Monetary Policy and Labor Markets in a Developing Economy *

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Abstract

We study the distributional effects of monetary policy in a developing economy with extensive employment informality. In particular, we examine how monetary policy impacts labor income growth and employment transitions using micro-level panel data. Adopting high-frequency identification, we construct a series of monetary policy surprises for Brazil that serves as an external instrument in a proxy-SVAR, thus allowing us to recover monetary policy shocks. Following a monetary contraction, both formal and informal workers experience declines in real income, with effects that are similarly pronounced across the low and middle-income quartiles, while higher earners suffer less. A monetary contraction also reduces the likelihood of large income gains, shifting the income growth distribution leftward. Moreover, a shock that raises the interest rate increases informality and unemployment persistence by making transitions to formal employment less frequent.

Keywords: Monetary policy; labor market; informality; income distribution; developing countries.

JEL Codes: D31; E52; J31

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1 Introduction

Monetary policy impacts labor markets, but its effects are not uniform across all workers. This heterogeneity is particularly important in developing economies, which often have volatile labor markets and a high proportion of informal workers. Research on the heterogeneous consequences of monetary policy on labor markets can inform policymakers about policy design and suggest complementary interventions to mitigate potentially adverse effects on vulnerable groups. This paper examines the heterogeneous effects of monetary policy in Brazil, a developing country with a sizable informal sector, to shed light on its impact on distinct segments of the labor force. We find that an unanticipated increase in the interest rate leads to declines in labor income across the low and middle parts of the income distribution, with comparable effects for both formal and informal workers. A monetary contraction also reduces the likelihood of large income gains, shifting the income growth distribution leftward. Moreover, monetary contractions increase the persistence of informality and unemployment by reducing the likelihood of transitions into formal employment.

We examine the impact of decisions made by the Central Bank of Brazil's Monetary Policy Committee (COPOM). The COPOM announces its decision on the policy interest rate target a few hours after financial markets have closed. To identify monetary policy surprises, we use price changes in deposit interest rate (DI) futures contracts, which are closely related to the policy interest rate. Specifically, we define the surprise as the difference between the opening price of the DI rate futures contract on the day after the COPOM meeting and the closing price immediately before the announcement.

We use this monetary policy surprise series as an external instrument in the estimation of a proxy-SVAR model of the Brazilian economy, thus recovering a series of monetary policy shocks. We then adopt a local projections approach (Jordà, 2005) to estimate labor income responses to monetary policy. We classify workers into four income groups and study their one-year-ahead labor income responses. All income groups exhibit a negative mean income growth response, ranging from approximately -0.29 to -1.36 percentage points, after an unexpected 0.25 percentage point increase in the interest rate, with the highest earners being the least affected. We find quantitatively similar mean results for both formal and informal sector workers; quartile-specific effects—particularly for the second and fourth quartiles—are larger for informal workers.

Moreover, we measure monetary policy's impact on the income *growth* distribution by employing quantile regressions. A 0.25 percentage point monetary policy shock shifts the income growth distribution to the left, with an average income drop of 0.67 percentage points. The movement in the right tail is larger, indicating that events of substantial income growth become less likely. This feature is more pronounced for informal sector workers than for formal sector workers.

We also study transitions across employment states. We start this analysis by focusing on workers employed in both the initial and final periods of a one-year comparison. For workers starting in an informal job, a monetary policy contraction reduces the probability of transitioning to the formal sector and increases the probability of remaining informal. For those who started in a formal job, the impact on the likelihood of changes in formality status (conditionally on remaining employed) is close to zero. Additionally, we analyze the impact of monetary policy shocks on employment transitions, including transitions between unemployment and employment. A contractionary monetary policy shock decreases the probability of transitioning from unemployment or informality to the formal sector and increases the chance of becoming unemployed. Therefore, monetary contractions increase the persistence of both unemployment and informality.

Finally, we provide a framework that helps interpret these findings. In it, we extend a standard New Keynesian framework by incorporating a labor market block in which workers potentially differ in their exposure to aggregate shocks. This structure links the aggregate output gap to the income and labor market dynamics of formal, informal, and unemployed individuals. It clarifies how monetary policy affects all groups through common channels, while allowing for differences in exposure, which helps rationalize the empirical patterns we have documented.

Related Literature. Our paper is related to a strand of literature that identifies monetary policy surprises and estimates responses to exogenous monetary policy shocks. See Ramey (2016) for a thorough review. We use the high-frequency identification along the lines of Gertler and Karadi (2015) and Nakamura and Steinsson (2018).[1] A few recent papers focus on the heterogeneity of responses across the income and wealth distribution (Andersen et al., 2022; Amberg et al., 2022; Bergman et al., 2022; Holm et al., 2021; Nakamura, 2024). Relative to these, our main contribution lies in studying a developing country in which the labor market experience of a typical worker is subject to significant risk and where informality is widespread. We further contribute by examining monetary policy shocks in an understudied economic setting characterized by high macroeconomic volatility.

Our work additionally innovates by analyzing the impacts of monetary policy on the transition rates between different employment conditions. This dimension of heterogeneity helps us understand how monetary policy might result in different consequences for labor market participants depending on their formality or employment status. On that point, we build on Gomes et al. (2020). While they investigate the overall pattern of workers' transition rates between formal and informal sectors and the associated earnings innovations, we measure how these rates change when a monetary policy shock occurs.

A second related literature strand provides empirical descriptions of the income risk faced by workers. Important contributions include Guvenen et al. (2014) and Guvenen et al. (2021). Our focus on a developing economy with a large informal sector is related to Gomes et al. (2020), Engbom et al. (2022), and Blanco et al. (2022). The well-identified moments from microdata this literature provides can inform quantitative macroeconomic modeling. However, further research is needed to disentangle the underlying sources of income risk, identify patterns of heterogeneous exposure to these sources, and study how policy interventions can mitigate or contribute to these risk sources. Our study contributes to this line of research by analyzing labor

[1]See also Aruoba and Drechsel (2024) and Gorodnichenko et al. (2023) for recent applications exploiting machine learning and natural language processing.

income risk and heterogeneity in individual exposure to monetary policy shocks.

The framework we develop to interpret the empirical results builds on recent heterogeneous-agent New Keynesian (HANK) research while adapting it to the context of developing economies. Broer et al. (2022) document that monetary policy affects job-loss risk more strongly for lower-income workers, highlighting the role of heterogeneous labor market exposure in transmission. Alves et al. (2021) show that the distribution of labor and transfer income responses ("incidence") is quantitatively important for the aggregate consumption effects of monetary policy in HANK models. Our contribution brings these insights to an environment with a large informal sector. Unlike Lahcen (2020), who studies the long-run equilibrium effects of monetary policy on informality and unemployment through inflation and firm formalization decisions calibrated to Brazil, we focus on short-run transmission. In particular, we model how monetary shocks propagate through heterogeneous exposure across formal, informal, and unemployed workers, linking these empirically measured exposures to the state of the aggregate economy. This allows us to connect the HANK and informality literatures and to provide a unified view of how monetary policy shapes both aggregate and distributional outcomes in developing economies.

Outline. The rest of the paper is organized as follows. Section 2 describes the estimation of the monetary policy shock series and validates it by presenting monthly impulse-response functions of key economic variables. Section 3 describes the microdata used in the paper. Section 4 presents and discusses the results on labor income growth and its distribution. Section 5 covers the effects of monetary policy shocks on labor market transitions. In Section 6, we discuss our empirical results and interpret them in light of both informality and macroeconomic standard frameworks. Section 7 concludes.

2 Identification Strategy

Assessing the effects of monetary policy on labor market outcomes requires exogenous variation in the monetary policy stance. Our identification strategy proceeds in two steps. First, we estimate high-frequency monetary policy surprises from asset price movements in a narrow window around monetary policy announcements, following Kuttner (2001), Gürkaynak et al. (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018), among others. Second, we use these surprises as external instruments in a proxy-SVAR of the Brazilian economy to recover a structural series of monetary policy shocks, mirroring Olea et al. (2021) and Känzig (2021)'s treatment of oil supply news shock.

2.1 Monetary Policy Surprises

High-frequency identification leverages the significant volume of information disclosed in each monetary policy announcement. The identification hypothesis postulates that, in the immediate period following the public statement, monetary policy news is the primary driver of fluctuations in the prices of interest rate futures contracts. This is due to the assumption that other economic factors are not undergoing systematic or abrupt shifts during this particularly narrow time frame. The starting prices at the beginning of the brief interval already encompass all publicly available information. Consequently, any observed price variations are attributed to an unanticipated change in the interest rate.

The Brazilian Central Bank (BCB)'s Monetary Policy Committee (COPOM) was created in 1996 and sets the policy interest-rate target (Selic). Brazil has operated an inflation-targeting regime since 1999. The National Monetary Council (CMN) sets the inflation target, and the BCB implements policy to achieve it. In 2021, the BCB was granted formal operational autonomy with staggered four-year, non-coincident terms for the governor and directors. Throughout COPOM's existence, debate over political influence has recurred, with news coverage sometimes associating surprise rate cuts with potential pressure on the central bank. This, along with other factors, may lead to monetary policy surprises.[2]

The COPOM convenes every 45 days to establish an interest rate target to reach its inflation objective. Its announcements are made around 7 p.m. local time, after financial markets have closed. We consider price variations of the shortest maturity one-day interbank deposit rate (DI rate) futures contracts to identify the monetary policy surprises.[3] Due to the usual schedule of COPOM meetings, we define the surprises as the difference between the opening price the day after the meeting and the closing price immediately before the announcement.[4] We then aggregate the surprise series to a monthly frequency by summing all events within each month, assigning zero values to months without meetings. The resulting monthly aggregate becomes our external instrument for identifying and estimating the structural monetary policy shock.

Our surprise sample consists of 179 policy events from January 2003 to December 2023. Data about the days of COPOM meetings and interest rates announced come from the Brazilian Central Bank (2024a). The future contract prices are provided by Bloomberg. Figure 1 displays the high-frequency monetary policy surprise series alongside the corresponding policy rate changes.

2.2 Monetary Policy Shocks

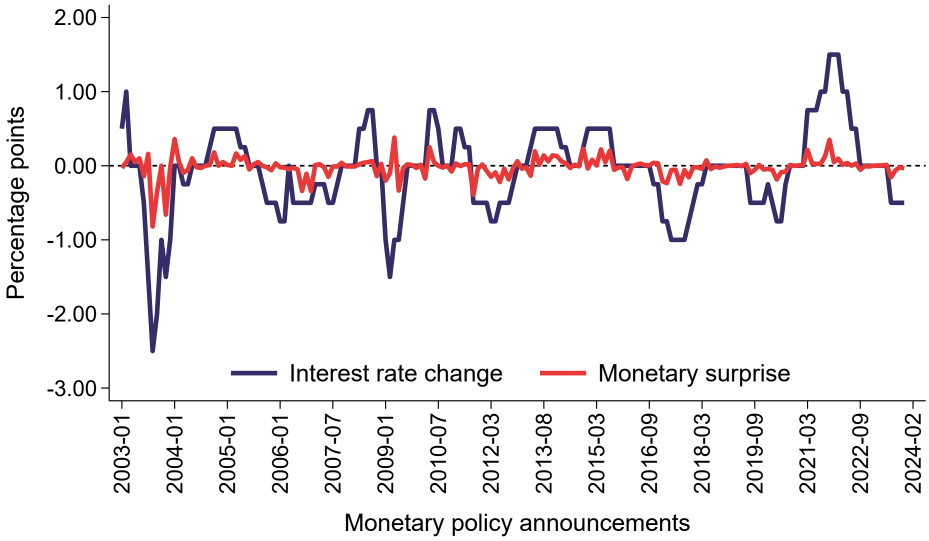
Drawing on the proxy-SVAR approach of Stock and Watson (2012) and Mertens and Ravn (2013), we employ the high-frequency monetary policy surprises as an external instrument in an otherwise standard monthly SVAR model of the Brazilian economy. The presumption is that these surprises are strongly correlated with the unobserved monetary policy innovations yet orthogonal to all other structural disturbances, providing a valid proxy that cleanly identifies

[2]See Minella et al. (2003) for a discussion on the implementation of Brazil's inflation-targeting regime. Cortes and Paiva (2017) and Oliveira and Simon (2023) discuss credibility issues of monetary policy in Brazil.

[3]In Brazil, the DI rate future contracts are used in place of actual repo interest rate (Selic) contracts. The DI rate and Selic are closely related in practice, and market participants view DI future contracts as a representation of the future path of interest rates.

[4]See Appendix A for more details. As a robustness exercise, we implemented an orthogonalization procedure to account for the potential lack of exogeneity of the estimated monetary policy surprises, as noted by Cieslak (2018); Miranda-Agrippino and Ricco (2021); Bauer and Swanson (2021). We find no evidence of this problem in our series, as the orthogonalized version is very close to the original one. Hence, we work with the original monetary policy surprise series for the rest of the paper.

Figure 1: Policy Interest Rate Changes and Monetary Policy Surprises



Note: Estimated series of high-frequency monetary policy surprises and the announced change in the policy interest rate for each COPOM meeting between January 23, 2003, and December 14, 2023.

exogenous monetary policy shocks. Appendix A.2 details the model and its assumptions, and outlines the procedure for recovering the structural monetary policy shocks series from the estimated model.

We estimate the VAR using monthly data for Brazil for the period from January 2003 to December 2023. Our specification considers a parsimonious set of endogenous variables that captures the key transmission channels of monetary policy. Specifically, we include: (i) the Selic interest rate; (ii) the logarithm of the consumer price index, serving as our price measure; (iii) the logarithm of the IBC-Br index, proxying economic activity; (iv) the unemployment rate, reflecting labor market slack; (v) the logarithm of the nominal BRL/USD exchange rate, a key conduit of monetary policy transmission in an open economy like Brazil; and (vi) the credit-to-GDP ratio, summarizing financial conditions.[5]

Following Sims et al. (1990), we estimate the VAR model in levels without explicitly modeling the possible cointegration relations among the variables.[6] We use the Akaike Information

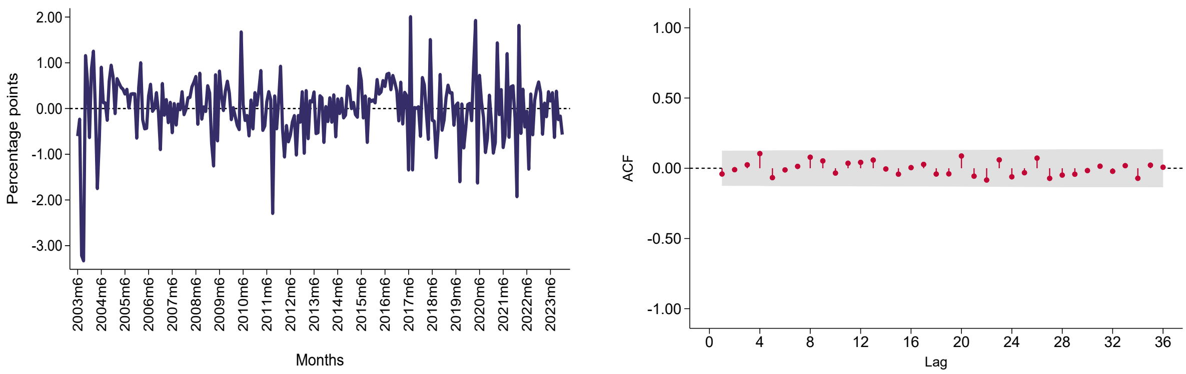
[5]All data are from Brazilian Central Bank (2025b). The interest rate, unemployment rate, and credit-to-GDP ratio are expressed in percentage terms, while the logarithmic variables are multiplied by 100. The Selic interest rate refers to the accumulated monthly rate, expressed on an annualized basis. The consumer price index is the *Índice Nacional de Preços ao Consumidor Amplo* (IPCA), Brazil's official inflation index calculated by the *Instituto Brasileiro de Geografia e Estatística* (IBGE), and is seasonally adjusted in levels. Economic activity is measured by the *Índice de Atividade Econômica do Banco Central* (IBC-Br), the central bank's economic activity index, a monthly proxy for GDP designed to provide more timely information (Brazilian Central Bank, 2025a). We use the seasonally adjusted version of this index. The unemployment rate series is calculated by the Central Bank of Brazil and published in the statistical appendix of its Inflation Report (Brazilian Central Bank, 2024b). It extends the official IBGE series by incorporating earlier survey methodologies to generate a longer historical series. The data are seasonally adjusted and presented as three-month moving averages. The exchange rate corresponds to the monthly average selling rate, expressed in Brazilian reais per U.S. dollar. Lastly, the credit variable is defined as the ratio of total credit granted by the National Financial System to nominal GDP, with the latter calculated as a 12-month rolling sum.

[6]The authors demonstrate that the dynamics of the system can be consistently estimated in a VAR in levels if

Criterion (AIC) to choose the optimal number of lags, which we set to five. Finally, we use the series of monetary policy surprises described in Section 2.1, aggregated to monthly frequency following Gertler and Karadi (2015), as the instrument for the monetary policy shocks. Note that the instrument is powerful in capturing the variation in the reduced form residuals of the policy variable. In fact, the robust F-statistic from the first stage is 19.2, well above the relevant threshold of 10 suggested by Stock and Yogo (2002). Figure 2 plots the series of structural monetary policy shocks recovered from the estimated model and shows that the shocks exhibit no significant autocorrelation, a desirable property that supports their interpretation as exogenous innovations.

Figure 2: Monetary Policy Shocks

(a) Monthly Series (b) Autocorrelation Function

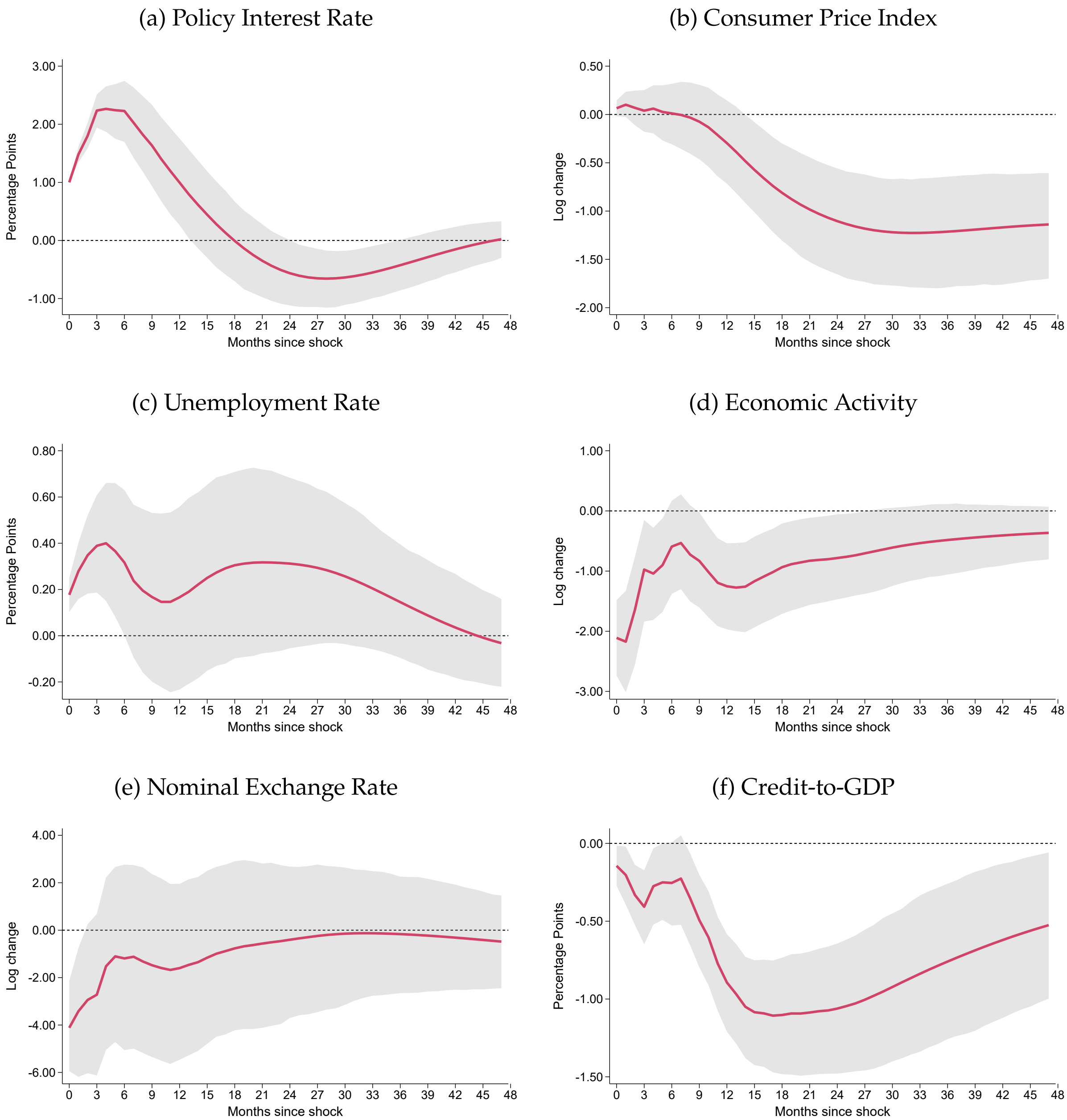


Note: Panel (a) plots the estimated series of the monetary policy shock recovered from the proxy-SVAR for the period 2003-2023. The underlying normalization assumes that a unit structural shock leads to a 0.25 percentage point increase in the policy interest rate. Panel (b) plots the autocorrelation function of the shock up to 36 lags with 95 percent confidence bands.

We next plot the impulse response functions (IRFs) to an instrumented one percentage point increase in the SELIC policy rate to assess the model's dynamic properties and validate its suitability as a sounding device for empirical monetary policy analysis. As shown in Figure 3, the policy rate jumps on impact and then decays over the following months. CPI declines with a lag and remains below baseline. Unemployment rises, but with relatively wide uncertainty bands. Real economic activity contracts sharply on impact and recovers only gradually. The nominal exchange rate appreciates on impact and subsequently mean-reverts (consistent with overshooting). Credit contracts quickly and persistently. Overall, the signs, timing, and persistence of the responses accord well with established economic theory.

cointegration among the variables exists.

Figure 3: Impulse Response Functions to a Monetary Policy Shock



Note: IRFs to an instrumented one percentage point increase in the SELIC policy rate. VAR model estimated in levels, with five lags, and a constant over the period from January 2003 to December 2023. The solid lines and shaded areas report the mean and the 68 percent confidence intervals computed using wild bootstrap with 1,000 replications.

In Sections 4 and 5, we estimate the responses of different labor market outcomes to the identified monetary policy shock series, after aggregating our originally monthly series to a quarterly frequency. In Appendix D.1, we discuss an alternative robustness exercise, where we replicate our main analysis in a reduced-form approach: instead of using the monetary policy shock, we estimate responses to the monetary policy surprise series itself. We also implement a second alternative, using a "smoothed" version of the surprise following Ottonello and Winberry (2020). In both cases, the findings are consistent with our baseline results and reinforce our primary conclusions.

3 Microdata and Sample Selection

To analyze the heterogeneity of individual responses to monetary policy shocks, we use microdata from the quarterly dissemination of *Pesquisa Nacional por Amostra de Domicílios Contínua* (PNADC), a household survey conducted by *Instituto Brasileiro de Geografia e Estatística* (IBGE), which is the agency responsible for the official collection of statistical information in Brazil (IBGE - Instituto Brasileiro de Geografia e Estatística, 2024). The PNADC is a national household survey that covers a wide range of demographic, educational, and labor market topics. A key feature is that it surveys individuals with both formal and informal employment. The survey design follows a rotation scheme known as 1-2(5), where each household is interviewed for five consecutive quarters, with a two-month break between interviews. During the visit, PNADC collects information on all household members. Hence, we can construct a panel dataset that follows the same individual for one year.[7]

Our data spans 32 quarters, from the first quarter of 2012 (the beginning of the PNADC) to the last quarter of 2019, as we restrict our attention to the pre-pandemic period for three reasons. First, the distribution of income innovations in the aftermath of the first pandemic waves and the subsequent recovery deviates significantly from the expansion and recession periods preceding it. This can be seen in Appendix E, which illustrates: (i) a sharp drop and strong rebound in mean and median income innovations by 2022, (ii) a marked decrease in the dispersion of income innovations, (iii) spikes in both left skewness and kurtosis, and (iv) strong shifts in transition rates across employment forms and unemployment. Second, methodological changes in PNADC were implemented during periods of social distancing. Third, multiple job preservation and income transfer programs were introduced, making the aftermath of the pandemic and the immediate recovery highly unusual for labor markets. To avoid confounding the effects of these extraordinary circumstances with those of monetary policy shocks, we exclude data from 2020 onward.

We restrict the sample to workers aged 18-65, excluding employers, unpaid workers, and those with missing income data. Our primary employed sample, used for income growth exercises, further excludes individuals who were initially unemployed (as they have no labor income) and those earning less than half the minimum wage. This employed sample consists of 550,478 individuals in the panel dataset (approximately 19,000 per quarter). For analyses concerning the entire labor force (e.g., employment transitions), we include the unemployed, resulting in a total sample size of 696,662.

An informal worker is defined as someone whose employment is not registered with the country's social security system, thereby lacking compliance with statutory labor rights and obligations. To assess a worker's formality status, we use their report of having an employment record in the *Carteira de Trabalho e Previdência Social* (CTPS), a document issued by the Brazilian

[7] We adopt the methodology implemented by Data Zoom (2025) to explore the panel aspect of the microdata.

Ministry of Labor that is mandatory for all private-sector employment. We also classify as formal workers the individuals employed in the public sector or the armed forces. In turn, informal workers are those without a CTPS entry and those who are self-employed. In our exercises, an individual's formality status is based on their employment situation in the quarter preceding the monetary policy shock event.

Our focus is on net real income growth.[8] Workers report their monthly gross labor income from their primary job. We obtain the value of disposable income by subtracting taxes and social security payments due. The social security contribution rules differ between private/public worker groups, as well as over time. We apply the official rules of the *Instituto Nacional do Seguro Social* (INSS), the Brazilian Social Security Institute, as well as the rules for the autonomous contributor category for informal workers who report contributing.

Formal workers are subject to income taxes, with the tax brackets depending on the nominal monthly income net of social security payments. We deduct imputed taxes from the labor income of formal workers according to the rules of the *Secretaria da Receita Federal do Brasil* (RFB), the Brazilian Internal Revenue Service. For informal workers who are not registered and face no income tax enforcement, we do not adjust their income.[9]

After applying the required discounts to nominal income, we calculate real labor income using the monthly regional inflation price indexes of *Índice Nacional de Preços ao Consumidor Amplo* (IPCA) provided by IBGE. Real earnings are expressed in Reais (R$) of December 2023. Lastly, we account for other pecuniary benefits received annually by formal workers. Brazilian labor legislation entitles formal workers to receive an additional thirteenth salary every year plus one-third of a salary as vacation allowance. We adopt a multiplier of 13.33 when calculating formal workers' annualized income to account for these benefits. For informal workers, we multiply their monthly real earnings by 12 to obtain annual income.

For one-year income growth, we compare real annual income in the first and last quarters in which each individual appears in the panel. Our timing convention sets the monetary policy shock in the second quarter of the worker's survey appearance. Hence, letting t represents the period of the shock, one-year income growth is calculated as the percentage change from $Y_{i,t-1}$ to $Y_{i,t+3}$, where $Y_{i,t}$ represents worker i's annualized real disposable labor income.[10]

4 Impact of Monetary Policy on Labor Income

4.1 Econometric Specification

To estimate how the impact of monetary policy shocks on individual labor income varies across the income distribution, for each quarter t, we sort workers into four groups g corresponding to the income distribution quartiles in $t-1$, the quarter preceding the shock. We then estimate the

[8]As a robustness check, we repeat our main exercises described in the following sections using gross income. The results, available at Appendix D.2, are quantitatively and qualitatively very similar to the net income case.

[9]See Appendix B.2 for more details.

[10]We winsorize the 99th percentile of the income growth distribution to discipline events of atypical income growth.

following equation:

$$\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} = \sum_{g=1}^{4} G_{i,g,t} \left[\alpha_{g,h} + \beta_{g,h} shock_t\right] + \delta_h U_{t-1} + \epsilon_{i,t+h}, \tag{1}$$

where we set $h = 3$ so that the dependent variable is the one-year real disposable income growth expressed as a percentage.[11] $G_{i,g,t}$ is a dummy indicating if worker i belongs to income group g in quarter t. Its interaction with the terms in brackets creates group-specific intercepts $\alpha_{g,h}$ and coefficients $\beta_{g,h}$ capturing the response to the shock for each group. Each $\beta_{g,h}$ measures the one-year income growth for group g associated with a monetary policy shock that leads to a 0.25 percentage point increase in the policy interest rate. We include the quarterly average unemployment rate of the previous quarter, U_{t-1}, to control for overall economic conditions that affect all groups during a given period.

We estimate Equation 1 for two sub-samples of workers. In the first one, we consider only those who were employed in both periods of the one-year window. For the second, we reintroduce the workers who were working initially but were unemployed after one year (and, thus, lost all of their income). The four quartiles are defined separately for each sub-sample. In both cases, we estimate (1) by Ordinary Least Squares (OLS) and calculate bootstraped standard errors with clustering at the time dimension.

The exercise described thus far measures how the conditional mean of labor income growth changes in response to monetary policy shocks for different income level groups. We also explore the heterogeneity across other moments (quantiles) of the conditional income growth distribution.[12] To do this, we employ quantile regressions to estimate the following equation at the 10th, 25th, 50th, 75th, and 90th quantiles:

$$\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} = \alpha_{q,h} + \beta_{q,h} shock_t + \delta_{q,h} U_{t-1} + \epsilon_{q,i,t+h}, \tag{2}$$

where q indicates the selected quantile. We also revisit the analysis of the mean effects that were previously examined, but now without splitting the sample into different income groups. As before, the left-hand side is percentage income growth, U_{t-1} is the quarterly average unemployment rate of the previous period, and $h = 3$. The coefficient of interest, $\beta_{q,h}$, represents the magnitude of the response of the selected quantile of the income growth distribution to a monetary policy shock with a 0.25 percentage point impact. Essentially, this analysis maps out how the conditional distribution of income *growth* responds to a monetary policy shock event.

[11] We choose $h = 3$ as this is the longest horizon available with our microdata. In Appendix D.4, we show impulse responses for average labor income growth considering the other available horizons ($h = 0, 1, 2$). We find increasing impacts as h grows, consistent with the notion that monetary policy takes time to produce its effects.

[12] Here, we work solely with the "employed in both periods" sub-sample.

4.2 Heterogeneous Responses and the Income Distribution

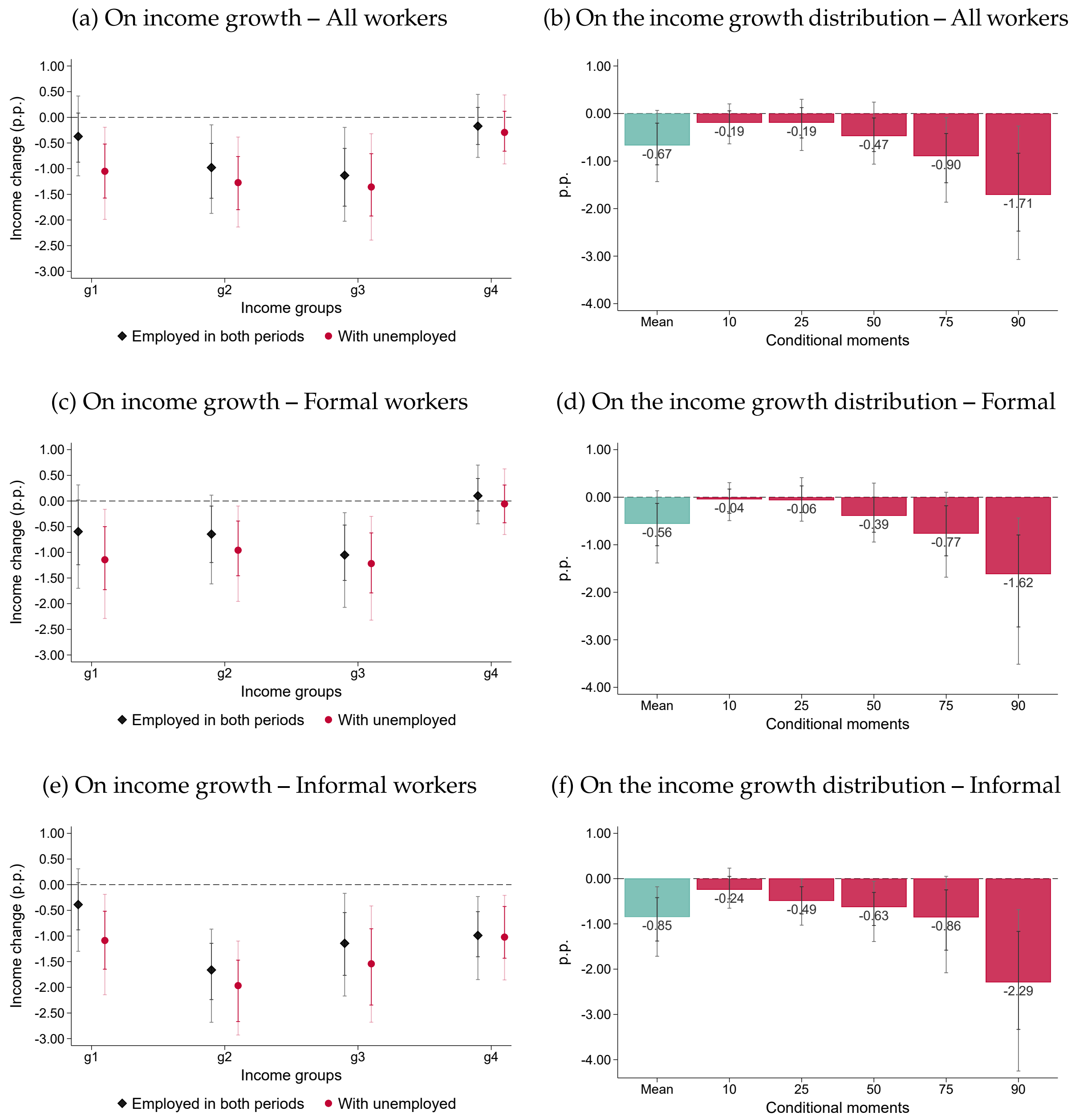
The left column of Figure 4 shows the coefficient estimates $\hat{\beta}_{g,h}$ of Equation 1 for the one-year horizon ($h = 3$), that is, the response of one-year income growth of each group g to a monetary policy shock with a 0.25 percentage point impact on the policy interest rate. The four income groups are displayed along the horizontal axis. The vertical lines represent 68 and 90 percent confidence bands. The figure presents estimates for the two sub-samples of workers: those employed in both periods of the one-year window and those employed in the first period but unemployed in the last one.[13]

Start with Panel (a), which plots the results for all workers. The mean income drop conditional on being employed in the two periods of the one-year window displays a U-shape, with stronger negative responses from the two intermediary groups (−0.98 for group 2 and −1.13 for group 3), while the lowest and highest groups show less variation in their income (−0.37 and −0.17, respectively). However, when we reintroduce those who moved to unemployment, we find that (i) the income drop following the monetary shock is larger for all groups (although only slightly at the highest end of the distribution), and (ii) the magnitude of such a drop for the lowest income group becomes closer to that of the two intermediary groups. This suggests that workers at the left end of the income distribution are particularly affected by a contractionary monetary shock through the extensive margin of employment.

To assess the heterogeneity of the effects between formal and informal workers, we estimate Equation 1 separately for each sector, determined by the worker's formality status in the quarter preceding the monetary policy event. However, the sorting of workers into the income groups is not conditioned on their formality status. Panels (c) and (e) of Figure 4 show the results. Except in the lowest income group, the income decrease following a monetary policy shock is always larger for informal workers. In the second and last quartiles of the income distribution, this difference is larger. In both sectors, as we saw in the overall case, the impact of the shock on the lowest group is significantly amplified when we also consider movements to unemployment. On the other end of the income distribution, however, higher earners seem to be affected almost exclusively through their income, as the estimates for the two sub-samples are very close in each sector. The magnitude of the impact, however, differs by formality status, with formal workers remaining essentially unaffected, while informal workers display income drops close to one percentage point.

[13]See also Table C1 available at Appendix C.

Figure 4: The effects of a monetary policy shock of 0.25 p.p.



Note: Panels (a), (c), and (e) show the mean income responses for the four quartiles of the income distribution to a monetary policy shock with a 0.25 percentage point impact on the policy interest rate when considering, respectively, all workers, formal workers, and informal workers. Panels (b), (d), and (f) display the impact of a monetary policy shock of the same magnitude on the different quantiles of the income growth distribution, once again considering the entire sample of employed workers, those in the formal sector, and those in the informal sector. Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

The right column of Figure 4 presents the results of our second exercise, described by Equation 2. It displays the estimates $\hat{\beta}_{q,h}$, that is, the impact on each given quantile of the income growth distribution of a 0.25 percentage point monetary policy shock. Panel (b) exhibits the results when considering all workers. The estimates $\hat{\beta}_{q,h}$ are all negative: when a 0.25 percentage point shock occurs, the entire income growth distribution shifts leftward. Moreover, the shift in the right tail is larger: while the 10th quantile experiences an income decline of 0.19 percentage points, the 90th quantile declines by 1.71 percentage points. In other words, the right tail of the income growth distribution compresses more, and high-income growth events become less likely in response to the monetary policy shock. The average income growth is reduced by 0.67 percentage points.

Panels (d) and (f) of Figure 4 present the results separately for formal and informal workers. Qualitatively, the pattern is similar in both sectors: all estimates are negative, with the right tail of the income growth distribution exhibiting a stronger response. The magnitude of the responses, however, is larger (more negative) in the informal sector for all percentiles.

In the previous exercises, we treated monetary policy shocks symmetrically, in the sense that a one-unit tightening and a one-unit easing produce identical but sign-reversed responses. This does not need to be the case. We test for potential asymmetric responses by splitting our shock series into its positive and negative components and estimating analogous specifications of Equations (1) and (2) with sign-dummies interactions. This yields two sets of coefficients ($\beta^{(-)}$ for expansionary shocks and $\beta^{(+)}$ for contractionary shocks). The results can be found at Appendix D.3. In our sample, expansionary (negative shock) events yield positive income growth for the different groups and a rightward shift in the distribution of income growth. The responses to contractionary events are closer to zero and often insignificant.

Gomes et al. (2020) demonstrate that transitions between formal and informal employment help explain the asymmetric patterns of income growth based on initial employment status. They also highlight that the cyclical nature of these transitions is crucial for understanding income growth fluctuations during business cycles. For these reasons, we now examine the impact of monetary policy on transitions among formal employment, informal employment, and unemployment.

5 Impact of Monetary Policy on Employment Transitions

In this section, we examine the impact of monetary policy on labor market transitions, including transitions between formal and informal employment and between employment and unemployment. We use a larger dataset that includes both employed and unemployed individuals, without imposing income restrictions, as described in Appendix B.1. We will again focus on one-year transitions, which is the longest period observable in the PNADC data.

We perform two sets of analyses. The first examines transitions between formal and informal employment among individuals employed in both the initial and final periods of the one-year timeframe. The second includes those unemployed in either the initial or final period and examines transitions between unemployment and formal or informal employment.

We construct a set of indicators representing all possible transitions. Once again, our timing notation specifies quarter t as the period of the monetary policy shock, and we compare the employment status of individuals in $t-1$ (initial period) and $t+3$ (final period). For example, the indicator FU_{it} represents the transition from formal employment to unemployment for individual i. This indicator is defined only for individuals in formal employment in the initial period $t-1$. It takes a value of 1 if the individual is unemployed in the final period $t+3$, and 0 if the individual remains in formal employment or moves to informal employment.

We employ a linear probability model to estimate the impact of monetary policy shocks on the likelihood of a specific transition. For each indicator, D_{it}, we estimate the following equation using OLS:

$$D_{it} = \alpha_D + \beta_D shock_t + \delta_D U_{t-1} + \varepsilon_{i,t}. \tag{3}$$

Here, β_D measures the change in the probability of transition D_{it} occurring as a result of a monetary policy shock that leads to 0.25 percentage point increase in the interest rate, given the lagged level of unemployment (U_{t-1}).

Table 1: Transition rates across employment conditions

(a) Conditional on remaining employed

		Final F	Final I
Initial	F	0.90	0.10
	I	0.13	0.87

(b) With unemployment

		Final F	Final I	Final U
Initial	F	0.87	0.09	0.04
	I	0.12	0.82	0.05
	U	0.26	0.36	0.38

Note: Panel (a) displays the one-year transition probabilities between the formal and the informal sectors for workers who were employed in both the initial and the final periods of the one-year window. Panel (b) displays the one-year transition probabilities between the two types of employment and unemployment. Both tables show the average for all the one-year transitions in the 2012-2019 horizon.

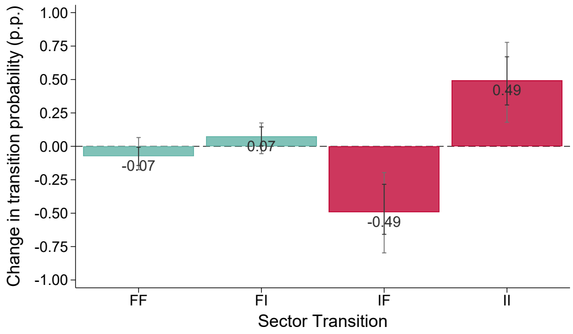
First, we focus on understanding how monetary policy affects transitions in the labor market between different formality statuses (employed in the formal or informal sector). Our analysis is limited to workers employed in both the initial and final periods of a one-year time frame. We use four dummy variables to represent the four possible formal and informal employment transitions: FF, FI, IF, and II. The results are shown in Panel (a) of Figure 5.[14] A monetary policy shock that leads to a 0.25 percentage point increase in the policy interest rate is associated with the probability of each transition changing by $\hat{\beta}_D \times 100$ percentage points, as estimated by OLS.

Monetary policy shocks have a very small impact on individuals who start in the formal sector. For those starting in the informal sector, however, the impact is larger: a 0.49 percentage point increase in the probability of staying informal and a corresponding decrease in the chance of moving to a formal job, rendering informality more persistent. This is a non-trivial effect given that the baseline IF transition rate is 13 percent (see Table 1).

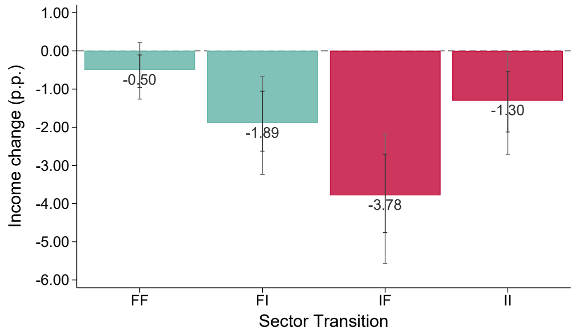
[14]See also Table C3 in Appendix C.

Figure 5: The effects of a 0.25 p.p. monetary policy shock

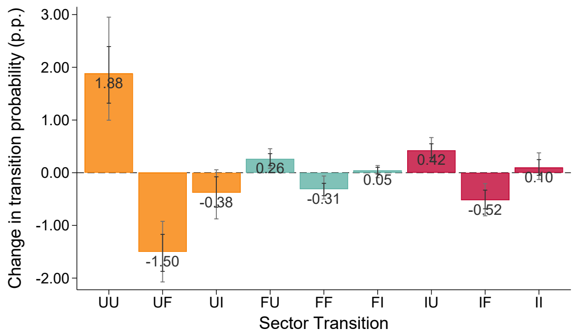
(a) On the probability of employed transitions



(b) On income growth by employment transition



(c) On the probability of all transitions



Note: Panel (a) plots the impact of a 0.25 percentage point monetary policy shock on the probability of each particular one-year transition conditional on being employed in the two limiting periods. Panel (b) shows the income response to the monetary shock for workers who experienced each of the four possible employed transitions. Panel (c) shows the impact of the monetary shock on the probability of transitioning between different employment statuses, including movements to and from unemployment. Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

As this exercise focuses on workers employed in both periods, we can repeat the analysis of the impact of monetary policy on income growth, but now taking into account each specific sector transition. We estimate model (2) using OLS, considering only workers who experienced transition D_{it} during the one-year window. The results are shown in Panel (b) of Figure 5. All groups experience a reduction in their income, with workers transitioning between the formal and the informal sectors facing the largest income drop in response to a monetary policy shock. Those remaining in their original sectors also see a decline, albeit smaller.[15]

Next, we analyze the effect of monetary policy shocks on employment transitions, including the movement to and from unemployment. We categorize individuals into nine possible transitions: FF, FI, FU, IF, II, IU, UF, UI, and UU, where F stands for the formal sector, I for the informal sector, and U for unemployment.[16] We estimate equation (3) by OLS for each

[15] In Appendix D.5, we show how the monetary policy shock affects transition probabilities for employed workers in the four different quartiles of the income distribution. Individuals at the lowest end of the distribution, in both formal and informal jobs, suffer a large increase in their probability of becoming unemployed.

[16] The indicators representing employment in both periods (for example, FF) are not equal to the variables defined

possible transition and report the results for each $\hat{\beta}_D \times 100$ in Panel (c) of Figure 5.[17]

A 0.25 percentage point monetary policy shock leads to a 1.88 percentage point increase in the probability of remaining unemployed and decreases of 1.50 and 0.38 percentage points in the probabilities of moving from unemployment to a formal job and an informal job, respectively. Similarly, for those who begin the period in the informal sector, the 0.25 percentage point shock leads to a 0.52 percentage point drop in the probability of moving to a formal job and an increase in the probability of becoming unemployed. Remaining in a formal job also becomes less likely, with a 0.31 percentage point drop, with unemployment being the most common alternative (0.26 percentage point increase). Again, these are non-trivial changes given the baseline transition rates reported in Table 1.

As with the labor income case, we also perform an additional exercise allowing for asymmetric responses depending on the sign of the monetary policy shock. The complete results, available in Appendix D.3, reveal that the effects of monetary policy on the labor transitions are broadly mirrored, albeit with larger magnitudes for expansionary (negative) shocks. Expansionary shocks provide a significant boost to the labor market, increasing transitions from unemployment to formal employment (UF) by 1.60 percentage points and from informal to formal employment (IF) by 0.83 percentage points. Contractionary shocks primarily act by increasing unemployment persistence (UU) and reducing formal job finding rates from unemployment (UF).

6 Interpreting the Results

This section provides a framework that can be used to interpret the results provided above. The technical details of the framework, including its complete specification, log-linearization, and formal connections to the empirical moments, are provided in Appendix F.

6.1 A Framework for Interpreting the Results

To interpret our empirical findings, we develop a simple framework that accounts for how monetary policy affects income and employment across workers. Following Werning (2015), Alves et al. (2021), and Broer et al. (2022), we build on heterogeneous agent models where workers differ in their sensitivity to aggregate conditions.

Workers vary in their productivity types and employment status (formal, informal, or unemployed) and face two sources of heterogeneity in their exposure to aggregate risk. First, their income exhibits type-specific elasticities to business cycle conditions, as in the incidence function approach of Alves et al. (2021). Second, their employment transition probabilities vary across types, as in the work of Broer et al. (2022). Together, these two dimensions of heterogeneity generate distributional effects of monetary policy.

in the previous paragraphs. This is because now the indicators attribute a value equal to zero to the workers who moved to unemployment. In the previous case, those workers were not included in the estimation.

[17] See also Table C4 in Appendix C.

6.1.1 Key Elements of the Framework

The framework has three main building blocks. First, a standard aggregate New Keynesian block governs aggregate dynamics. It features an IS curve, a Phillips curve, and a Taylor rule that jointly determine how monetary policy shocks affect the output gap. Second, workers face idiosyncratic productivity risk, modeled through a Markov chain that determines transitions across productivity types independently of aggregate conditions. Third, employment transitions between formal work, informal work, and unemployment respond to the output gap.

The cyclical sensitivity of employment transitions is the key mechanism linking monetary policy to labor market flows. When the output gap turns negative following a contractionary shock, transitions to formal employment become less frequent while unemployment and informality become more persistent. This mechanism is consistent with our empirical evidence, which shows that unexpected monetary policy contractions reduce formal job-finding rates and increase the duration of unemployment and informality spells.

Individual income for employed workers in sector $e \in \{f, i\}$ with productivity type s follows:

$$\log y_t(s, e) = \log \overline{y}(s, e) + \gamma_{(s,e)} x_t, \tag{4}$$

where $\overline{y}(s, e)$ is steady-state income, x_t is the output gap, and $\gamma_{(s,e)} > 0$ captures the income elasticity to aggregate conditions. Higher values of $\gamma_{(s,e)}$ indicate greater cyclical sensitivity. The heterogeneity in these elasticities across worker types generates differential income responses to monetary shocks.

Employment transition probabilities are given by:

$$\lambda_{ee',t} = \overline{\lambda}_{ee'} + \eta_{ee'} x_t, \tag{5}$$

where e and e' denote origin and destination employment states, $\overline{\lambda}_{ee'}$ are steady-state transition rates, and $\eta_{ee'}$ captures cyclical sensitivity. The constraint that probabilities sum to one implies $\sum_{e'} \eta_{ee'} = 0$. Our estimates suggest $\eta_{uf} > 0$ and $\eta_{if} > 0$ (transitions to formal employment decline in downturns) and $\eta_{uu} < 0$ and $\eta_{ii} < 0$ (unemployment and informality become more persistent).

This specification connects naturally to our local projection estimates, which measure linear responses to monetary policy shocks. The framework is local in nature, valid for small fluctuations around the steady state, matching the empirical approach we employ.

6.1.2 Connecting the Framework to Our Findings

The framework helps organize our main empirical results. The income responses we document in Section 4 reflect two channels. First, the direct exposure channel operates through the income elasticities $\gamma_{(s,e)}$: when the output gap falls, workers' incomes decline proportionally to their elasticities. Second, the composition channel works through changing employment transitions: workers who would have moved to better jobs (with higher steady-state income) are less likely to do so, and some workers transition to unemployment or informality.

The transition dynamics documented in Section 5 map directly to the parameters $\eta_{ee'}$ in equation (5). Our finding that contractionary shocks reduce transitions from unemployment and informality to formal employment ($\eta_{uf} > 0$, $\eta_{if} > 0$) while increasing persistence in unemployment and informality ($\eta_{uu} < 0$, $\eta_{ii} < 0$) provides direct evidence that employment transitions respond cyclically to monetary policy.

The quantile regression results, which show that high-income growth events become less frequent following contractionary shocks, can be understood through both channels. Workers with high income elasticities experience larger drops in their current income. Additionally, the reduction in favorable employment transitions means fewer workers experience the income gains associated with moving to better jobs. This truncation of the right tail of the income growth distribution is a natural consequence of the cyclical behavior of employment transitions.

Finally, the framework accounts for results that are broadly similar for formal and informal workers. Both sectors respond to the same aggregate output gap through their respective income elasticities, and both experience cyclical changes in transition rates. The similarity in responses suggests that $\gamma_{(s,f)}$ and $\gamma_{(s,i)}$ do not differ substantially, and that transitions between sectors are sufficiently frequent that both groups face comparable exposure to aggregate fluctuations. This interpretation is consistent with evidence that transitions between formal and informal work are common, as we discuss in the next section.

6.2 Discussion and Policy Implications

Labor Market Integration and Worker Mobility. The results above suggest that monetary policy affects formal and informal workers in similar ways. Changes in the policy rate alter income growth and employment transitions across both groups, with contractionary shocks leading to higher unemployment and greater persistence in informality. At the same time, such shocks induce movements of workers between formal and informal employment, indicating that these markets are fluid and interconnected.

This fluidity challenges the view that Brazil's labor market is deeply segmented into distinct formal and informal sectors, as argued by Botelho and Ponczek (2011). Instead, our results align more closely with recent evidence that emphasizes high mobility across sectors and similar worker characteristics within them (Gomes et al., 2020; Aristizábal-Ramírez et al., 2025).

The finding that monetary policy shocks trigger sectoral reallocation is consistent with the idea that the formal and informal sectors share a large common pool of workers. In the data, transitions between sectors are frequent—roughly 15 percent of workers change status annually (Gomes et al., 2020). Moreover, these transitions—especially those into and out of unemployment—are strongly cyclical: during downturns, workers are more likely to move from unemployment into informality and less likely to enter formal jobs. This cyclical reallocation pattern helps explain why our estimated responses display both higher informality persistence and weaker formal job creation following contractionary monetary shocks.

These patterns are also consistent with micro evidence showing that, within firms, formal and informal workers perform similar tasks and exhibit comparable characteristics. Using matched employer–employee data, Ulyssea (2018) finds that formal and informal workers receive similar salaries once he controls for firm fixed effects in a Mincerian wage regression. Brotherhood et al. (2025) show that Brazilian firms of all sizes employ both formal and informal workers, often very similar in terms of age, education, and gender composition. This coexistence within firms suggests that informality is not necessarily a distinct labor market segment but a flexible margin of adjustment that firms use to manage regulatory and economic shocks. These micro-level patterns help explain why monetary shocks produce similar income effects across sectors.

Transmission Mechanisms. Formal and informal workers experience comparable income responses to monetary policy shocks—a pattern that reflects multiple transmission channels operating simultaneously. Credit conditions, aggregate demand exposure, and cost adjustments affect both sectors. Although individual channels may operate with different intensities across formal and informal employment, their combined effects produce similar net impacts on worker incomes. This similarity is sustained by high labor mobility: workers move between sectors to dissipate large wage differentials, preventing persistent income divergences. When monetary policy contractions reduce formal job availability, workers shift to informal employment rather than remaining unemployed, with informality serving as a buffer. The increased informality persistence we document thus reflects workers' responses to changing macroeconomic conditions.

These patterns challenge dual labor market models where formal and informal sectors operate as disconnected markets. Our evidence instead points to integrated labor markets responding to aggregate shocks through comparable elasticities.[18] Rather than insulating the economy from monetary policy shocks, the informal sector transmits them in parallel with the formal sector, ensuring broad propagation across the labor market.

Policy Implications. What do these findings imply for policy design? First, informal workers are not insulated from monetary policy changes. Because policy affects a broader share of the population, both the benefits of expansionary policy and the costs of disinflation are amplified. Second, contractionary shocks generate persistent effects by reducing job-finding rates and increasing unemployment duration. These transition dynamics imply larger distributional impacts over longer horizons, as reduced transition rates generate cumulative losses. Third, standard unemployment metrics may understate policy effects when workers shift between employment types rather than moving between employment and unemployment.

In sum, monetary policy has meaningful and persistent effects on labor markets in developing economies. The integration of formal and informal labor markets means monetary policy shocks propagate broadly, while endogenous employment transitions amplify and extend these effects over time.

[18] Related discussions in Alberola and Urrutia (2020) and Ospina (2023) show how informal labor markets influence monetary policy transmission and design.

7 Concluding Remarks

This paper documents the distributional effects of monetary policy on labor income growth and employment transitions in Brazil, a developing economy where informality is widespread. We find that contractionary monetary policy shocks lead to a contraction of labor income growth for both formal and informal workers. The income drop is more pronounced for workers in the low and middle-income groups, with a real income drop of up to 1.4 percent in response to a 0.25 percentage point increase in the policy interest rate. Moreover, the high-frequency identification approach used to construct monetary policy shocks for Brazil demonstrates that these shocks lead to significant changes in the distribution of income growth. An unexpected increase in the policy interest rate shifts the income growth distribution to the left, with a more pronounced shift in the right tail, indicating a reduction in high-income growth events. This effect is more noticeable among informal workers than formal workers.

Furthermore, monetary policy contractions increase the persistence of informality and unemployment. Both unemployed and informal-sector workers are less likely to transition to formal employment following a contractionary shock, thus making unemployment and informality more persistent states as a result. These findings highlight that monetary policy has substantial implications for labor market flows.

Our study provides insights into the heterogeneous effects of monetary policy in a developing economy with a significant informal sector. Policymakers must consider these distributional impacts when designing and implementing monetary policy to mitigate adverse effects on vulnerable groups and support overall economic stability and growth. Future research should continue to explore these dynamics, particularly in the context of ongoing economic challenges and structural changes.

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Appendix for "Monetary Policy and Labor Markets in a Developing Economy"

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A Estimation Details – Monetary Policy Events

A.1 Monetary Policy Surprises

In this appendix, we detail the estimation process for our monetary policy surprises. As described in the text, the surprise corresponds to the price variation of the shortest maturity future contract for the DI rate between the opening prices the day after the announcement and the closing prices before the announcement. We work with the `OD1 Comdty` security from Bloomberg. It automatically updates the prevailing contract as time passes and older futures reach maturity. Some details need to be taken into consideration:

1. We identified a few contradictions between the summary table of COPOM meetings and the official minutes of each meeting regarding the dates of some of the events.[19] We use the minutes as the correct information. They also show that, before 2004, some meetings finished while financial markets were still open. Therefore, we can't be sure that the announcement was made only after market closing. For those dates (listed below), we adjusted our surprise definition. Instead of comparing opening prices in $t + 1$ to closing prices in t, we measure the price change between opening prices in $t+1$ and opening prices in t. This ensures we capture the moment of the monetary policy decision announcement.

Day of the meeting	
04/Mar/1999	18/Dec/2002
23/Aug/2000	22/Jan/2003
22/May/2002	19/Feb/2003
19/Jun/2002	19/Mar/2003
17/Jul/2002	23/Apr/2003
21/Aug/2002	21/May/2003
18/Sep/2002	18/Jun/2003
14/Oct/2002	23/Jul/2003
23/Oct/2002	20/Aug/2003
20/Nov/2002	14/Apr/2004

2. A few meetings took place on the eve of a holiday, which means that financial markets were not open the next day. For these events (listed below), we use the next business day opening prices when calculating our monetary surprise.

[19] The summary table is available at Brazilian Central Bank (2024a). The official minutes for the meetings are available at Brazilian Central Bank (2024c).

Day of the meeting	Next business day
18/Jun/2003	20/Jun/2003
24/Jan/2007	26/Jan/2007
06/Jun/2007	08/Jun/2007
10/Jun/2009	12/Jun/2009
20/Apr/2011	Removed[20]
29/May/2013	31/May/2013
03/Jun/2015	05/Jun/2015

3. Finally, one needs to be careful about meetings that have happened on the last business day of the month. On these dates, the underlying future contract of the OD1 Comty security expires on the day of the meeting. This means that the opening prices the next day will correspond to those of a different contract. Hence, the correct measure for the monetary surprise is obtained by comparing opening prices for the OD1 Comdy in $t + 1$ and closing prices for the OD2 Comdty in t to measure the price change of the same underlying contract following a monetary policy announcement. The dates of the meetings affected by this concern are shown below.

Day of the meeting
31/May/2006
31/Aug/2011
30/Nov/2011
31/Aug/2016
30/Nov/2016
31/May/2017
31/Oct/2018
31/Jul/2019

The issue of lack of exogeneity in surprises obtained from high-frequency identification has been raised by several studies (Cieslak, 2018; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2021). These studies demonstrate that high-frequency future contract price changes can sometimes be predicted using information available before the announcement. To address this concern, we perform a robustness test inspired by the approach proposed by Bauer and Swanson (2022) and construct a monetary policy surprise that is orthogonal to the available information. We regress the change in future prices against a set of market expectation variables collected earlier on the day of each announcement. Due to the large number of potential controls, we use a ridge regression shrinkage estimator to obtain the residual, which we define as the orthogonal monetary policy surprise series. This set of market expectations is available for the time frame from November 2001 to August 2021, which restricts our orthogonal monetary

[20] Holiday followed by a weekend.

surprise series. We set the shrinkage penalty by k-fold cross-validation. The resulting orthogonal surprise is almost indistinguishable from our original monetary surprise: for the overlapping horizon of the two series (2001-2021), the correlation between them is 0.99. It indicates that the lack of exogeneity of surprises identified using high-frequency methods is not present in our setting. Hence, in the paper, we adopt the original surprise, as it allows us to cover a larger horizon when estimating the Proxy-SVAR. The orthogonal alternative is available upon request.

A.2 Monetary Policy Shocks

Consider the following monthly reduced-form VAR(p) model of the Brazilian economy:

$$\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{B}_p \mathbf{y}_{t-p} + \mathbf{u}_t, \tag{A1}$$

where p is the lag order, t is the month-year pair, $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables, $\mathbf{u}_t$ is an $n \times 1$ vector of reduced-form innovations, $\mathbf{b}$ is an $n \times 1$ vector of constants, and $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices. The covariance matrix of the reduced-form innovations is time invariant and denoted by $\mathrm{var}(\mathbf{u}_t) = \mathbf{\Sigma}$.

We assume that the reduced-form innovations are related to the structural shocks via the linear mapping

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t, \tag{A2}$$

where $\mathbf{S}$ is a nonsingular $n \times n$ structural impact matrix and $\boldsymbol{\varepsilon}_t$ is an $n \times 1$ vector of structural shocks. By definition, the structural shocks are mutually uncorrelated, that is, $\mathrm{var}(\boldsymbol{\varepsilon}_t) = \mathbf{\Omega}$ is diagonal. Therefore, from the linear mapping of the shocks, we have that

$$\mathbf{\Sigma} = \mathbf{S}\mathbf{\Omega}\mathbf{S}'. \tag{A3}$$

Without loss of generality, we denote the monetary policy shock as the first shock in the VAR model, that is, $\varepsilon_{1,t}$.

Using the external instruments approach, we can identify the structural impact vector associated with the monetary policy shock, represented by the first column of matrix $\mathbf{S}$. Let z_t denote the monthly external instrument available, which in our case is the high-frequency monetary policy surprise series. For z_t to be a valid instrument, we need the following:

$$E[z_t \varepsilon_{1,t}] = \alpha \neq 0, \tag{A4}$$

$$E[z_t \varepsilon_{i,t}] = 0 \quad \text{for } i \neq 1. \tag{A5}$$

Assumption (A4) is the relevance requirement and assumption (A5) is the exogeneity condition. Under these assumptions, the impact vector associated to the monetary policy shock, denoted by $\mathbf{s}_1$, can be identified up to sign and scale as follows:

$$\mathbf{s}_1 = \frac{E[\mathbf{u}_t z_t]}{\alpha}. \tag{A6}$$

Given the dependency of $\mathbf{s}_1$ on the unobserved scalar α, a normalization procedure is required. To facilitate interpretation, we assume that a unit positive value of the monetary policy shock $\varepsilon_{1,t}$ has a positive effect of magnitude x on the policy interest rate $y_{1,t}$.[21] Technically, this means that $s_{1,1} = x$, where $s_{1,1}$ is the first element of the vector $\mathbf{s}_1$. From (A6), it holds that

$$\frac{E[u_{i,t}z_t]}{E[u_{1,t}z_t]} = \frac{\alpha s_{1,i}}{\alpha s_{1,1}} = \frac{s_{1,i}}{x} \quad \text{for } i \neq 1, \tag{A7}$$

where the scalars $s_{1,i}$ represent the other elements of vector $\mathbf{s}_1$. Note that equation (A7) is the population estimand of the IV-regression of each reduced-form residual $u_{i,t}$ on the residual associated with the monetary policy shock $u_{1,t}$ using z_t as an instrument. Therefore, estimating each $s_{1,i}$ with 2SLS regressions fully identifies the vector $\mathbf{s}_1$, enabling us to recover the monetary policy shock's impact on all endogenous variables.

After obtaining the impact vector $\mathbf{s}_1$, it is straightforward to compute other objects of interest, such as impulse-response functions and the structural monetary policy shock series. To calculate the shock series, first define $\mathbf{e}$ as the $n \times 1$ standard basis vector (i.e., the first element equals 1 and the others equal zero). Then, from the linear mapping assumption (A2), we have that

$$\varepsilon_{1,t} = \mathbf{e}'\boldsymbol{\varepsilon}_t = \mathbf{e}'\mathbf{S}^{-1}\mathbf{u}_t. \tag{A8}$$

Next, we must eliminate $\mathbf{S}^{-1}$ from the shock's formula as it is not identifiable in our setup (we only identify $\mathbf{s}_1$). To do so, define ω_1^2 as the first entry of matrix $\boldsymbol{\Omega}$, that is, the variance of $\varepsilon_{1,t}$. Note that, since $\boldsymbol{\Omega}$ is diagonal, we have that $[(1/\omega_1^2)\mathbf{e}] = \boldsymbol{\Omega}^{-1}\mathbf{e}$ and $(1/\omega_1^2) = \mathbf{e}'\boldsymbol{\Omega}^{-1}\mathbf{e}$. Then, after multiplying and dividing the shock by $(1/\omega_1^2)$, we can write it as

$$\varepsilon_{1,t} = \frac{[(1/\omega_1^2)\mathbf{e}]'\mathbf{S}^{-1}\mathbf{u}_t}{(1/\omega_1^2)} = \frac{[\boldsymbol{\Omega}^{-1}\mathbf{e}]'\mathbf{S}^{-1}\mathbf{u}_t}{\mathbf{e}'\boldsymbol{\Omega}^{-1}\mathbf{e}} = \frac{\mathbf{e}'\boldsymbol{\Omega}^{-1}\mathbf{S}^{-1}\mathbf{u}_t}{\mathbf{e}'\boldsymbol{\Omega}^{-1}\mathbf{e}}. \tag{A9}$$

Note also that, since $\mathbf{s}_1$ is the first column of $\mathbf{S}$, we can write it as $\mathbf{s}_1 = \mathbf{S}\mathbf{e}$, which implies that $\mathbf{e} = \mathbf{S}^{-1}\mathbf{s}_1$. Then, we can update the shock's formula as

$$\varepsilon_{1,t} = \frac{\mathbf{s}_1'\mathbf{S}'^{-1}\boldsymbol{\Omega}^{-1}\mathbf{S}^{-1}\mathbf{u}_t}{\mathbf{s}_1'\mathbf{S}'^{-1}\boldsymbol{\Omega}^{-1}\mathbf{S}^{-1}\mathbf{s}_1} = \frac{\mathbf{s}_1'(\mathbf{S}\boldsymbol{\Omega}\mathbf{S}')^{-1}\mathbf{u}_t}{\mathbf{s}_1'(\mathbf{S}\boldsymbol{\Omega}\mathbf{S}')^{-1}\mathbf{s}_1} = \frac{\mathbf{s}_1'\boldsymbol{\Sigma}^{-1}\mathbf{u}_t}{\mathbf{s}_1'\boldsymbol{\Sigma}^{-1}\mathbf{s}_1}, \tag{A10}$$

where the second equality relies on the nonsingularity of $\mathbf{S}$ and the third equality comes from equation (A3). Note that the right-hand side of the above result can be entirely estimated, allowing the shock to be fully identified.

[21] Känzig (2021) adopted a similar approach in the context of oil supply news shocks.

B Data

B.1 Sample Restrictions

Table B1 describes the sample restrictions applied to the microdata and the resulting number of observations dropped.

Table B1: Sample Restrictions

	Income Growth		Transition	
	Δ	N	Δ	N
Original number of observations (individual-quarter)		18,088,581		18,088,581
Drop missing values				
Year	0	18,088,581	0	18,088,581
Quarter	0	18,088,581	0	18,088,581
Gender	0	18,088,581	0	18,088,581
Age	0	18,088,581	0	18,088,581
Individual id	-1,368,997	16,719,584	-1,368,997	16,719,584
Labor force indicator	-3,456,172	13,263,412	-3,456,172	13,263,412
Age Selection				
Keep age between 18 and 65 years	-2,649,892	10,613,520	-2,649,892	10,613,520
Employer				
Drop if occupation is employer (8)	-269,918	10,343,602	-269,918	10,343,602
Employees that work for no money				
Drop if no monetary compensation (10)	-248,447	10,095,155	-248,447	10,095,155
Missing income				
Drop employees with missing income	-27,776	10,067,379	-27,776	10,067,379
Less than 1/2 minimum wage				
Drop employees with income <1/2 min wage	-741,149	9,326,230	-	-
Repeated id in same quarter				
Drop if same id appears more than once	0	9,326,230	0	10,067,379
Panel Structure – Unique Individuals				
Employed in both periods		**527,379**		-
Formal sector		327,541		-
Informal sector		199,838		-
Employed in the first period		**550,478**		-
Formal sector		340,433		-
Informal sector		210,045		-
In the labor force in both periods		-		**696,662**

Note: The table shows the number of observations (individual-quarter) dropped with each restriction applied (under columns Δ) and the size of the remaining sample (under columns N) when aggregating all quarters. The bottom part of the table shows the number of unique individuals in the panel, that is, the number of workers who appear in the survey in quarters one year apart.

Next, Table B2 presents some descriptive statistics on the resulting "Income Growth" sample.

Our analysis in the text performs two sets of exercises with this sample: one considering only workers who were employed in both the initial and final periods of the one-year window, and one also including individuals who were initially employed but were unemployed after one year. The four income quartiles are defined separately for each of these two sub-samples.

Table B2: Descriptive Statistics of the Income Growth Sample

	All	By income groups			
		q1	q2	q3	q4
Employed in both periods					
N	527,379	132,884	131,189	131,862	131,444
% male	60.0%	53.1%	55.5%	66.0%	65.6%
% informal	36.5%	55.9%	31.5%	30.7%	28.3%
% informal (t-1)	37.9%	60.1%	31.9%	30.9%	28.5%
mean age	39.41	38.57	37.65	39.36	42.04
mean real net income	33,084.59	15,804.20	20,414.74	28,738.81	66,302.09
median real net income	22,711.21	14,906.98	18,863.54	27,058.03	50,869.21
Employed in the first period					
N	550,478	138,007	137,503	137,736	137,232
% male	60.0%	53.1%	55.3%	66.0%	65.7%
% informal	36.6%	56.8%	31.4%	30.6%	28.4%
% informal (t-1)	38.2%	61.4%	31.8%	30.7%	28.6%
mean age	39.18	38.25	37.37	39.18	41.95
mean real net income	32,766.59	15,730.94	20,178.47	28,352.30	65,361.05
median real net income	22,532.51	14,872.26	18,634.30	26,696.19	50,072.21

Note: real income is measured in 2023-Q4 Brazilian Reais (R$).

Including those who were out of a job at the end of the one-year window leads to a slight increase in the share of initially informal workers and to small decreases in the average worker's age and income.

Table B3 shows descriptive statistics of one-year real disposable income (percentage) growth for our "employed in both periods" panel after winsorizing the right tail of the distribution at the 99th percentile. The winsorized distribution still presents positive skewness, with its mean and median differing even in sign.

Table B3: One-year growth of real disposable income

Percentiles		Smallest		
1%	-68.41	-98.77		
5%	-47.32	-98.07		
10%	-34.56	-98.07		
25%	-12.65	-97.57	**Obs.**	527,379
50%	-0.99		**Mean**	6.95
		Largest		
75%	17.35	204.11	**Std. Dev.**	42.68
90%	53.62	204.11	**Variance**	1,822.00
95%	88.95	204.11	**Skewness**	1.91
99%	204.10	204.11	**Kurtosis**	8.84

Note: real income is measured in 2023-Q4 Brazilian Reais (R$). Growth expressed in percentage points. Values correspond to the "employed in both periods" sample of workers after winsorizing the right tail of the distribution at the 99th percentile.

B.2 Social Security and Income Tax Schedules

This appendix provides the income tax and social security schedules used to calculate net income, as described in Section 3.

Table B4: Income tax schedules

Year	Wage Base (R$)	Rate (%)	Deduction (R$)
2023	up to 2,112.00	-	-
May+	2,112.01 to 2,826.65	7.5	158.4
	2,826.66 to 3,751.05	15.0	370.4
	3,751.06 to 4,664.68	22.5	651.73
	above 4,664.68	27.5	884.96
2015-Apr to	up to 1,903.98	-	-
2023-Apr	1,903.99 to 2,826.65	7.5	142.80
	2,826.66 to 3,751.05	15.0	354.80
	3,751.06 to 4,664.68	22.5	636.13
	above 4,664.68	27.5	869.36
2015	up to 1,787.77	-	-
Jan-Mar	1,787.78 to 2,679.29	7.5	134.08
	2,679.30 to 3,572.43	15.0	335.03
	3,572.44 to 4,463.81	22.5	602.96
	above 4,463.81	27.5	826.15
2014	up to 1,787.77	-	-
	1,787.78 to 2,679.29	7.5	134.08
	2,679.30 to 3,572.43	15.0	335.03
	3,572.44 to 4,463.81	22.5	602.96
	above 4,463.81	27.5	826.15
2013	up to 1,710.78	-	-
	1,710.79 to 2,563.91	7.5	128.31
	2,563.92 to 3,418.59	15.0	320.60
	3,418.60 to 4,271.59	22.5	577.00
	above 4,271.59	27.5	790.58
2012	up to 1,637.11	-	-
	1,637.12 to 2,453.50	7.5	122.78
	2,453.51 to 3,271.38	15.0	306.80
	3,271.39 to 4,087.65	22.5	552.15
	above 4,087.65	27.5	756.53

Note: The source of the information presented in this table is the official website of RFB: https://www.gov.br/receitafederal/pt-br/assuntos/meu-imposto-de-renda/tabelas.

Table B5: Social security contribution schedules

Year	Wage Base (R$)	Rate (%)	Year	Wage Base (R$)	Rate (%)
2023	up to 1,320.00	7.5	2019	up to 1,751.81	8.0
May+	1,320.01 to 2,571.29	9.0		1,751.82 to 2,919.72	9.0
	2,571.30 to 3,856.94	12.0		2,919.73 to 5,839.45	11.0
	3,856.95 to 7,507.49	14.0	2018	up to 1,693.72	8.0
2023	up to 1,302.00	7.5		1,693.73 to 2,822.90	9.0
Jan-Apr	1,302.01 to 2,571.29	9.0		2,822.91 to 5,645.80	11.0
	2,571.30 to 3,856.94	12.0	2017	up to 1,659.38	8.0
	3,856.95 to 7,507.49	14.0		1,659.39 to 2,765.66	9.0
2022	up to 1,212.00	7.5		2,765.67 to 5,531.31	11.0
	1,212.01 to 2,427.35	9.0	2016	up to 1,556.94	8.0
	2,427.36 to 3,641.03	12.0		1,556.95 to 2,594.92	9.0
	3,641.04 to 7,087.22	14.0		2,594.93 to 5,189.82	11.0
2021	up to 1,100.00	7.5	2015	up to 1,399.12	8.0
	1,100.01 to 2,203.48	9.0		1,399.13 to 2,331.88	9.0
	2,203.49 to 3,305.22	12.0		2,331.89 to 4,663.75	11.0
	3,305.23 to 6,433.57	14.0	2014	up to 1,317.07	8.0
2020	up to 1,045.00	8.0		1,317.08 to 2,195.12	9.0
Mar+	1,045.01 to 2,089.60	9.0		2,195.13 to 4,390.24	11.0
	2,089.61 to 3,134.40	12.0	2013	up to 1,247.70	8.0
	3,134.41 to 6,101.06	14.0		1,247.71 to 2,079.50	9.0
2020	up to 1,830.29	8.0		2,079.51 to 4,159.00	11.0
Jan-Fev	1,830.30 to 3,050.52	9.0	2012	up to 1,174.86	8.0
	3,050.53 to 6,101.06	11.0		1,174.87 to 1,958.10	9.0
				1,958.11 to 3,916.20	11.0

Note: Public employees and the military have a fixed contribution rate of 11%. The rate for autonomous contributions is 20%, and the wage base must be at least the minimum wage. Informal workers can decide the wage base value they declare when paying for Social Security. We don't observe this information in our data. We chose to deduct 20% of the minimum wage for informal workers who contribute autonomously if their earnings are equal or higher to the minimum wage. For those who affirm to contribute but have gross income smaller than the minimum wage, we deduct 5% of the minimum wage (the "low income facultative contribution" scheme). The source of the information presented is the official website of INSS: https://www.gov.br/inss/pt-br/direitos-e-deveres/inscricao-e-contribuicao/tabela-de-contribuicao-mensal/tabela-de-contribuicao-historico.

C Results Tables

Table C1: The effects of a monetary policy shock of 0.25 p.p. on income growth

	Employed in both periods			With unemployed		
Income Group	All	Formal	Informal	All	Formal	Informal
G1	-0.372	-0.596	-0.388	-1.051	-1.144	-1.087
	(0.484)	(0.626)	(0.471)	(0.550)	(0.641)	(0.609)
G2	-0.978	-0.645	-1.661	-1.271	-0.958	-1.967
	(0.543)	(0.556)	(0.573)	(0.538)	(0.563)	(0.585)
G3	-1.131	-1.051	-1.142	-1.357	-1.219	-1.542
	(0.577)	(0.557)	(0.625)	(0.627)	(0.608)	(0.751)
G4	-0.171	0.101	-0.989	-0.293	-0.055	-1.021
	(0.371)	(0.328)	(0.455)	(0.419)	(0.377)	(0.501)
N	527,379	327,541	199,838	550,478	340,433	210,045

Table C2: The effects of a monetary policy shock of 0.25 p.p. on the income growth distribution

Conditional moment	All Workers	Formal Workers	Informal Workers
Mean	-0.667	-0.557	-0.850
	(0.460)	(0.456)	(0.480)
10 Quantile	-0.195	-0.041	-0.244
	(0.269)	(0.253)	(0.277)
25 Quantile	-0.190	-0.065	-0.493
	(0.332)	(0.283)	(0.321)
50 Quantile	-0.471	-0.393	-0.627
	(0.393)	(0.386)	(0.381)
75 Quantile	-0.895	-0.766	-0.856
	(0.535)	(0.560)	(0.650)
90 Quantile	-1.709	-1.616	-2.291
	(0.855)	(0.926)	(1.135)
N	527,379	327,541	199,838

Table C3: The effects of a monetary policy shock of 0.25 p.p. on employed transitions

	FF	FI	IF	II
Transition	-0.074	0.074	-0.492	0.492
	(0.071)	(0.075)	(0.182)	(0.186)
N	331,699	331,699	285,447	285,447
Income	-0.504	-1.890	-3.784	-1.298
	(0.437)	(0.794)	(1.078)	(0.762)
N	299,636	32,063	36,570	248,877

Table C4: The effects of a monetary policy shock of 0.25 p.p. on all transitions

Transition	Response	N
UF	-1.503 (0.361)	49,980
UI	-0.379 (0.303)	49,980
UU	1.882 (0.562)	49,980
FF	-0.310 (0.124)	344,814
FI	0.045 (0.066)	344,814
FU	0.264 (0.118)	344,814
IF	-0.521 (0.183)	301,868
II	0.097 (0.156)	301,868
IU	0.425 (0.137)	301,868

D Robustness

D.1 Monetary Surprises in Reduced-Form

In the main text, we describe how we obtain a sequence of monetary policy surprises by adopting high-frequency identification. We then employ this series as an instrument of exogenous variation in monetary policy to recover monetary shocks from a proxy-SVAR. Our main results consist of estimating the income and employment transition responses to those shocks. In this appendix, we present a robustness exercise in which we estimate the microdata responses to the monetary surprise itself (the instrument), providing a "reduced-form" alternative to our main exercises. Figure D1 displays the results for the entire sample of workers (both formal and informal sectors). The lessons of the paper remain. Unanticipated increases in the interest rate lead to labor income falling for all quartiles of the income distribution (Panel a). In this reduced-form approach, the magnitude of income reductions for the two intermediary groups is similar to that observed in our baseline. We now find greater drops for both the lowest and highest ends of the earnings distribution. We also find more pronounced impacts on the different quantiles of the income growth distribution (Panel b). However, the qualitative pattern remains: there is a shift of the entire curve to the left, and it is more pronounced in its right tail, yielding events of high income growth less likely.

For transitions between employed states (Panel c), the robustness check yields results that are highly consistent with the baseline. In both scenarios, a monetary contraction leads to a statistically significant decrease in the probability of transitioning from an informal to a formal job (IF) and a corresponding significant increase in the probability of remaining in an informal job (II). Quantitatively, the effects in the robustness check are slightly more pronounced: a shift of 0.56 percentage points (compared to 0.49 in the baseline).

The analysis of transitions involving unemployment (Panel d) further confirms the robustness of our main results. In line with our baseline, the reduced-form estimation shows that a monetary tightening significantly increases the persistence of unemployment (UU) and lowers the probability of an unemployed individual finding a formal sector job (UF). Similarly, the transition from informal to formal employment (IF) remains significantly negative. While the magnitudes are moderately attenuated in the robustness specification – for example, the probability of remaining unemployed (UU) increases by 1.23 percentage points compared to 1.88 in the baseline – the primary channels of impact are unchanged. Some transitions that were significant in the baseline, such as the decline in finding an informal job from unemployment (UI) and the rise in informal-to-unemployment transitions (IU), are not statistically significant in the robustness check, though the key finding of a more challenging transition to formal employment holds firm across both exercises.

Figure D1: The effects of a monetary surprise of 0.25 p.p.

Notes: Panel (a) shows the mean income responses of the four quartiles of the income distribution to a 0.25 percentage point monetary policy surprise when considering the entire sample of workers. Panel (b) displays the impact of a 0.25 percentage point monetary policy surprise on the different quantiles of the income growth distribution, once again considering the entire sample of workers. Panel (c) shows the income response to the monetary policy surprise for workers who experienced each of the four possible employed transitions. Panel (d) shows the impact of the monetary policy surprise on the probability of transitioning between different employment statuses, including movements to and from unemployment. Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

D.1.1 Smoothed Monetary Surprises

As a robustness check, we construct an alternative monetary policy surprise series that weights each high-frequency surprise by the amount of time remaining in the quarter after it occurs. This "smoothed" approach, following Ottonello and Winberry (2020), recognizes that surprises occurring early in a quarter provide more time for firms and households to respond before the quarter ends, and should therefore have a greater impact on quarterly outcomes.

Specifically, for each surprise ϵ_i occurring on day d_i of quarter q with D total days, we assign:

- Weight to current quarter: $(D - d_i)/D$;
- Weight to next quarter: d_i/D.

The smoothed quarterly series is then:

$$\tilde{\epsilon}_q = \sum_{i \in q} \epsilon_i \frac{D - d_i}{D} + \sum_{j \in q-1} \epsilon_j \frac{d_j}{D}. \tag{D1}$$

This approach ensures that a surprise on the first day of the quarter receives nearly full weight, while one on the last day receives minimal weight, with the "unused" intensity carrying over to the following quarter.

Figure D2 presents the results using this smoothed surprise series. The findings are qualitatively consistent with our baseline results, and very close to the original monetary policy surprise just discussed. Panel (a) shows that unanticipated policy interest rate increases lead to income declines across all quartiles, with the overall pattern remaining similar to the baseline in Figure 4. The middle quartiles continue to show the largest drops (approximately 1.5–2.0 percentage points), though effects at the extremes are now somewhat more pronounced than in the baseline, particularly for the highest earners.

Panel (b) demonstrates that the entire income growth distribution shifts leftward following a contractionary surprise, with stronger compression of the right tail—consistent with our baseline finding that high-income growth events become substantially less likely. The 90th percentile declines by 3.14 percentage points, compared to 1.71 in the baseline, while the mean drops by 1.60 percentage points versus 0.67 in the baseline. The larger magnitudes reflect the time-weighting scheme's emphasis on shocks with more time to propagate.

For employment transitions, Panel (c) confirms the key result from Section 5 that monetary policy contractions increase informality persistence. A 0.25 percentage point surprise raises the probability of staying informal (II) by 0.95 percentage points and reduces the probability of transitioning from informal to formal employment (IF) by the same magnitude—effects that are nearly double the baseline estimates of 0.49 percentage points shown in Figure 5.

Panel (d) shows transitions including unemployment. The pattern mirrors our main results in Figure 5: contractionary surprises significantly reduce transitions from unemployment to formal employment (UF) by 2.08 percentage points, increase unemployment persistence (UU) by 1.96 percentage points, and decrease informal-to-formal transitions (IF) by 0.93 percentage points. These magnitudes are even larger than our baseline (1.50, 1.88, and 0.52 percentage points respectively), confirming that the key channels remain robust – monetary policy tightening makes transitions to formal employment substantially more difficult while increasing persistence in both unemployment and informality.

Overall, this time-weighting approach produces results that are qualitatively and quantitatively consistent with our main findings. The robustness of the key patterns across different shock aggregation methods—whether using the structural shocks from the proxy-SVAR in our baseline or the smoothed surprises here—strengthens confidence in our conclusions about the distributional effects of monetary policy in Brazil's labor market.

Figure D2: The effects of a smoothed monetary surprise of 0.25 p.p.

Notes: Panel (a) shows the mean income responses of the four quartiles of the income distribution to a 0.25 percentage point smoothed monetary policy surprise when considering the entire sample of workers. Panel (b) displays the impact of a 0.25 percentage point smoothed monetary policy surprise on the different quantiles of the income growth distribution, once again considering the entire sample of workers. Panel (c) shows the income response to the smoothed monetary policy surprise for workers who experienced each of the four possible employed transitions. Panel (d) shows the impact of the smoothed monetary policy surprise on the probability of transitioning between different employment statuses, including movements to and from unemployment. Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

D.2 Results Using Gross Income

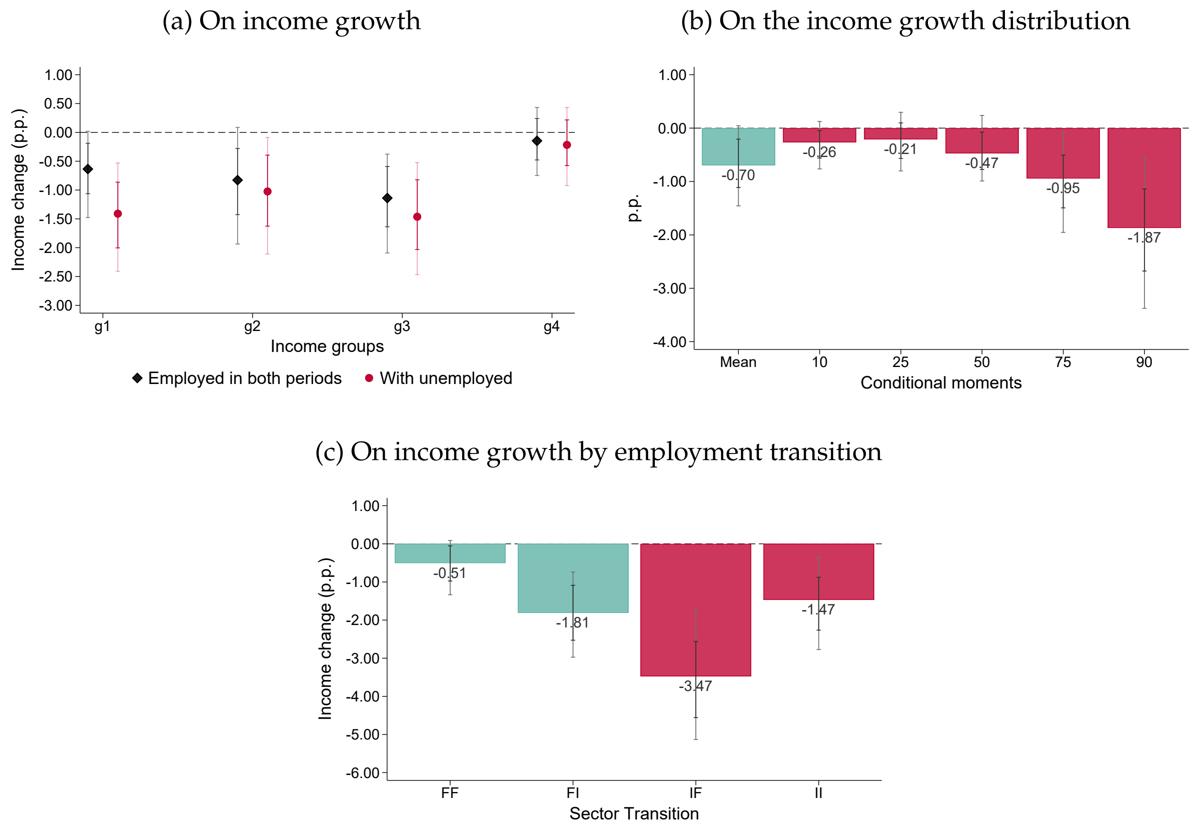
This appendix assesses the robustness of our main findings by replicating the baseline analysis using gross labor income. This exercise ensures that our results are not driven by tax or social security deductions and that the observed effects of monetary policy on labor income are not sensitive to the definition of income used.

Figure D3 presents the main results using gross income. Panel (a) shows the response of one-year income growth across income quartiles for the entire sample of workers following a 0.25 percentage point monetary policy shock. The results closely mirror those from the baseline: all income groups experience income declines, with larger effects for the middle of the distribution and smaller effects for the highest earners.

Panel (b) displays the impact of the monetary policy shock across the conditional quantiles of the income growth distribution for the entire sample of workers. The entire distribution shifts to the left, with a stronger compression of the right tail, indicating a reduction in the likelihood of large income gains. The magnitude and shape of these shifts are highly consistent with those found in our baseline using net income.

Finally, Panel (c) reports income responses by employment transition type. As before, the largest declines occur among workers switching between the formal and informal sectors, while those remaining in formal employment exhibit smaller changes. The direction, relative magnitudes, and statistical significance of these effects all remain robust when gross income is used.

Figure D3: The effects of a 0.25 p.p. monetary policy shock on gross income



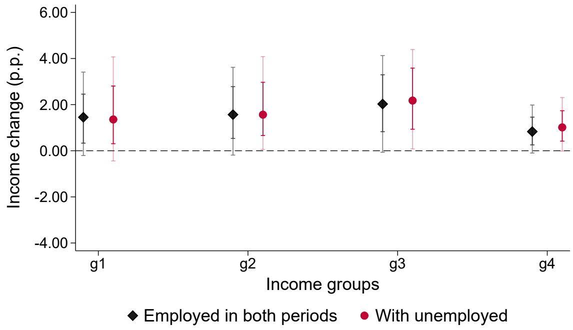
Note: Panel (a) shows the mean *gross* income responses of the four quartiles of the income distribution to a 0.25 percentage point monetary policy shock when considering the entire sample of workers. Panel (b) displays the impact of a 0.25 percentage point monetary policy shock on the different quantiles of the *gross* income growth distribution, once again considering the entire sample of workers. Panel (c) shows the *gross* income response to the monetary policy shock for workers who experienced each of the four possible employed transitions. Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered along the time dimension.

D.3 Asymmetry in Responses to Expansionary and Contractionary Shocks

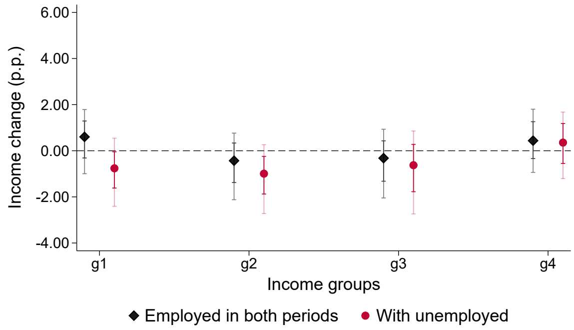
In this appendix, we show the results of relaxing the assumption that labor market responses to monetary policy shocks are symmetric relative to the event's sign. We do so by explicitly estimating separate responses to contractionary ($shock > 0$) and expansionary ($shock < 0$) events.

Figure D4: The asymmetric effects of a monetary policy shock of 0.25 p.p. on income growth

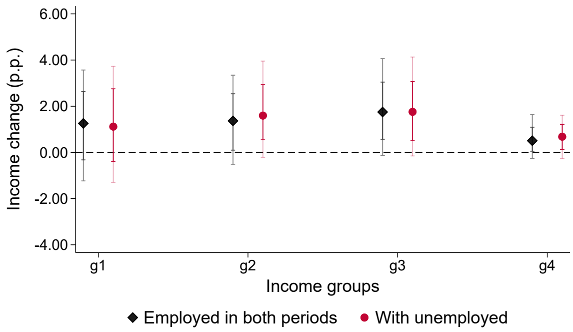
(a) Expansionary – All workers



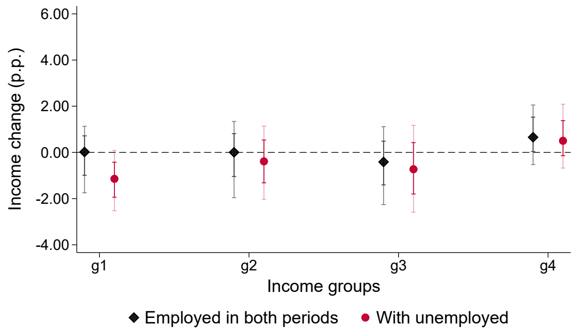
(b) Contractionary – All workers



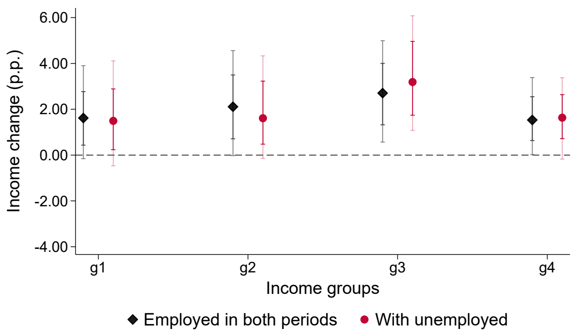
(c) Expansionary – Formal workers



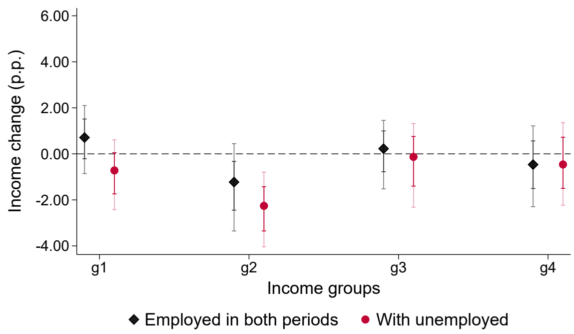
(d) Contractionary – Formal



(e) Expansionary – Informal workers



(f) Contractionary – Informal



Note: Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

We start with the responses of labor market income. Analogous to Equation 1, we have the specification (D2) below.

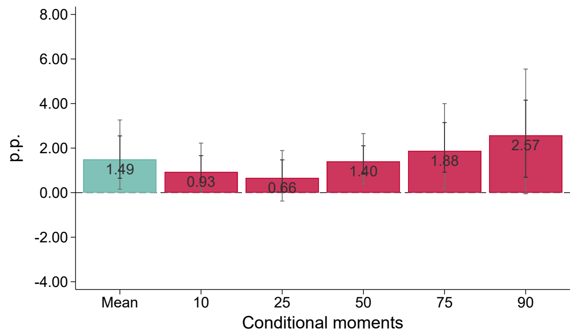
$$\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} = \sum_{g=1}^{4} G_{i,g,t} \left[\alpha_{g,h} + \beta_{g,h}^{(+)} shock_t^{(+)} + \beta_{g,h}^{(-)} shock_t^{(-)} \right] + \delta_h U_{t-1} + \epsilon_{i,t+h}, \tag{D2}$$

where

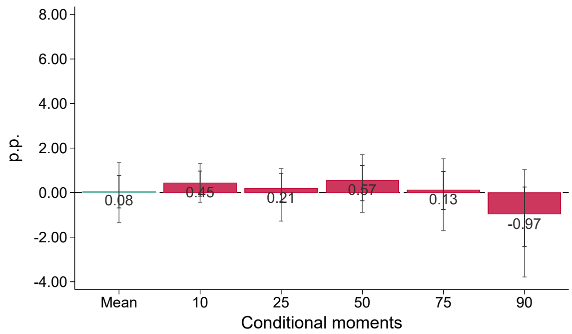
$$shock_t^{(+)} = \max\{shock_t, 0\} \quad \text{and} \quad shock_t^{(-)} = \min\{shock_t, 0\}.$$

Figure D5: The asymmetric effects of a monetary policy shock of 0.25 p.p. on the income growth distribution

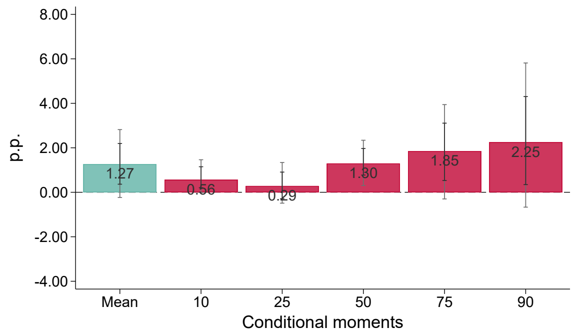
(a) Expansionary – All workers



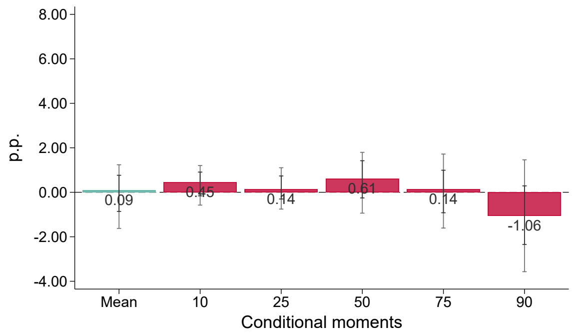
(b) Contractionary – All workers



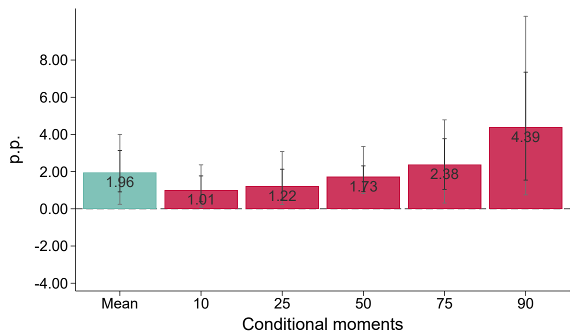
(c) Expansionary – Formal workers



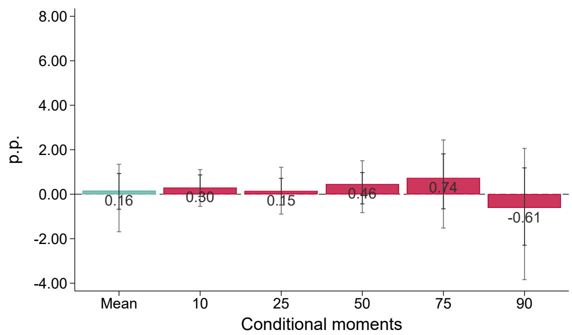
(d) Contractionary – Formal



(e) Expansionary – Informal workers



(f) Contractionary – Informal



Note: Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

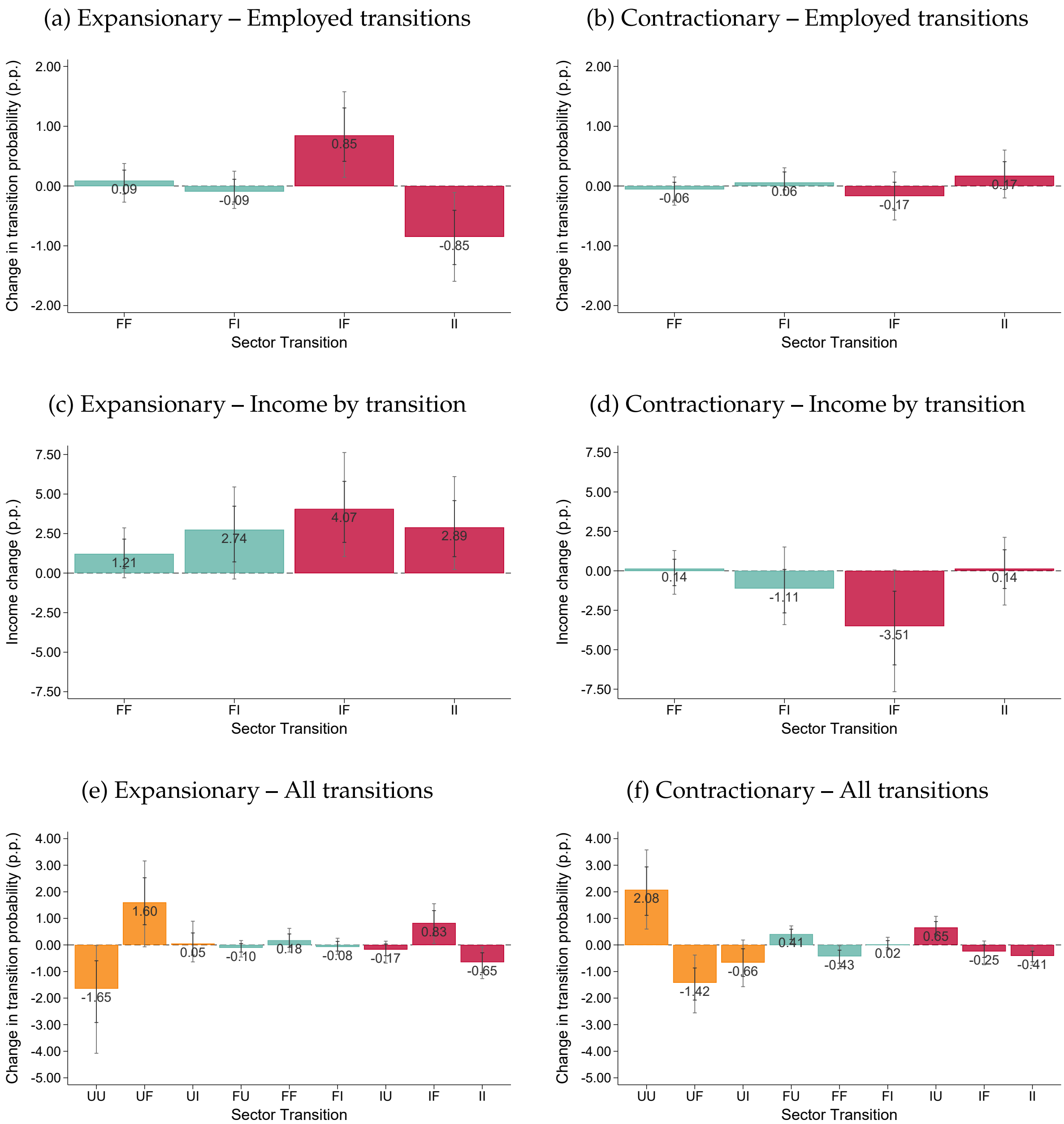
Similarly, the analog of Equation 2 is given below, in specification (D3), which we estimate for different quantiles and the mean:

$$\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} = \alpha_h + \beta_h^{(+)} shock_t^{(+)} + \beta_h^{(-)} shock_t^{(-)} + \delta_h U_{t-1} + \epsilon_{i,t+h}. \tag{D3}$$

We also perform the sign segmentation for our transitions exercises of Section 5. Analogous to Equation 3, we have

$$D_{it} = \alpha_D + \beta_D^{(+)} shock_t^{(+)} + \beta_D^{(-)} shock_t^{(-)} + \delta_D U_{t-1} + \varepsilon_{i,t}. \tag{D4}$$

Figure D6: The asymmetric effects of a monetary policy shock of 0.25 p.p. on transitions



(a) Expansionary – Employed transitions

(b) Contractionary – Employed transitions

(c) Expansionary – Income by transition

(d) Contractionary – Income by transition

(e) Expansionary – All transitions

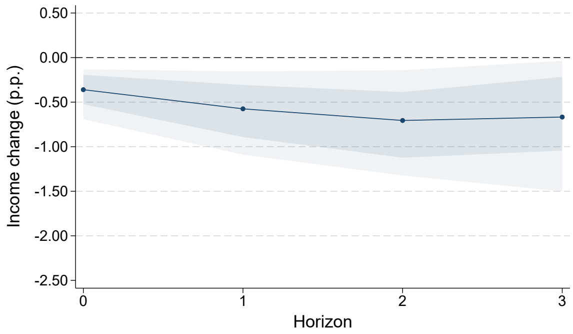
(f) Contractionary – All transitions

Note: Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

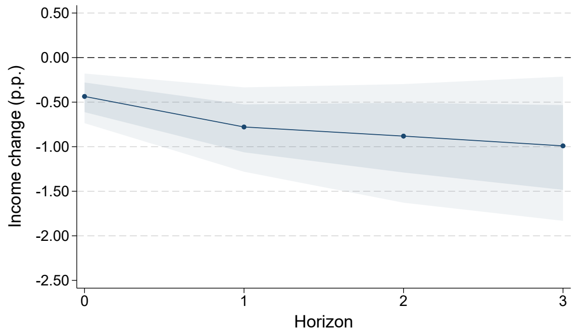
D.4 Impulse Responses of Average Income Growth for Different Horizons

Figure D7: The effects of a monetary policy shock of 0.25 p.p. on average income growth for different horizons

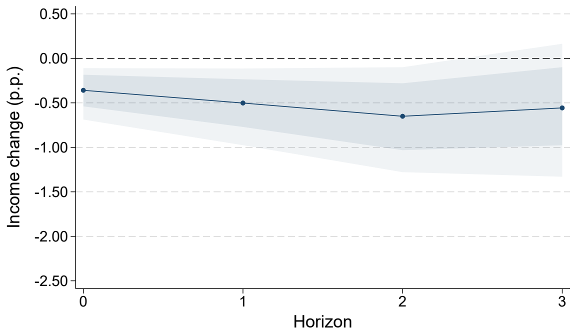
(a) Employed in both periods – All workers



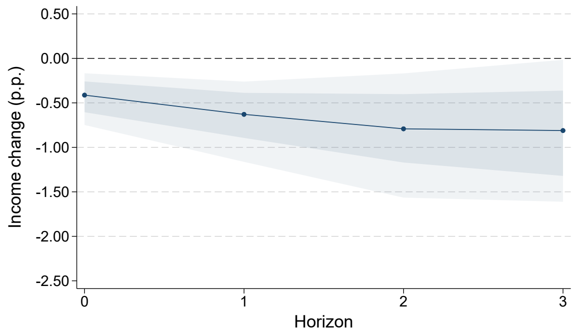
(b) With unemployed – All workers



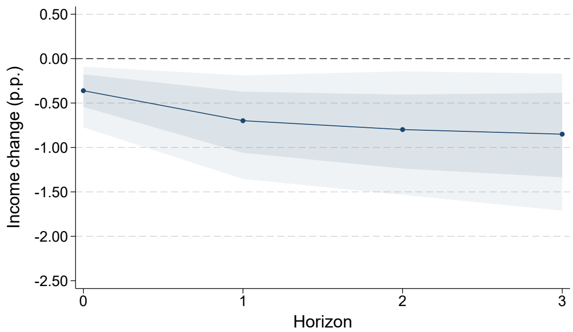
(c) Employed in both periods – Formal workers



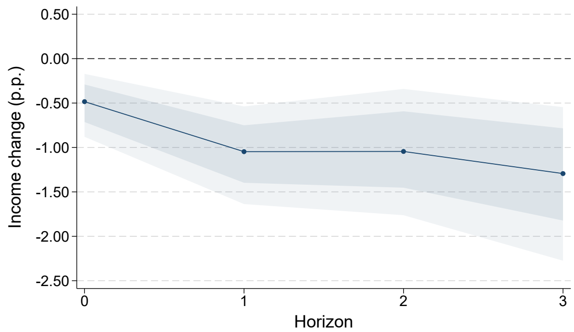
(d) With unemployed – Formal workers



(e) Employed in both periods – Informal workers



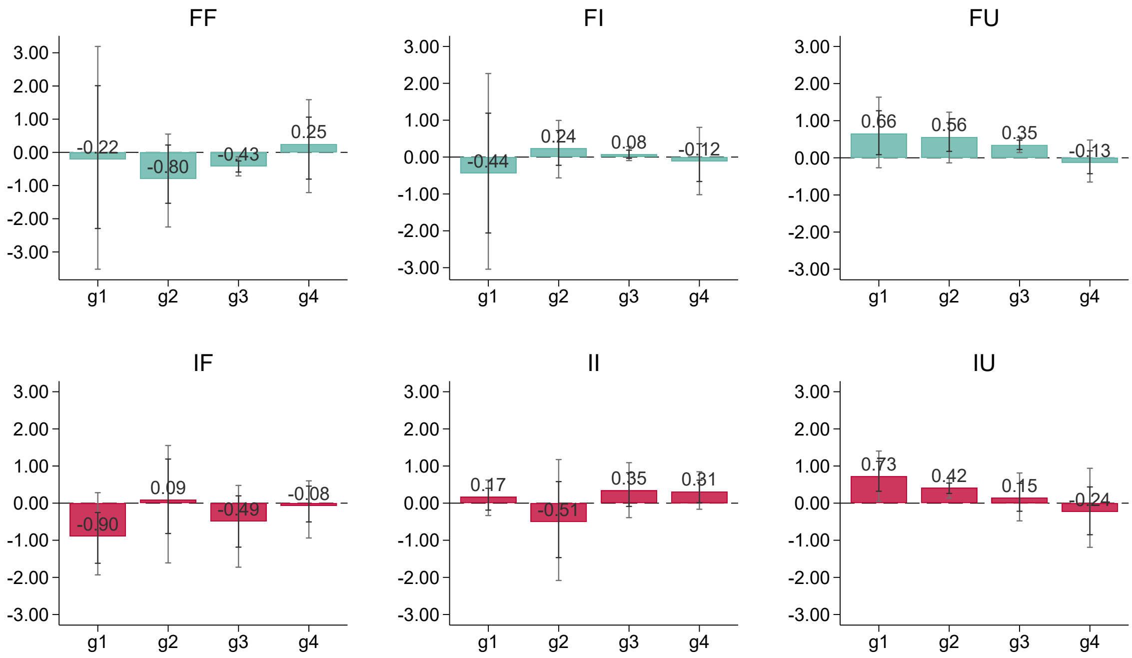
(f) With unemployed – Informal workers



Note: Shaded areas represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

D.5 Impact of Monetary Policy on Employed Transitions by Income Group

Figure D8: The effects of a monetary policy shock of 0.25 p.p. on employed transitions by income group



Note: The figure shows the impact of a monetary policy shock of 0.25 percentage point on the probability of the six feasible employment transitions for workers initially employed, separately for each of the four quartiles of the labor income distribution. Vertical lines represent 68 and 90 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

E Labor Markets During the Covid-19 Pandemic

Figure E1: Moments of the distribution of 1-year real disposable income growth

Note: The figure shows measures of the first four moments of 1-year real disposable income growth, measured as $\Delta y_t = \frac{y_t - y_{t-4}}{y_{t-4}}$, at a quarterly frequency, from 2013Q1 to 2023Q4.

Figure E2: Transition rates between employment statuses over time

Note: The figure shows the evolution over time of the transition rates between $t-4$ and t, at a quarterly frequency, from 2013Q1 to 2023Q4. F stands for formal sector, I for informal sector, and U for unemployment. Panel (a) displays the probabilities of staying employed in the same sector, while Panel (b) displays the probabilities of switching to the other sector. Panel (c) shows the transition rates from the two sectors to unemployment, and Panel (d) shows the transition rates for those starting unemployed (which includes staying unemployed).

F Model Specification

This appendix provides technical details of the framework in Section 6.1, presenting the model specification, log-linearized equations, steady state, and connections to our empirical findings.

F.1 Model Environment and Specification

Individual States and Transitions. Workers are characterized by two state variables: an idiosyncratic productivity type $s \in S$ and an employment status $e \in \{f, i, u\}$, where f denotes formal employment, i informal employment, and u unemployment. The distribution of workers across these states is denoted $m_{s,e,t}$, with $\sum_{s,e} m_{s,e,t} = 1$. Idiosyncratic productivity evolves according to an exogenous Markov chain with transition matrix M, where $M_{ss'}$ gives the probability of transitioning from productivity type s to type s'. This component captures persistent individual-level heterogeneity independent of aggregate conditions.

Employment transitions, by contrast, respond endogenously to aggregate conditions. The probability of transitioning from employment state e to state e' at time t is given by:

$$\lambda_{ee',t} = \overline{\lambda}_{ee'} + \eta_{ee'} x_t, \tag{F1}$$

where $\overline{\lambda}_{ee'}$ represents the steady-state transition probability, $\eta_{ee'}$ captures the cyclical sensitivity of the transition, and x_t is the output gap. Since transition probabilities must sum to one for each origin state, $\sum_{e'} \lambda_{ee',t} = 1$, which implies $\sum_{e'} \eta_{ee'} = 0$. This specification is local, valid for small fluctuations in x_t around zero. It matches our empirical approach, where we estimate linear responses to monetary shocks. We do not model the non-linearities necessary to ensure non-negativity constraints are always satisfied, which would be required for a global analysis with large shocks.

Aggregate Block. Aggregate dynamics are governed by a standard New Keynesian block:

$$x_t = E_t x_{t+1} - \sigma(i_t - E_t \pi_{t+1} - r^*), \tag{F2}$$

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t, \tag{F3}$$

$$i_t = i^* + \phi_\pi \pi_t + \phi_x x_t + \epsilon_t^{MP}, \tag{F4}$$

where x_t is the output gap, i_t the nominal rate, π_t inflation, r^* the natural real rate, i^* the steady-state nominal rate, ϵ_t^{MP} the monetary shock, and $\{\sigma, \beta, \kappa, \phi_\pi, \phi_x\}$ are standard parameters.

Income. Per-capita labor income for a worker of productivity type s in employment sector $e \in \{f, i\}$ is given by:

$$\log y_t(s,e) = \log \overline{y}(s,e) + \gamma_{(s,e)} x_t, \tag{F5}$$

where $\overline{y}(s,e)$ denotes steady-state income and $\gamma_{(s,e)} > 0$ is the type-specific income elasticity with respect to the output gap. This specification follows Alves et al. (2021). The heterogeneity in $\gamma_{(s,e)}$ captures differential exposure to aggregate conditions, where workers with higher elasticities experience larger income fluctuations arising from differences in hours worked, wage flexibility, firm of sectoral exposure to aggregate demand, or job-specific productivity. For unemployed workers, we assume constant benefits $y_t(s,u) = b$.

Law of Motion for the Distribution. The distribution of workers evolves according to:

$$m_{s',e',t+1} = \sum_s M_{ss'} \sum_e \lambda_{ee',t} m_{s,e,t}. \tag{F6}$$

Workers at state (s', e') in period $t+1$ are those who transitioned from any origin state (s, e) through the joint process of employment transitions ($\lambda_{ee',t}$) and productivity transitions ($M_{ss'}$).

Aggregation. The employment share in sector e is $m_{e,t} = \sum_s m_{s,e,t}$. Total income in sector $e \in \{f, i\}$ is:

$$Y_{e,t} = \sum_s \overline{y}(s,e) e^{\gamma(s,e) x_t} m_{s,e,t}, \tag{F7}$$

with per-capita income $\bar{y}_{e,t} = Y_{e,t}/m_{e,t}$.

F.2 Log-Linearization and Steady State

Log-Linearization. We log-linearize the model around the steady state where $x = 0$ and $m_{s,e,t} = \overline{m}_{s,e}$ for all (s, e). Define log-deviations:

$$\hat{m}_{s,e,t} = \log(m_{s,e,t}/\overline{m}_{s,e}), \tag{F8}$$

$$\hat{Y}_{e,t} = \log(Y_{e,t}/\overline{Y}_e). \tag{F9}$$

For transition probabilities, we define the relative deviation:

$$\tilde{\lambda}_{ee',t} = \frac{\lambda_{ee',t} - \overline{\lambda}_{ee'}}{\overline{\lambda}_{ee'}} = \frac{\eta_{ee'}}{\overline{\lambda}_{ee'}} x_t. \tag{F10}$$

Adding-up of probabilities and total mass implies $\sum_{s,e} \overline{m}_{s,e}\, \hat{m}_{s,e,t} = 0$, a zero-weighted mean for distribution deviations. The individual income equation is already log-linear: $\log y_t(s,e) = \log \overline{y}(s,e) + \gamma_{(s,e)} x_t$.

Log-linearizing equation (F6), we obtain:

$$\hat{m}_{s',e',t+1} = \sum_{s,e} \Omega_{s',e',s,e} \left(\tilde{\lambda}_{ee',t} + \hat{m}_{s,e,t} \right), \tag{F11}$$

where the steady-state weights are $\Omega_{s',e',s,e} = M_{ss'} \overline{\lambda}_{ee'} \overline{m}_{s,e} / \overline{m}_{s',e'}$. These weights capture shock propagation through idiosyncratic transitions (M) and employment transitions ($\overline{\lambda}$), with $\sum_{s,e} \Omega_{s',e',s,e} = 1$ by construction.

Log-linearizing equation (F7), we obtain:

$$\hat{Y}_{e,t} = \sum_{s} \omega_{s,e} \left[\gamma_{(s,e)} x_t + \hat{m}_{s,e,t} \right], \tag{F12}$$

where $\omega_{s,e} = \overline{y}(s,e)\overline{m}_{s,e}/\overline{Y}_e$ are income-share weights satisfying $\sum_s \omega_{s,e} = 1$. This decomposes aggregate income changes into two channels. The **direct exposure channel** ($\sum_s \omega_{s,e}\gamma_{(s,e)}x_t$) captures how workers' incomes respond to the output gap with heterogeneous elasticities $\gamma_{(s,e)}$, operating even with a fixed distribution across types. The **composition channel** ($\sum_s \omega_{s,e}\hat{m}_{s,e,t}$) reflects endogenous shifts in the distribution across productivity types as employment transitions respond to aggregate conditions, causing aggregate income to fall beyond the direct exposure effect when workers move to low-productivity types or lose employment.

Steady State. The steady state is characterized by $x = 0$, $\lambda_{ee'} = \overline{\lambda}_{ee'}$ for all (e, e'), $\overline{m}_{s',e'} = \sum_{s,e} M_{ss'}\overline{\lambda}_{ee'}\overline{m}_{s,e}$, and $\overline{Y}_e = \sum_s \overline{y}(s,e)\overline{m}_{s,e}$. The steady-state distribution $\{\overline{m}_{s,e}\}$ is the invariant distribution of the joint Markov chain $(M, \overline{\lambda})$, normalized to sum to one.

F.3 Mechanisms and Connection to Empirical Findings

Model Mechanisms. The model generates distributional dynamics through three key mechanisms. Heterogeneous income elasticities $\gamma_{(s,e)}$ capture workers' different exposures to the output gap, so contractionary policy causes larger income declines for workers with higher elasticities. Cyclical employment transitions respond to aggregate conditions through $\eta_{ee'}x_t$, making favorable transitions (e.g., unemployment to formal employment) less likely during contractions while increasing persistence in unemployment and informality. Endogenous distribution dynamics amplify initial shocks through composition effects as the distribution evolves according to equation (F11).

Matching Empirical Findings. To match our empirical findings, we require $\gamma_{(s,e)} > 0$ for all (s, e) (all income groups decline in contractions), with middle-income groups having highest average elasticities possibly due to income floors at the bottom and higher stability at the top. For transitions, we require $\eta_{uf} > 0$, $\eta_{if} > 0$ (formal employment access declines), $\eta_{uu} < 0$, $\eta_{ii} < 0$ (unemployment and informality persist), and $\eta_{fu} < 0$, $\eta_{iu} < 0$ (separations increase), consistent with adding-up $\sum_{e'} \eta_{ee'} = 0$. These signs ensure contractionary shocks reduce formal job-finding rates, increase persistence in non-employment and informality, and raise unemployment separations.

Income Growth by Quartile. Consider a worker starting at state (s, e) whose one-year income growth depends on their destination state (s', e'), the evolution of the output gap, and their income elasticities in both periods. From equation (F5), one-year income growth is:

$$\log y_{t+3}(s',e') - \log y_{t-1}(s,e) = \left[\log \overline{y}(s',e') - \log \overline{y}(s,e)\right] + \gamma_{(s',e')}x_{t+3} - \gamma_{(s,e)}x_{t-1}. \tag{F13}$$

Note: We adopt the same one-year window used in the empirical specification, comparing outcomes between $t-1$ and $t+3$ (consistent with the PNADC 1-2(5) rotation).

This decomposes income growth into steady-state differences between origin and destination plus a cyclical component. A contractionary shock operates through direct impact (income falls by $\gamma_{(s,e)}x_t$), persistence (negative gaps continue as $x_{t+4} < 0$), foregone transitions (with $\eta_{if} > 0$ and $\eta_{uf} > 0$), and increased unemployment risk ($\eta_{fu} < 0$ and $\eta_{iu} < 0$). Middle quartiles experience the largest drops due to high elasticities combined with exposure to adverse transitions, while the lowest quartile likely faces income floors and the highest quartile likely enjoys greater job security. The quantile regression results showing truncation of the right tail reflect that contractionary shocks suppress favorable transitions and create persistently negative gaps, eliminating high-income growth realizations that require such favorable conditions—explaining why the 90th percentile shifts more than the median. The similar responses across formal and informal workers suggest $E[\gamma_{(s,f)}] \approx E[\gamma_{(s,i)}]$ and reflects frequent sectoral transitions (Gomes et al., 2020), so workers in both sectors face comparable exposure to aggregate fluctuations through comparable income elasticities and cyclical transition dynamics.

Model Extensions and Limitations. This framework is intentionally simple to maintain transparency about the key mechanisms. Natural extensions include modeling consumption-saving decisions and heterogeneous marginal propensities to consume (for consumption and aggregate demand implications), government transfers with their own incidence parameters (for automatic stabilizers), richer transition dynamics with additional worker characteristics, and general equilibrium closures that enable welfare analysis. For now, the framework achieves our stated goal: providing a coherent, data-disciplined interpretation of how monetary policy affects income distribution with substantial informal employment.