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Inflation Heterogeneity and Differential Effects of Monetary and Oil Price Shocks*

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Resumen

Este trabajo examina los efectos heterogéneos de la política monetaria y de los shocks de precios del petróleo sobre la inflación a lo largo de la distribución del ingreso en Chile. Encontramos que un shock contractivo de política monetaria reduce significativamente la inflación para todos los deciles de ingreso, con una caída mayor entre los hogares de altos ingresos. Esta respuesta diferencial está impulsada principalmente por cambios de precios en la categoría de Transporte, que representa una mayor proporción del gasto de estos hogares. En contraste, un shock en el precio del petróleo incrementa significativamente la inflación acumulada. Aunque el impacto inicial es más fuerte para los hogares de altos ingresos, el efecto se vuelve mayor para los hogares de ingresos bajos y medios a medida que el shock se propaga hacia otros sectores, impulsado por una respuesta de precios relativamente más intensa en la categoría de Alimentos. Además, documentamos una dispersión sustancial en las tasas de inflación a nivel de hogar y mostramos que los hogares de bajos ingresos experimentaron una inflación acumulada más alta que sus contrapartes de altos ingresos entre 2009 y 2023.

Abstract

This paper examines the heterogeneous effects of monetary policy and oil price shocks on inflation across the income distribution in Chile. We find that a contractionary monetary policy shock significantly reduces inflation for all income deciles, with a larger decline for high-income households. This differential response is mainly driven by price changes in the Transport category, which accounts for a larger share of expenditures among these households. By contrast, an oil price shock significantly increases cumulative inflation. Although the initial impact is stronger for high-income households, the effect becomes larger for low- and middle-income households as the shock propagates to other sectors, driven by a comparatively stronger price response in the Food category. Moreover, we document substantial dispersion in household-level inflation rates and show that low-income households experienced higher cumulative inflation than their high-income counterparts between 2009 and 2023.

* The views expressed are those of the authors and do not necessarily reflect the views of the Central Bank of Chile or its board members.

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1 Introduction

Heterogeneity in households' consumption baskets, coupled with differences in price-setting dynamics across sectors, implies that changes in the cost of living are not uniform across households. This phenomenon, commonly referred to as inflation heterogeneity, means that shocks or policies that affect relative prices have distributional consequences. Yet, evidence on these effects remains scarce, particularly for developing economies.

This paper contributes to closing this gap by studying the heterogeneous effects of monetary policy and oil price shocks on inflation across the income distribution in a small, open, developing economy such as Chile. To this end, we use Chilean household expenditure data and consumer price index (CPI) information to compute decile-level inflation rates from 2009 to 2023. We then employ the local projections approach to estimate the causal effect of monetary and oil price shocks on the difference in cumulative inflation across income groups. For monetary policy shocks, we update the monetary policy surprise series developed by Aruoba et al. (2021); for oil price shocks, we use the oil supply news series developed by Känzig (2021). Additionally, we calculate household-level inflation rates to characterize inflation heterogeneity for Chilean households.

We find that a contractionary monetary policy surprise leads to a decrease in cumulative inflation across income deciles, but the magnitude of the decline is greater for high-income households. In the Chilean case, this pattern is driven by a stronger price response in the Transport category, which accounts for a larger share of their spending. This result contrasts with the findings of Cravino et al. (2020) and Ampudia et al. (2024), who show — based on survey expenditure data — that the inflation of high-income households is less sensitive to an unexpected tightening in monetary policy in the U.S. and some European countries, respectively.

To our knowledge, this is the first study to analyze the effect of oil price shocks on inflation rates across income deciles. We find that an unexpected increase in oil prices raises cumulative inflation for all income groups, but the timing and magnitude of the effect vary across deciles. High-income households experience higher cumulative inflation during the first two years following the shock. As it propagates through broader sectors of the economy, the shock increasingly affects middle- and low-income households through rising prices in the Food category, which accounts for a larger share of their spending. These dynamics reveal that oil price shocks have mixed and time-

varying distributional consequences across income groups.

With respect to inflation heterogeneity, we find a significant dispersion in household-level inflation rates with an interquartile range (IQR) reaching up to 8 percentage points (pp.). This IQR is higher than that reported in Lauper and Mangiante (2023) for the U.S., which ranges between 0.5 pp. and 3 pp. using household expenditure survey data. Our dispersion measure aligns more closely with findings based on scanner consumer data and household-level prices. Kaplan and Schulhofer-Wohl (2017) find that the IQR fluctuates between 6 pp. and 9 pp. for the U.S., while Kiss and Strasser (2024) and Strasser et al. (2023) find that this dispersion measure ranges from 3 pp. to 9 pp. for some European countries. These results suggest that the variability in consumption baskets for Chilean households is relatively high compared to what is typically documented using household expenditure survey data. Moreover, and consistent with the existing literature, we find that low-income households experience higher inflation rates than high-income households.

The rest of the document is organized as follows. In Section 2, we review the related literature, and in Section 3, we describe the datasets used in the project. Section 4 characterizes the inflation heterogeneity and the price-setting statistics along the income distribution. In Section 5, we present the empirical strategy to estimate the effects of monetary and oil price shocks, and discuss the main results of the estimations in Section 6. Finally, in Section 7, we conclude.

2 Related Literature

This paper contributes to three strands of the literature. First, it connects with the literature on inflation heterogeneity at the household level. For the U.S., Hobijn and Lagakos (2005) and Lauper and Mangiante (2023) show significant dispersion in household-level inflation rates using survey expenditure data. More recently, Kaplan and Schulhofer-Wohl (2017) and Argente and Lee (2020) use scanner data to compute household-level inflation series and report greater dispersion than that found in studies relying on survey data. Also using scanner data, Kiss and Strasser (2024), Messner and Rumler (2024), and Strasser et al. (2023) corroborate these findings for several European countries. Although scanner data provide granular information for studying inflation heterogeneity, such data typically cover only a subset of items included in household expenditure surveys.

The literature also finds that low-income households experience higher inflation rates than their high-income counterparts. This pattern has been documented by Hobijn and Lagakos (2005), Kaplan and Schulhofer-Wohl (2017), and Argente and Lee (2020) for the U.S.; Kiss and Strasser (2024), Ampudia et al. (2024), Strasser et al. (2023), Messner and Rumler (2024), and Jovanovic and Josimovski (2021) for Europe, and Baez Ramirez et al. (2021) for Turkey. In the case of Chile, Cobb (2012) and Bentancor and Pincheira (2014) corroborate this finding using survey expenditure data. We contribute to this strand by characterizing the extent of inflation heterogeneity —in terms of dispersion and its relationship with income— in an emerging economy such as Chile.

Second, this paper relates to a growing literature on the distributional effects of monetary policy. For instance, Coibion et al. (2017) and Mumtaz and Theophilopoulou (2017) find that contractionary monetary policy shocks increase short-term consumption and income inequality. In turn, Doepke and Schneider (2006) and Berriel (2010) emphasize the financial channel of monetary policy and show that debtors benefit from inflationary shocks. Within this literature, our focus is on inflation heterogeneity across the income distribution. Orchard (2022) analyzes the cyclical behavior of price indices and shows that monetary policy affects the inflation of low-income households to a greater extent. In studies closely aligned with ours, Cravino et al. (2020) and Lauper and Mangiante (2023) find that high-income households' inflation reacts less to an unexpected tightening of monetary policy in the U.S. compared to middle-income households. Similarly, Ampudia et al. (2024) report a comparable result for six European countries using survey expenditure data; however, their analysis using scanner data reveals the opposite pattern, with stronger inflation responses for high-income households. To the best of our knowledge, this is the first study to examine this question in the context of an emerging economy. In contrast to prior findings, our results suggest that the inflation of high-income households reacts more strongly to a monetary policy shock than that of middle- and low-income households.

Finally, this paper contributes to the literature on the effects of energy price shocks on inflation heterogeneity. Känzig (2023) shows that carbon price shocks significantly raise energy prices, affecting low-income households more strongly in the U.K. From a theoretical perspective, Auclert et al. (2023), Pieroni (2023), and Bobasu et al. (2024) employ HANK models to show that energy price shocks have a larger impact on low-income households, as energy accounts for a larger share of their spending. Chan et al. (2024)

find similar results using a TANK model. However, these studies do not examine inflation heterogeneity across the income distribution.

A related study by Corsello and Riggi (2023) analyzes the effects of energy price shocks on inflation across the income distribution. Using a sign-restricted VAR, they find that these shocks have a stronger inflationary impact on low-income households in Italy. In contrast to our findings, their results do not indicate a reversal in the inflation differential between low- and high-income households as the shock propagates through the economy. The authors also use a TANK model with heterogeneous consumption baskets to account for their empirical results.

We contribute to this literature by studying how supply-driven oil price shocks affect inflation across the income distribution in a net oil-importing emerging economy. Although these shocks initially affect high-income households more, their impact reverses as they propagate through the economy, leading to higher inflation for low-income households. To the best of our knowledge, this is the first empirical study documenting this distributional pattern for oil price shocks.

3 Data

This section describes the data used in the analysis and explains how household-level inflation rates are constructed. It begins with the household expenditure data and then presents the price data. Finally, it explains the computation of household-level inflation rates.

3.1 Expenditure data

Data on household expenditures come from the "Household Budget Survey" (EPF, "Encuesta de Presupuestos Familiares" in Spanish), a nationally representative survey conducted every five years by Chile's National Statistics Institute (INE, "Instituto Nacional de Estadísticas" in Spanish). This survey is the primary source for updating the official consumption basket used to calculate Chile's Consumer Price Index (CPI).

The EPF collects detailed information on household expenditures using the Classification of Individual Consumption by Purpose (COICOP), developed by the United Nations Statistics Division. This classification includes

three aggregation levels: division, group, and class.[1] The survey also gathers data on total household income in each wave.

In this study, we use data from all nationally representative waves of the EPF: 2006, 2011, and 2016.[2] To ensure comparability across waves, we use household expenditure data at the class level and exclude categories not available in the 2016 wave. This harmonization retains 98% and 97% of total expenditure in the 2006 and 2011 waves, respectively. Income deciles are constructed independently for each wave using total household income.

Figure 1 illustrates that consumption baskets vary significantly along the income distribution. The expenditure shares of Food and Housing & Utilities decline as income rises, whereas Transport represents a growing share of spending at higher income levels.

Among households in the lowest income decile, Food is the largest expenditure category, accounting for 26% of total spending, followed by Housing & Utilities at 23%, and Transport at 10%. In contrast, in the highest income decile, Transport becomes the largest category, at 20% of spending, while Food and Housing & Utilities account for 10% and 12%, respectively.[3] These pronounced differences in expenditure composition underscore substantial heterogeneity in household consumption patterns along the income distribution.

Taken together, Food, Housing & Utilities, and Transport represent the most important expenditure categories across income deciles. Together, these categories account for 60%, 56%, and 42% of total expenditure among low-, middle-, and high-income households, respectively. These results highlight the central role of these categories in explaining inflation dynamics along the income distribution.

[1]The INE adapts the COICOP to the Chilean context. With this adjustment, the classification includes five aggregation levels: division (2-digit), group (1-digit), class (1-digit), subclass (2-digit), and product (2-digit).

[2]Survey waves prior to 2006 were only representative of the urban population in the capital region.

[3]The results in Figure 1 are based on EPF 2016 data. Findings are consistent across the 2011 and 2006 waves. See Figures B.1 and B.2 in Appendix B.

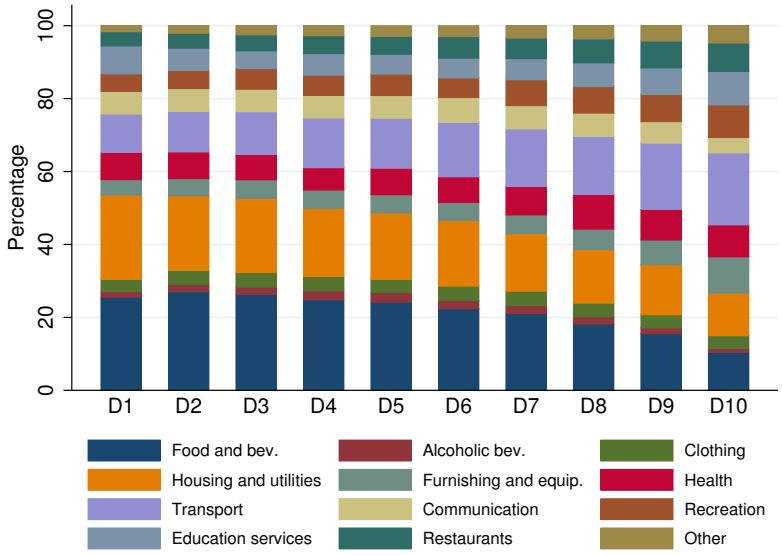

Figure 1: Consumption baskets along income distribution

Notes. The figure shows the composition of household expenditures at COICOP division-level aggregation. The data come from EPF 2016.

3.2 Price information

We use monthly Consumer Price Indices (CPIs) at the COICOP class-level of aggregation.[4] We use CPI series based on the 2009, 2013, and 2019 base years, which are constructed using expenditure data from the three EPF waves described above. We combine these series to construct monthly price indices at the COICOP class level for the period 2009m1–2023m6, which we then use to compute household-specific price indices. In certain analyses, we aggregate the series to the division level.

Following Nakamura and Steinsson (2008), we calculate price statistics for the Chilean economy to characterize structural differences in price-setting dynamics at the division level. For this purpose, we use a Panel of establishment-variety prices at a monthly frequency, which represents the most granular price data available from the INE. In this dataset, a group of varieties con-

[4]CPI data also follow INE's COICOP adaptation. However, at the subclass and product levels, the classification differs from that in the EPF.

stitutes a product under the Chilean COICOP adaptation.[5] Due to privacy concerns, this Panel excludes price information for fuel, electricity, communication, education, and tourism. Consequently, our analysis of price statistics covers approximately 65% of total expenditure in the EPF.[6]

Tables A.3 and A.4 present the frequency and size of price changes by COICOP division across the CPI base years previously described. Table A.3 shows that Food, Housing & Utilities, and Transport exhibit the highest frequency of price changes. Among all categories, Transport shows the highest price change frequency, ranging from 57% to 59%, followed by Food (51% and 53%), and Housing & Utilities (41% and 50%).

Regarding the size of price changes, Table A.4 shows shows that average price changes range from 4% to 6% for Transport and from 7% to 9% for Housing & Utilities, making them the categories with the smallest price changes. Food falls in the intermediate range, with size changes fluctuating between 7% and 10%.

Taken together, these findings suggest that Food, Housing & Utilities, and Transport are not only the most important categories in household spending but also play a key role in price dynamics due to their high frequency of price changes. These categories are therefore likely to be central to shaping inflation outcomes across households.

3.3 Measures of inflation

To construct household-level inflation rates, we merge EPF expenditure data with CPI series at the class level using the COICOP classification. Because the price data cover only a subset of EPF categories, we drop unmatched classes across datasets. After this adjustment, we retain 88 classes, which represent, on average, 95% of aggregate expenditure across waves.[7]

The inflation rate for a household h in period t (π_t^h) is:

$$\pi_t^h = \sum_{j=1}^{88} [\omega_{j,2006}^h \mathbb{1}_{\{t<2014\}} + \omega_{j,2011}^h \mathbb{1}_{\{2014\leq t<2019\}} + \omega_{j,2016}^h \mathbb{1}_{\{2019\leq t\}}] \pi_{jt}, \quad (1)$$

[5] For more information about establishment-level variety data, see INE (2018).

[6] Table A.1 provides the comprehensive list of the items excluded from the establishment-variety dataset.

[7] Table A.2 in Appendix A shows the number of items included in each level of COICOP classification for the EPF and CPI data.

where π_{jt} is the inflation rate of class j and $\omega^h_{j,T_{EPF}}$ is the weight of class j in the consumption basket of household h based on the wave T_{EPF} of the EPF. Equation (1) accounts for changing consumption weights by updating the basket according to the corresponding EPF wave.

We characterize inflation dynamics by computing the median monthly inflation rate for each income decile, which is robust to outliers in household-level inflation rates.

4 Inflation Heterogeneity

This section documents the extent of inflation heterogeneity across Chilean households. Figure 2 characterizes the distribution of household-level inflation rates for each month between 2010 and 2023. In the figure, the top and bottom red dashed lines represent the 90th and 10th percentiles of the distribution. The green dashed lines show the 75th and 25th percentiles. The blue solid line represents the median of the distribution, whereas the black dashed line shows the official inflation reported by the INE.

The figure shows that dispersion in household-level inflation rates is substantial. The interquartile range (IQR) varies from 1.1 pp. to 7.8 pp. over the sample period, with an average of 3.2 pp.[8] This IQR range is higher than dispersion measures reported for the U.S. based on expenditure survey data. According to Lauper and Mangiante (2023), the IQR fluctuates between 0.5 pp. and 3 pp., while Hobijn and Lagakos (2005) report standard deviations ranging from 0.5 pp. to 2 pp. Although these dispersion measures are not directly comparable, both suggest that inflation dispersion in Chile is relatively high.

Our measure of inflation dispersion also exceeds estimates reported in some studies combining scanner data with CPI series.[9] For the U.S., Kaplan and Schulhofer-Wohl (2017) find that the IQR varies between 0.7 pp. and 3.8 pp., while Messner and Rumler (2024) report that the IQR fluctuates between 0.9 pp. and 4.2 pp. in Austria. At the same time, inflation dispersion in Chile

[8]Table A.5 shows that the correlation between the selected percentiles for each EPF wave is close to 1, implying that changes in consumption baskets over time have no significant effect on the distribution of household-level inflation rates

[9]Scanner data cover a subset of expenditure categories included in expenditure survey data, primarily Food and Alcoholic Beverages. Scanner data expenditure weights are built by aggregating household expenditures to mimic granular consumption categories in the CPI.

aligns more closely with findings based on barcode-level data and household-level prices. In this context, Kaplan and Schulhofer-Wohl (2017) find that the IQR fluctuates between 6.2 pp. and 9 pp. for the U.S. between 2004 and 2013. For some European countries, Kiss and Strasser (2024) and Strasser et al. (2023) show that the IQR varies from 2.8 pp. to 9 pp. between 2006 and 2018. Previous results suggest that this high dispersion in Chile reflects substantial variability in consumption baskets, relative to what is typically documented using household expenditure survey data.

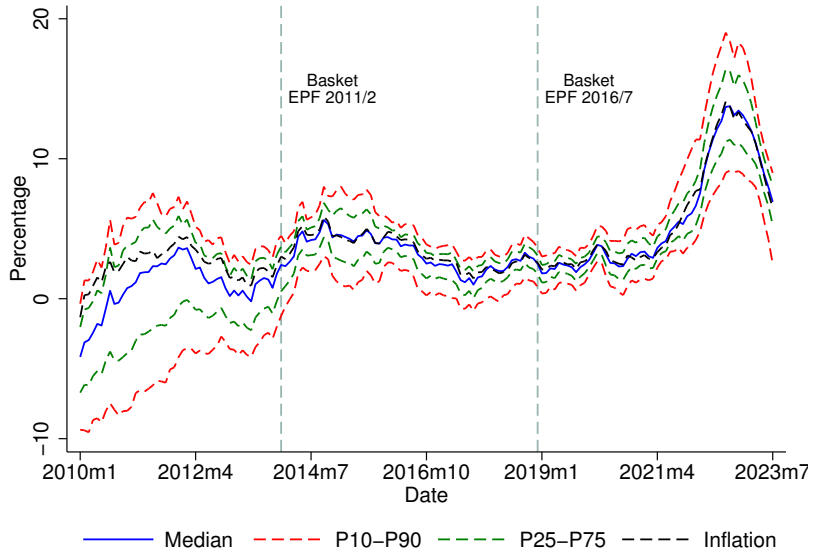

Figure 2: Distribution of household inflation rates

Notes. The figure depicts selected percentiles of the distribution of annual inflation rates at the household level for each time period. The grey dotted lines show the periods when the official consumption basket changes. Inflation corresponds to CPI inflation reported by the INE.

Moreover, we find that inflation rate dispersion across households remains relatively stable during periods of price stability but widens during episodes of CPI volatility. At the beginning of the sample, when the official inflation rate was increasing, the IQR reached up to 7.8 pp. Later, during the post-COVID pandemic inflation surge, the IQR increased to 5.2 pp. Lauper and Mangiante (2023) find a similar pattern in the relationship between official inflation and inflation rate dispersion across households for the U.S. In

particular, they show that inflation dispersion tends to rise during recession periods.

Additionally, Figure 2 is consistent with two well-documented facts in the inflation heterogeneity literature. First, the distribution of household-level inflation rates shifts in parallel to aggregate inflation; second, the median inflation rate closely resembles the CPI inflation reported by the INE, especially after 2013. Similar patterns have been documented for the U.S. by Hobijn and Lagakos (2005) and Kaplan and Schulhofer-Wohl (2017), and for several European countries by Strasser et al. (2023) and Kiss and Strasser (2024).

Focusing on the difference in annual inflation rates between income deciles, Figure 3 shows that high-income households generally face lower inflation rates than their middle- and low-income counterparts. On average, the difference is -1.3 pp. and -0.6 pp. relative to deciles 1 and 5, respectively. [10] The higher inflation experienced by low-income households is consistent with findings by Hobijn and Lagakos (2005), Kaplan and Schulhofer-Wohl (2017), and Argente and Lee (2020) for the U.S., Strasser et al. (2023) for some European countries, and previous results by Cobb (2012) and Bentancor and Pincheira (2014) for Chile.

We observe extended periods where the difference is negative, alternating with shorter periods where the sign of the difference reverses. When the difference is negative, high-income households face inflation rates up to 6 pp. and 2.5 pp. lower than those of low- and middle-income households, respectively. In contrast, during periods of higher inflation for high-income families, the difference reaches only 2.8 pp. and 1.8 pp. for low- and middle-income households, respectively.

To delve into the factors contributing to the divergence in inflation rates across households, Figure 4 presents the decomposition of mean inflation for deciles 1 and 10.[11] The figure shows that, on average, Food and Housing & Utilities are the most important inflation drivers for both low- and high-income households. In both cases, Transport becomes more important toward the end of the sample period, and this increase is especially pronounced for high-income households. This is consistent with the fact that these categories account for larger expenditure shares across all income deciles and

[10] Figure B.3 in Appendix B characterizes the distribution of annual inflation rates within each decile using the median and the IQR of the distribution.

[11] In Figure B.4 in Appendix B, we show that the decomposition for decile 5 closely resembles that of decile 1.

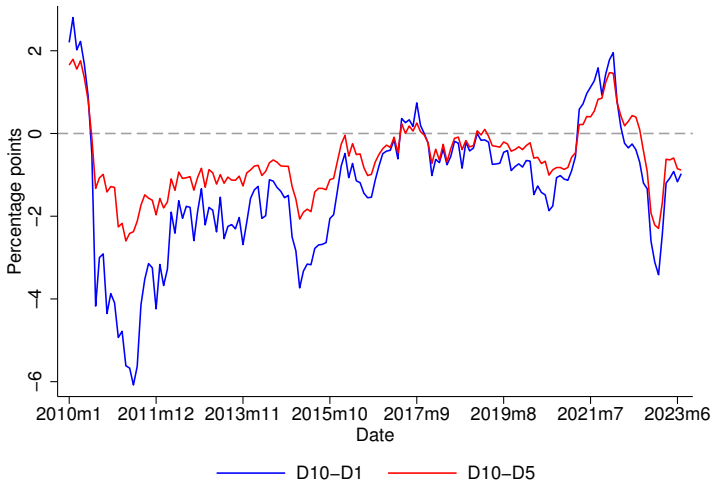

Figure 3: Difference in inflation rates at the decile level

Notes. The figure depicts the difference in annual inflation rates between deciles. The blue line represents the difference between deciles 10 and 1. The red line shows the difference between deciles 10 and 5.

exhibit high frequencies of price changes.

The results in this section suggest that neglecting inflation heterogeneity can mask important distributional consequences of aggregate shocks that affect relative prices. We also show that Food, Housing & Utilities, and Transport play a central role in the evolution of inflation at the decile level.

5 Empirical strategy

In this section, we describe the empirical strategy used to analyze the effects of monetary policy and oil price shocks on household inflation along the income distribution. We identify causal effects by exploiting unexpected changes in the monetary policy rate and exogenous variations in global oil supply. To this end, we update the monetary policy surprise series constructed by Aruoba et al. (2021), which captures unanticipated movements in the nominal interest rate set by the Central Bank of Chile. This series measures the gap between analysts' forecasts and the interest rate announced at each monetary policy meeting. For oil price shocks, we use the oil supply news series developed by Känzig (2021), who uses high-frequency data to

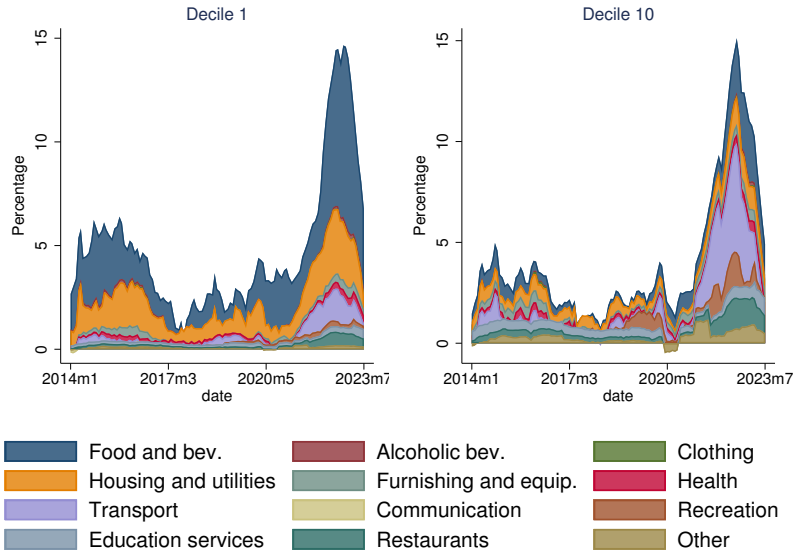

Figure 4: Composition of inflation at the decile level

Notes. The figure presents the decomposition of the weighted mean inflation for each decile using the EPF weights.

identify supply-driven changes in oil futures prices around OPEC production announcements.[12]

We estimate the response of median inflation in each income decile to monetary and oil price shocks using the local projections method proposed by Jordà (2005). The specification for each income decile h is:

$$\Delta p^h_{t+s,t-1} = \alpha_s + \beta^h_s mps_t + \gamma^h_s oil_t + X_t \Psi^h + \epsilon^h_{t+s} \tag{2}$$

where $\Delta p^h_{t+s,t-1} = p^h_{t+s} - p^h_{t-1}$ and p^h_t refers to the log of the price index for decile h in period t. The dependent variable therefore captures cumulative inflation from period $t-1$ to $t+s$. The variable mps_t denotes the monetary policy surprise in period t, and oil_t corresponds to the (log) oil price in period t. Following Känzig (2021), we instrument oil_t using the exogenous oil supply shock $news_t$ in equation (2). The vector X_t includes twelve lags of the dependent variable, mps_t, and oil_t, as well as six lags of the unem-

[12]The OPEC refers to the Organization of the Petroleum Exporting Countries.

ployment rate and the Chilean stock market index (IPSA), to account for macroeconomic dynamics.

We use monthly data from 2009m1 to 2023m6, with the horizon for impulse-response functions (IRFs) set at 36 months ($s = \{0, 1, ..., 36\}$). We estimate equation (2) as a system of equations using GMM and report joint tests of significance for the impulse response coefficients associated with monetary and oil price shocks.

To assess the significance of the differential response in inflation between income deciles, we estimate a specification similar to equation (2) where the dependent variable is the difference in cumulative inflation between income deciles h and h':

$$\Delta p^{h}_{t+s,t} - \Delta p^{h'}_{t+s,t} = \alpha_s + \beta^{h,h'}_s mps_t + \gamma^{h,h'}_s oil_t + X_t \Psi^{h,h'} + \epsilon^{h,h'}_{t+s} \tag{3}$$

where X_t includes twelve lags of the dependent variable, mps_t, and oil_t, as well as six lags of the unemployment rate and the IPSA.

To further explore the sources of heterogeneity in inflation responses, and to study the underlying sectoral channels, we estimate CPI price responses at the COICOP division level as follows:

$$\Delta p^{d}_{t+s,t-1} = \alpha_s + \beta^{d}_s mps_t + \gamma^{d}_s oil_t + X_t \Psi^{d} + \epsilon^{d}_{t+s} \tag{4}$$

where $\Delta p^{d}_{t+s,t-1} = p^{d}_{t+s} - p^{d}_{t-1}$ and p^{d}_{t+s} denotes the log price of the division-level CPI series d. As before, X_t includes twelve lags of the dependent variable, mps_t, and oil_t, as well as six lags of the unemployment rate and the IPSA.

Using the estimation results of equation (4), we decompose the cumulative inflation response of each decile h as follows:

$$\tilde{\beta}^{h}_s = \sum_{d=1}^{12} \omega^{h}_d \hat{\beta}^{d}_s \quad \text{and} \quad \tilde{\gamma}^{h}_s = \sum_{d=1}^{12} \omega^{h}_d \hat{\gamma}^{d}_s, \tag{5}$$

where ω^{h}_d denotes the expenditure share of division d in the total spending of the decile h, and $\hat{\beta}^{d}_s$ and $\hat{\gamma}^{d}_s$ are the estimated coefficients obtained from equation (4) for each CPI division in the COICOP classification. Since $\tilde{\beta}^{h}_s$ and $\tilde{\gamma}^{h}_s$ are constructed using estimated parameters, they may differ from the directly estimated coefficients $\hat{\beta}^{h}_s$ and $\hat{\gamma}^{h}_s$ from equation (2) due to aggregation effects. This decomposition is therefore intended to be illustrative of the role of expenditure patterns rather than an exact accounting identity.

6 Results

In this section, we present the main findings of our analysis. First, we analyze the results of the monetary policy shocks; then, we review the effects of oil price shocks.

6.1 Response to a monetary policy shock

Figure 5 displays the IRFs of the official CPI and the decile-level inflation rate to a 25-basis-point unexpected increase in the central bank's interest rate estimated using equation (2). The blue line represents the point estimate for each horizon, while the grey area depicts the 90% confidence interval. The *joint test p-value* shows the p-value for the test of joint significance of impulse response parameters related to monetary policy surprises.

Panel (a) of Figure 5 shows that an unexpected interest rate increase reduces cumulative inflation, but the effect becomes statistically significant only 18 months after the shock. This delayed response is consistent with the literature, which finds that inflation reacts to monetary shocks with some lag (Romer and Romer, 2004; Gertler and Karadi, 2015; Aruoba et al., 2021). Cumulative CPI inflation declines by 2.1% and 2.9% two and three years after the shock, respectively.

At the decile level, Panels (b), (c), and (d) show that a tightening of the monetary policy rate significantly reduces cumulative inflation for deciles 1, 5, and 10 from 18 months after the shock. Specifically, we find that cumulative inflation for low-income households (decile 1) falls by up to 1.7% after two years and 2.2% after three years. For middle-income households (decile 5), we observe a decline of 2.1% and 2.3% two and three years after the shock, respectively. In the case of high-income households (decile 10), cumulative inflation falls by up to 2.0% two years after the shock and 2.1% three years after the shock.

These findings suggest that the inflation of low-income households is relatively less responsive to monetary policy shocks. To analyze whether this hypothesis is correct, Figure 6 presents the estimation results of equation (3) comparing the cumulative inflation response of decile 10 with deciles 1 and 5.

Panel (a) of Figure 6 shows that high-income households experience a significantly lower inflation rate than their low-income counterparts. During the first 18 months after the shock, the difference is marginal, although high-

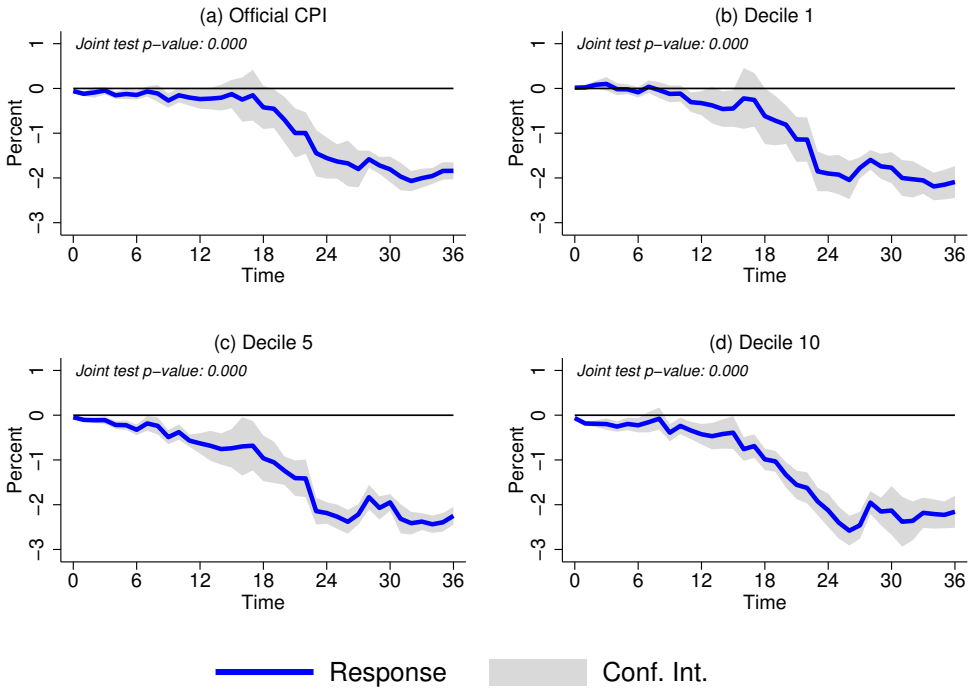

Figure 5: Response of cumulative inflation to a monetary policy shock

Notes. The figure shows IRFs to a monetary policy shock of 25 basis points. The solid blue lines represent the point estimates. The grey area depicts the 90 percent confidence interval. The *joint test p-value* corresponds to the p-value for the test of joint significance of the estimated parameters related to monetary policy surprises. The sample period is 2009m1-2023m6.

income households experience slightly lower inflation. However, from 18 to 32 months post-shock, households in the highest income decile face significantly lower cumulative inflation, averaging -0.3 pp. over this period, reaching a trough of -0.6 pp. at 27 months. Towards the end of the analysis, the difference reverses slightly.

In Panel (b), we also observe a greater reduction in cumulative inflation for high-income households compared to middle-income households following a monetary policy surprise, although with a smaller magnitude than in Panel (a).[13] The difference is not significant during the first 21 months post-shock.

[13]The p-value of the joint test shows that the IRF is significantly different from zero.

However, between months 21 and 32, the difference becomes negative and significant. It averages -0.2 pp. during that period, reaching a trough of -0.3 pp. 28 months after the shock. Subsequently, the response is not significant.

Regarding the difference in cumulative inflation for deciles 5 and 1, Panel (c) shows that the reduction in cumulative inflation of middle-income households is significantly higher than that of their low-income counterparts. Unlike previous findings, the difference becomes statistically significant as early as six months after the shock and reaches its minimum of -0.4 pp. 15 months post-shock. Then, the difference vanishes by 30 months after the shock.

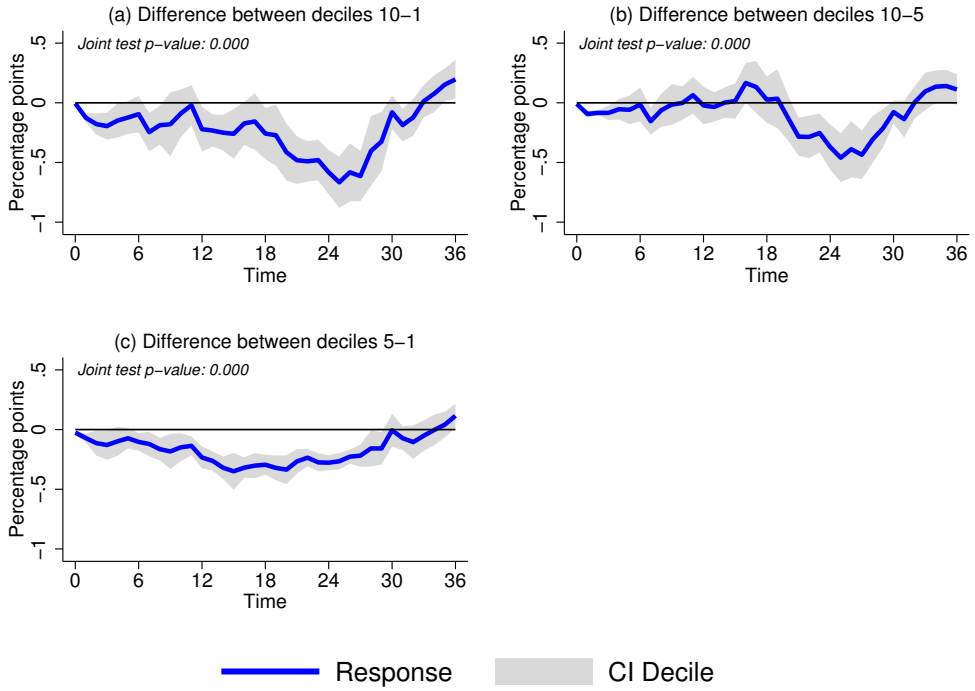

Figure 6: Difference in cumulative inflation responses of income deciles to a monetary policy shock

Notes. The figure shows IRFs to a monetary policy shock of 25 basis points. The solid blue lines represent the point estimates. The grey area depicts the 90 percent confidence interval. The *joint test p-value* corresponds to the p-value for the test of joint significance of the estimated parameters related to monetary policy surprises. The sample period is 2009m1-2023m6.

The results in Figure 6 indicate that the cumulative inflation of high-income households is significantly lower than that of deciles 1 and 5 in response to a contractionary monetary policy shock. This suggests that monetary policy surprises have distributional effects, affecting low-income households more severely. These results contrast with the findings of Cravino et al. (2020) and Ampudia et al. (2024), who find that cumulative inflation of high-income households is less responsive to an unexpected tightening in monetary policy. In the case of Cravino et al. (2020), they show that the difference in cumulative inflation between top- and middle-income households is up to 0.5 pp. over a 48-month horizon to a 100 bp monetary policy shock. Similarly, Ampudia et al. (2024) show that the difference between extreme income quintiles is 0.075 pp. using survey expenditure data, which is consistent with previous findings for the U.S., although the shock is only 25 bp instead of 100 bp.

To better understand the mechanisms behind these heterogeneous responses, we examine the response of key expenditure categories to a monetary policy shock. Figure 7 shows that the response of cumulative inflation of Food, Housing & Utilities, and Transport decreases significantly following a tightening in monetary policy, although the timing and magnitude differ.[14] In the case of Food, the response is approximately zero in the first 18 months after the shock, then it becomes negative and significant, reaching -3.9% by 34 months after the shock. Regarding Housing & Utilities, we find that the response of cumulative inflation is close to zero in the first 18 months after the shock, then it declines significantly and remains around -1.3% from 24 months after the shock onward. Finally, the response of cumulative inflation for the Transport category is negligible in the 15 months post-shock, then it declines significantly, reaching -6.5% at 31 months after the shock. Afterward, it partially reverts, rising to -3.5% at 36 months. These results highlight that Transport, the category which accounts for the largest share of expenditures among high-income households, exhibits the strongest decline in cumulative inflation. This explains the higher sensitivity observed among high-income households.

Figure 8 shows the decomposition of the response of cumulative inflation based on equation (5) by consumption category. Panel (a) shows that Food is the primary driver of the response for low-income households, accounting for an average of 35% of the response from 18 months after the shock. Its

[14]Figure B.5 in Appendix B shows the IRFs for all consumption categories.

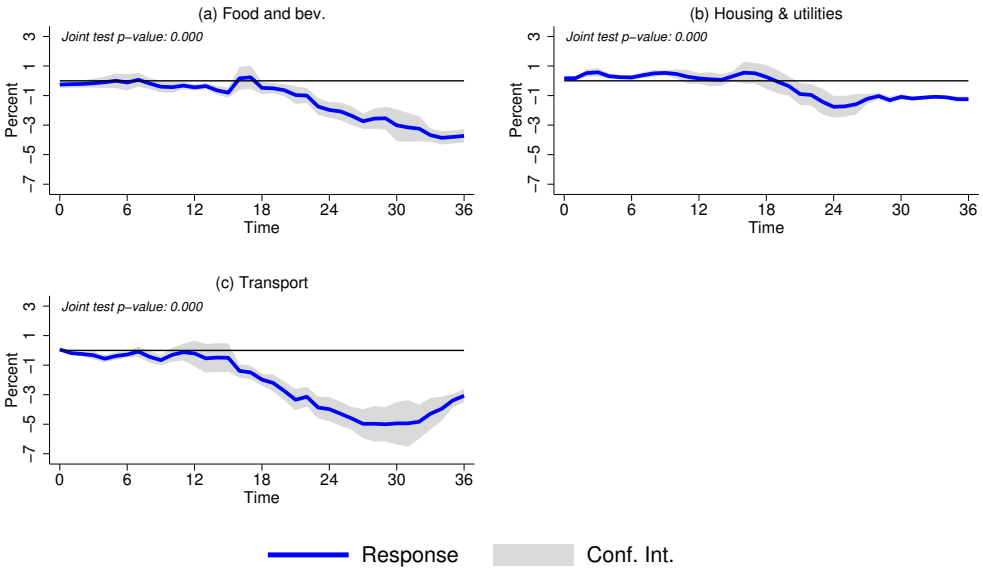

Figure 7: Response of cumulative inflation of main consumption categories to a monetary policy shock

Notes. The figure shows IRFs to a monetary policy shock of 25 basis points for the main consumption categories. The solid blue lines represent the point estimates. The grey area depicts the 90 percent confidence interval. The *joint test p-value* corresponds to the p-value for the test of joint significance of the estimated parameters related to monetary policy surprises. The sample period is 2009m1-2023m6.

relevance ranges from 21% to 51% between 18 and 36 months after the shock. The second most important category is Transport, which accounts for an average of 23% of the response, followed by Housing & Utilities at 12%.

Panel (b) shows that for decile 5 (middle-income), both Food and Transport contribute equally —28% on average— to the cumulative inflation response. As Transport reacts more quickly to monetary tightening, it explains 37% of the response at 18 months but only 19% at 36 months. In contrast, Food's importance grows from 16% at 18 months to 50% by 36 months. Housing & Utilities remains a minor contributor, averaging 9%.

Panel (c) indicates that for high-income households, where Transport is the largest spending category, it is the main driver of their inflation response. This category accounts for, on average, 42% of the response from 18 months

post-shock, peaking at 47% 28 months after the shock. In this case, Food and Housing & Utilities only represent 11% and 6% of the cumulative inflation response, on average, between 18 and 36 months after the shock.

Taken together, the findings in this section show that a contractionary monetary policy shock reduces cumulative inflation across all income deciles, but the response is more pronounced for high-income households. The pattern is mainly explained by the stronger response of Transport prices relative to Food and Housing & Utilities.

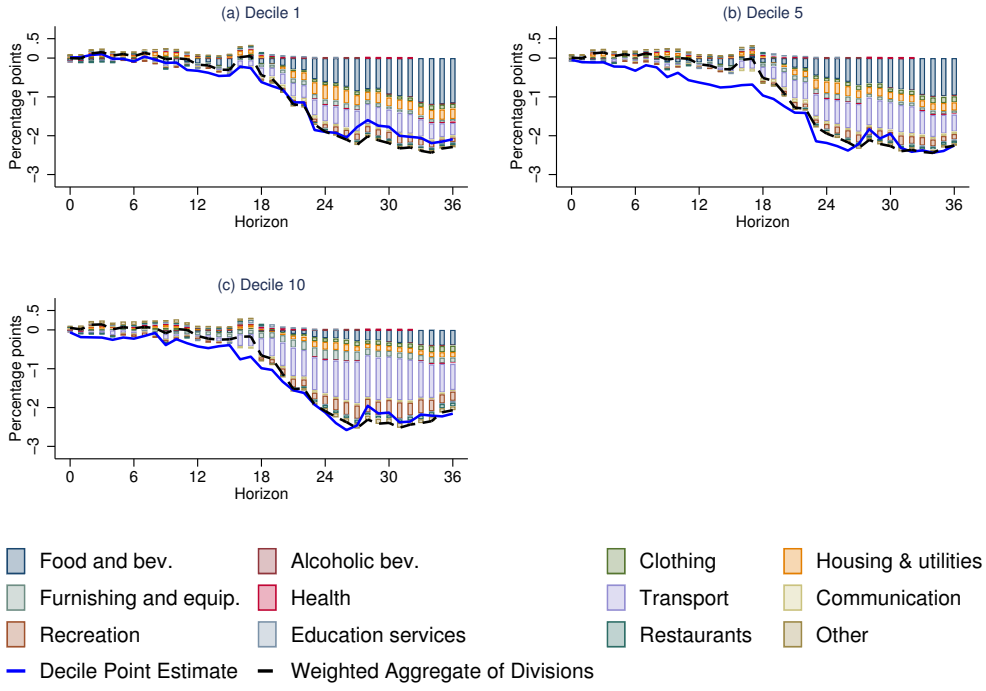

Figure 8: Decomposition of decile-level response to a monetary policy shock by consumption category

Notes. The figure shows the decomposition by expenditure categories according to equation (5). The solid blue line is the IRF estimated according to equation (2). The dashed black line represents the weighted sum of price division responses at the decile level. The sample period is 2009m1-2023m6.

6.2 Response to an oil news shock

In this section, we examine the impact of a one-standard-deviation shock to the oil price, equivalent to an increase of 22 USD, on decile-level inflation.[15] Figure 9 presents the estimation results for the official CPI and income deciles 1, 5, and 10.

Panel (a) shows that an unexpected increase in the oil price leads to a significant rise in cumulative CPI inflation. The average estimated response is approximately 1.2% over the entire horizon. During the first 27 months following the shock, the response is significant and exhibits an increasing pattern, peaking at 2.7% at month 27. Subsequently, the response is not significant and turns slightly negative during the last three months. These results align with the findings of Känzig (2021), who report that a negative oil supply news shock leads to a significant increase in cumulative U.S. CPI inflation over a 30-month horizon.

For low-income households, Panel (b) of Figure 9 indicates that the cumulative inflation does not react to the oil price shock during the first 18 months. In the subsequent 9 months, the response rises significantly, reaching up to 2.5%, with an average effect of 1.5% during this interval. Thereafter, the response remains statistically significant, albeit at a lower magnitude, until month 34. Beyond this point, the response returns to zero.

Regarding decile 5 (Panel (c)), the cumulative inflation response is positive but only marginally significant during the first 18 months after the shock, with an average of 0.7%. From then on, the response becomes significant, peaking at 1.7% 25 months after the shock. Later, the response turns negative and becomes marginally significant in the final periods.

With respect to the high-income decile (Panel (d)), we observe a significant increase in its cumulative inflation for almost the entire 27 months after the shock. In contrast to deciles 1 and 5, it reacts strongly immediately after the shock and reaches a peak of 2.1% around 20 months post-shock. Afterward, the inflation response for high-income households declines and turns negative, becoming marginally significant from month 33 onward.

To analyze whether oil price shocks have heterogeneous effects along the income distribution, Figure 10 displays the results of estimating equation (3).

Panel (a) shows that high-income households experience a significantly higher cumulative inflation than their low-income counterparts during the

[15] A one-standard-deviation shock corresponds to an increase of 31% in the oil price.

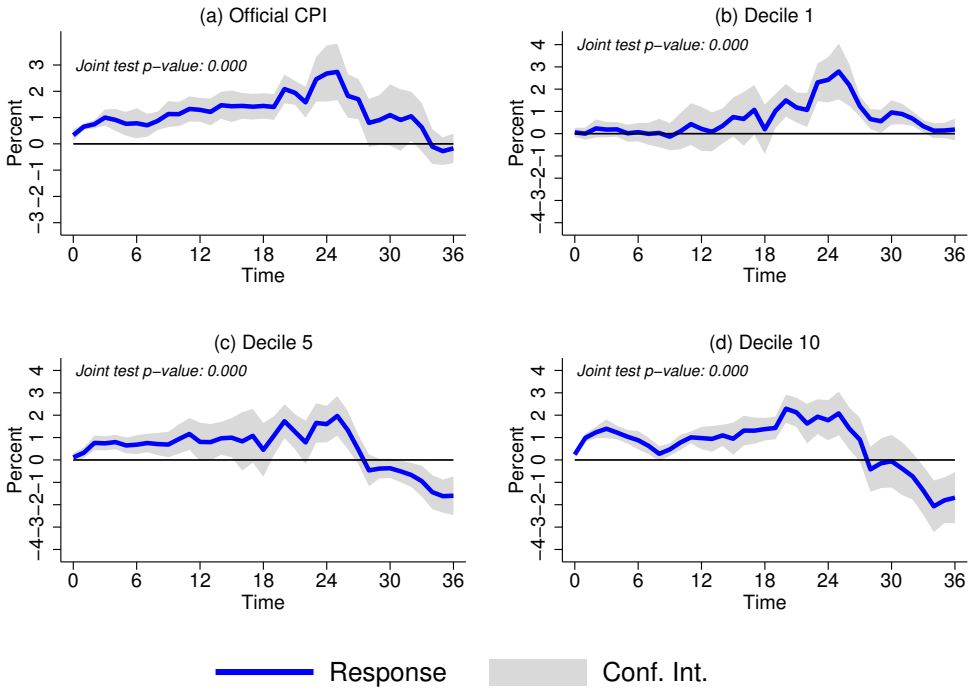

Figure 9: Response of cumulative inflation to an oil price shock

Notes. The figure shows IRFs to an oil price shock of one standard deviation (≈ 22 USD). The solid blue lines are the point estimates. The grey area depicts the 90 percent confidence interval. The *joint test p-value* corresponds to the p-value for the test of joint significance of the estimated parameters related to oil price shocks. The sample period is 2009m1-2023m6.

first 22 months after the shock. Throughout this period, the average difference reaches 0.7 pp. with a peak of 1.2 pp. in month 14. Around two years after the shock, this situation reverses, and the inflation of the low-income decile becomes significantly higher. On average, this difference is -0.8 pp. and reaches a trough of -1.5 pp. 35 months after the shock.

With respect to the difference between deciles 10 and 5, Panel (b) indicates that this difference is positive and slightly significant during the first 7 months post-shock. On average, this difference reaches 0.3 pp. during this period. Subsequently, the response is no longer significant until month 25 after the shock. From month 26 onward, the difference becomes significant and

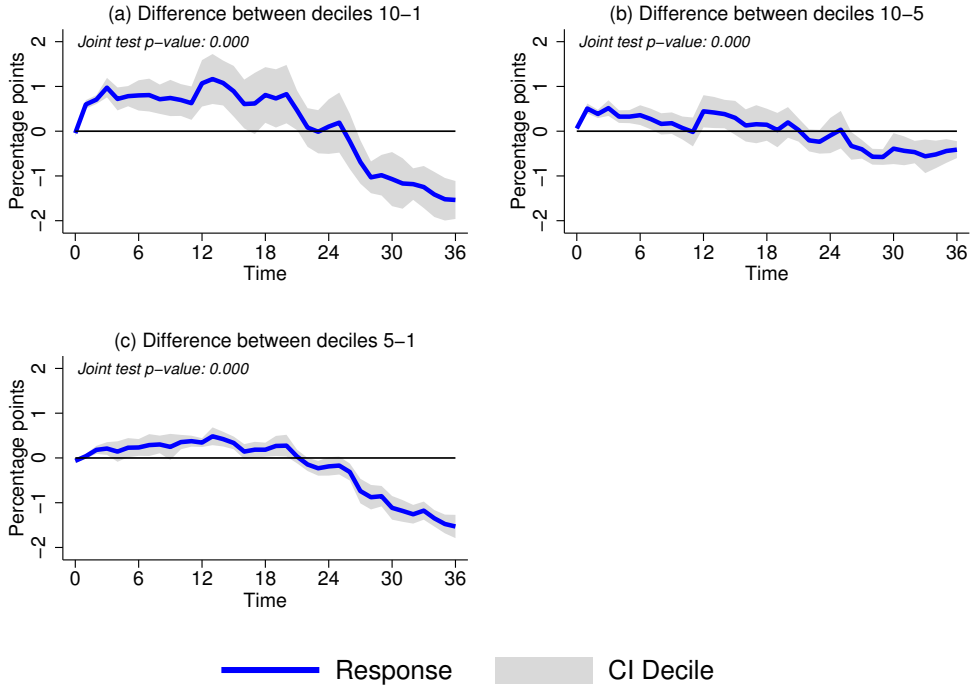

Figure 10: Difference in inflation responses of income deciles to an oil price shock

Notes. The figure shows IRFs to an oil price shock of one standard deviation ($\approx$ 22 USD). The solid blue lines are the point estimates. The grey area depicts the 90 percent confidence interval. The *joint test p-value* corresponds to the p-value for the test of joint significance of the estimated parameters related to oil price shocks. The sample period is 2009m1-2023m6.

changes its sign, resulting in 0.5 pp. higher inflation for the middle-income decile, on average.

Regarding the difference between deciles 5 and 1, Panel (c) indicates that the difference in cumulative inflation between these deciles is slightly positive and marginally significant in the first 21 months after the shock. Then, this difference becomes negative and remains significant during the 26 months post-shock. In this period, low-income households experience up to 1.2 pp. higher cumulative inflation than their middle-income counterparts.

To understand the drivers behind the reversion in the response of the dif-

ference in cumulative inflation, Figure 11 shows the response of cumulative inflation of the main consumption categories to an oil supply news shock.[16] In the figure, we observe that the shock leads to a significant, immediate, and highly persistent increase in the cumulative inflation of the Food and Transport categories, while the response of Housing & Utilities is muted. During the first 18 months after the shock, Transport's cumulative inflation response is, on average, 65% higher than that of Food. This implies that, initially, the shock has a stronger impact on the prices that are more relevant for high-income households. Thereafter, the pattern reverses and the cumulative inflation response for the Food category surpasses that of Transport by 13% on average. This indicates that, as the oil price shock propagates to other sectors of the economy, it increasingly affects the prices paid by low-income households.

To assess the contribution of each consumption category to decile-level inflation responses, Figure 12 shows the decomposition of cumulative inflation responses by expenditure categories. Although the weighted sum does not perfectly match the IRFs estimated by equation (2), we observe that Food is the main driver of the response of low-income households, followed by Transport. During the first two years after the shock, Food accounts for 46% of the response and Transport 26%, on average. Beyond this horizon, Food becomes more dominant, accounting for 56% of the response, while Transport declines to 15%. The pattern for middle-income households is similar, with Food and Transport explaining, on average, 37% and 33% of the response during the first 24 months following the shock, respectively. At longer horizons, Food and Transport account for 47% and 20% of the response, respectively.

Turning to high-income households, although Food's importance also rises in the third year, Transport remains the most important driver, reflecting the fact that this expenditure category represents roughly twice the budget share of Food in the consumption basket of decile 10. During the first two years, Food and Transport account for 16% and 51% of the average response, respectively. In the third year, the importance of Food rises to 22% and Transport declines to 34%.

Taken together, these findings highlight the significant and heterogeneous impact of the oil price shock on household inflation along the income distribution. High-income households initially experience higher cumulative infla-

[16] Figure B.6 in Appendix B shows the IRFs for all consumption categories.

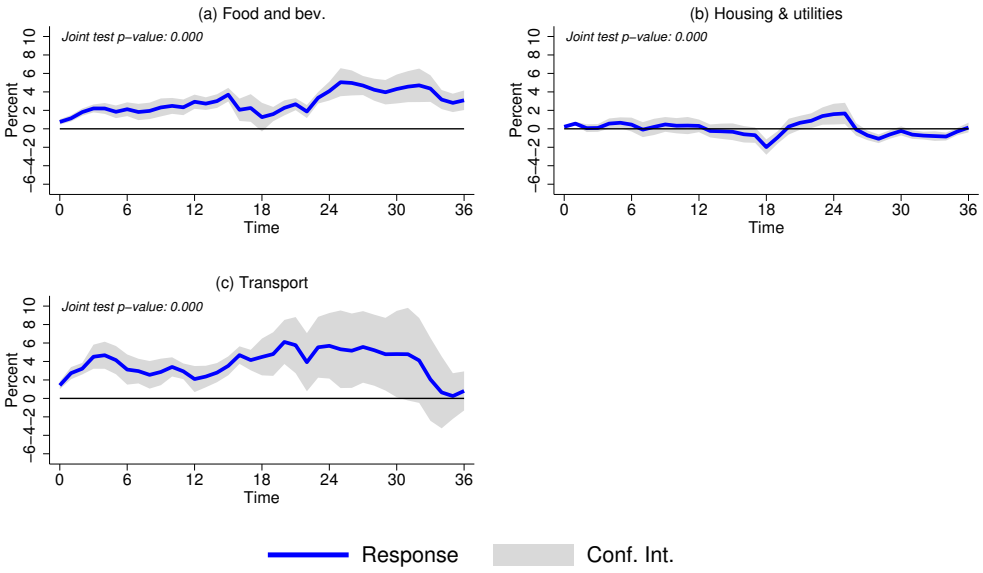

Figure 11: Response of cumulative inflation of main consumption categories to an oil price shock

Notes. The figure shows IRFs to an oil price shock of one standard deviation ($\approx$ 22 USD) for the main consumption categories. The solid blue lines are the point estimates. The grey area depicts the 90 percent confidence interval. The *joint test p-value* corresponds to the p-value for the test of joint significance of the estimated parameters related to oil price shocks. The sample period is 2009m1-2023m6.

tion. However, as the shock spreads to other sectors, it affects middle- and low-income households more strongly through its impact on Food prices. This pattern implies that the distributional effects of oil price shocks are time-varying.

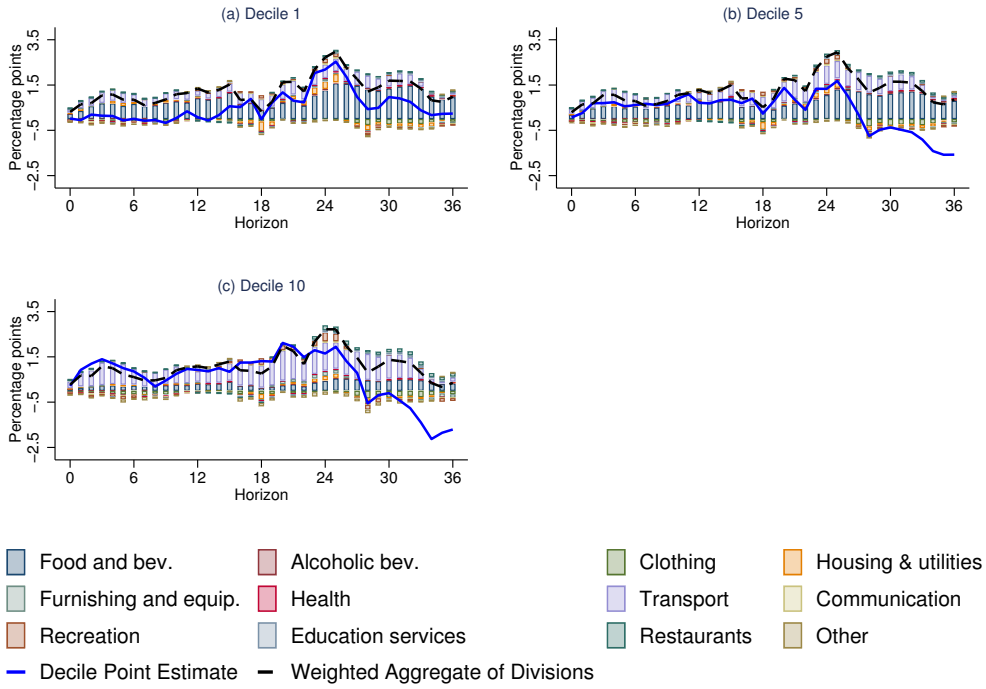

Figure 12: Decomposition of decile-level response to an oil price shock by consumption category

Notes. The figure shows the decomposition by expenditure categories according to equation (5). The solid blue line is the IRF estimated according to equation (2). The dashed black line represents the weighted sum of price division responses at the decile level. The sample period is 2009m1-2023m6.

7 Conclusions

The heterogeneity in households' consumption baskets and price-setting dynamics across productive sectors generate inflation heterogeneity. This implies that aggregate shocks or policies that distort relative prices have distributional effects. However, this channel has been barely studied, and the existing evidence focuses primarily on developed countries.

In this paper, we analyze the heterogeneous effects of monetary and oil price shocks on cumulative inflation along the income distribution for an emerging economy, Chile. We find that an unexpected monetary policy tight-

ening reduces cumulative inflation for all income deciles, but the response is stronger for high-income households. This pattern is primarily driven by a greater price sensitivity in the Transport category, which accounts for a larger share of total spending among high-income households. This result contrasts with existing evidence for the U.S. and Europe, where high-income households are less responsive to monetary policy.

With respect to the oil price shock, we find that it leads to a significant increase in cumulative inflation for all income deciles. Initially, the shock affects high-income households more strongly because of a stronger response of Transport prices immediately after the shock. Subsequently, as the shock passes through other sectors in the economy, it more severely affects low- and middle-income households due to a relatively larger response of Food prices. These results show that oil price shocks have time-varying distributional effects. To the best of our knowledge, this is the first paper to document the heterogeneous effects of oil price shocks across the income distribution, in this case for an emerging economy.

In terms of inflation heterogeneity, we find a significant dispersion in household-level inflation rates, with an IQR reaching up to 8 pp. This IQR is higher than those reported for the U.S. using expenditure survey data. In line with the literature, we also find that low-income households experience higher inflation than their high-income counterparts.

Taken together, these findings highlight the importance of accounting for inflation heterogeneity when evaluating the distributional consequences of aggregate shocks. They also suggest that the sectoral composition of household consumption plays a central role in shaping inflation experiences across the income distribution.

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A Tables

Table A.1: Products excluded in the establishment-variety prices dataset

Products
Actual rentals paid by tenants for main residence
Water supply
Refuse collection
Maintenance charges in multi-occupied buildings
Electricity
Natural gas through networks
Liquefied hydrocarbons
Domestic services by paid staff
Toll facilities
Passenger transport by air
Combined passenger transport
Mobile telephone equipment
Internet access provision services
Broadband internet provision services
Bundled telecommunication services
Mobile communication services
Fixed communication services
Sporting services - attendance
Cultural services - attendance
Subscription to streaming services and rentals of audio-visual content
Package holidays
Early childhood education
Primary education
Lower secondary education
Secondary education
Post-secondary non-tertiary education
Short-cycle tertiary education
Bachelor's or equivalent
Master, Doctorate or equivalent
Post-secondary non-tertiary education
Insurance
Financial intermediation services
Fees in parents association
Child care services

Table A.2: Characterization of the items in EPF and CPI COICOP Classification

Division		Group		Class		Subclass		Product	
		CPI	EPF	CPI	EPF	CPI	EPF	CPI	EPF
1	Food and non-alcoholic beverages	2	3	11	12	35	52	76	251
2	Alcoholic beverages	2	4	4	6	4	6	8	15
3	Clothing and footwear	2	3	5	7	10	26	28	104
4	Housing and utilities	4	6	9	14	11	15	16	47
5	Furnishings and equipment	6	7	10	13	13	43	36	128
6	Health	3	4	7	8	8	18	22	79
7	Transport	3	4	10	15	14	23	24	81
8	Information and communication	2	4	2	4	2	5	6	23
9	Recreation, sport and culture	5	7	16	22	22	33	37	136
10	Education services	5	6	5	6	5	17	11	140
11	Restaurants and accommodation	2	3	2	4	3	8	7	54
12	Miscellaneous goods and services	5	8	7	15	9	39	32	128
	Total	**41**	**59**	**88**	**126**	**136**	**285**	**303**	**1,186**

Table A.3: Frequency of Price Changes

Division		2009		2013		2019	
		Mean Freq.	Frac. Up	Mean Freq.	Frac. Up	Mean Freq.	Frac. Up
1	Food and non-alcoholic beverages	53.4	55.8	50.5	55.2	50.9	60.8
2	Alcoholic beverages	33.8	64.0	32.3	64.8	39.2	62.4
3	Clothing and footwear	21.8	33.4	20.8	41.2	44.2	44.4
4	Housing \& Utilities	49.6	61.9	41.1	58.8	47.3	59.0
5	Furnishings and equipment	21.9	52.0	25.3	56.4	34.2	55.1
6	Health	25.6	68.2	22.4	76.0	13.1	82.1
7	Transport	59.0	53.1	58.1	56.8	57.2	70.2
9	Recreation, sport and culture	23.4	44.0	24.8	51.9	39.6	54.3
11	Restaurants and accommodation	11.2	81.5	11.0	76.9	21.8	70.7
12	Miscellaneous goods and services	22.0	56.6	19.9	63.9	28.4	59.9

Notes. *Mean Freq.* corresponds to the mean frequency of price change over time for each COICOP division. *Frac. Up.* represents the fraction of positive price changes.

Table A.4: Size of Price Changes

	Division	2009		2013		2019	
		Positive	Negative	Positive	Negative	Positive	Negative
1	Food and non-alcoholic beverages	8.2	7.2	9.1	8.1	10.2	9.2
2	Alcoholic beverages	4.3	2.9	4.9	4.0	11.3	11.0
3	Clothing and footwear	18.8	20.2	21.6	19.7	27.1	22.4
4	Housing \& Utilities	8.6	8.2	7.8	7.1	8.6	5.6
5	Furnishings and equipment	12.2	12.0	15.1	13.9	17.8	14.9
6	Health	8.1	8.1	8.4	9.0	9.3	10.2
7	Transport	4.8	3.8	4.1	3.4	6.6	4.0
9	Recreation, sport and culture	12.5	11.2	15.0	12.3	14.7	10.9
11	Restaurants and accommodation	8.6	9.6	8.6	8.4	9.5	9.0
12	Miscellaneous goods and services	11.5	9.7	13.8	11.8	16.3	14.1

Notes. *Positive* corresponds to the mean size of positive price changes over time for each COICOP division. *Negative* represents the mean size of negative price changes over time.

Table A.5: Correlation between statistics of different EPF waves

Statistic	Corr(2006,2011)	Corr(2006,2016)	Corr(2011,2016)
P10	1.00	0.99	1.00
P25	0.99	0.98	1.00
P50	1.00	0.99	1.00
P75	1.00	1.00	1.00
P90	1.00	1.00	1.00
Mean	1.00	1.00	1.00

B Figures

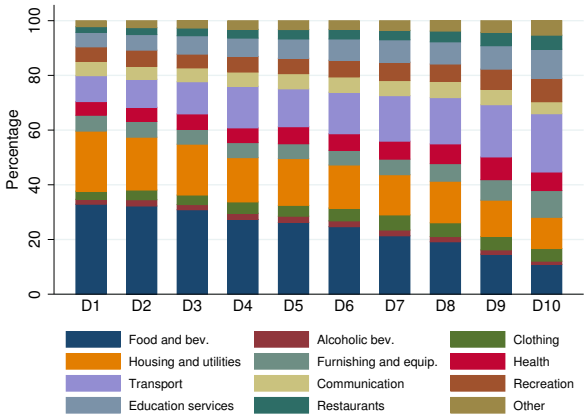

Figure B.1: Consumption baskets along income distribution - EPF 2011

Notes. The figure shows the composition at COICOP division-level aggregation of expenditures. The data comes from EPF 2011.

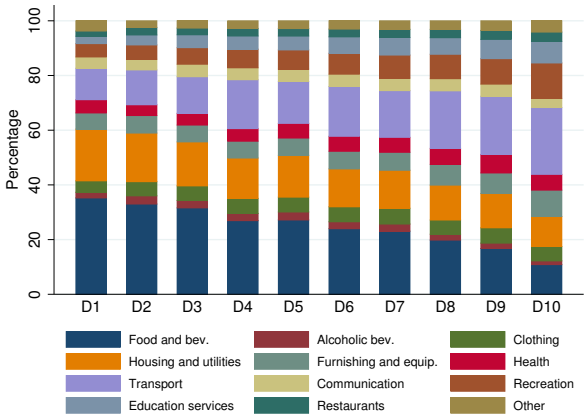

Figure B.2: Consumption baskets along income distribution - EPF 2006

Notes. The figure shows the composition at COICOP division-level aggregation of expenditures. The data comes from EPF 2006.

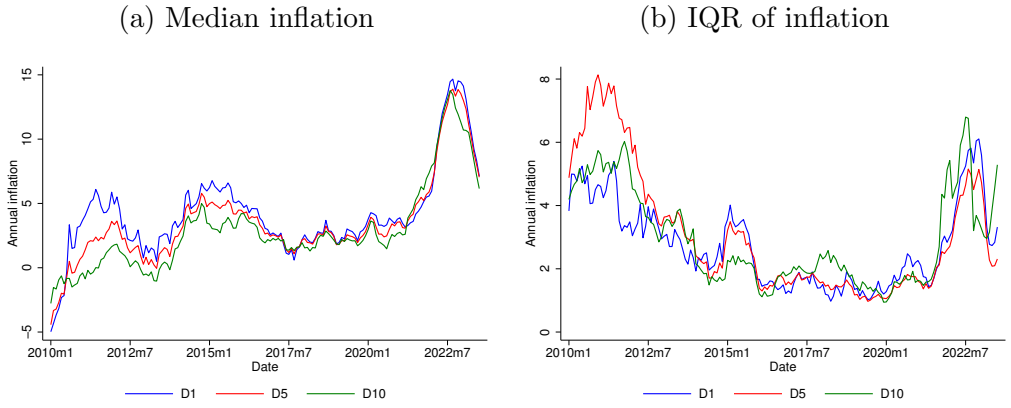

Figure B.3: Inflation heterogeneity at income decile level

Notes. The figure use expenditure data from waves 2006, 2011 and 2016 of the EPF. Median and IQR inflation correspond to monthly median and IQR of household-level inflation rates distribution.

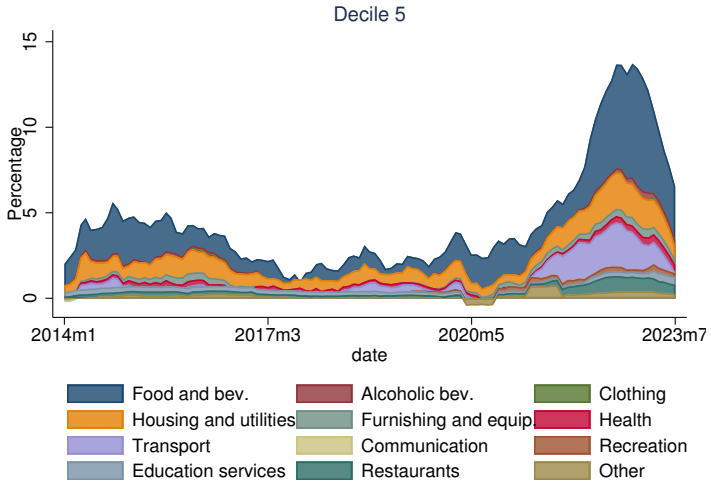

Figure B.4: Composition of inflation at decile level

Notes. The figure presents the decomposition of the weighted mean inflation for each decile using the EPF weights.

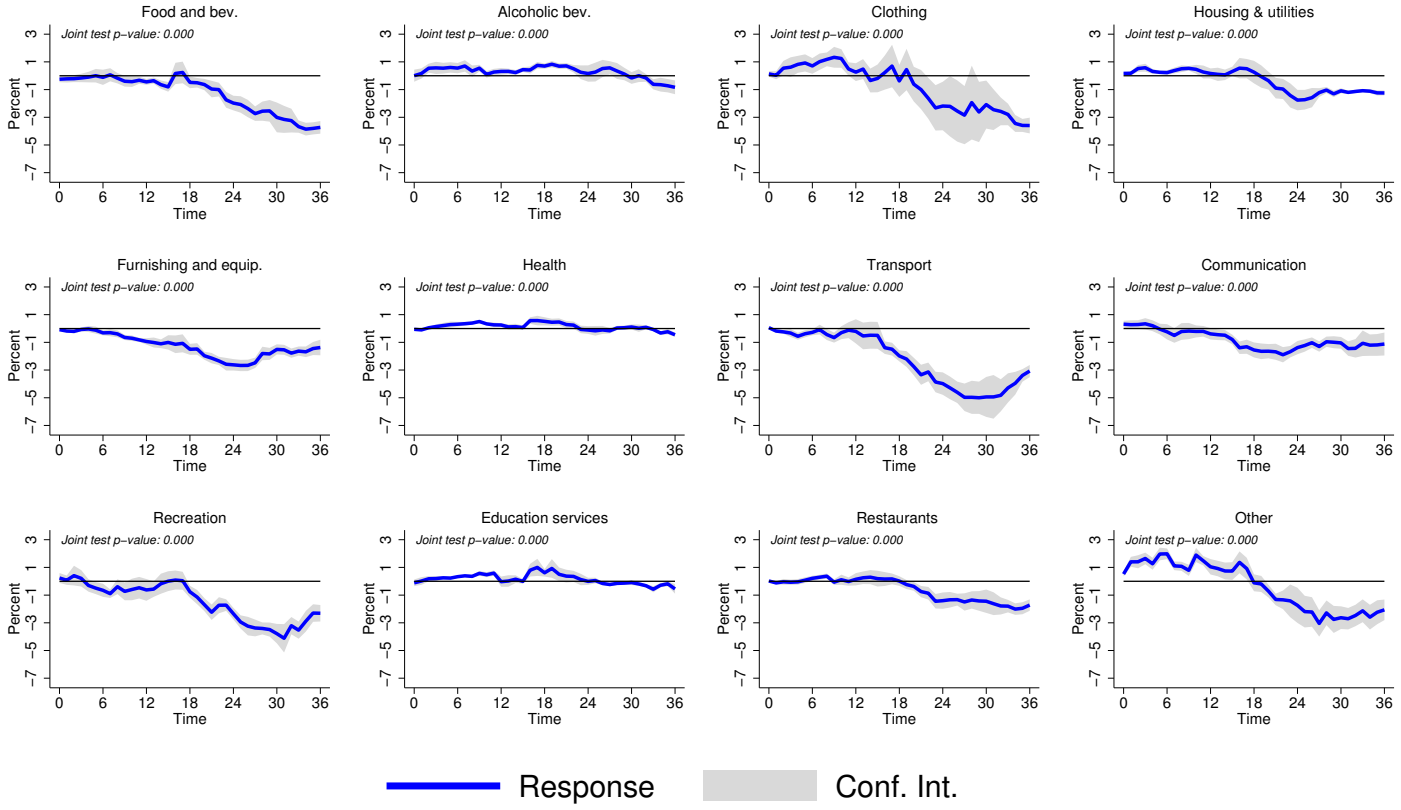

Figure B.5: Response of cumulative inflation of the consumption categories to a monetary policy shock

Notes. The figure shows IRFs to a monetary policy shock of 25 basis points for the main consumption categories. The solid blue lines are the point estimates. The grey area depicts the 90 percent confidence interval. The *joint test p-value* corresponds to the p-value for the test of joint significance of the estimated parameters related to monetary policy shocks. The sample period is 2009m1-2023m6.

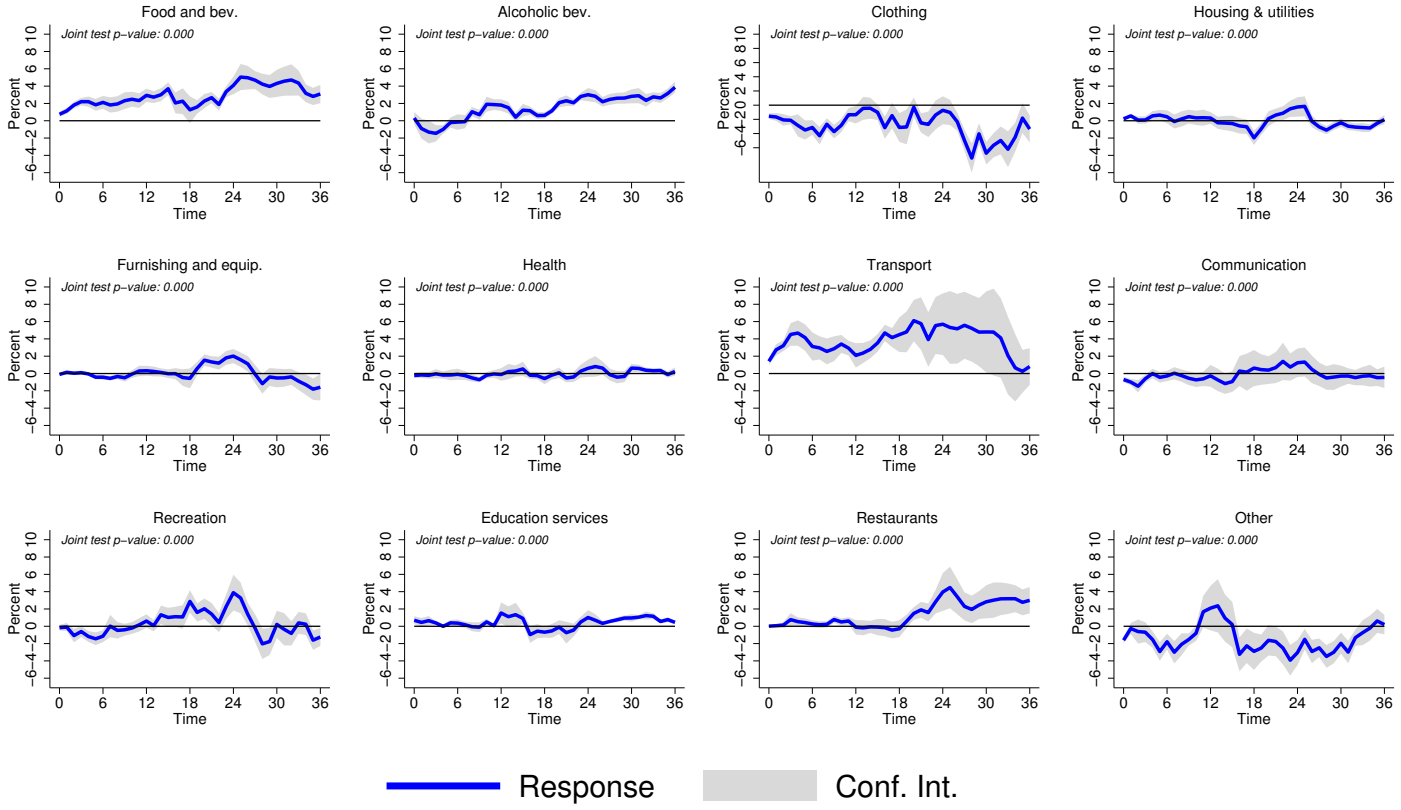

Figure B.6: Response of cumulative inflation of the consumption categories to an oil price shock

Notes. The figure shows IRFs to an oil price shock of one standard deviation ($\approx$ 22 USD) for the main consumption categories. The solid blue lines are the point estimates. The grey area depicts the 90 percent confidence interval. The *joint test p-value* corresponds to the p-value for the test of joint significance of the estimated parameters related to oil price shocks. The sample period is 2009m1-2023m6.

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