Monetary Policy Shocks, Transmission Mechanisms, and Income Distribution: Empirical Evidence from Chile

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Abstract

This research identifies monetary policy shocks by orthogonalizing changes in the monetary policy rate with central bank forecast information and market expectations. Ensuring exogeneity, we control for the predictability of high-frequency and narrative approaches using pre-announcement data. Additionally, we leverage survey data to construct surprises as a robustness measure. Utilizing a Bayesian framework, we quantify the impacts of a contractionary monetary policy shock on the aggregate economy. Our findings align with conventional macroeconomic theory and effectively address price and output puzzles. The paper further explores income inequality in the Chilean economy by analyzing labor income distribution using microeconomic data and impulse response functions within a microsimulation framework. This method allows us to distribute aggregate responses to monetary policy shocks across micro-level data, facilitating a detailed examination of the impact on employment status and nominal gross income. We find that the impact on income inequality, while present, is minimal. The extensive margin affects lower quintiles through employment status fluctuations, while the intensive margin impacts higher quintiles less due to their diversified income sources and assets.

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1 Introduction

Monetary policy, which mainly aims to keep prices stable and support steady economic growth, can also unintentionally affect income and wealth inequality. We will examine how decisions made by central banks can shape the distribution of wealth and income in an emerging economy.

Macroeconomic policy decisions, such as adjusting interest rates and implementing quantitative easing, have far-reaching economic effects. These actions influence borrowing costs, credit availability, and the overall cost of capital, affecting investment, consumption, and employment levels. However, the consequences of these policy tools are not uniform across different segments of the population. This interconnection has been the subject of extensive research focusing on understanding how different monetary policy measures, such as conventional and unconventional monetary policy shocks, can impact wealth and income inequality.

Kaplan, Moll and Violante (2018) describes the mechanisms through which monetary policy, directly and indirectly, affects heterogeneity among households and can potentially affect inequality. Direct effects involve the partial equilibrium consequences of changes in the interest rates on households' economic behavior, where multiple forces collide. One of these forces is the *intertemporal substitution channel*: when real rates fall, households tend to save less or borrow more, increasing their consumption demand. Also, a decrease in policy rates will reduce interest payments for households with outstanding debts, which will diminish households' financial income.

Another distributional force is the *interest rate exposure channel*: when the real interest rate falls, it increases financial asset prices, and it will depend on the household's balance sheet exposures to real interest changes (difference between all maturing assets and liabilities) whether these falls will redistribute from households with positive unhedged interest rates exposure to households with negative exposure (Auclert, 2019). In addition, the *portfolio composition channel* shows that higher equity prices result in capital gains that benefit high-income households (holding most of the financial assets), which will raise wealth inequality. If low-income households tend to hold relatively more currency than high-income households, inflationary actions would result in a transfer from low-income households toward high-income households (Coibion et al., 2017).

Indirect effects are those involving general equilibrium responses of prices and wages, therefore of labor income and employment, to a change in monetary policy (Ampudia et al., 2018). The *income composition channel* is based on the fact that most households rely primarily on labor earnings, while others receive larger shares of their income from alternative sources (investments, government payments, businesses, etc). Low-income households tend to rely more on government transfers, middle-income households rely heavier on labor income, and high-income households (Amaral, 2017). Hence, the influence of monetary policy on each individual household is contingent upon the primary source from which that household derives its income.

Additionally, households exhibit disparities in relation to the position of their earnings within the broader distribution. Monetary policy and business cycles tend to exert a more pronounced influence on lower-income households' wages and employment opportunities. (Heathcote et al., 2010) find that, at the top of the earnings distribution, labor demand shifts in favor of skilled workers, increasing both wage and earnings inequality, while lower-skilled workers are more likely to lose their jobs during recessions.

To analyze the distributional effects of monetary policy, we need to identify monetary policy shocks. The literature has increasingly utilized measures of monetary surprises to isolate the unexpected component of monetary policy changes. By contrasting actual policy decisions with market expectations inferred from financial instruments (e.g., interest rate futures), we can explore the extent to which they deviate from what the market had foreseen. The works of Cochrane and Piazzesi (2002) and Faust et al. (2004) have exemplified this methodology, where they employed surprise measures to better understand the interplay between monetary policy and macroeconomic variables within the framework of structural VAR models. By closely examining market movements within a narrow timeframe surrounding policy announcements, researchers are able to capture the immediate impact of the policy adjustment. Bernanke and Kuttner (2005) and Hanson and Stein (2015) have leveraged this approach to explore the effects of monetary policy on asset prices and market volatility, shedding light on the swift market reactions that follow these announcements.

The attractiveness of monetary policy surprises in these contexts lies in their concentration on alterations in interest rates within a limited timeframe from monetary policy meetings' announcements. This approach effectively mitigates concerns regarding reverse causality and potential endogeneity issues. The Central Bank's board's capacity to respond to financial market fluctuations within the announcement's immediate temporal vicinity is limited. Consequently, the fluctuations in asset prices can be unequivocally attributed to the announcements themselves rather than the opposite scenario (Bauer and Swanson, 2023).

In addition, the narrative approach involves integrating qualitative information from central bank officials' statements and speeches with quantitative data Romer and Romer (2004). It analyzes the language used in speeches, minutes of policy meetings, or interviews to identify periods of monetary policy changes. This approach provides insights into policymakers' intentions and can help distinguish between exogenous monetary policy shocks and endogenous responses to economic conditions. Gertler and Karadi (2015) employ this approach to investigate the role of central bank communication in shaping expectations. Furthermore, external instruments, like changes in international interest rates, have been utilized to proxy for monetary policy shocks. These instruments offer a way to capture the influence of global monetary conditions on domestic economic variables, as demonstrated in the work of Ramey (2016) and Stock and Watson (2018).

The early literature on monetary policy and inequality focused on distinctive measures of inequality and how they were affected by different types of monetary policy shocks in advanced economies. Romer and Romer (1998) examine the influence of monetary policy on poverty and inequality both over the business cycle in the United States and over the longer run in a large sample of countries, where their findings reveal that expansionary monetary policy provides temporary relief from poverty, with the optimal outcome achievable through stabilizing output and maintaining low inflation. Coibion et al. (2017) use the Consumer Expenditure Survey (CEX), a detailed household-level data source of the United States, to construct a wide range of inequality measures for labor income, total income, consumption, and total expenditures. They find that a contractionary monetary policy shock is characterized by a widening of the earnings distribution above the median but a tightening of the earnings distribution below the median, leading to only small effects on inequality.

Similar investigations have been carried out in other countries. Mumtaz and Theophilopoulou (2017) use detailed micro-level information from the UK to construct quarterly historical measures of inequality from 1969 to 2012, and their results indicate that contractionary monetary policy shocks lead to an increase in earnings, income, and consumption inequality. Moreover, the impact of a contractionary policy on income and consumption across various quantiles indicates that lower-income households experience a more pronounced negative effect than those at the upper distribution level. Furceri et al. (2018) use a local projections method with panel data of 32 advanced and emerging economies from 1990 to 2013 and find that, using unexpected changes in monetary policy rates that are orthogonal to unexpected changes in economic activity and inflation, a decrease in the policy rate reduces, on average, income inequality by about 1% in the short term and by about 2% in the medium term.

Kuester et al. (2016) use a New Keynesian business-cycle model with rich household heterogeneity and find that systematic monetary policy, especially through nominal interest rates, significantly impacts income distribution by affecting employment and asset prices. The findings reveal that contractionary monetary policies disproportionately harm wealth-poor households, reducing employment and labor income, whereas wealth-rich households benefit from higher asset markups. Following Kaplan et al. (2018) and Colciago et al. (2019), household heterogeneity influences monetary policy transmission when many agents possess minimal liquid assets, as observed in many economies. These agents, insensitive to interest rate fluctuations, primarily adjust their consumption in response to income changes. Therefore, the impact of monetary policy extends beyond the traditional interest rate channel, affecting the economy through the responses in wages and prices, which leads to changes in employment and labor income due to policy-induced general equilibrium effects.

Given the limitations on income and wealth data in Chile, we lack quarterly or even annual data, which prevents the implementation of dynamic models with explicit inequality measures. Consequently, we proceed by conducting simulations with microdata, utilizing the macroeconomic results from aggregate impulse response functions. This paper relates closer to the research pioneered by Ampudia et al. (2018), Albert and Gómez-Fernández (2022), Mäki-Fränti et al. (2022) and Lenza and Slacalek (2024). This approach builds a connection between macroeconometric modeling and simulations on microdata. The authors build and estimate structural vector autoregression models to infer the overall macroeconomic ramifications of the European Central Bank's (ECB) or Federal Reserve's (FED) monetary policy on the economy. In the second leg of the analysis, the investigation distribute the collective responses of variables such as wages, the unemployment rate, stock prices, and house prices obtained from the macroeconomic model across the spectrum of households' employment statuses, nominal gross income, and net wealth. The microsimulation process involves conducting computations for the evolution of net wealth at the household level, whereas calculations related to labor income are executed at the individual level.

We will look into monetary policy transmission in the Chilean economy, using a Bayesian VAR (BVAR) to study the effects on aggregate macroeconomic data. We provide novel monetary policy shocks using the Central Bank of Chile's forecast information, market expectations, and high-frequency data. In the second stage of the paper, we use simulation techniques to distribute the aggregate effects estimated in the BVAR across individual households, using data on their income and asset composition. We will rely on the Chilean Household Finance Survey (EFH in spanish), the country's main survey collecting household-level data on household balance sheet details.

2 Monetary Policy in Chile

The Central Bank of Chile has continually adjusted its approach to monetary policy meetings, reflecting changes in the economic environment and the effectiveness of its policies. In the early 2000s, the Bank held monetary policy meetings about once a month, a frequency chosen to address the dynamic and often unpredictable economic conditions of the time. This approach allowed the Bank to be agile and responsive to the fluctuating economic landscape.

As the Chilean economy started to stabilize and the inflation-targeting regime became more established, the Central Bank recognized the potential to reduce the frequency of its meetings. The initial high frequency was essential for closely monitoring the economy and responding to fluctuations. However, with growing confidence in the economy and the success of the monetary policy, a shift to less frequent meetings was deemed appropriate. In 2017, the Central Bank reduced its monetary policy meetings to eight per year. This decision aligned practices with those of major central banks and improved the predictability and stability of monetary policy while maintaining the flexibility to respond to economic changes. The policy rate is crucial for influencing Chile's monetary and financial conditions, aiming to withhold its primary mandate: maintain low and stable inflation (Costa, 2023).

2.1 High-Frequency Approach

Accurately identifying the impacts of monetary policy changes is crucial. One common method involves using high-frequency data to study these effects. This approach seeks to capture financial markets' immediate and short-term reactions to policy announcements (Cook and Hahn, 1989; Kuttner, 2001; Cochrane and Piazzesi, 2002).

A distinct characteristic of this methodology is the careful selection of a narrow time window that encapsulates the critical period around Federal Open Market Committee (FOMC) announcements in the US. Typically, researchers concentrate on variations in interest rates within a span of one to two days prior to and subsequent to these announcements. The rationale behind this choice is grounded in the notion that this timeframe is sufficiently sensitive to reflect market reactions to new information while minimizing the influence of confounding factors (Bernanke and Kuttner, 2005; Hanson and Stein, 2015).

By isolating this specific time window, researchers aim to approximate a scenario where the only notable event is the FOMC announcement and its subsequent policy decision. This assumption, while simplifying the analytical framework, allows researchers to infer the market's perception of the monetary policy change with a degree of confidence. It serves as a controlled environment for understanding how financial markets process the central bank's actions and statements and subsequently adjust asset prices, exchange rates, and interest rates.

Several studies have addressed the issue of lack of exogeneity in monetary policy surprises obtained from high-frequency identification. Miranda-Agrippino (2016) and Miranda-Agrippino and Ricco (2021) point out that high-frequency instruments are predictable and autocorrelated, which would be an indication of the sluggish adjustment of expectations, and market-based revisions of expectations that follow policy announcements correlate with central banks' private macroeconomic forecasts.

Exogeneity ensures that the effects of such policy surprises on the economy are accurately measured. By ensuring that these surprises are independent of other economic and financial variables, exogeneity helps establish causality and unbiased estimation. Bauer and Swanson (2023) accounts for the predictability of high-frequency monetary policy surprises by orthogonalizing the surprises with respect to macroeconomic and financial data that pre-date

Table 1: High-Frequency Identification

(a) First Stage

Expectation Variable	First Stage
Current Inflation Expectation	0.011
	(0.019)
Inflation 11 Months Ahead	0.004
	(0.009)
Inflation 23 Months Ahead	0.032
	(0.024)
NER 2 Months Ahead	-0.000
	(0.000)
NER 11 Months Ahead	-0.001
	(0.000)
NER 23 Months Ahead	0.001
	(0.001)
IMACEC One Month Prior	0.000
	(0.002)
Current GDP Expectation	0.000
	(0.002)
Personal Economic Perception	0.001
	(0.001)
Economic Perception 5 Years Ahead	-0.001
	(0.001)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) MP Estimation

	MPR Change
MP Shock: Residuals	2.263***
	(0.513)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the announcements. We address this concern by regressing the daily change in 3-month Chilean swap contracts against a set of market expectation variables collected before the monetary policy announcement.

The market expectations variables are retrieved from the Central Bank of Chile's Economic Expectations Survey (EEE in Spanish). Table 1a shows that all coefficients are essentially zero. Hence, the predicted component of the orthogonal surprise is very close to the original series.For each monetary policy meeting m, we regress the communicated interest rate change against the orthogonalized monetary policy surprise as an instrument:

$$\triangle mpr_m = \alpha + \beta SURPRISE_m + \varepsilon_m,$$

The resulting fitted values from Table 1b, $\hat{\Delta} mpr_m$, represent the first stage of an instrument variable approach and can be interpreted as an exogenous component of the monetary policy rate. We focus on the daily change of 3 months of interest rate swap contracts in monetary policy announcement days between 2007 and 2020. The Central Bank of Chile provides data about the days of monetary authority meetings, interest rates announced, and market expectations surveys. Bloomberg provides data on interest rate swap contracts.

2.2 Romer and Romer Approach

We proceed to construct our measure of monetary policy shock along the lines of the narrative method pioneered by Romer and Romer (2004), where they use central bank forecasts and contemporaneous information of macroeconomics series to extract the systematic element from monetary policies. The monetary policy shock, therefore, represents the changes in interest rates that are unanticipated and not influenced by current and expected economic states that remain invariant to information available to the Board of the Central Bank of Chile. On a policy-meeting frequency, we estimate the policy rate change as follows:

$$\Delta i_m = c + \alpha i_{m,t-1} + \sum_{k=0}^{K} \beta_{\pi_k} \pi_{m,t+k} + \sum_{k=0}^{K} \beta_{\Delta\pi_k} \Delta\pi_{m,t+k} + \sum_{k=0}^{K} \beta_{y_k} \Delta y_{m,t+k} + \sum_{k=0}^{K} \beta_{\Delta y_k} \Delta y_{m,t+k} + \delta_1 tc_m + \delta_2 \Delta tc_m + \varepsilon_m,$$

where Δi_m represents the change in the policy rate at meeting m, and $i_{m,t-1}$ is the level of the policy rate before meeting m. The meeting m occurs in period t. Following Romer and Romer (2004), we incorporate central bank forecasts for GDP $y_{m,t+k}$, CPI $\pi_{m,t+k}$ for the horizon $t+k$, and the exchange rate before the meeting tc_m. Additionally, we consider the corresponding forecast changes, denoted $\Delta\pi_{m,t+k}$ and $\Delta y_{m,t+k}$, and the exchange rate change between meetings Δtc_m.

Historical forecasts from the Central Bank of Chile are utilized for every policy meeting, whenever available shortly before a meeting. Central Bank of Chile's forecasts, available from public monetary policy reports,[1] span from 2000 to 2023, and we use annual GDP and CPI forecasts for the current

[1]Refer to Figure 1 for a word map (in Spanish) of monetary policy reports from the Central Bank of Chile.

Figure 1: Word Cloud from Monetary Policy Reports

Source: Central Bank of Chile and author's calculations.

and next year to ensure consistent and extensive coverage. The forecast reports' periodicity is three or four times per year, often coinciding with policy meetings. For meetings without accompanying forecasts, we iteratively assign them a forecast following this procedure: first, we use the same or previous month's forecasts of a monetary policy report, and secondly, following Cloyne and Hürtgen (2016), if monetary policy reports were unavailable in the temporal proximity, we use Consensus Economics data as a proxy.

Bernanke et al. (2005)'s work emphasizes the importance of forecasts in aggregating various macroeconomic data and shedding light on future economic trends. As depicted in Table 2, the positive coefficients indicate a substantial reaction to forecasted inflation and output growth increases, suggesting a tendency towards more stringent monetary policies under these conditions. The observed negative coefficient for the lagged policy rate is consistent with a trend toward mean reversion in policy rates during the examined period. The model's R^2 value, close to 0.3, corroborates prior research by Romer and Romer (2004) and Holm et al. (2021), reinforcing these findings.

Table 2: Romer and Romer Estimation for Chile

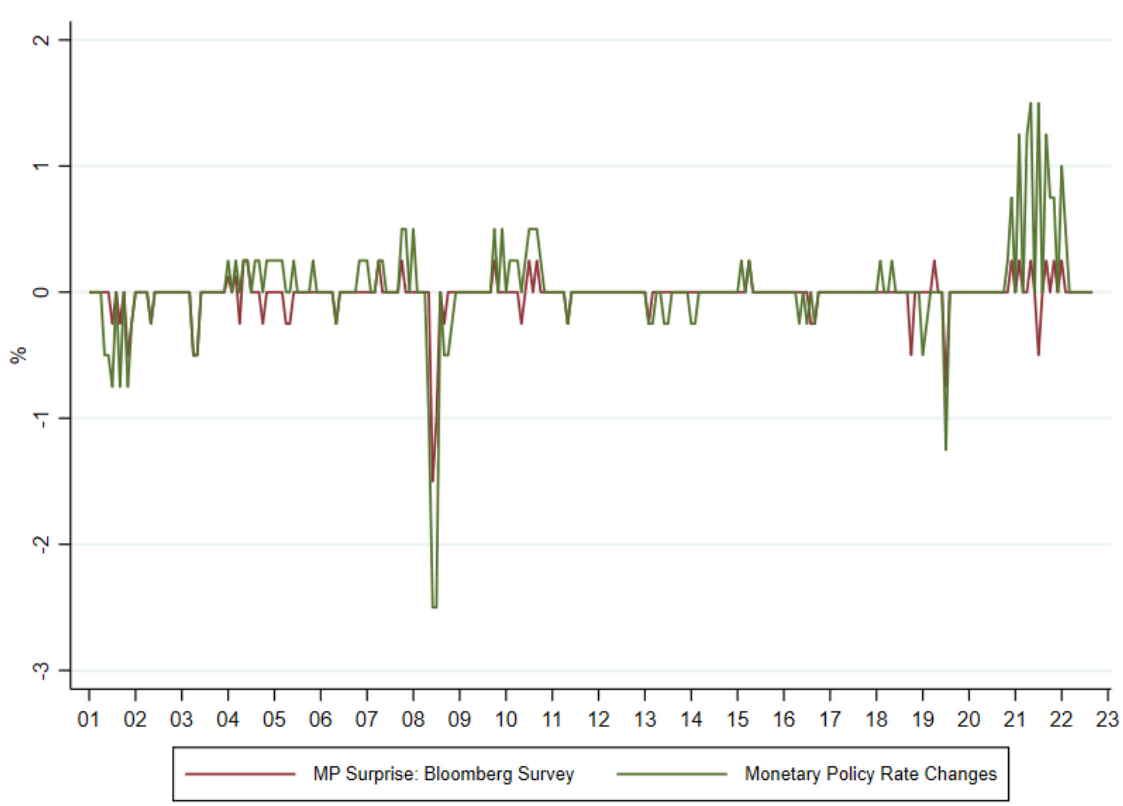
	MPR Change
MPR Previous Meeting	-0.111***
	(0.026)
GDP Growth, Current Year	0.046***
	(0.012)
GDP Growth, Next Year	0.022
	(0.025)
Inflation, Current Year	0.140***
	(0.033)
Inflation, Next Year	0.047
	(0.087)
Exchange Rate Before Meeting	0.000
	(0.000)
Δ GDP Growth, Current Year	-0.036
	(0.026)
Δ GDP Growth, Next Year	-0.021
	(0.075)
Δ Inflation, Current Year	0.004
	(0.040)
Δ Inflation, Next Year	-0.036
	(0.071)
Δ Exchange Rate Between Meetings	-0.001
	(0.001)
N =287	$R^2 = 0.34$

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.3 Bloomberg Survey Forecasts Approach

As a robustness check, we follow Aruoba et al. (2021), who use survey surprises that are constructed using the difference between the monetary policy rate decided in the Monetary Policy Meeting and the expected monetary policy rate by a select group of academics, consultants, and advisors of financial institutions. Bloomberg's survey system, unlike similar surveys, guarantees improved synchronization with the official schedule of policy meetings, ensuring the pertinence of the respondents' inputs. The survey data collection period aligns with the two weeks preceding the monetary policy meeting. Participants have the option to revise their answers throughout this time frame and until the afternoon on the day preceding the meeting, with the system logging the precise date of any such updates.

Figure 2: Bloomberg Survey's Surprise Measures in Chile



Source: Central Bank of Chile and Bloomberg, author's calculations.

3 Methodology

The prevailing approach to identification in macroeconomics involves applying different sets of recursive zero constraints to the concurrent coefficients. This technique, pioneered by Sims (1980) and referred to as "triangularization", has been widely utilized. Blanchard and Perotti (2002) exemplified that the policy variable does not respond within the period to the other endogenous variable, motivated by decision lags of policymakers or adjustments costs, for which they assume that government spending does not respond to the contemporaneous movements in output or taxes. Bernanke and Blinder (1992) describe that there can be sluggish responses of the other endogenous variables when exposed to policy variable shocks, for which they impose the federal funds rate last in the Cholesky ordering. A more general approach to this method is known as a structural VAR, where it uses either economic theory or outside estimates to constrain parameters (Blanchard and Watson, 1986; Bernanke, 1986).

Another common strategy is a narrative approach, which relies on historical accounts and statements from central bank officials. This method analyzes the language used in speeches, minutes of policy meetings, or interviews to identify periods of monetary policy changes. Examples of the use of narrative methods are Romer and Romer (1998), where they construct monetary shock series based on Federal Open Market Committee (FOMC) minutes, and Romer and Romer (2010) use narrative series of tax changes based on legislative documents.

Studies utilizing high-frequency data, such as news releases coinciding with FOMC meetings and the behavior of federal funds futures, aim to identify unexpected policy actions taken by Central Banks. The distinction in these analyses lies in their reliance on timing and the utilization of high-frequency data, often at a daily or even more granular level. This granularity allows for more credible assumptions than those applied in monthly or quarterly analyses. Essentially, the closer the observation interval to the actual policy decision, the more reasonable it is to assert that any identified shocks are genuinely unanticipated by the markets (Kuttner, 2001; Faust and Rogers, 2003; Faust et al., 2004; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018).

The *external instruments* method has gained prominence in the literature as a valuable tool for addressing the structural identification problem in econometric analysis. Numerous studies, Stock and Watson (2012); Mertens and Ravn (2013), have employed this method to disentangle the causal relationships between macroeconomic variables when the underlying structural model is either unknown or subject to ambiguity. This strategy leverages information derived from sources external to the VAR model, such as narrative evidence, shocks generated by estimated DSGE models, or high-frequency data. The rationale behind this approach is that these external data sources serve as noisy indicators of the actual shock. Following Ramey (2016), suppose that Z_t represents one of these external series. This series will be a valid instrument for identifying the shock ε_{1t} if the following two conditions hold:

$$E[Z_t \varepsilon_{1t}] \neq 0 \tag{1a}$$

$$E[Z_t \varepsilon_{it}] = 0, i = 2, 3, ..., N \tag{1b}$$

The first condition is the relevance condition, where the external instrument must be contemporaneously correlated with the structural policy shock. The second condition is the exogeneity condition, where the external instrument must be contemporaneously uncorrelated with the other structural shocks. If the external instrument satisfies these two conditions, it can be used to identify the shock ε_{1t}.

Several studies have investigated the role of monetary policy in Chile. Calvo and Mendoza (1999) use a recursively identified VAR model using the lending rate as the policy instrument, where they find the common price puzzle of monetary policy (Sims, 1992; Hanson, 2004). Parrado (2001) apply a structural VAR approach where a domestic monetary contraction generates a transitory fall in output and monetary aggregates; therefore, there is no evidence of price and exchange rate puzzles. Chumacero (2005) present a structural VAR model where they find that the price puzzle is only a puzzle for a model in which important nonneutralities are a major driving force.

More recent studies for Chile have used measures of monetary policy shocks in different frameworks. Pescatori (2018) blend the traditional recursive identification strategy with the use of the monetary policy surprise data, which acts as an instrument for the change in the policy rate, where a persistent increase in the policy interest rate results in a reduction in economic activity but with an initial price puzzle. Aruoba et al. (2021) estimate a Bayesian VAR model using a monetary policy surprise measure based on Bloomberg survey expectations, and they conclude that an unexpected increase in monetary policy rate of 25 basis points decreases output by 0.5 percentage points and inflation by 0.2 percentage points, while also causing a depreciation. Beltran and Coble (2023) use a structural VAR model with pure and information surprise components as instruments and observe that an increase in a pure monetary policy shock of 10 basis points has contractionary and persistent effects on activity, prices, and credit growth. Specifically, they find a faster effect on activity than the inflation reaction, falling in the first month 0.3 percentage points and standing below its long-term level.

Our identification approach follows Aruoba et al. (2021), which relies on valid structural estimation with an internal instrument as in Plagborg-Møller and Wolf (2021). This can be carried out by ordering first the orthogonalized monetary policy shock in the BVAR, which will yield valid impulse response estimates even if the shock of interest is noninvertible and affected by measurement error (Li et al., 2024). Under the conditions (1a) and (1b), and the orthogonality criteria to leads and lags of the structural shock, we can estimate the causal impact of monetary policy by enhancing the BVAR model with the unexpected monetary policy shock series as an internal instrument. We estimate a monthly Bayesian VAR[2] with the natural logarithms of the index of economic activity (IMACEC), the consumer price index (CPI), the stock market index (IPSA), the CLP-USD exchange rate (NER), the wage index (WAGE) as well as the level of the unemployment rate, and the monetary policy rate.

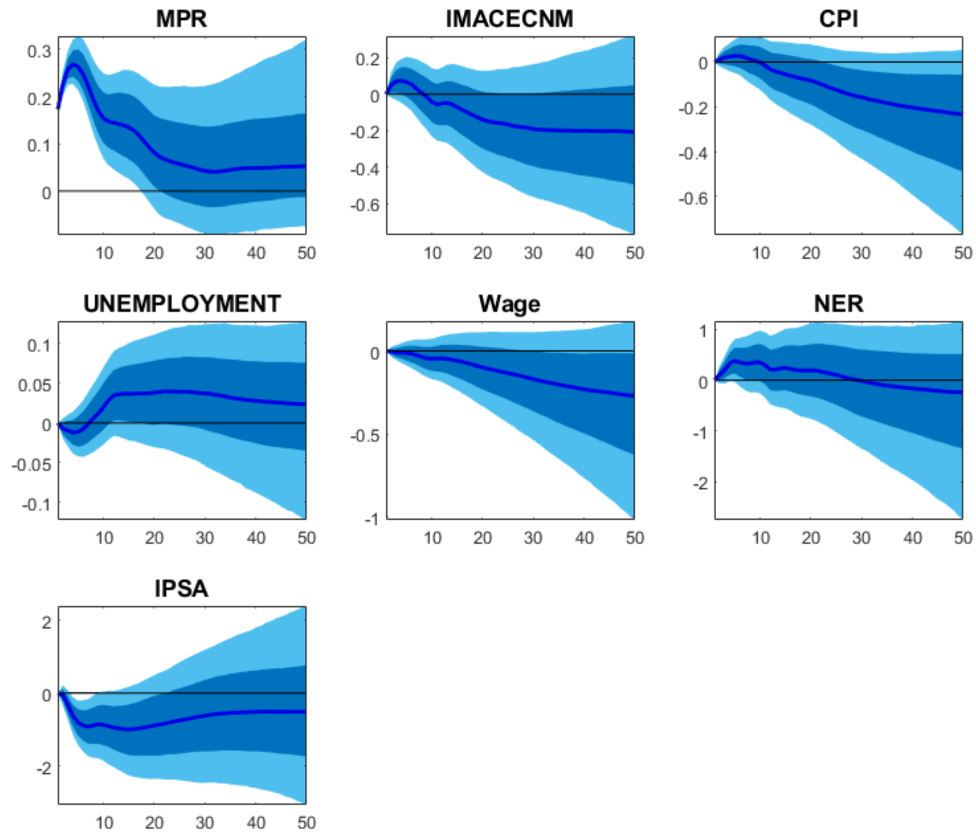
Table 3: Baseline variables for specification

Variable	Description
Economic activity	Monthly indicator of economic activity (Imacec), (2018 index=100), BCCH.
Inflation	Historical Headline Index CPI, BCCH.
Unemployment rate	Monthly national unemployment rate, INE.
Wage index	Nominal general wage index, INE (January 2006=100).
Stock Market Index	IPSA index is composed of the 30 stocks with the highest average annual trading volume in the Santiago Stock Exchange.
Exchange rate	Nominal exchange rate (Observed dollar $CLP/USD), BCCH.
Monetary policy rate	Target interest rate for interbank transactions that the central bank intends to achieve by means of its monetary policy instruments, BCCH.

Figure 3 shows the results for a monetary tightening policy using the high-frequency identification approach. We can see that a contractionary monetary policy shock of 20 basis points initially slows down economic activity, causing a 0.2 percentage points drop at its peak. The price level also falls by 0.2 percentage points over three years. Additionally, the stock market index declines by one percentage point within five months of the policy change. Alongside this, the unemployment rate rises, and the wage index goes down, pointing to potential job losses (extensive margin) and reduced wages for workers (intensive margin).

[2]The Bayesian VAR employs Minnesota-type priors. In this setup, the initial lag of each variable within its equation is set with a prior mean of 1, whereas all other coefficients, including lags of other variables in the same equation and higher lags of the variable itself, have a prior mean of 0. The variances of the priors for each parameter are structured in a way that they diminish as the lags increase.

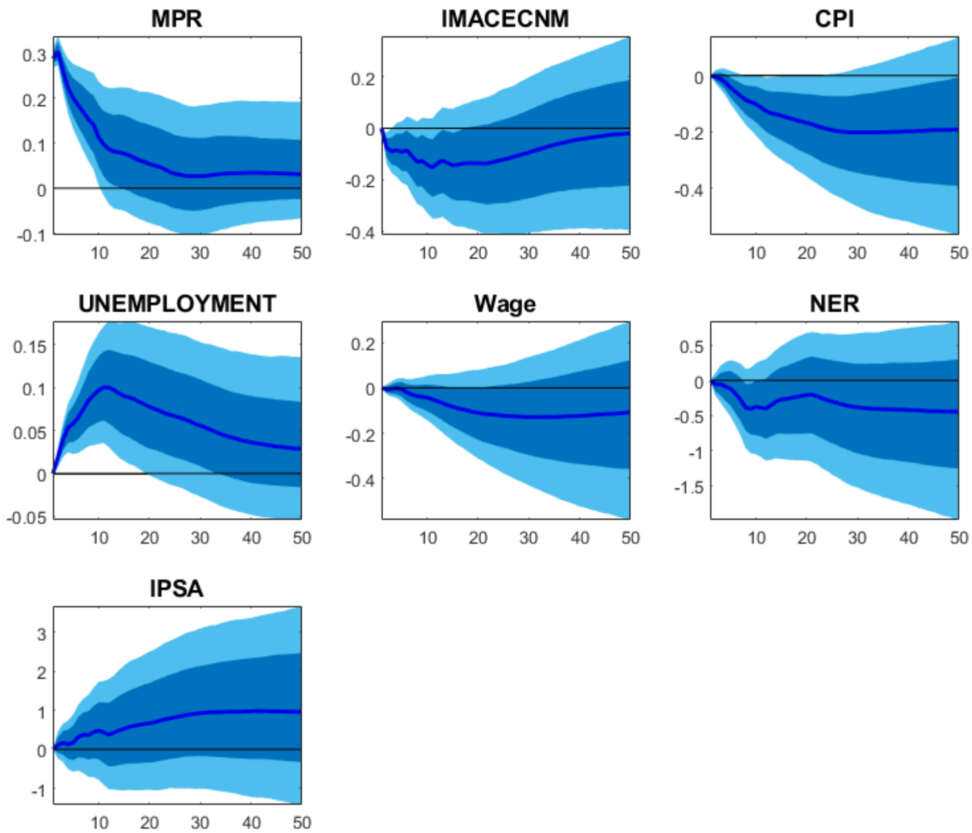
Figure 3: IRF to monetary policy shock in Chile: High-Frequency Approach



Notes: The sample goes from 2007m3 to 2019m12. Dark shades represent credibility sets at 5%-95% and light shades at 16%-84%. The *x* axis is at a monthly frequency. Shock sized to one standard deviation on the monetary policy rate.

Figure 4 shows the results for a contracionary monetary policy using Romer and Romer (2004) identification approach. A tighter monetary policy of 30 basis points significantly impacts economic activity, resulting in an estimated decline of approximately 0.2 percentage points. Consistent with the findings of Aruoba et al. (2021) and Beltran and Coble (2023), our analysis indicates that output responds more rapidly than price levels within the six-month period following a monetary policy shock. Consequently, the price level experiences a point two percentage point reduction over a two-year period, and the stock market shows an increase of half a percentage point within twelve months following the policy shock. In line with these effects, there is a marginal uptick of one basis point in the unemployment rate, accompanied by a corresponding decline in the wage index.

Figure 4: IRF to monetary policy shock in Chile: Romer and Romer Approach

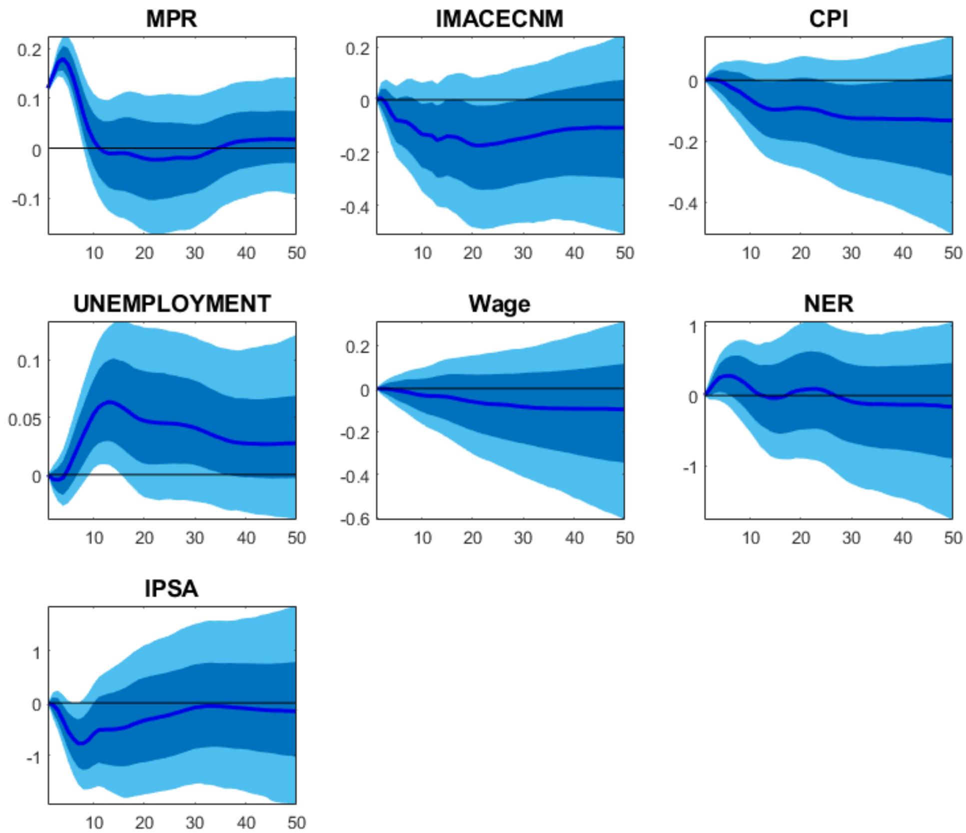


Notes: The sample goes from 1997m4 to 2019m12. Dark shades represent credibility sets at 5%-95% and light shades at 16%-84%. The *x* axis is at a monthly frequency. Shock sized to one standard deviation on the monetary policy rate.

Pescatori (2018) and Aruoba et al. (2021) use a monetary policy surprise constructed from the Bloomberg Survey. It offers current forecasts for nearly all macroeconomic announcements, widely utilized by market participants and academic researchers as consensus market expectations. It has been shown that its forecasts are more accurate and have greater explanatory power for the effects on S&P 500 futures trading and returns than alternative surveys, aligning more closely with market consensus (Chen et al., 2013). The survey typically covers a wide range of topics, such as GDP growth, inflation rates, and employment dynamics, helping to explore market sentiment where the respondents base their forecasts on the latest available information.

We construct the monetary policy surprise series utilizing data from the Bloomberg Survey and apply our methodology to derive the results presented

Figure 5: IRF to monetary policy shock in Chile: Survey Approach



Notes: The sample goes from 2001m3 to 2019m12. Dark shades represent credibility sets at 5%-95% and light shades at 16%-84%. The *x* axis is at a monthly frequency. Shock sized to one standard deviation on the monetary policy rate.

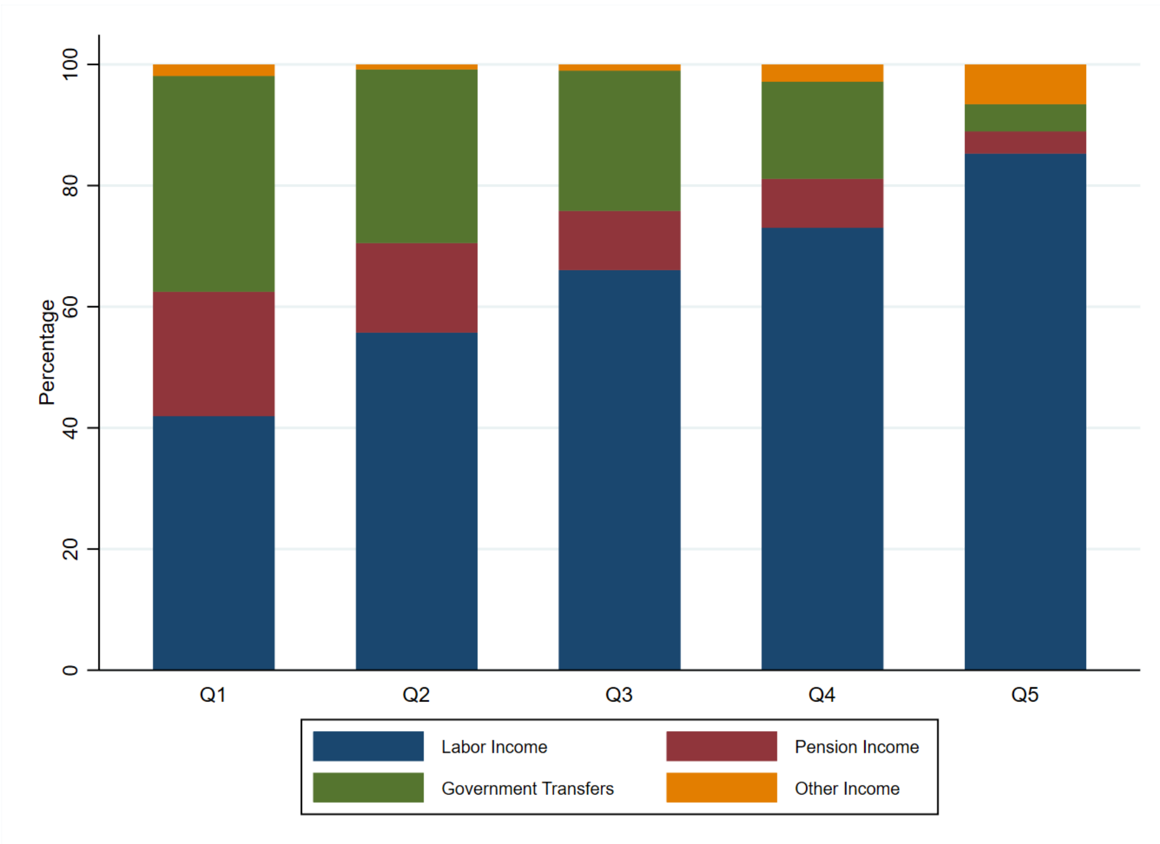
in Figure 5. These findings align with the general outcomes associated with our previously identified monetary policy shocks. Notably, the commonly referred to as the price and output puzzles are substantially mitigated. Additionally, there is a pronounced increase in unemployment following the monetary policy shock, which continues to underscore the impact of monetary policy adjustments on labor market conditions.

The microsimulations in the subsequent section will utilize the impulse response functions derived from the Romer and Romer approach, as it is our preferred method for identifying monetary policy shocks. This preference is due to the extensive duration of the series and the rich information set it incorporates. As demonstrated in this section, our findings are robust to alternative identification schemes.

4 Reduced-Form Simulation on Income Inequality

To analyze inequality within our framework, we will utilize the Chilean Household Finance Survey (EFH), the primary survey in Chile that collects detailed household-level data on balance sheets. The survey captures information on demographic characteristics, assets (real assets, financial assets, pensions), debts, income (labor earnings, subsidies, rental, and financial income), means of payment, and financial behavior.

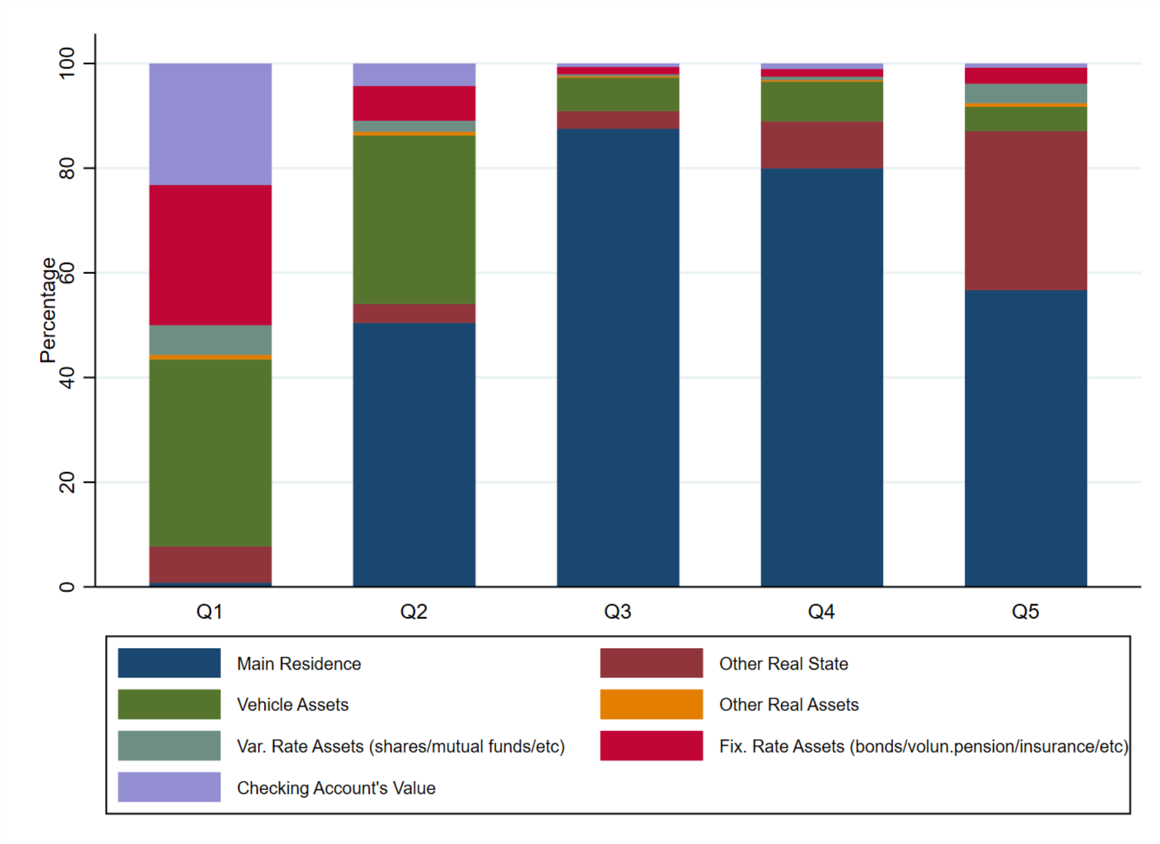
Figure 6: Income Composition by Quintile in Chile



Source: Household Finance Survey 2021 (EFH), author's calculations.

Labor income, comprising wages and salaries, predominantly tilts towards the higher quintiles owing to factors like education and occupation. Government transfers, aimed at supporting individuals in need, hold a pivotal role for those in lower quintiles, mitigating income disparities. Pension income emerges as a substantial factor for retirees in the upper quintiles, reflecting prolonged careers and robust retirement plans. Furthermore, asset ownership makes diverse income sources, including investments and rentals, more pronounced in the upper of the population.

Figure 7: Wealth Composition by Quintile in Chile



Source: Household Finance Survey 2021 (EFH), author's calculations.

The distribution of key assets across quintiles provides a comprehensive view of wealth disparities. Main residence values, reflective of real estate ownership, exhibit considerable variation across quintiles, with higher importance in middle quintiles. Vehicle assets are an important share of households' wealth composition in the lower quintiles. Financial assets, including stocks, bonds, life insurance, and mutual funds, demonstrate substantial diversity in ownership and value. Those in higher quintiles typically possess more extensive and diversified portfolios, contributing to greater financial asset wealth. Checking account values as a measure of liquid assets also differ across quintiles, reflecting prominence in the first quintile.

4.1 Earnings Heterogeneity Channel: IRFs to Microdata

The earnings heterogeneity channel addresses the varied responses in employment status and work hours resulting from changes in monetary policy. It can be conceptualized as an extensive margin effect, where changes in monetary policy influence transitions from employment to unemployment (extensive margin) and also labor income changes (intensive margin).

To examine this channel, probit models offer insights into the marginal effects of different variables on the probability of employment. The probit model assumes that the probability of being employed, denoted as $P(\text{Employed})$, follows a cumulative normal distribution. The model equation can be expressed as:

$$P(\text{Employed} = 1) = \Phi(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k)$$

where $P(\text{Employed})$ represents the probability of being employed, Φ denotes the cumulative standard normal distribution function $\beta_0, \beta_1, \ldots, \beta_k$ are the coefficients to be estimated, and $X_1, X_2, \ldots, X_k$ are the predictor variables. Following Lenza and Slacalek (2024), the explanatory variables are gender, education, age, marital status, and household size. Using the estimated parameter vector $\hat{\beta}$, we compute the predicted probability of having a job for each individual, $\hat{Y}$. Then, we draw an individual-specific random number from a uniform distribution (employment shock), and we calculate a measure of the probability of being unemployed:

$$\triangle_k = \underbrace{\varepsilon_k}_{\text{individual-specific}} - \underbrace{\hat{Y}}_{\text{predicted probability}}$$

We then use $\triangle$ to construct a ranking of the marginal probability of becoming unemployed. Using this ranking, we determine the marginal employee losing her job so that the increase in the simulated sample unemployment rate matches the change in the unemployment target. Because there is randomness in the employment shock, we replicate the process multiple times. In each iteration, we calibrate the threshold value, which indicates the number of individuals changing employment status, to align with the overall increase in unemployment as estimated in the BVAR impulse response.

The simulation is conducted 500 times, and we report the average outcomes from these simulation rounds. The results of the conditional probit model can be seen in Table 4.

Table 4: Employment Estimation with Probit Model

Employment Status	
Male	0.536***
	(0.028)
Education (years)	0.174***
	(0.012)
Living with partner	0.326***
	(0.050)
Annulled	0.480
	(0.432)
Separated	0.321***
	(0.074)
Widowed	0.134
	(0.082)
Single	0.056
	(0.040)
Divorced	0.326***
	(0.079)
Age	0.212***
	(0.005)
Age^2	-0.002***
	(0.000)
Household Members	-0.049***
	(0.010)
Children	-0.081**
	(0.039)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Income Composition Channel

The income composition mechanism is wherein households exhibit heterogeneity in their primary sources of income. The majority of the households rely predominantly on earnings from their first and second source of labor income. This analysis specifically examines individuals transitioning from employment to unemployment. In these cases, wages are substituted with unemployment benefits, which are determined based on the individuals' demographic profiles. To ensure precise estimations, we leverage the OECD Statistics on Benefits and Wages database, which provides detailed net replacement rates for unemployment across different family structures and income brackets, enabling accurate matching for those moving from employment to unemployment.

Table 5: Heckman Estimation Model

Labor Income	
Age	0.120***
	(0.025)
Age^2	-0.001***
	(0.000)
Education (years)	0.416***
	(0.020)
Male	0.391***
	(0.055)
Living with partner	-0.077
	(0.049)
Annulled	-1.081***
	(0.379)
Separated	-0.150**
	(0.070)
Widowed	-0.100
	(0.100)
Single	-0.231***
	(0.035)
Divorced	-0.074
	(0.072)
Children	-0.101***
	(0.036)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Employment Status	
Age	0.213***
	(0.005)
Age^2	-0.002***
	(0.000)
Education (years)	0.166***
	(0.013)
Male	0.520***
	(0.029)
Living with partner	0.312***
	(0.051)
Annulled	0.563
	(0.434)
Separated	0.313***
	(0.076)
Widowed	0.138
	(0.085)
Single	0.009
	(0.041)
Divorced	0.342***
	(0.081)
Household Members	-0.057***
	(0.011)
Children	-0.090**
	(0.040)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

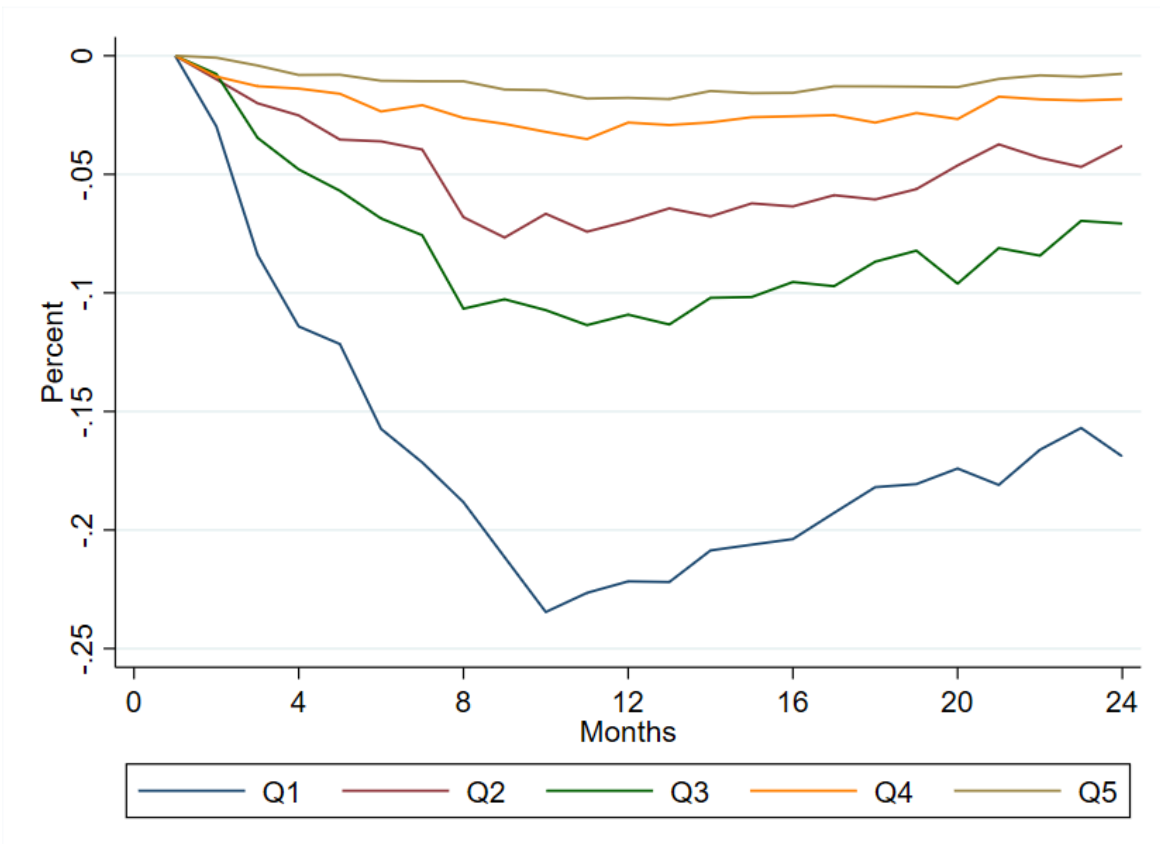
Also, we employ a two-step Heckman model that encompasses both wage and selection equations to estimate the natural logarithm of wages for newly employed individuals. Our exclusion criteria include marital status and household size, which we assume may influence work status but not the wages of those already employed. The remaining variables in the model encompass gender, education, and age. The estimates of Table 5 derived from the Heckman selection model align with findings in the literature. We assume that the labor earnings of previously employed individuals reflect the changes in the overall wage level response from the macroeconomic model.

5 Distributional Impacts of Monetary Policy

5.1 Employment Status

Based on the findings from the macroeconomic model, we observe that following a contractionary monetary policy shock of 30 basis points, there is an overall increase in the unemployment rate and a decrease in the wage index, leading to worsening aggregate inequality. How does this general worsening of inequality manifest in terms of employment across different income quintiles?

Figure 8: Employment Effect by Quintile



Source: Household Finance Survey 2021 (EFH), author's calculations.

Figure 8 shows that the monetary policy shock leads to a sustained decrease in employment across all income levels. The largest increase occurs in the lowest income quintile, while the smallest increase is seen in the highest quintile. Specifically, the employment for the lowest-earning households decreases by about 0.2 percentage points from the starting level, whereas in the other quintiles, it increases between 0.03 and 0.1 percentage points. This more pronounced decrease in employment among the lower income quintiles can be attributed to their higher initial unemployment rates.

We find that a monetary policy shock has a greater impact on employment rates in the third quintile than in the second or fourth quintile. This effect may be attributed to the heterogeneous economic behavior across these income groups: households with lower incomes typically depend more heavily on transfer payments, while middle-income families rely predominantly on labor earnings. In contrast, high-income households mainly generate their income from capital investments and business operations.

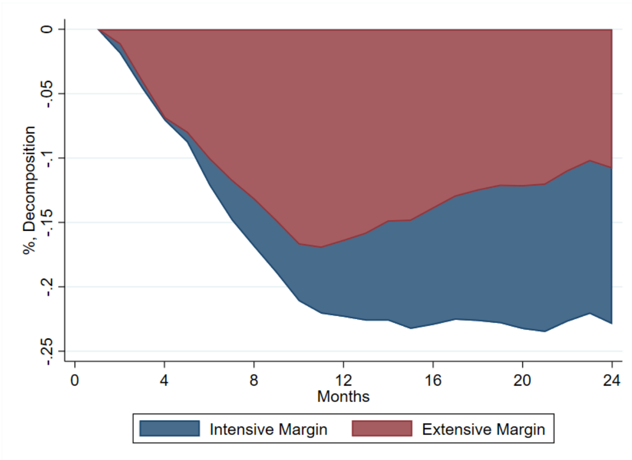
5.2 Labor Income

The impact of monetary policy on income is analyzed through two channels: the income composition mechanism, which uses probit models to study how changes in predictors affect employment probabilities based on household income sources, and the earnings heterogeneity channel, which assesses diverse employment responses by substituting unemployment benefits with wages estimated through a two-step Heckman model.

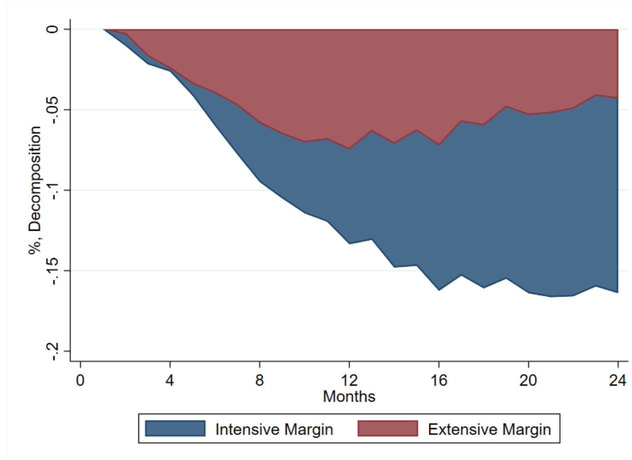
Figure 9 breaks down the overall decrease in income into two components: the extensive margin (earnings heterogeneity channel) and the intensive margin (income composition mechanism). Across the distribution, except for the highest quintile, the dominant factor contributing to the overall income effect is the transition from employment to unemployment. Notably, this overall income effect is most pronounced in the first quintile, where getting a job or losing a job causes a large portion of their income variability, and employment status is crucial for determining the incomes of lower-income households. In the upper quintile, the extensive margin is relatively smaller than the intensive margin, where income changes for those already employed cause more income fluctuations for this group.

These results are consistent with labor market studies across different geographical regions. Blanco et al. (2022) demonstrate that in Argentina, dispersion in the lower tail of one-year earnings changes exhibits countercyclical trends (increasing during recessions) while dispersion in the upper tail shows procyclical trends (decreasing during economic downturns). These patterns align with similar economic behaviors noted in Brazil (Engbom et al.,

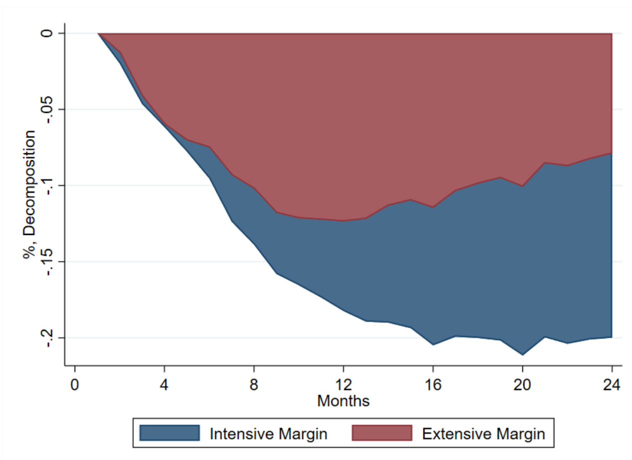
Figure 9: Labor Income Effect by Quintile



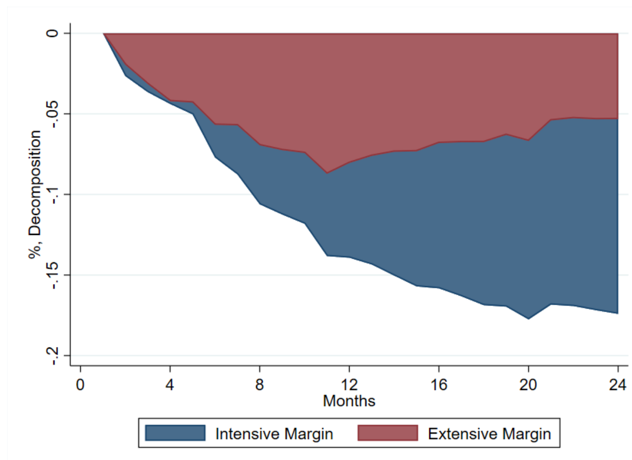
(a) First Quintile



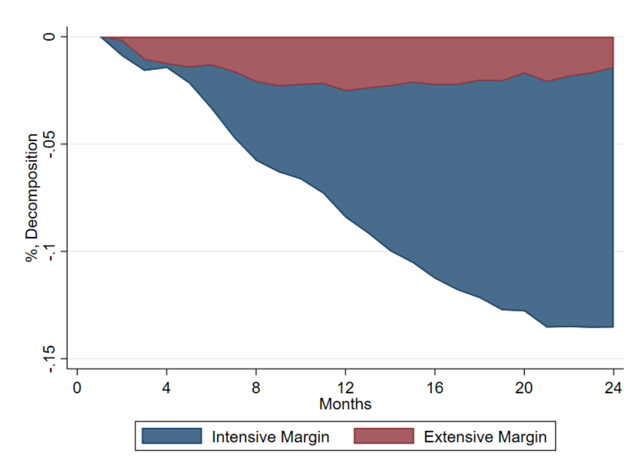
(b) Second Quintile



(c) Third Quintile



(d) Fourth Quintile



(e) Fifth Quintile

2022) and the United States (Guvenen et al., 2021). Furthermore, in European countries, there is a pronounced variability in the residual one-year earnings changes at the lower spectrum of the permanent income distribution, contrasting with the minimal variability observed at the upper end (Arellano et al., 2022; Kramarz et al., 2022).

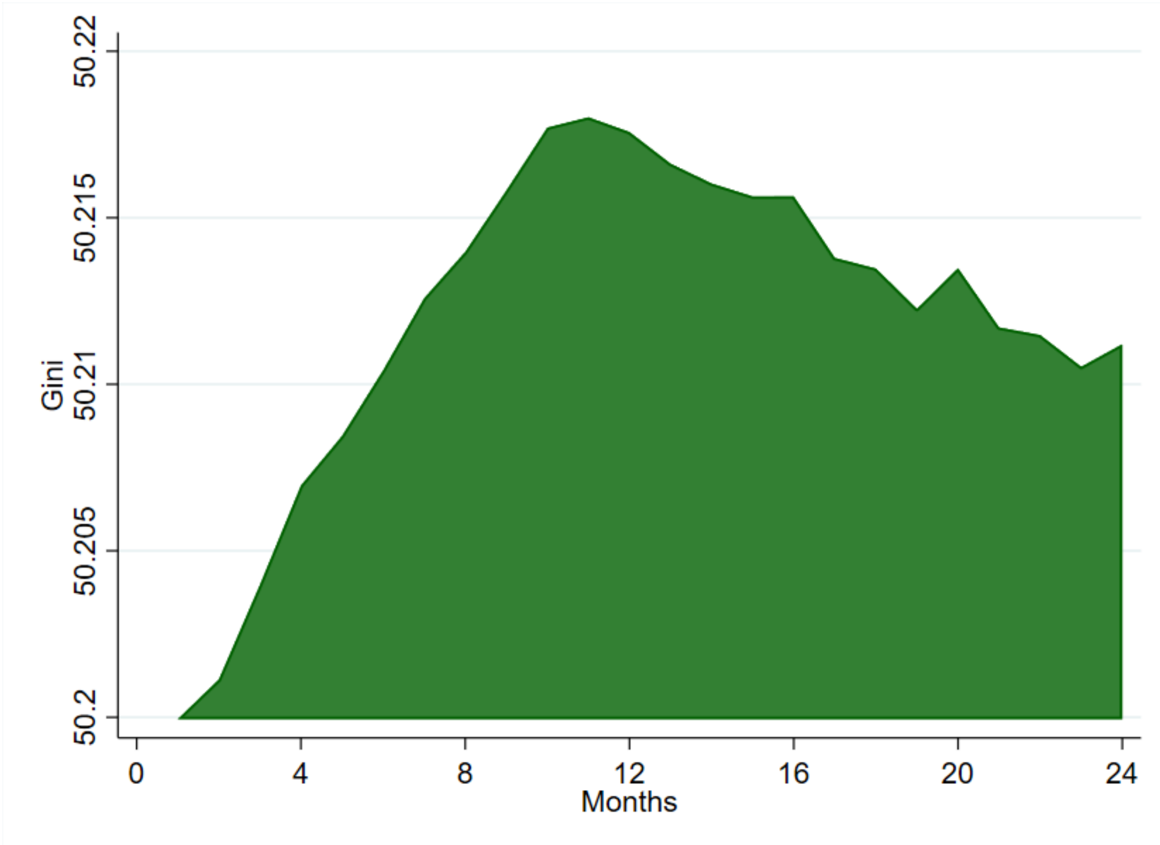
Recent research on monetary policy and labor markets has further explored these channels. Hubert and Savignac (2023) quantify the distributional effects of monetary policy on labor income using French-matched administrative and survey data. Consistent with our results, the authors find a U-shaped impact of ECB monetary policy shocks along the labor income distribution, driven by the extensive margin (unemployment transitions) at the lower end and the intensive margin (income changes for the employed) at the upper end. In Brazil, B. P. Gomes et al. (2023) suggest that monetary policy shocks influence individuals in the informal sector notably more: expansionary shocks enhance their prospects of transitioning to formal employment, while contractionary shocks diminish these prospects. The study also reveals that contractionary shocks decrease the likelihood of individuals moving from unemployment or informal work into formal roles, thereby increasing the persistence of both unemployment and informality.

In the case of Chile, Madeira and Salazar (2023) estimate that a contractionary monetary shock increases the idiosyncratic volatility of labor earnings within the secondary and services sectors. This heightened earnings risk is also evident among low-income workers in the primary sector. Furthermore, Albagli et al. (2023) demonstrate that Chile exhibits the highest labor market flexibility among OECD countries. This enhanced flexibility facilitates more effective management of cyclical economic fluctuations and boosts aggregate productivity through the more efficient allocation of the workforce.

Figure 10 illustrates the effect of a contractionary monetary policy shock on the Gini Index in Chile, observed over a 24-month period. It shows that the Gini Index reached its peak approximately ten months after the policy. This pattern indicates a more adverse effect on lower-income households. However, despite this impact, the resulting change in the Gini Index remains minimal.

This result is consistent with findings from similar studies, confirming a consistent pattern across different countries. Lenza and Slacalek (2024) find that quantitative easing reduces the Gini coefficient from 43.14 to 43.09 in the Euro Area, where in lower income segments, the risk primarily stems from the

Figure 10: Impact on Gini Index



Source: Household Finance Survey 2021 (EFH), author's calculations.

extensive margin, whereas in upper quintiles, the intensive margin plays a more significant role. They observe the biggest impact in Spain, whereas Germany has a smaller impact. Mäki-Fränti et al. (2022) determine that monetary easing marginally increases income inequality in Finland, primarily through mechanisms that favor upper-income quintiles. In particular, following a 25 basis point monetary policy shock, the Gini coefficient increases modestly by only 0.09 percentage points over two years. Samarina and Nguyen (2024) observe that expansionary monetary policy lessens income inequality in the euro area, especially in peripheral countries. It primarily does so by increasing wages and employment through macroeconomic mechanisms. However, the role of the financial channel is less definitive, as higher asset prices and returns from monetary easing might mitigate these equalizing effects. McKay and Wolf (2023) report that household heterogeneity affects monetary policy transmission, but the overall effects on consumption and inequality are limited in the United States.

6 Conclusion

This paper examines the impact of monetary policy on income distribution in Chile using Bayesian Vector Autoregression (BVAR) and microsimulation techniques. We introduce novel monetary policy shocks based on the Central Bank of Chile's forecast information, market expectations, and high-frequency data. Our Bayesian VAR model with internal instruments aligns with established macroeconomic theories and addresses price and output puzzles.

Using microsimulations, we distribute the aggregate effects estimated by the Bayesian VAR across individual households to assess the impact on income distribution. We find that the effects on income inequality are limited, and our results highlight the important roles of the intensive and extensive margins in influencing income distribution across different income quintiles.

The extensive margin, which concerns changes in employment status, exhibits more substantial impacts, particularly on lower income quintiles. These groups see a more significant fluctuation in employment rates, which in turn leads to greater variability in their income levels. Following this, the intensive margin, which refers to how sources of income like wages and asset returns are affected, shows smaller yet noticeable changes across the quintiles. Specifically, higher income quintiles experience less volatility in their income sources, primarily due to more diversified income streams and assets that can buffer against economic shocks.

Future research should advance this understanding by examining the impacts of monetary policy on wealth inequality in Chile. Additionally, it would be beneficial to delineate the interconnections between monetary policy and fiscal measures, and how these relationships can inform governmental strategies for redistribution policies.

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