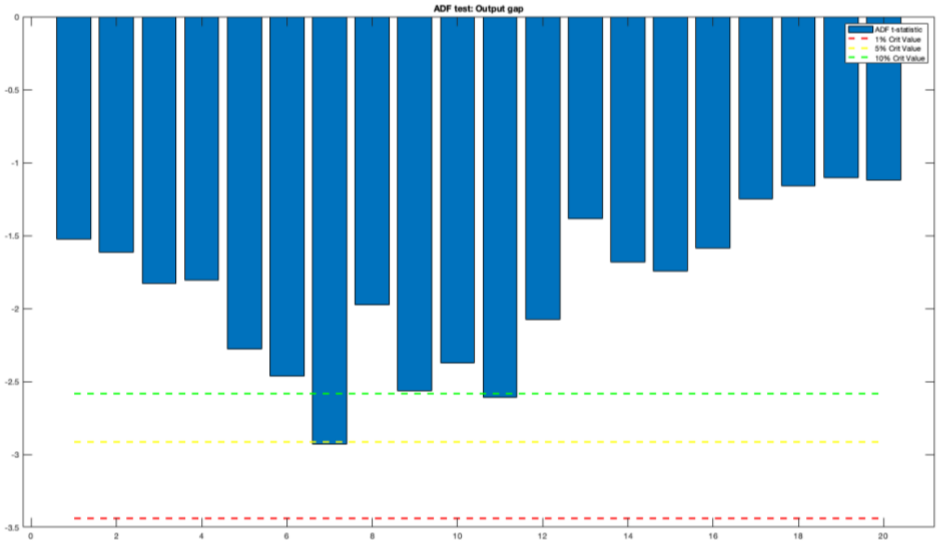
E.3 Figure: ADF-tests



Note: *The ADF-test tests the null hypothesis of a unit root against the alternative hypothesis of the time series being stationary, i.e., it is a one-sided hypothesis test. If the t-statistic is significantly different from zero, we can reject the null hypothesis. Before performing the test, we need to assess whether the time series can be expressed with a constant, both a constant and a time trend, or none. From appendix E.1 we conclude that GDP, the CPIs and the policy rate have a time-trend, while the REER do not seem to trend in any direction. We include a constant in all of them as none of them fluctuate around zero.*

Results: *The policy rate is the only variable where the null hypothesis can be rejected at all conventional levels, i.e., at the 1 percent, 5 percent and 10 percent significance level. We therefore conclude that the policy rate is trend-stationary. The REER, GDP and CPI all have a unit root.*

E.4 Figure: ADF-test of output gap



Note: *An explanation of the ADF-test can be found in appendix E.3 above. Based on the plot of output gap in E.2, we include only a constant in the ADF-test. We can reject the null hypothesis at lag 7 and 11.*

E.5 Table: AIC and BIC

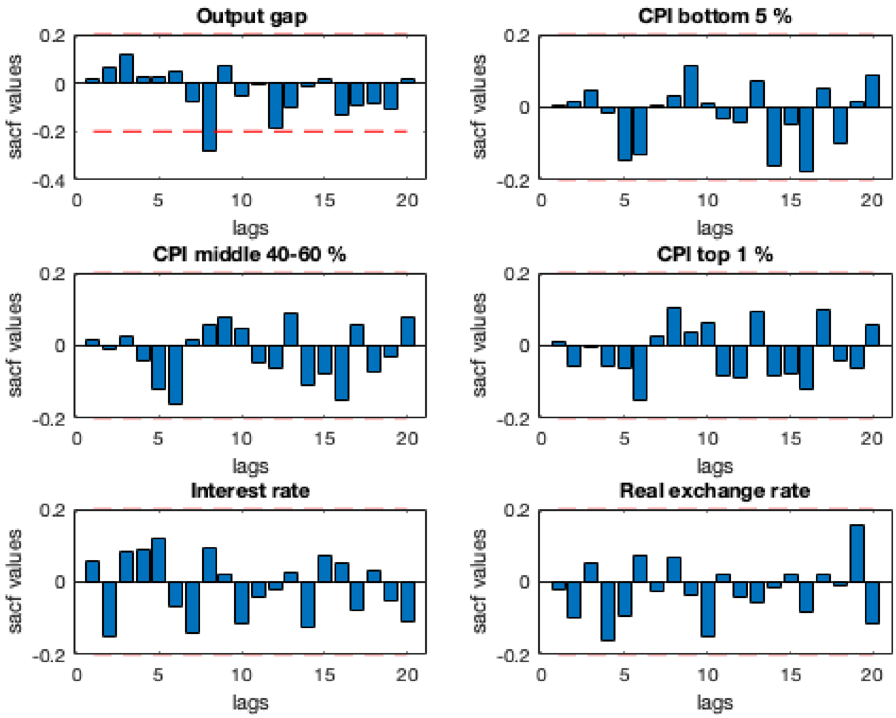
Lag	AIC	BIC
1	-3.0522	-2.9445
2	-3.2515	-3.0515
3	-3.2450	-2.9526
4	-3.2615	-2.8769
5	-3.2545	-2.7775
6	-3.2546	-2.6853
7	-3.2270	-2.5654
8	-3.2815	-2.5276

Note: *When computing criteria functions for different lag lengths, the appropriate lag length is the one that minimizes the function. In the table we have computed AIC and BIC for 1-8 lags. AIC proposes 8 lags as the optimal lag length, while BIC proposes 2 lags.*

E.6 Figure: Eigenvalues of the Companion Form:

```
Eigenvalues of the companion form:
    0.9517
    0.8249
    0.8249
    0.5028
    0.3813
    0.3813
    0.4643
    0.4643
    0.1107
    0.6714
    0.6714
    0.9395
    0.9395
    0.9837
    0.7322
    0.7322
    0.6138
    0.6138
```

E.7 Figure: Autocorrelation in Residuals



Note: *The figures plot the sample autocorrelation functions for the residuals of the variables included in the VAR model. It is important that the estimated residuals behave well, i.e., we want to avoid a lot of significant autocorrelation. The autocorrelation is significant at the 5 % significance level if it moves beyond the red line. In our baseline model, we only find significant autocorrelation at the 8th lag in the residual of output gap.*

Appendix F: Top 10 Expenditure Shares

In the tables listed below, expenditure shares at the three-digit level are ranked from the largest to the smallest difference relative to another income-group. In addition, the tables report the mean frequency of price change and standard deviation of the 12-month price change. Note that the measure of price frequency of "imputed rentals for housing" was not reported in Wulfsberg (2016) and is therefore assumed to be equal to that of "actual rentals for housing".

F.1 Tables: Bottom 5 percent vs. Middle 40-60 percent

	Income percentile						
Category	**1-5**	**40-60**	**Difference**	f_t	f_t^+	f_t^-	σ
Actual rentals for housing	0.181	0.018	-0.163	7.4	5.1	2.3	0.009
Electricity, gas and other fuels	0.066	0.049	-0.017	31.8	17.5	14.3	0.162
Tobacco	0.020	0.008	-0.011	11.1	9.8	1.3	0.042
Education	0.014	0.003	-0.010	7.1	6.7	0.4	0.023
Transport services	0.033	0.026	-0.008	8.1	7.7	0.4	0.042
Food	0.136	0.130	-0.007	31.4	20.0	11.4	0.023
Telephone services	0.021	0.015	-0.006	8.1	3.2	4.9	0.039
Alcoholic beverages	0.020	0.015	-0.005	18.2	14.5	3.7	0.022
Audio-visual, photography and information processing equipment	0.022	0.018	-0.004	18.2	8.7	9.5	0.037
Medical products, appliances and equipment	0.016	0.013	-0.003	12.6	8.7	3.9	0.018
Mean				15.4	10.2	5.2	0.042
Median				11.9	8.7	3.8	0.030

Note: *The table reports the largest expenditures shares from the perspective of bottom 5 percent relative to the middle 40-60th percentile.*

	Income percentile						
Category	**1-5**	**40-60**	**Difference**	f_t	f_t^+	f_t^-	**σ**
Purchase of vehicles	0.025	0.082	0.057	36.0	30.4	5.6	0.017
Imputed rentals for housing	0.140	0.184	0.044	7.4	5.1	2.3	0.011
Operation of personal transport equipment	0.025	0.061	0.036	46.0	29.8	16.2	0.037
Maintenance and repair of the dwelling	0.015	0.033	0.018	20.2	5.5	14.7	0.016
Social protection	0.005	0.018	0.013	5.2	5.1	0.1	0.039
Clothing	0.038	0.049	0.010	12.6	6.7	5.9	0.038
Other recreational items and equipment, gardens and pets	0.015	0.023	0.008	13.9	7.5	6.4	0.020
Package holidays	0.011	0.018	0.007	10.3	7.7	2.6	0.031
Recreational and cultural services	0.016	0.023	0.007	9.0	7.9	1.1	0.017
Furniture and furnishings, carpets and other floor coverings	0.011	0.017	0.006	11.7	7.9	3.8	0.032
Mean				17.2	11.4	5.9	0.026
Median				12.2	7.6	4.7	0.025

Note: *the table reports the largest expenditures shares from the perspective of the middle 40-60th percentile relative to the bottom 5 percent.*

F.2 Tables: Middle 40-60 percent vs. Top 1 percent

	Income percentile						
Category	**40-60**	**100**	**Difference**	f_t	f_t^+	f_t^-	σ
Imputed rentals for housing	0.184	0.144	-0.040	7.4	5.1	2.3	0.011
Food	0.130	0.098	-0.032	31.4	20.0	11.4	0.023
Operation of personal transport equipment	0.061	0.037	-0.024	46.0	29.8	16.2	0.037
Actual rentals for housing	0.018	0.000	-0.017	7.4	5.1	2.3	0.009
Electricity, gas and other fuels	0.049	0.035	-0.014	31.8	17.5	14.3	0.162
Out-patient services	0.013	0.005	-0.009	6.9	6.8	0.1	0.022
Medical products, appliances and equipment	0.013	0.006	-0.007	12.6	8.7	3.9	0.018
Telephone services	0.015	0.008	-0.007	8.1	3.2	4.9	0.039
Social protection	0.018	0.011	-0.007	5.2	5.1	0.1	0.039
Newspapers, books and stationery	0.011	0.007	-0.004	16.3	14.8	1.5	0.022
Mean				17.3	11.6	5.7	0.038
Median				10.4	7.75	3.1	0.023

Note: *the table reports the largest expenditures shares from the perspective of the middle 40-60th percentil relative to the top 1 percent.*

Category	Income percentile 40-60	100	Difference	f_t	f_t^+	f_t^-	σ
Maintenance and repair of the dwelling	0.033	0.077	0.044	20.2	5.5	14.7	0.016
Purchase of vehicles	0.082	0.102	0.020	36.0	30.4	5.6	0.017
Transport services	0.026	0.044	0.019	8.1	7.7	0.4	0.042
Operation of personal transport equipment	0.008	0.027	0.019	7.8	7.0	0.8	0.013
Clothing	0.049	0.065	0.016	12.6	6.7	5.9	0.038
Insurance	0.020	0.035	0.015	22.3	20.0	2.3	0.023
Recreational and cultural services	0.023	0.034	0.011	9.0	7.9	1.1	0.017
Restaurant services	0.028	0.036	0.008	6.8	5.5	1.3	0.011
Package holidays	0.018	0.026	0.008	10.3	7.7	2.6	0.031
Footwear	0.008	0.015	0.007	11.8	6.2	5.6	0.034
Mean				14.5	10.5	4.0	0.024
Median				11.1	7.4	2.5	0.020

Note: *the table reports the largest expenditures shares from the perspective of the top 1 percent relative to the middle 40-60th percentile*

F.3 Tables: Bottom 5 percent vs. Top 1 percent

	Income percentile						
Category	**1-5**	**100**	**Difference**	f_t	f_t^+	f_t^-	σ
Actual rentals for housing	0.181	0.000	-0.181	7.4	5.1	2.3	0.009
Food	0.136	0.098	-0.039	31.4	20.0	11.4	0.023
Electricity, gas and other fuels	0.066	0.035	-0.031	31.8	17.5	14.3	0.162
Tobacco	0.020	0.005	-0.015	11.1	9.8	1.3	0.042
Telephone services	0.021	0.008	-0.012	8.1	3.2	4.9	0.039
Out-patient services	0.016	0.005	-0.011	6.9	6.8	0.1	0.022
Medical products, appliances and equipment	0.016	0.006	-0.011	12.6	8.7	3.9	0.018
Education	0.014	0.005	-0.008	7.1	6.7	0.4	0.023
Audio-visual, photography and information processing equipment	0.022	0.015	-0.007	18.2	8.7	9.5	0.037
Newspapers, books and stationery	0.013	0.007	-0.006	16.3	14.8	1.5	0.022
Mean				15.1	10.1	5.0	0.040
Median				11.9	8.7	3.1	0.023

Note: *the table reports the largest expenditures shares from the perspective of the bottom 5 percent relative to the top 1 percent.*

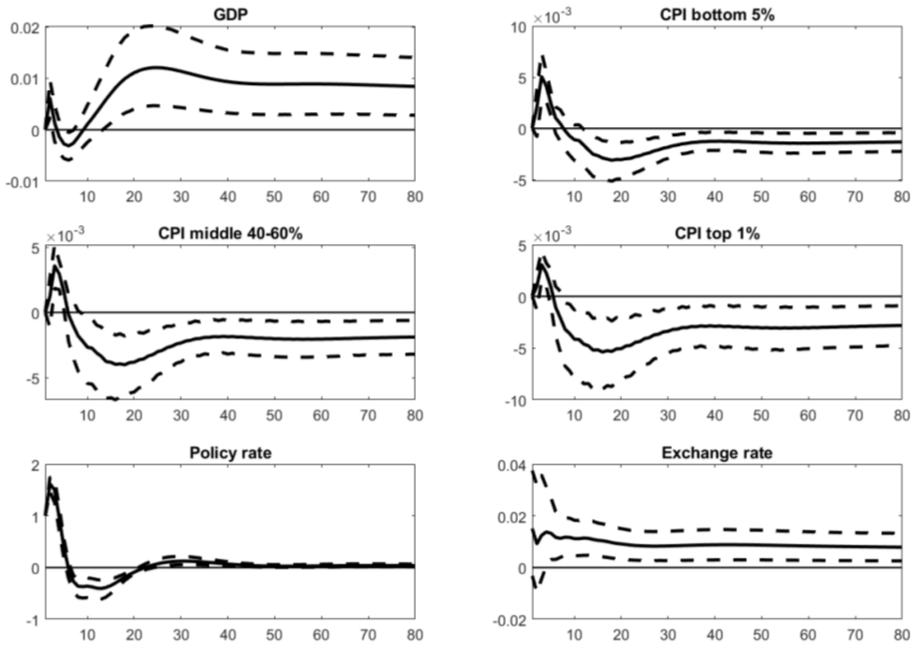
	Income percentile						
Category	**1-5**	**100**	**Difference**	f_t	f_t^+	f_t^-	σ
Purchase of vehicles	0.025	0.102	0.077	36.0	30.4	5.6	0.017
Maintenance and repair of the dwelling	0.015	0.077	0.061	20.2	5.5	14.7	0.016
Clothing	0.038	0.065	0.027	12.6	6.7	5.9	0.038
Other major durables for recreation and culture	0.004	0.027	0.023	7.8	7.0	0.8	0.013
Insurance	0.015	0.035	0.020	22.3	20.0	2.3	0.023
Recreational and cultural services	0.016	0.034	0.018	9.0	7.9	1.1	0.017
Package holidays	0.011	0.026	0.015	10.3	7.7	2.6	0.031
Operation of personal transport equipment	0.025	0.037	0.012	46.0	29.8	16.2	0.037
Transport services	0.033	0.044	0.011	8.1	7.7	0.4	0.042
Footwear	0.006	0.015	0.009	11.8	6.2	5.6	0.034
Mean				18.4	12.9	5.5	0.027
Median				12.2	7.7	4.1	0.027

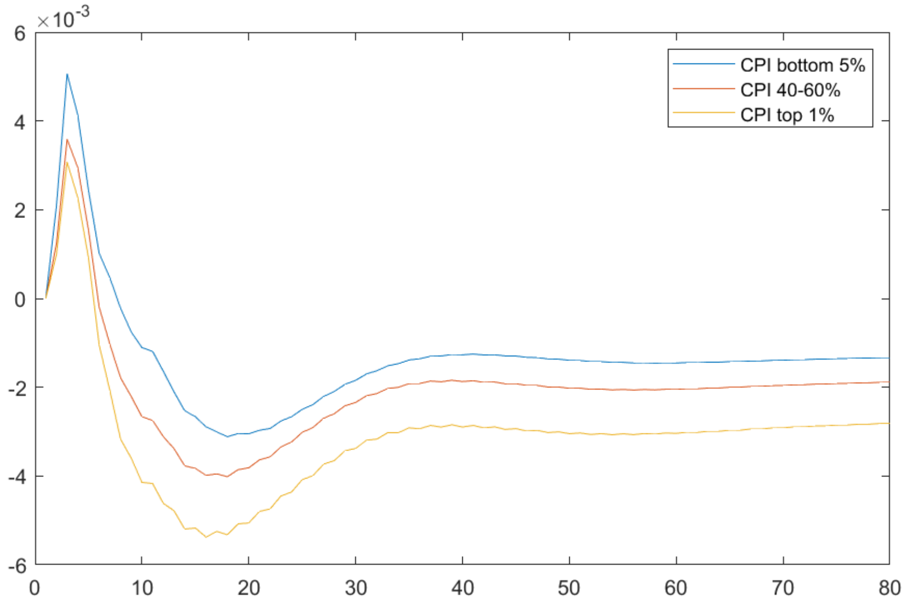
Note: *the table reports the largest expenditures shares from the perspective of the top 1 percent relative to the bottom 5 percent.*

Appendix G: Robustness Check

G.1 Model 1

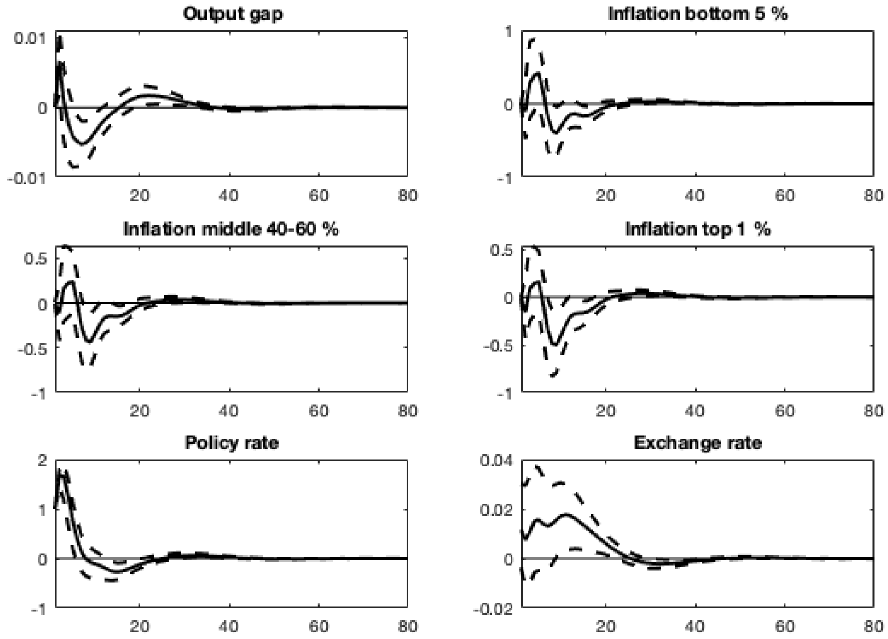
Model 1 is estimated using GDP (in log-level) instead of output gap. The model has a maximum eigenvalue of 0.9972, i.e., it is stable. There is some sign of autocorrelation in the residual of GDP at lag eight, however this is not too worrisome as it is not too large.

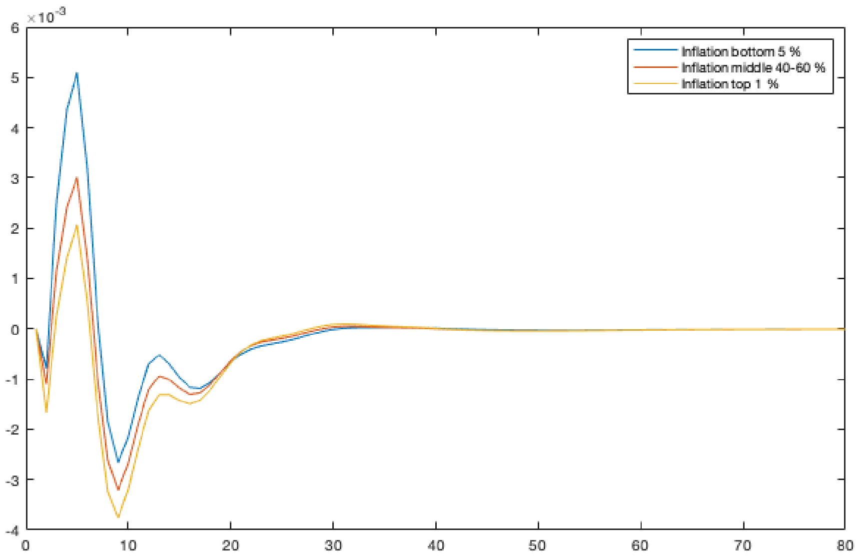




G.2 Model 2

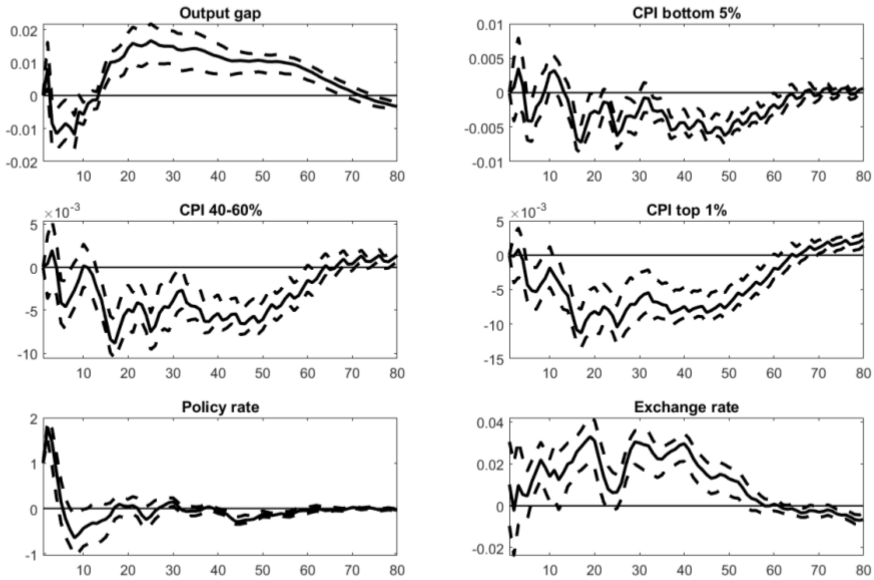
In model 2 we have taken the 12-month log-difference of the CPI rates to create annual inflation. The model has a maximum eigenvalue of 0.9516. At three lags, the model has some significant autocorrelation in the residuals of all the variables, except for the residual of the exchange rate.

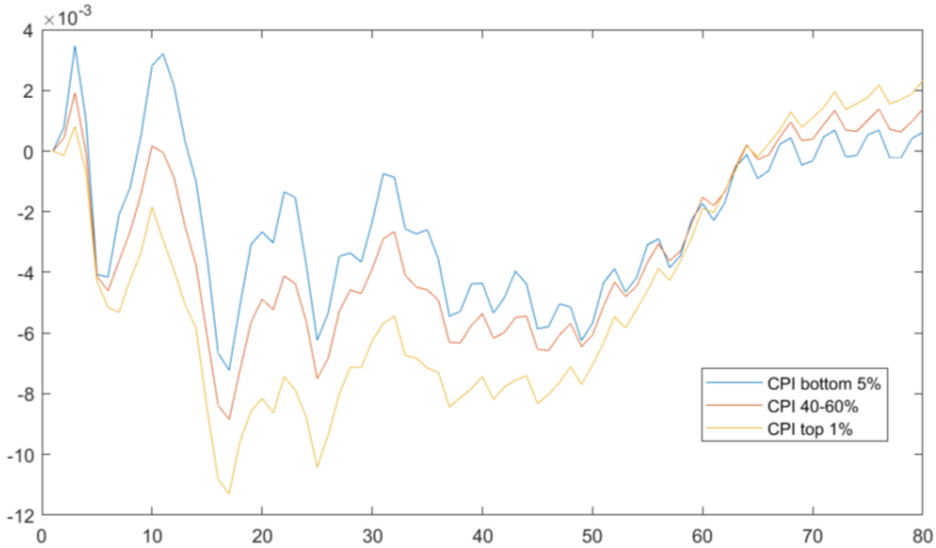




G.3 Model 3

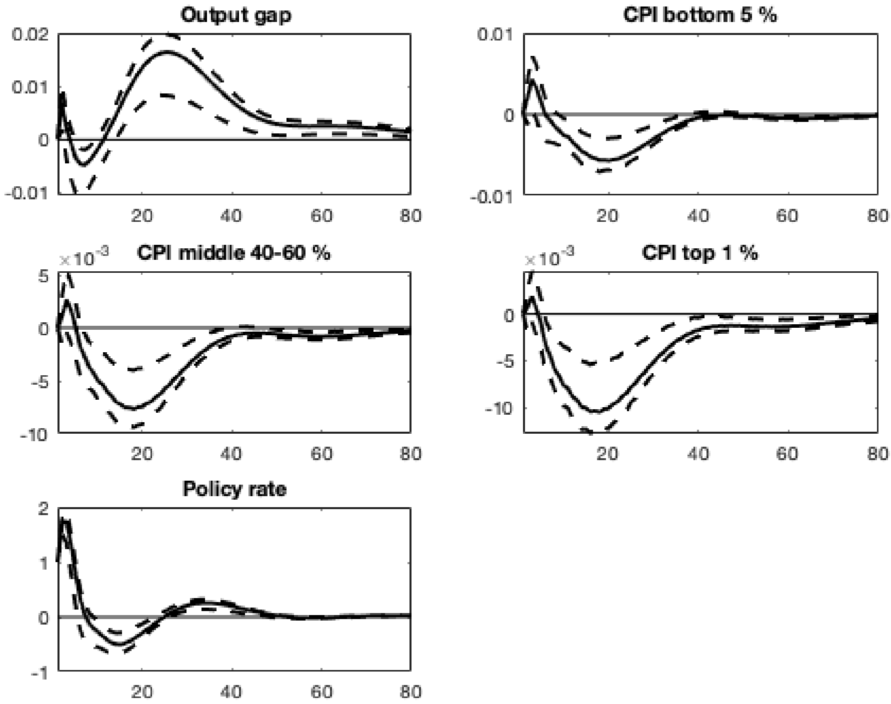
In model 3 we have included eight lags instead of three. The model has a maximum eigenvalue of 0.9937, i.e., it is stable. There is some significant autocorrelation in the residuals of all the three CPIs for the bottom 5 percent and the middle 40-60 percent income groups at lag two, as well as at lag 20 of the policy rate. However, we are not able to reduce this autocorrelation by including more lags, and it does not look too worrisome.

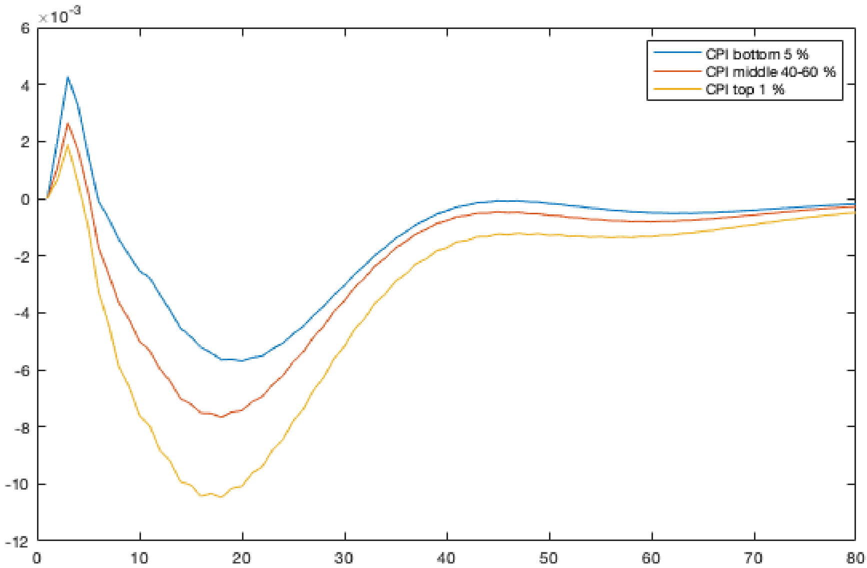




G.4 Model 4

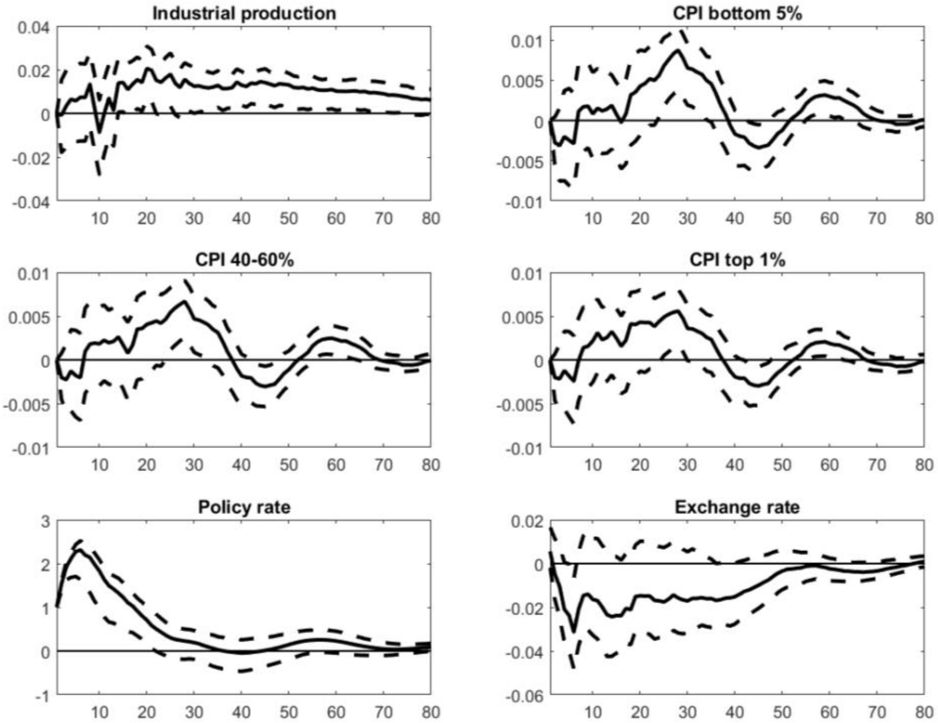
In model 4 we have omitted the exchange rate from the system. The model is stable with a maximum eigenvalue of 0.9611, i.e., it is stable. There is no significant autocorrelation in the residual, except from in the residual of GDP where there is some autocorrelation at lag eight. The size of the autocorrelation is consistent with what is found in the other models, i.e., it is not too large.

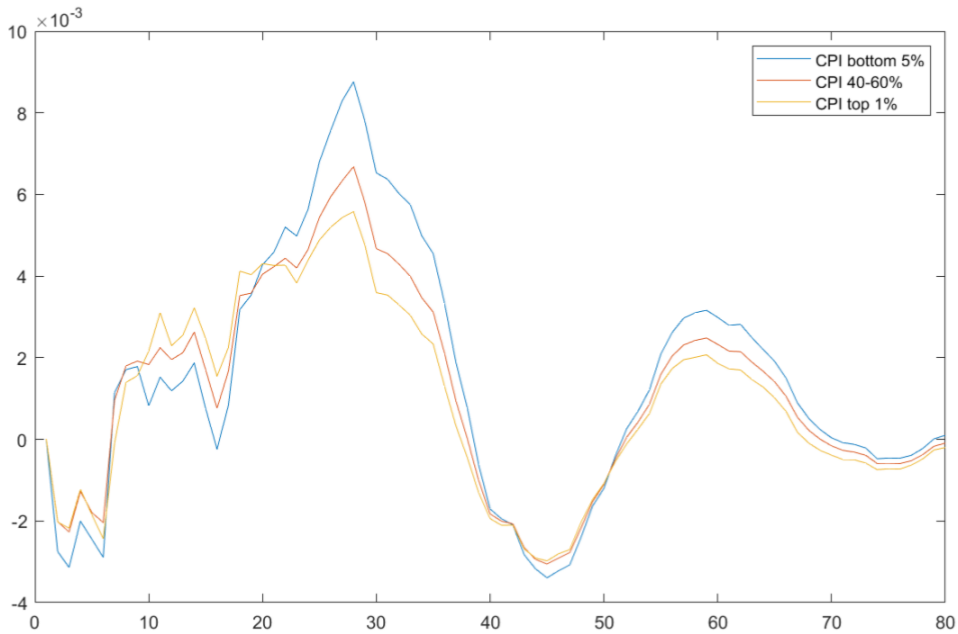




G.5 Model 5

In model 5 we have estimated the structural VAR model using monthly data. As GDP is not available on a monthly frequency, we use industrial production as our measure of output. We include 14 lags. The model has a maximum eigenvalue of 0.9771, i.e., it is stable. There is no significant autocorrelation in the residuals.





G.6 Model 6

In model 6 we have estimated the structural VAR model with income-specific CPIs that are constructed based on CPI at the three-digit level, i.e., at a lower level of aggregation. We include three lags. The model has a maximum eigenvalue of 0.9507, i.e., it is stable. There is some significant autocorrelation in the residuals of output gap. However, the autocorrelation is only found at two lags and is not too worrisome.