Monetary Policy and Labor Markets in a Developing Economy *

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Abstract

We document a set of empirical findings regarding the distributional effects of monetary policy on labor income growth and on employment transitions in a developing economy, a setting where informality is a relevant phenomenon. To do so, we first construct a series of monetary policy shocks for Brazil using a high-frequency identification approach. We find asymmetric impacts of monetary policy depending on the sign of the monetary policy shock, with contractions leading to responses of greater magnitude than expansions. The decline in labor income following contractionary monetary policy shocks is particularly severe for the lowest-income informal workers. Contractions also increase the persistence of informality and unemployment and decrease the chance of moving to a formal job.

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

JEL Codes: D31; E52; J31

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1 Introduction

Monetary policy affects labor markets. And naturally, not every worker is equally affected by a change in policy. Research on the heterogeneous consequences of monetary policy can inform policymakers on policy design and suggest other interventions that can help alleviate any negative effects on particularly affected groups. Developing economies typically have volatile labor market conditions and a high share of informal workers. In this paper, we investigate the heterogeneous effects of monetary policy in Brazil, a developing country with a large informal sector.

Our main findings are: (i) A surprise increase (decrease) in interest rate lowers (raises) the labor income across all the income distribution; (ii) This finding remains consistent when we separate the worker sample into formal and informal categories. The impact on labor income is more pronounced for workers in the highest income group; (iii) When we split the sample into contractionary and expansionary surprise monetary policy changes, an asymmetry becomes evident. Monetary contractions have a greater impact on labor income than expansions of comparable magnitude, with low-income informal workers being particularly affected; (iv) Our analysis of employment status transitions reveals that monetary contractions make both informal employment and unemployment more persistent and make transitions towards formal employment more difficult.

We study the effects of decisions taken by the Central Bank of Brazil's Monetary Policy Committee (COPOM). The COPOM announces its decision on the interest rate target a few hours after the financial markets have closed. To identify monetary policy surprises, we use price changes in deposit rate (DI rate) futures contracts, which are closely related to the target 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. However, high-frequency identification strategies can suffer from a lack of exogeneity in the surprise variable due to the potential incorporation of pre-existing information. To address this concern, we follow the procedure proposed by Bauer and Swanson (2022) to construct a monetary policy surprise that is orthogonal to the available information. This is achieved by regressing the change in the future prices against a set of market expectation variables collected earlier in the day of each announcement. We then use a ridge regression shrinkage estimator to obtain the residual, our monetary policy surprise series.

We use this monetary policy surprise series as an instrument in a local projections approach to estimate labor income responses to monetary policy shocks. We classify workers into four income groups and study their one-year income responses. All income groups display a negative income growth response that varies from about -1.5 to -4.5 percent after an unexpected one-percentage-point increase in the interest rate. The estimated response is greater for the highest income group. We then segment the sample of workers into those working in the formal and informal sectors. Results are qualitative and quantitatively similar, but also suggest that the response of informal worker income changes is stronger.

These results, however, mask an asymmetric response to contractionary and expansionary monetary policy shocks. To study possible asymmetries and state-contingent effects of monetary policy, we separate monetary policy shocks into surprise expansions and contractions. We then repeat the local projections for these two sub-samples. The income decrease estimates that follow contractionary shocks are much larger in magnitude than the income increase estimates to expansionary shocks. The response of informal workers is typically larger in magnitude. With this segmentation on shock sign, income group, and formality status, the pattern of responses is no longer increasing in income. Low-income informal workers display a particular vulnerability to monetary tightening.

Last, we study transitions across employment states. We start this analysis by focusing on workers who were employed in both the initial and final periods of a one-year comparison. The results show that monetary policy shocks have a small impact on the likelihood of transitions for individuals who started in the formal sector. However, those who began in the informal sector are affected to a greater extent, with expansionary shocks resulting in an increase in the likelihood of transitioning to the formal sector, and contractionary shocks leading to a decrease in the likelihood of transitioning to a formal job. The section also analyzes the effect of monetary policy shocks on employment transitions, including the movement to and from unemployment, and finds that a contractionary shock decreases the probability of transitioning from unemployment or informality to the formal sector. Therefore, monetary contractions are shown to make both unemployment and informality more persistent.

Related Literature Our paper contributes to two strands of economic literature. The first strand identifies monetary policy surprises and estimates responses to 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), while choosing our strategy to respond to the criticism of predictability raised by Bauer and Swanson (2021, 2022) and Miranda-Agrippino and Ricco (2021).[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). Relative to this strand, 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. Our work also stands out 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 shock hits. We also expand the analysis to include transitions to and from unemployment.

A second related strand provides empirical descriptions of the income risk faced by workers.

[1]See also Aruoba and Drechsel (2022) and Gorodnichenko et al. (2023) for recent applications exploiting machine learning and natural language processing.

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). Our study contributes to this literature by examining exposure to underlying aggregate shocks, particularly monetary policy.

The rest of the paper is organized as follows. Section 2 describes the estimation of the monetary policy shocks series and validates its findings by presenting monthly impulse-response functions of key labor market variables. Section 3 presents and discusses the results for labor income growth and Section 4 for employment transitions. Section 5 concludes.

2 Monetary Policy Shock

Some exogenous variation in monetary policy variables is required for empirically assessing the impact of monetary policy on labor market outcomes. Therefore, the first step of our analysis is to estimate a series of monetary policy shocks. To accomplish this, we first construct a time series of monetary policy surprises, that we later use as an instrument for interest rate changes. We obtain this series using a high-frequency identification strategy, as proposed by Gertler and Karadi (2015) and Nakamura and Steinsson (2018).

High-frequency identification leverages the significant information disclosed on 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 any fluctuations in the prices of interest rate futures contracts. This is due to the assumption that other economic factors are not undergoing abrupt shifts during this particularly narrow time frame. The starting prices at the beginning of the brief interval already encompass all publicly accessible information. Consequently, any observed price variations are attributed to an unanticipated change in the interest rate.

The Central Bank of Brazil has been implementing an inflation-targeting system since 1999. The Monetary Policy Committee (COPOM) convenes every 45 days to establish an interest rate target aimed at reaching its inflation objective. Announcements are made around 7 p.m. local time, after financial markets have closed. To identify the monetary policy surprises, we consider price variations of the shortest maturity one-day interbank deposit rate (DI rate) futures contracts.[2] 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 prior to the announcement.

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 show that high-frequency future contract price changes can be predicted by information that is available prior to the announcement. To address this concern, we follow the approach proposed by Bauer and Swanson (2022) and construct a monetary policy

[2]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.

surprise that is orthogonal to the available information. This is achieved by regressing the change in future prices against a set of market expectation variables collected earlier in 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 our monetary policy surprise series.[3]

Next, for each meeting m of the monetary authority, we regress the announced interest rate change against the orthogonalized monetary policy surprise, using it as an instrument:

$$\Delta i_m = \alpha + \beta surprise_m + \epsilon_m. \tag{1}$$

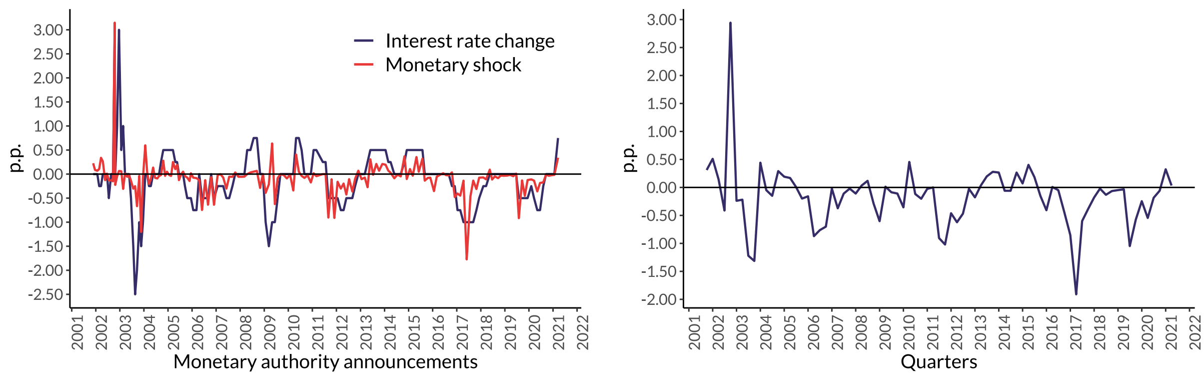
The resulting fitted values, $\widehat{\Delta i}_m$, represent the first stage of an instrumental variable approach. In this context, these values can be interpreted as an exogenous component of monetary policy, which we label as monetary policy shocks. As our microdata are quarterly, we then sum all shock realizations in the same quarter to create a quarterly time series of shocks. The shock value for each quarter t is given by

$$shock_t = \sum_{m \in t} shock_m, \quad \text{with} \quad shock_m = \widehat{\Delta i}_m. \tag{2}$$

Our sample consists of 175 events between 2001 and 2021, resulting in 79 observations at a quarterly frequency. We restrict the data to this time interval to ensure availability of market expectations for all the variables adopted in the orthogonalization stage. Data about the days of monetary authority meetings and interest rates announced come from the Brazilian Central Bank (2023a). Data on the market expectations surveys also come from the Brazilian Central Bank (2023b). The future contract prices are provided by Bloomberg.

Figure 1: Monetary Policy Shocks

(a) Interest rate change and monetary policy shocks (b) Quarterly monetary policy shocks



[3] The list of variables used and the details about the ridge regression estimation are described in Appendix A.

2.1 Aggregate Responses

Before proceeding to the microdata, we check how reasonable the estimated monetary policy shock series is. We assess this by estimating monthly impulse-response functions of important labor market variables with monthly coverage. The impulse-responses are estimated by local projections à la Jordà (2005). Beyond serving as a validation of the estimated monetary policy shock series, this exercise also provides a first guidance on what to expect from the individual-level results.

We consider the aggregate unemployment rate and the average real monthly labor income for this analysis. The data come from *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, 2023). The survey's monthly dissemination relies on its rotating sample scheme to provide information at a very aggregate level about Brazil's labor market and overall demographics. The underlying microdata, which we will use later on, is available only in the quarterly dissemination.

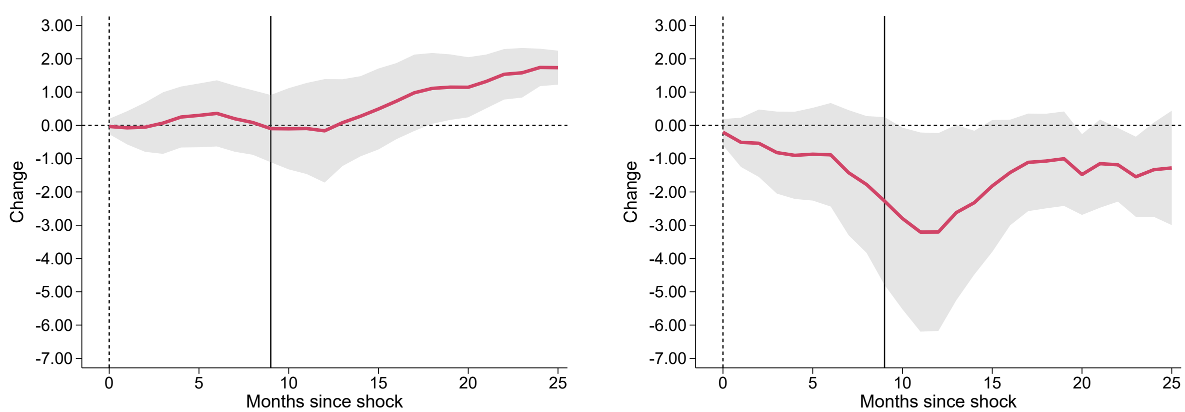
Let $\Delta_h Y_t$ represent the change in variable Y between months $t+h$ and $t-1$ (in the case of income, $\Delta_h Y_t$ represents the growth rate). For each horizon $h = 0, \dots, 24$, we estimate the following local projection:

$$\Delta_h Y_t = \alpha_h + \theta_h shock_t + \boldsymbol{x}_t' \gamma_t + \epsilon_{t+h}, \tag{3}$$

where we now use a monthly frequency aggregation of the monetary policy shock. We include twelve lags of the shock as controls in $\boldsymbol{x}_t$. The parameter θ_h gives the impulse response for each horizon h. Figure 2 reports the estimated values for $\hat{\theta}_h$.

Figure 2: Aggregate responses to a 1 p.p. monetary shock

(a) Unemployment Rate (b) Average Real Labor Income



Notes: Shaded areas represent 90% confidence intervals. Vertical line at $h = 9$ months (3 quarters after the shock).

In response to a one percentage point monetary shock happening at a given moment, the aggregate unemployment rate remains relatively unchanged for thirteen months. It then presents a steadily growing response until it reaches a level around two percentage points higher two years after the shock. The average real labor income responds immediately to the shock with a continuous decrease, reaching its lowest point around one year after the shock. A recovery process follows but does not fully returns to the starting level in the twenty-four-month horizon.

The vertical line in the figure indicates the horizon that we can observe in the microdata: nine months (three quarters) after the shock. In that window, average labor income has already responded to the monetary shock, but not reached its through. Unemployment, however, has not started to increase yet.

3 Impact of Monetary Policy on Labor Income

3.1 Data and Sample Selection

To analyze the heterogeneity of individual responses to monetary policy, we use microdata from the PNADC quarterly dissemination. As mentioned earlier, the PNADC is a national household survey covering a broad range of demographic, education, and employment topics. It has the feature of surveying individuals with both formal and informal employment. The survey design follows a rotation scheme known as 1-2(5), where each household receives an interview for five consecutive quarters, participating in the survey in one month and then waiting for the next two. During the visit, PNADC collects information about all the individuals living in the same household. Hence, we can construct a panel dataset that follows the same individual for one year.

Our data spans thirty-eight quarters, starting in the first quarter of 2012 (beginning of the PNADC) and ending in the second quarter of 2021. We restrict our sample to workers between the ages of 18 and 65, excluding employers, those who work without pay, and those with missing data on income. In our exercises on income growth, we restrict the sample further by dropping those unemployed—as they have no labor income—and those who receive less than half a minimum wage. Our final sample has 777,470 employed individuals in the panel dataset (approximately 19,000 per quarter). The number rises to 1,043,015 individuals when we include the unemployed.

An informal worker is defined as someone whose employment record is not registered through the country's social security system. As such, there is no compliance with statutory labor rights and obligations. To assess if a worker belongs to the formal or informal sector, we use their report of an employment record in their *Carteira de Trabalho e Previdência Social* (CTPS). The CTPS is a document issued by the Brazilian Ministry of Labor that is mandatory for all private sector employment. We also classify as formal workers the individuals employed in the public sector and in the armed forces. In turn, the informal workers are those without a CTPS entry and the self-employed. In our exercises, the formality status of an individual is based on their employment formalization status in the quarter previous to the monetary policy shock.

Our focus is on net real income growth. Workers report their monthly gross labor income from the main job. We obtain the value of disposable income by subtracting taxes and social security payments due. The rules governing the contribution scheme of private and public workers differ between groups and over time. We apply the official rules of the *Instituto Nacional do Seguro Social* (INSS), the Brazilian Social Security Institute. Informal workers might also contribute to social security on their own. When they report doing so, we apply the rules for the autonomous contributor category.

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. Informal workers are not registered and face no income tax enforcement, so we do not adjust their income.

Having applied 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 March 2022. Lastly, we correct for other pecuniary benefits received annually by formal workers. In particular, Brazilian labor legislation entitles formal workers to receive an additional thirteenth salary every year plus one-third of a salary as vacation allowance. We account for these benefits by adopting a multiplier of 13.33 when calculating formal workers' annualized income. For informal workers, we multiply monthly real earnings by 12 to get annual income.

For one-year income growth, we compare real annual income in the first and last quarter in which each individual appears in the panel. In our timing convention, the monetary shock occurs in the second quarter of the worker's appearance in the survey. Hence, letting t represent the period of the shock, one-year income growth is calculated as

$$\frac{Y_{i,t+3} - Y_{i,t-1}}{Y_{t-1}},$$

where Y_i represents worker i's annualized real disposable labor income.[4]

3.2 Estimation Especification

To estimate the varying impact of monetary shocks on individual labor income across the income distribution, for each quarter t, we sort workers into four groups g. The groups correspond to the quartiles of the income distribution in $(t-1)$, the quarter before the shock occurs. We then estimate the following model:

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

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

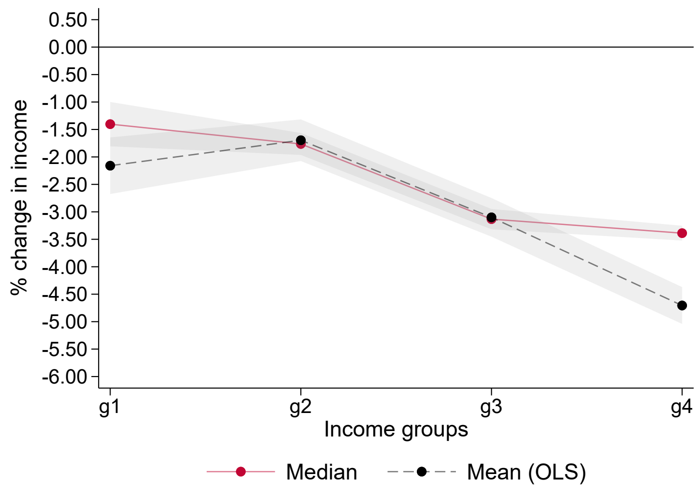
where we set $h = 3$ so the dependent variable is the one-year real (percentage) disposable income growth. $G_{i,g,t}$ is a dummy indicating if worker i belongs to group g in quarter t. Its interaction with the terms in the brackets creates group-specific intercepts $\alpha_{g,h}$ and coefficients $\beta_{g,h}$ of response to the shock. Each $\beta_{g,h}$ measures the one-year income growth for group g associated with a one percentage point monetary policy shock. We include the quarterly average (aggregate) unemployment rate, $\bar{U}_t$, to control for overall quarter-specific economic conditions affecting all groups. We estimate model (4) by OLS and quantile regression, calculating robust standard errors in both cases.

3.3 Heterogeneous labor income responses across the income distribution

Figure 3 shows the coefficient estimates $\hat{\beta}_{g,h}$ for the one-year horizon ($h = 3$), that is, the response of one-year income growth to a 1 percentage point monetary policy shock. The four income groups are displayed along the horizontal axis. Shaded areas represent 90 percent confidence bands. The figure presents estimates using both OLS and a median quantile regression.

All income groups face a decline in income after a monetary policy shock that raises the interest rate. Higher income workers experience a stronger income drop in response to the shock. OLS and quantile regression yield similar results for the two intermediate groups. On the other hand, conditional mean income growth seems to respond more to the shock than conditional median income growth for those at the top and the bottom of the income distribution. Overall, high-income workers experience a drop in income approximately twice as large as low-income workers. As we discuss in Appendix B, the income growth distribution in our sample presents positive skewness and a long right tail due to outliers, even after winsorizing. For this reason, its mean and median differ. However, the results in Figure 3 show that, while means and medians income growth are different, their qualitative and quantitative responses to monetary shocks are comparable.

Figure 3: The effects of a 1 p.p. monetary shock on labor income

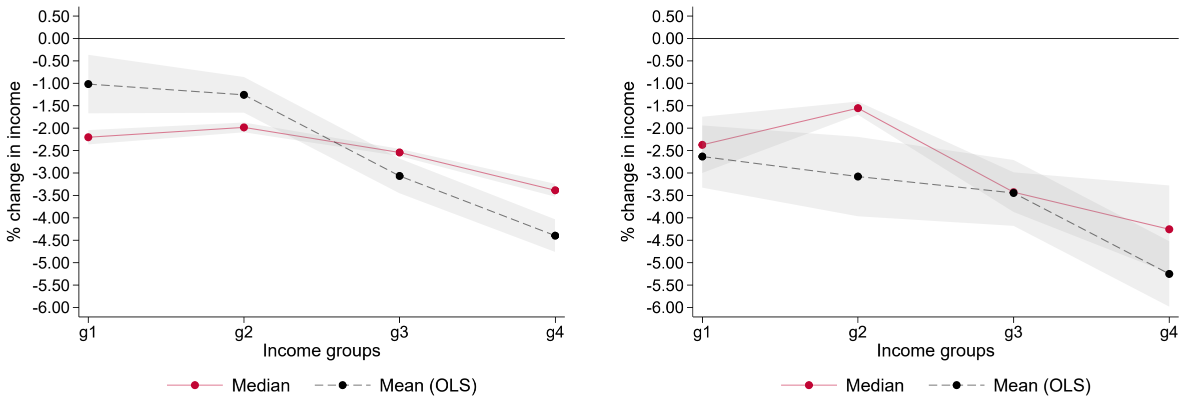


Notes: Shaded areas represent 90% confidence intervals.

To assess the heterogeneity of the effects between formal and informal workers, we estimate model (4) separately for each sector, according to the formality status of each worker in the quarter before the shock. The sorting of the workers into the income groups, however, is unconditional with regard to the formality status. Figure 4 reports the results. A similar pattern for both formal and informal workers emerges. Workers in both sectors experience drops in their incomes in response to changes in monetary policy, with stronger reactions among those with higher incomes. Informal workers faced stronger reactions compared to formal workers. This feature is more prominent for the OLS estimates.

Figure 4: The effects of a 1 p.p. monetary shock on labor income by formality status

(a) Formal (b) Informal

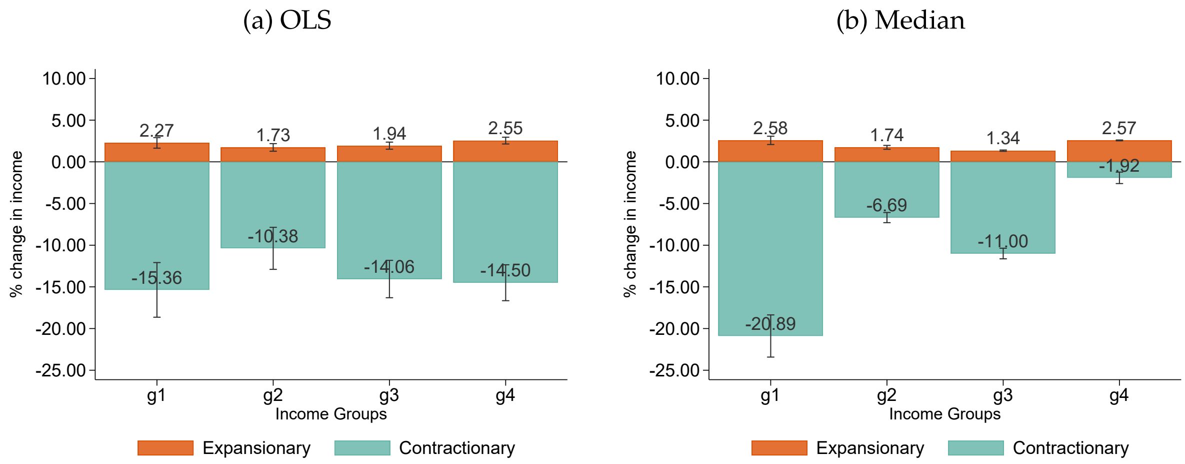


Notes: Shaded areas represent 90% confidence intervals.

We turn now to how changes in monetary policy affect workers' labor income asymmetrically during expansionary and contractionary shocks. To do so, we divided our results based on whether the change in monetary policy was positive or negative. Positive changes in monetary policy ("expansionary shocks") are represented by quarters where the value of $shock_t$ is less than 0. Negative changes in monetary policy ("contractionary shocks") are represented by quarters where the value of $shock_t$ is greater than 0.

The impact of monetary policy on income growth differs depending on whether the policy change is expansionary or contractionary, as shown in Figure 5. Contractionary shocks have a stronger effect on income growth compared to expansionary shocks. This is true for all income groups. The impact of contractionary shocks is at least five times greater than that of expansionary shocks. The poorest group is especially affected by contractionary monetary policy. Their income reacts more strongly to these changes than the overall results suggest. The median income growth for the three higher-income groups is less affected, but for the poorest group, quantile regression estimates are even higher than those from OLS.

Figure 5: The effects of a 1 p.p. monetary shock on labor income by shock sign

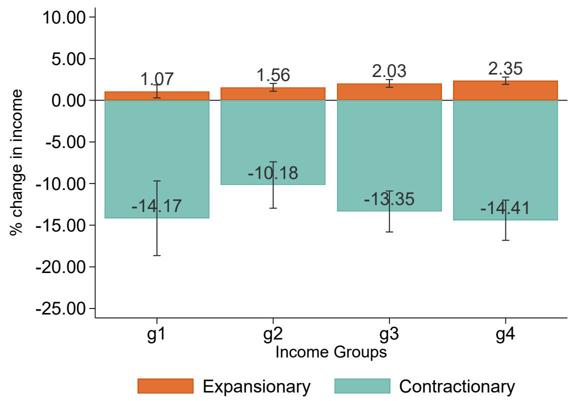


Notes: Dark thin lines represent 90% confidence intervals.

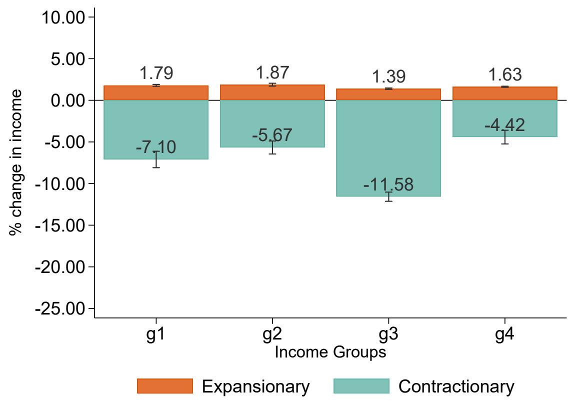
Figure 6 shows the results for formal and informal workers separately. The results for both groups are similar, with informal workers being slightly more sensitive to changes in monetary policy. The poorest informal workers benefit more from expansionary policy changes and are hurt more by contractionary policy changes than formal workers. For both groups, the richest workers have the highest average income growth in response to expansionary policy changes. The conditional median income growth in response to expansionary policy changes is similar to the average response for both formal and informal workers. However, the effects of contractionary shocks are now less severe. The exception is the lowest-income group of informal workers, who experience a drop in income of almost 19.6 percentage points.

Figure 6: The effects of a 1 p.p. monetary shock on labor income by shock sign and formality status

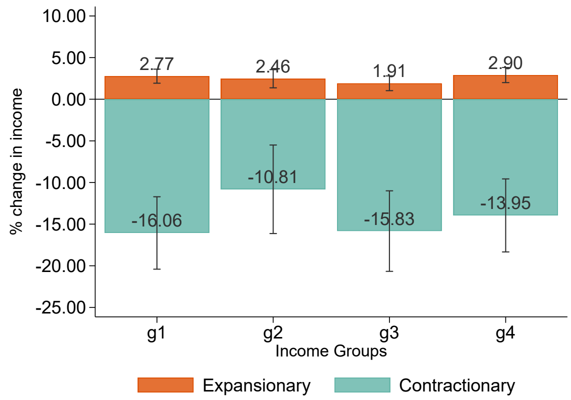
(a) Formal - OLS



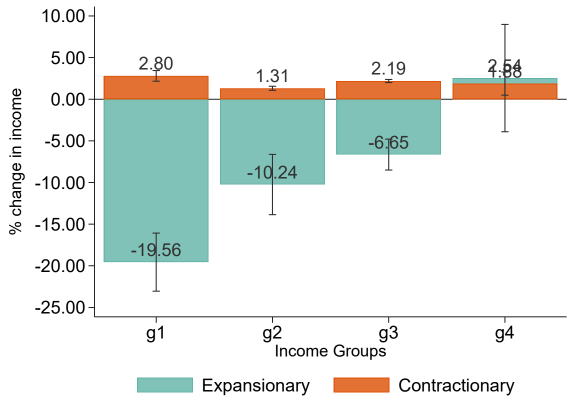
(b) Formal - Median



(c) Informal - OLS



(d) Informal - Median



Notes: Dark thin lines represent 90% confidence intervals.

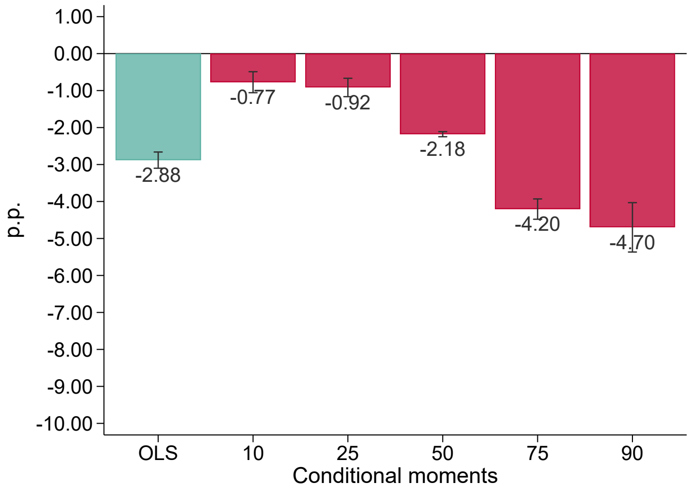
3.4 Heterogeneous impacts of monetary policy on the income growth distribution

In this section, we explore how heterogeneous the results are for different quantiles of the conditional distribution of income growth. To do so, we use quantile regressions to estimate the following model at the 10th, 25th, 75th, and 90th quantiles:

$$\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} = \alpha_h + \beta_h shock_t + \delta_h \bar{U}_t + \epsilon_{i,t+h}. \tag{5}$$

We also look at the median and mean effects that were previously analyzed. Once again, the left-hand side is percentage income growth, $\bar{U}_t$ is the quarterly average unemployment rate, and $h = 3$. The coefficient of interest, β_h, represents the magnitude of the response of the selected quantile of the income growth distribution to a 1 percentage point monetary policy shock. In essence, this analysis maps out how the conditional distribution of income growth responds to this shock.

Figure 7: The effects of a 1 p.p. monetary shock on different quantiles of the income growth distribution



Notes: Dark thin lines represent 90% confidence intervals.

Figure 7 presents the results obtained using all employed workers. All the estimates for β_h are negative: when a 1 percentage point monetary shock hits, the entire distribution of income growth shifts to the left. Moreover, the right tail moves by more: while the 10th quantile now experiences an income growth rate 0.77 percentage points smaller, the 90th quantile declines 4.70 percentage points. In other words, the right-tail of the income growth distribution is compressed and high income growth events become less likely as a response to the monetary shock.

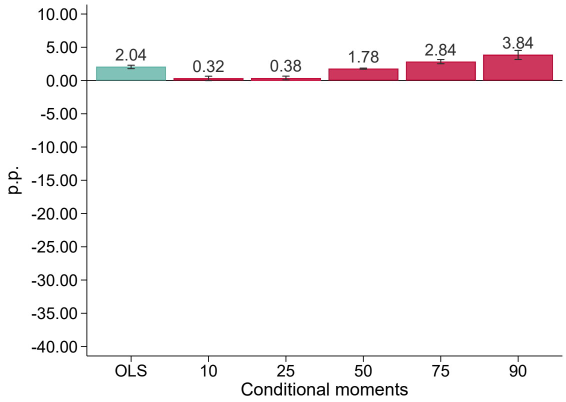
Figure 8: The effects of a 1 p.p. monetary shock on different quantiles of the income growth distribution by formality status

(a) Formal (b) Informal

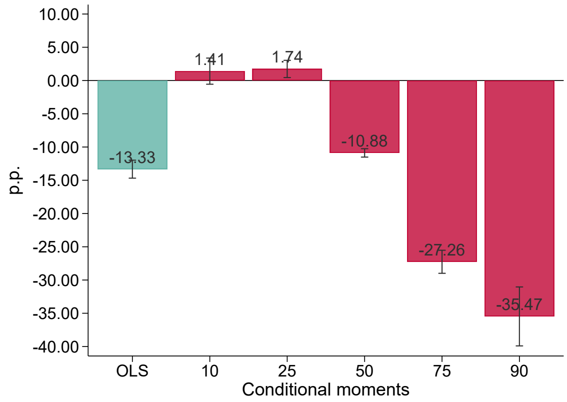
Notes: Dark thin lines represent 90% confidence intervals.

Figure 9: The effects of a 1 p.p. monetary shock on different quantiles of the income growth distribution by shock sign

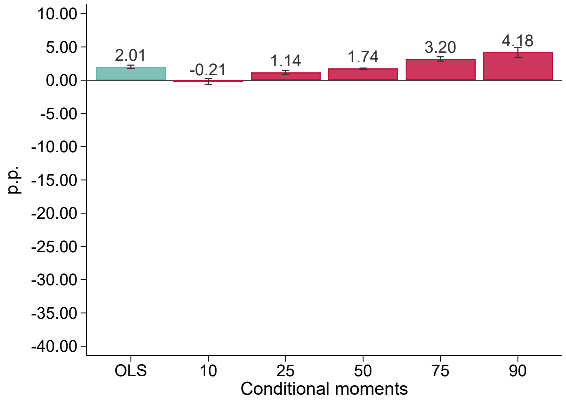
(a) All workers - Expansionary Shock



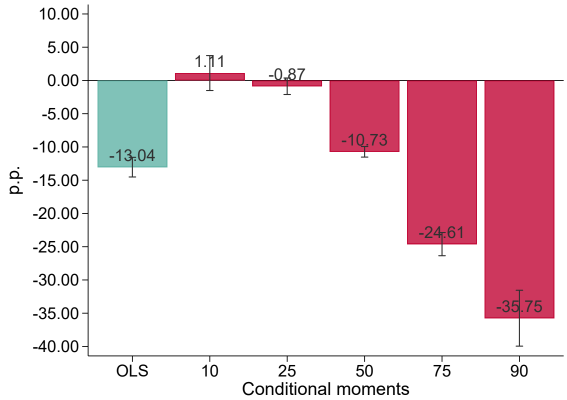
(b) All workers - Contractionary Shock



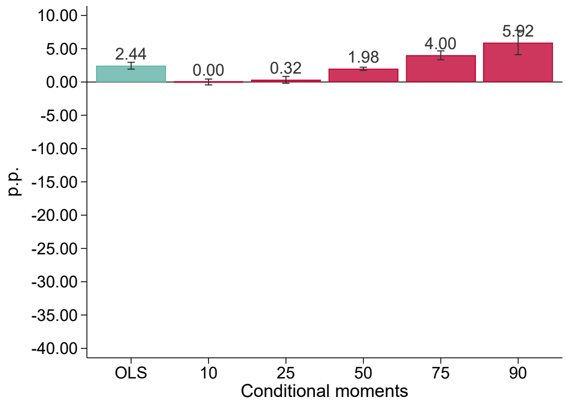
(c) Formal - Expansionary Shock



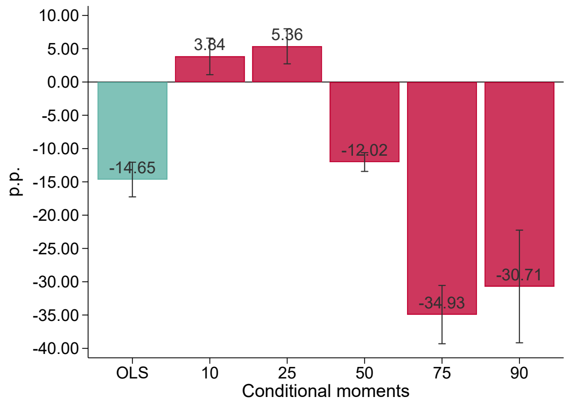
(d) Formal - Contractionary Shock



(e) Informal - Expansionary Shock



(f) Informal - Contractionary Shock



Notes: Dark thin lines represent 90% confidence intervals.

Figure 8 presents the results for formal and informal workers separately. The pattern is similar in both sectors: all estimates are negative, with the right tail of the income growth distribution showing a stronger response, especially in the informal sector. Informal workers also experience stronger effects at the mean and median. The formal sector exhibits a response of almost 2% at the 25th quantile, a significant drop in the lowest group of the conditional distribution.

We again separate the estimation by the sign of the monetary policy shock to examine asymmetric responses (Figure 9). As before, contractionary shocks result in significantly more change in income growth than expansionary shocks, with most estimates exhibiting opposing signs. In both cases, the right tail of the income growth distribution moves more, similar to the linear case. Expansionary monetary policy shocks result in an increase in the higher quantiles of the conditional distribution of income growth, meaning that high growth occurs more frequently. On the other hand, estimated responses to contractionary events are negative for the higher quantiles. Even focusing only on the effect on the conditional mean, the response to contractionary shocks is more than 10 percentage points larger than the value obtained from the linear case when using the entire sample of workers.

Though the formal and informal sectors exhibit similar responses, a few noteworthy differences for the informal sector emerge. Firstly, this group displays higher absolute estimates overall. Secondly, the positive impact of expansionary shocks on the higher quantiles of the distribution is significant, reaching almost 6 percentage points. Lastly, the estimates for the 10th and 25th quantiles in response to contractionary shocks are positive for informal workers, meaning that events of low growth or high decrease in income become less likely. Positive coefficients for lower quantiles and negative coefficients for higher quantiles indicate a concentration of the distribution around its median.

4 Impact of Monetary Policy on Employment Transitions

In this section, we examine the impact of monetary policy on labor market transitions, such as moving from formal to informal employment or from employment to unemployment. We use a larger dataset that includes both employed and unemployed individuals and does not impose restrictions on income, as described in the appendix (see "Sample Restrictions"). Our focus will be on one-year transitions, which is the longest period available in the data.

We perform two sets of analyses. In the first, we examine the transitions between formal and informal employment among individuals who were employed in both the initial and final period of the one-year time frame. In the second set of analyses, we include those who were unemployed in either the initial or final period and examine the transitions between unemployment and formal or informal employment.

We construct a set of dummy variables that represent all possible transitions. Once again, our timing notation specifies quarter t as the period of the shock and compares the employment status of individuals in $t-1$ (initial period) and $t+3$ (final period). For example, the dummy variable FU_{it} represents the transition from formal employment to unemployment for individual i in quarter t. This dummy variable is defined only for individuals who were in formal employment in the initial period ($t-1$), and 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.

To estimate the impact of monetary shocks on the likelihood of a specific transition, we use a linear probability model. For each dummy variable, D, we estimate the following equation using OLS:

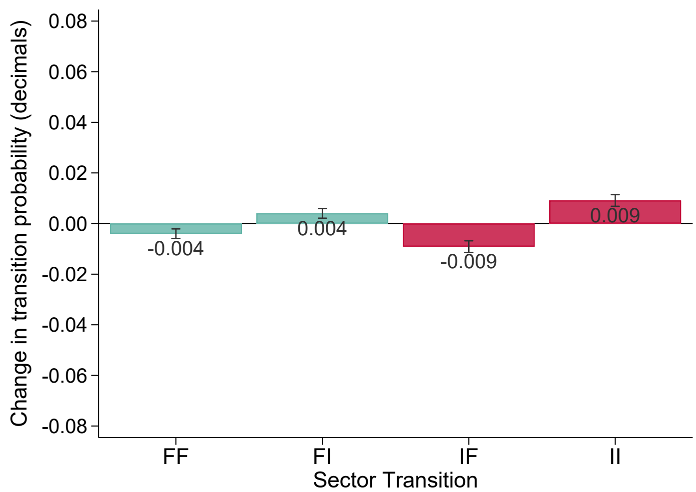
$$D_{it} = \alpha_D + \beta_D shock_t + \delta_D \bar{U}_t + \varepsilon_{i,t}. \tag{6}$$

Here, β_D measures the change in the probability of transition D occurring as a result of a one percentage point monetary policy shock, given the level of unemployment ($\bar{U}_t$).

4.1 One-year transitions when employed in both periods

In this subsection, we focus on understanding how monetary policy affects transitions in the labor market between different formality statuses (employed in formal or informal sector). To do so, we limit our analysis to workers who were employed in both the initial and final periods of the one-year time frame. We use four dummy variables to represent the four possible transitions between formal and informal employment: FF, FI, IF, and II. The results are shown in Figure 10 as decimal points. A monetary policy shock of one percentage point is associated with the probability of each transition becoming $\hat{\beta}_D \times 100$ percentage points higher, as estimated by OLS. Figure 11 displays the results when conditioning the estimation to different signs of the monetary policy shock.

Figure 10: The impact of a 1 p.p. monetary shock on transitions probabilities

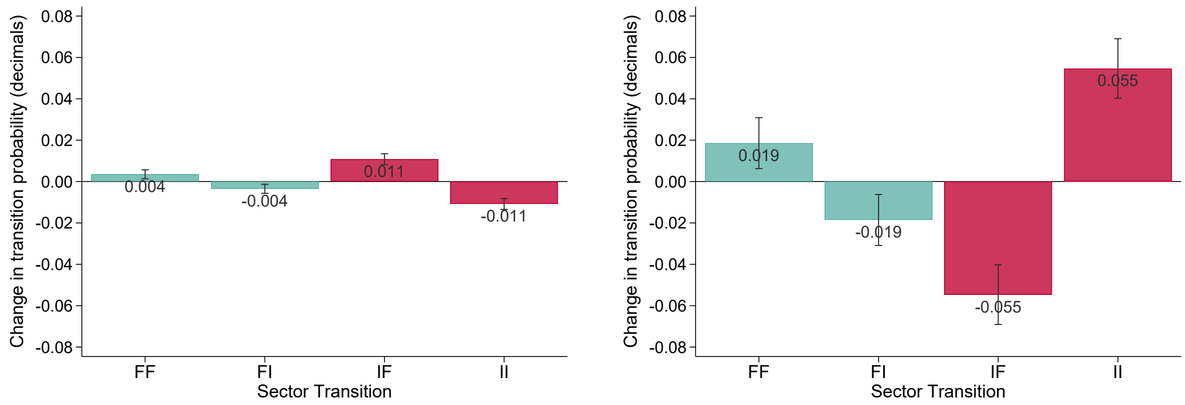


Notes: Dark thin lines represent 90% confidence intervals.

Overall, monetary policy shocks have a small impact on the likelihood of transitions across sectors for individuals who started in the formal sector. Although there is a slight increase in the estimates when only considering responses to contractionary shocks, the confidence bands also increase. Individuals who begin in the informal sector are affected to a greater extent. Expansionary shocks result in a one percentage point increase in the likelihood of transitioning to the formal sector, with an equivalent decrease in the likelihood of remaining in the informal sector (the results are of a similar magnitude when estimating a single regression regardless of the shock sign). On the other hand, contractionary shocks once again stand out, as a 1 percentage point shock leads to a 5.5 percentage point decrease in the likelihood of transitioning to a formal job, rendering informality more persistent.

Figure 11: The impact of a 1 p.p. monetary shock on transitions probabilities by shock sign

(a) Expansionary (b) Contractionary

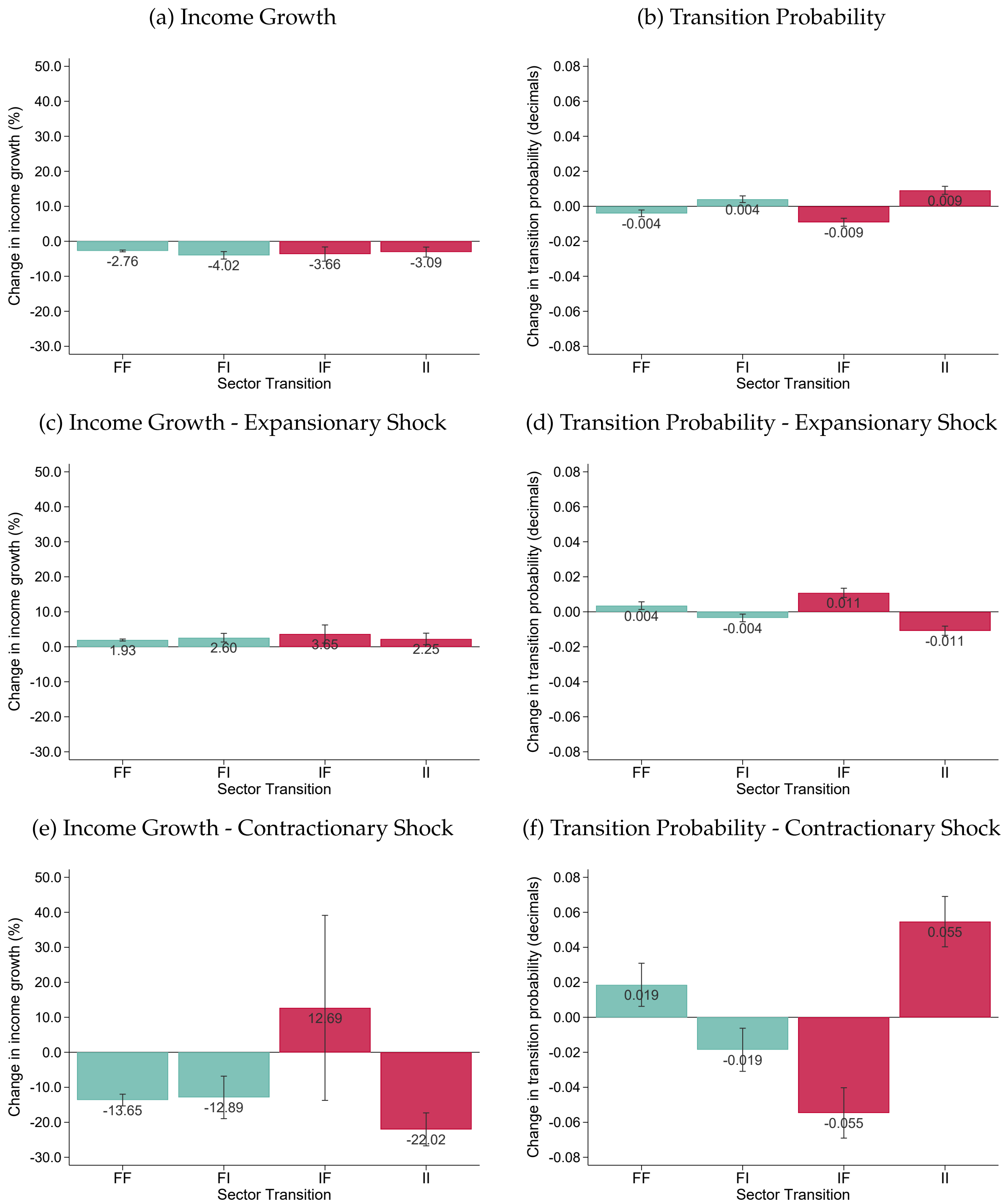


Notes: Dark thin lines represent 90% confidence intervals.

Given that the analysis so far has focused on workers who were employed during both periods, we can repeat the analysis of income growth, but now taking into account each specific sector transition. To do so, we estimate model (5) using OLS but only with workers who experienced transition D during the one-year window.

The results of the income growth and transition probability responses are presented side by side in Figure 12. Workers who start in the formal sector experience little change in their transition probabilities in the unconditional estimation. However, those who move to informality experience the largest drop in income as a response to a monetary policy shock among all the groups. Moreover, there is a similar negative income response for workers who stay in the informal sector compared to those who transition to it. In addition, an expansionary shock results in a higher probability of transition from informality to formality, which is accompanied by an increase in income for workers who experience this switch. On the other hand, those who remain in the formal sector see a smaller gain in income. Finally, contractionary shocks are particularly harsh for workers who remain in the informal sector. Not only is the likelihood of moving to a formal job reduced, but this group also experiences the largest drop in income, with a decrease of over 20 percentage points. Both workers who stay in the formal sector and those who move from it also experience a significant decline in income. This result, along with the positive estimate of the probability of staying in formal employment, suggests that the formal labor market adjusts earnings without making significant changes to employment levels.

Figure 12: The impact of a 1 p.p. monetary shock on income by transitions

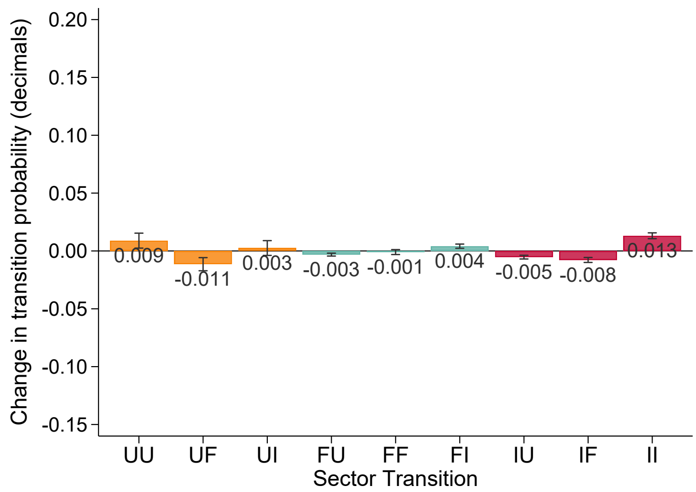


Notes: Dark thin lines represent 90% confidence intervals.

4.2 One-year transitions with unemployment

In this section, we analyze the effect of monetary policy shocks on employment transitions, including the movement to and from unemployment. To do so, we categorize individuals into a total of nine possible employment transitions: FF, FI, FU, IF, II, IU, UF, UI, and UU, where F stands for formal sector, I for informal sector, and U for unemployment.[5] We estimate model (6) by OLS for each possible transition, and report the results for each β_D in Figure 13 below. Additionally, Figure 14 shows the results when we consider the sign of the monetary policy shock.

Figure 13: The impact of a 1 p.p. monetary shock on transitions probabilities with unemployment



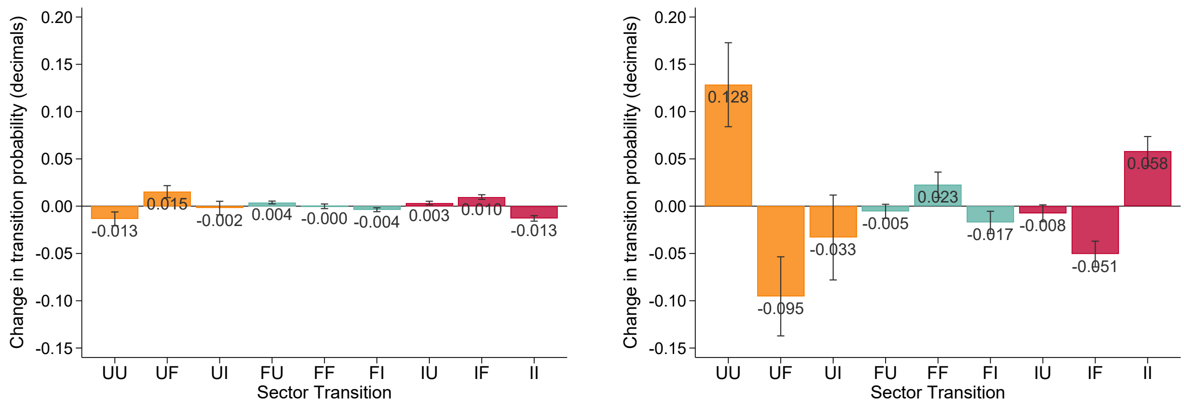
Notes: Dark thin lines represent 90% confidence intervals.

The results of a contractionary shock are significantly higher than those of an expansionary shock. Workers who were initially employed in the formal sector are more likely to remain in that sector and less likely to move to either informality or unemployment, as seen in the previous analysis. However, the probability of transitioning from unemployment or informality to the formal sector decreases sharply, by nearly 10 percentage points for unemployment and 5 percentage points for informality. Furthermore, a contractionary shock increases the likelihood of remaining unemployed or in the informal sector.

[5]The dummies representing employment in both periods (for example, FF) are not equal to the variables defined in the previous subsection. This is because now the dummies 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.

Figure 14: The impact of a 1 p.p. monetary shock on transitions probabilities with unemployment by shock sign

(a) Expansionary (b) Contractionary



Notes: Dark thin lines represent 90% confidence intervals.

5 Concluding Remarks

We document a set of empirical findings regarding the distributional effects of monetary policy on labor income growth and on employment transitions in a setting where informality is a relevant phenomenon. We find asymmetric impacts of monetary policy depending on the sign of the monetary policy shock, with contractions leading to responses of greater magnitude than expansions. The decline in labor income following contractionary monetary policy shocks is particularly severe for the lowest-income informal workers. Contractions also increase the persistence of informality and unemployment and decrease the chance of moving to a formal job.

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Appendix

A Monetary Shock Estimation Details

In this appendix, we detail the estimation process of the monetary shock series. As described in the text, our monetary 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. The OD1 Comdty security by Bloomberg automatically updates the prevailing contract as time passes and older futures reach maturity.

For the orthogonalization procedure, we collect market expectations from the *Boletim Focus* survey about the following list of economic variables:

- Interest rate (Selic) - 0 to 6 months forward.
- Inflation rate (IPCA) - 0 to 6 months forward.
- Industrial production - 0 to 6 months forward.
- Exchange rate as the Δlog to spot rate (USDBRL) - 0 to 6 months forward.
- Annual GDP - 0 to 2 quarters forward.
- Net government debt - 0 to 1 year forward.
- Primary deficit - 0 to 1 year forward.

We use ridge regression to accommodate such a large number of predictors. Compared to ordinary least squares, ridge regression adds a penalty to the size of the parameters, estimating β such as to minimize the following loss function

$$L(\hat{\boldsymbol{\beta}}) = \sum_{t=1}^{T} \left(y_t - \mathbf{X}_t' \hat{\boldsymbol{\beta}} \right)^2 + \lambda \sum_{j=1}^{k} \hat{\beta}_j^2, \tag{A1}$$

where λ is called the shrinkage penalty. We set λ by k-fold cross-validation, obtaining the value $\lambda^* = 34.71$. Table A1 reports the estimated coefficients for our ridge regression.

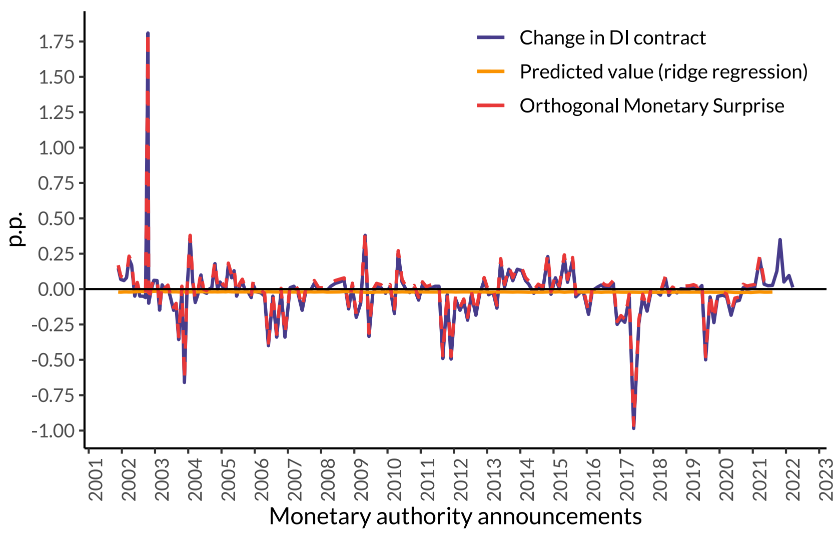
Table A1: Ridge Regression Coefficients

(Intercept)	-0.0245	IPCA_0	0.0006	GDP_0	0.0000
selic_0	0.0000	IPCA_1	0.0008	GDP_1	0.0000
selic_1	0.0000	IPCA_2	0.0003	GDP_2	0.0000
selic_2	0.0000	IPCA_3	0.0004	netdebt_0	0.0000
selic_3	0.0000	IPCA_4	0.0005	netdebt_1	0.0000
selic_4	0.0000	IPCA_5	-0.0001	primarydeficit_0	0.0000
selic_5	0.0000	IPCA_6	0.0007	primarydeficit_1	0.0001
selic_6	0.0000	USDBRL_0	-0.0048		
industry_0	0.0000	USDBRL_1	-0.0058		
industry_1	0.0000	USDBRL_2	-0.0059		
industry_2	0.0000	USDBRL_3	-0.0040		
industry_3	0.0000	USDBRL_4	-0.0034		
industry_4	0.0000	USDBRL_5	-0.0027		
industry_5	0.0000	USDBRL_6	-0.0024		
industry_6	0.0000				

Note: Estimated coefficients by ridge regression associated with market expectations for different economic variables. The number in the name of the regressor indicates the horizon for the forecast.

The orthogonal monetary surprise corresponds to the residual of the ridge regression after accounting for all information contained in the market expectations. We plot the original and the orthogonal monetary surprises together with the fitted value of the ridge regression in Figure A1. As would be expected given the small values estimated for the coefficients, the predicted component of the orthogonal surprise is practically irrelevant. Nevertheless, we adopt the orthogonal version of the surprise in the rest of our exercises.

Figure A1: Original, predicted and orthogonal monetary surprises

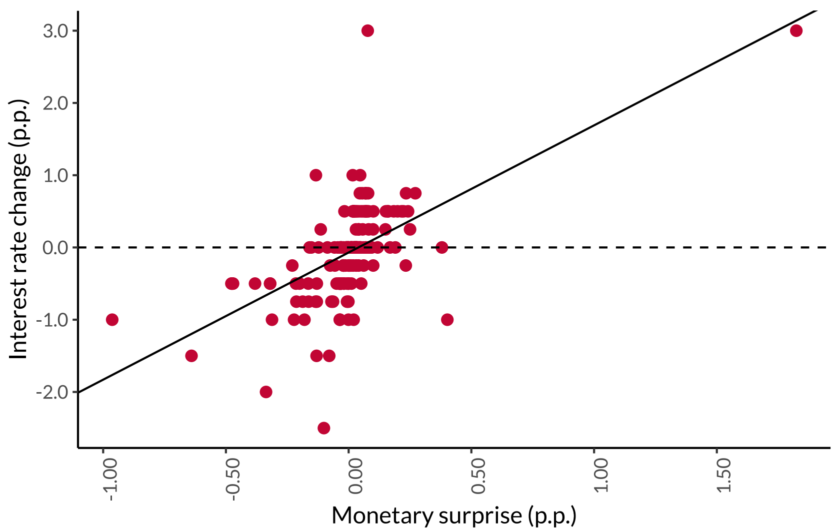


Finally, we employ the monetary surprise as an instrumental variable for the change in the interest rate announced after each monetary authority meeting. The resulting fitted value from the OLS estimation given in (1) corresponds to the monetary shock series. Figure A2 displays the interest rate change and the monetary surprise in each event of our sample, as well as the fitted line of the OLS estimation. Table A2 shows the detailed OLS results.

Table A2: Monetary Shock Estimation

	Dependent variable:
	Interest rate change
Monetary surprise	1.766***
	(0.185)
Constant	−0.073*
	(0.039)
Observations	175
R^2	0.346
Adjusted R^2	0.342
Residual Std. Error	0.510 (df = 173)
F Statistic	91.333*** (df = 1; 173)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure A2: Interest rate change and monetary surprise in days of announcements

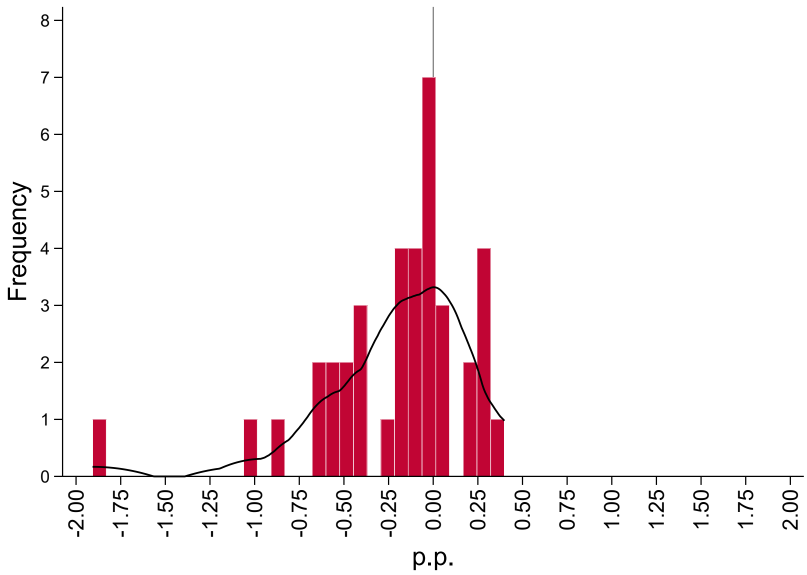


We next present some descriptive statistics of the estimated shock series when we restrict it to the same horizon as our microdata. We are left with 38 shock events, of which 27 are expansionary shocks and 11 are contractionary shocks.

Table A3: Estimated shock series restricted to the microdata horizon (p.p.)

	Percentiles	Smallest		
1%	-1,90745	-1,90745		
5%	-1,04823	-1,04823		
10%	-0,62356	-0,85256	**Obs**	38
25%	-0,44476	-0,62356		
50%	-0,06528		**Mean**	-0,20654
		Largest		
75%	0,03007	0,26205	**Std. Dev.**	0,43366
90%	0,26205	0,27507	**Variance**	0,18806
95%	0,31952	0,31952	**Skewness**	-1,73833
99%	0,39858	0,39858	**Kurtosis**	7,51638

Figure A3: Distribution of shock realizations restricted to the microdata horizon



B Sample Restrictions

Table B1 describes the sample restrictions applied to the microdata and the resulting number of observations dropped. Next, we present some descriptive statistics on the resulting samples.

Table B1: Sample Restrictions

	Income Growth		Transition	
	Δ	N	Δ	N
Original number of observations:		21.697.397		21.697.397
Drop missing values				
Year	0	21.697.397	0	21.697.397
Quarter	0	21.697.397	0	21.697.397
Gender	0	21.697.397	0	21.697.397
Age	0	21.697.397	0	21.697.397
Individual id	0	21.697.397	0	21.697.397
Labor force indicator	0	21.697.397	0	21.697.397
Age Selection				
Keep age between 18 and 65 years	-7.841.819	13.855.578	-7.841.819	13.855.578
Employer				
Drop if occupation is employer (8)	-339.280	13.516.298	-339.280	13.516.298
Employees that work for no money				
Drop if no monetary compensation (10)	-301.481	13.214.817	-301.481	13.214.817
Missing income				
Drop employees with missing income	-30.985	13.183.832	-30.985	13.183.832
Less than 1/2 minimum wage				
Drop employees with income <1/2 min wage	**-968.189**	**12.215.643**	-	-
Repeated id in same quarter				
Drop if same id appears more than once	-3	12.215.640	-4	13.183.828
Panel Structure				
Observations with 1 year income growth		777.470		-
Formal sector		481.749		
Informal sector		295.721		
Observations in the labor force in both periods		-		1.043.014
Observations with 1 year labor force indicator		-		1.755.548

The table shows the number of observations 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 individuals in the panel, that is, the number of workers who appear in the survey in quarters one-year apart. For those individuals, we can calculate one-year income growth or employment status change.

Table B2: Descriptive Statistics of the (Income Growth) Sample

	All	By income groups			
		g1	g2	g3	g4
N	777.470	170.594	187.221	204.420	215.235
% male	59,50	53,45	53,91	63,94	64,93
% informal	36,68	61,75	30,44	30,51	28,94
mean age (years)	39,37	38,96	37,45	39,04	41,68
mean real net income (R$)	30.346,77	14.802,49	18.258,20	25.135,27	57.045,63
median real net income (R$)	21.066,15	13.799,42	16.551,84	23.562,17	43.589,59

Table B3 shows descriptive statistics of one-year real disposable income (percentage) growth for our 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: Real disposable income one-year growth (winsorized, p.p.)

Percentiles		**Smallest**		
1%	-71,37	-99,16		
5%	-50,55	-98,77		
10%	-37,31	-98,72	**Obs.**	777.470
25%	-14,36	-98,07		
50%	-1,89		**Mean**	7,73
		Largest	**Std. Dev.**	47,51
75%	18,07	234,25		
90%	58,32	234,25	**Variance**	2.257,27
95%	97,00	234,25	**Skewness**	2,09
99%	234,25	234,25	**Kurtosis**	9,68

C 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 3.1.

Table C1: Social Security contribution schedules

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

Note: For public employees and the military, the contribution rate is fixed at 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 in this table is the official website of INSS: https://www.gov.br/inss/pt-br/saiba-mais/seus-direitos-e-deveres/calculo-da-guia-da-previdencia-social-gps/tabela-de-contribuicao-mensal/tabela-de-contribuicao-historico.

Table C2: Income tax schedules

Year	Wage Base (R$)	Rate (%)	Deduction (R$)
2015:	up to 1,903.98	-	-
Apr+	1,903.99 to 2,826.65	7.5	142.80
	2,826.66 to 3,751.05	15	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	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	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	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	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/orientacao-tributaria/tributos/irpf-imposto-de-renda-pessoa-fisica#tabelas-de-incid-ncia-mensal.