Monetary Policy and Labor Markets in a Developing Economy *

Diego B. P. Gomes † Felipe S. Iachan ‡

Ana Paula Ruhe § Cezar Santos ¶

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Abstract

We study the distributional effects of monetary policy in a developing economy setting where employment informality is prevalent. In particular, we examine how monetary policy impacts labor income growth and employment transitions. We construct a series of monetary policy surprises for Brazil, using a high-frequency identification approach. Both formal and informal workers experience declines in real income following a surprise monetary contraction, with a more pronounced effect for higher-income quartiles. A monetary contraction also reduces the likelihood of large income gains, generating a leftward shift in the income growth distribution. Moreover, surprise contractions increase the persistence of informality and unemployment 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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†International Monetary Fund; dgomes@imf.org

‡FGV EPGE Escola Brasileira de Economia e Finanças, Fundação Getulio Vargas; felipe.iachan@fgv.br

§FGV EPGE Escola Brasileira de Economia e Finanças, Fundação Getulio Vargas; ana.ruhe@fgv.edu.br

¶Inter-American Development Bank & CEPR; cezarsantos.econ@gmail.com

1 Introduction

Monetary policy impacts labor markets, but its effects are not uniform across all workers. This heterogeneity can be of particular importance 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 negative effects on vulnerable groups. This paper investigates these heterogeneous effects in Brazil, a developing country with a sizable informal sector, to shed light on how monetary policy impacts different segments of the labor force.

We find that an unanticipated increase in the interest rate leads to declines in labor income across the entire income distribution, with comparable effects for both formal and informal workers. Moreover, surprise monetary contractions increase the persistence of informality and unemployment by reducing the likelihood of transitions into formal employment.

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 financial markets have closed. To identify monetary policy surprises, we use price changes in deposit rate (DI rate) futures contracts 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.

We use this monetary policy surprise series in a reduced-form local-projection approach 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 display a negative mean income growth response ranging from about -1.14 to -1.48 percentage points after an unexpected 0.25 percentage point increase in the interest rate. We find quantitatively similar results for both formal and informal sector workers.

Moreover, we measure monetary policy's impact on the income *growth* distribution by employing quantile regressions. A 0.25 percentage point monetary surprise shifts the income growth distribution leftward, with an average income drop of 1.31 percentage points. The movement in the right tail is larger, meaning events of substantial income growth become less likely. This feature is equally pronounced for formal sector workers and informal 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 surprise monetary policy contraction reduces the probability of moving to the formal sector and increases the probability of staying informal. For those who started in a formal job, we find no effect of a monetary surprise on the likelihood of their transitions. Additionally, we analyze the effect of monetary policy surprises on employment transitions, including the movement to and from unemployment, and find that a contractionary monetary policy decreases the probability of transitioning from unemployment or informality to the formal sector. Therefore, monetary contractions increase the persistence of both unemployment and informality.

Related Literature Our paper relates to a strand of literature that identifies monetary policy surprises and estimates responses to exogenous monetary policy movements. 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). 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. 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 surprise occurs. We also expand the analysis to include transitions to and from unemployment.

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

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

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

The rest of the paper is organized as follows. Section 2 describes the estimation of the monetary policy surprises series and validates its findings by presenting monthly impulse-response functions of key labor market 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 on employment transitions. Section 6 concludes.

2 Monetary Policy Surprise

Assessing the impact of monetary policy on labor market outcomes requires exogenous variation in monetary policy variables. Therefore, the first step of our analysis is to estimate a series of monetary policy surprises. To accomplish this, we adopt a high-frequency identification strategy, as proposed by Gertler and Karadi (2015) and Nakamura and Steinsson (2018).

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 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 to reach its inflation objective. 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.[2]

[2]In Brazil, the DI rate future contracts are used in place of actual repo interest rate (Selic)

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.[3]

For each meeting, m, of the monetary authority, the estimated $surprise_m$ represents the unexpected variation in monetary policy. As our microdata has a quarterly frequency, we aggregate these surprises by summing all realizations within the same quarter to create a quarterly time series. The surprise value for each quarter t is given by

$$surprise_t = \sum_{m \in Q(t)} surprise_m, \tag{1}$$

where $Q(t)$ is the quarter for period t.

Our sample consists of 58 events between 2012 and 2019, resulting in 29 observations at a quarterly frequency.[4] Data about the days of monetary authority meetings and interest rates announced come from the Brazilian Central Bank (2024a). The future contract prices are provided by Bloomberg. Panel (a) of Figure 1 plots the monetary surprise series and Panel (b) its quarterly aggregation.

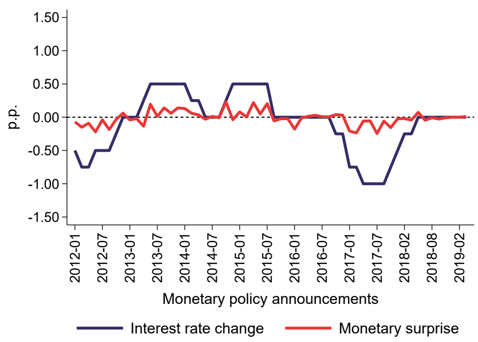
contracts. The DI rate and Selic are closely related in practice, and market participants view DI future contracts as a representation of the future path of interest rates.

[3]See Appendix B for more details. As a robustness exercise, we implemented an orthogonalization procedure to account for a potential lack of exogeneity of the estimated monetary policy surprises, as pointed out 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.

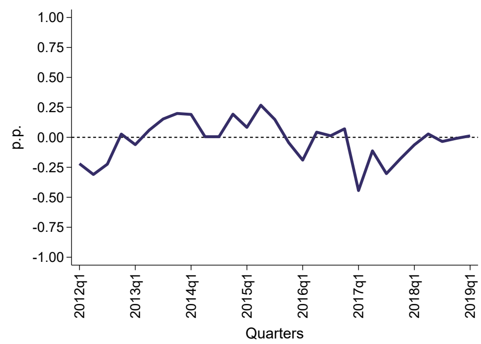
[4]Here, we are restricting attention to the same horizon of the labor-market microdata used in the rest of the analysis. We have calculated the series of monetary surprises starting in 1999, that is, since the beginning of the inflation-targeting system in Brazil and going until the end of 2023. This longer series is available upon request.

Figure 1: Monetary Policy Surprises and Aggregate Responses

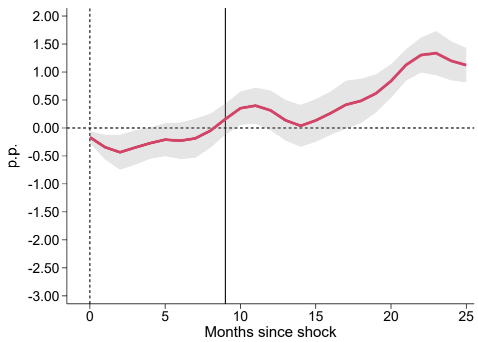
(a) Interest rate change and monetary surprise



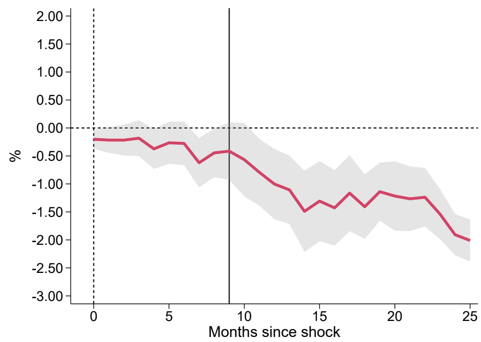
(b) Quarterly monetary policy surprise



(c) Unemployment rate response



(d) Average real labor income response



Notes: Panel (a) shows our estimated series of monetary policy surprises and the announced change in the interest rate for each monetary authority meeting between January 19, 2012, and March 21, 2019. Panel (b) shows the aggregated monetary policy surprise series at a quarterly frequency for the same period, as described by Equation 1. Panels (c) and (d) display the response to a 0.25 p.p. monthly monetary policy surprise of the aggregate unemployment rate and of the average real labor income, respectively. Shaded areas represent 68 percent confidence intervals with Newey-West standard errors. The vertical line marks $h = 9$ months (3 quarters after the surprise).

2.1 Aggregate Responses

Before proceeding to the microdata, we check how reasonable the estimated monetary policy surprise series is. We assess this by estimating monthly impulse-response functions of key labor market variables with monthly coverage. The impulse responses are estimated by local projections following Jordà (2005). In addition to ensuring the estimated monetary policy surprise series withstands scrutiny, this exercise provides initial insights into what to expect from the individual-level results.

For this analysis, we consider the aggregate unemployment rate and the average real monthly labor income. 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 $h = 0, \ldots, 24$, we estimate the following local projection:

$$\Delta_h Y_t = \alpha_h + \theta_h surprise_t + \boldsymbol{x}_t' \boldsymbol{\gamma}_t + \epsilon_{t+h}, \tag{2}$$

where we now use a monthly frequency aggregation of the monetary policy surprise. We include twelve lags of the surprise as controls in $\boldsymbol{x}_t$. The parameter θ_h gives the impulse response for each horizon h. Panels (c) and (d) of Figure 1 show the estimated values $\hat{\theta}_h$.

In response to a 0.25 percentage point monetary policy surprise, the aggregate unemployment rate shows little change for the first 15 months. It then steadily increases, reaching around 1.5 percentage points higher two years after the surprise. The average real labor income responds slowly initially, but the decrease accelerates around 6 months after the surprise, and there are no signs of recovery within the 24-month window analyzed.

The vertical line in the figure indicates the horizon that we can observe in the microdata: nine months (three quarters) after the surprise event. Within this window, average labor income shows a small decrease in response to the monetary surprise but is still far from its trough. Unemployment, however, has not yet exhibited a significant increase.

3 Microdata 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 wide range of demographic, education, and employment 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.

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 main 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 C, 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 pandemic aftermath and immediate recovery highly unusual for labor markets. To avoid confounding the effects of these extraordinary circumstances with monetary policy surprises, we exclude data from 2020 onwards.

We restrict the sample to workers aged 18-65, excluding employers, unpaid workers, and those with missing income data. For income growth exercises, we further exclude the unemployed (as they have no labor income) and those earning less than half the minimum wage. Our final employed sample consists of 527,379 individuals in the panel dataset (approximately 18,000 per quarter), rising to 696,662 when including the unemployed.

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 Ministry of Labor, 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, the informal workers are those without a CTPS entry and the self-employed. In our exercises, an individual's formality status is based on their employment situation in the quarter preceding the monetary policy surprise event.

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 contribution scheme rules differ between private/public worker groups and 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.[5]

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 surprise in the second quarter of the worker's survey appearance. Hence, letting t represent the period of the surprise, one-year income growth is calculated as

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

where $Y_{i,t}$ represents worker i's annualized real disposable labor income.[6]

[5]See Appendix A.2 for more details.

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

4 Impact of Monetary Policy on Labor Income

4.1 Estimation Specification

To estimate how the impact of monetary surprises 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 surprise. We then estimate the following equation:

$$\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} = \sum_{g=1}^{4} G_{i,g,t} \left[\alpha_{g,h} + \beta_{g,h} surprise_t \right] + \delta_h U_t + \epsilon_{i,t+h}, \tag{3}$$

where we set $h = 3$ so that the dependent variable is the one-year real disposable income growth expressed as a percentage. $G_{i,g,t}$ 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 surprise for each group. We normalize our surprise series such that each $\beta_{g,h}$ measures the one-year income growth for group g associated with a 0.25 percentage point monetary policy surprise. We include the quarterly average unemployment rate, U_t, to control for overall economic conditions affecting all groups in a given quarter. We estimate equation (3) by Ordinary Least Squares (OLS) and median quantile regression, calculating bootstrap standard errors with clustering at the time dimension in both cases.

The exercise described thus far measures how the conditional mean and median of labor income growth change with monetary policy surprises for different income level groups. We also explore the heterogeneity across quantiles of the conditional income growth distribution. To do this, we employ quantile regressions to estimate the following equation at the 10th, 25th, 75th, and 90th quantiles:

$$\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} = \alpha_h + \beta_h surprise_t + \delta_h U_t + \epsilon_{i,t+h}. \tag{4}$$

We revisit the analysis of the median and mean effects that were previously examined without splitting our sample into different income groups. As before, the left-hand side is percentage income growth, 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 0.25 percentage point monetary policy surprise. Essentially, this analysis maps out how the conditional distribution of income *growth* responds to a surprise monetary policy event.

4.2 Heterogeneous Responses and the Income Distribution

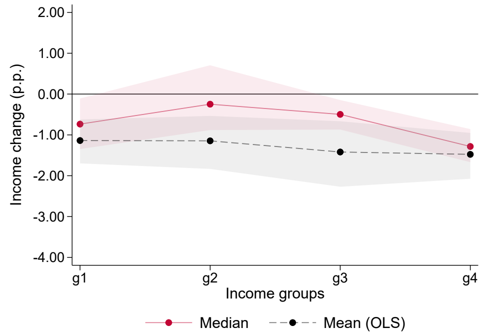
The left column of Figure 2 shows the coefficient estimates $\hat{\beta}_{g,h}$ of Equation 3 for the one-year horizon ($h = 3$), that is, the response of one-year income growth to a 0.25 percentage point monetary policy surprise of each group g. The four income groups are displayed along the horizontal axis. Shaded areas represent 68 percent confidence bands. The figure presents estimates using both OLS and a median quantile regression.

Start with Panel (a), which plots the results for all workers. All income groups experience a mean income drop of more than 1 percentage point following a surprise monetary tightening, with a flat pattern across the different groups. The conditional median income growth responds less to the monetary surprise than the conditional mean income growth for all groups, showing a slight inverse U shape. As discussed in Appendix A.1, the income growth distribution in our sample exhibits positive skewness and a long right tail due to outliers, even after winsorization. Consequently, the mean and median differ. However, the results in Figure 2 show that while the mean and median income growth values differ, their qualitative responses to monetary surprises are comparable.

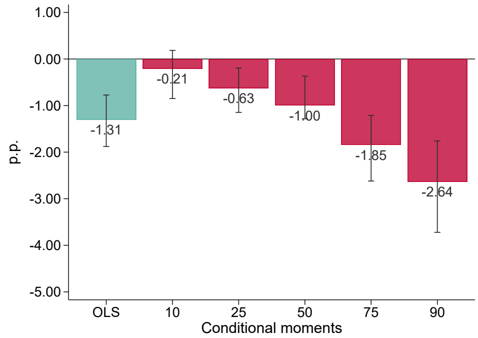
To assess the heterogeneity of the effects between formal and informal workers, we estimate equation (3) separately for each sector, according to the worker's formality status in the quarter preceding the monetary policy event. However, the sorting of workers into income groups is not conditioned on their formality status. Panels (c) and (e) of Figure 2 show the results. The two sectors differ for the intermediary income groups: informal workers in the second income group display the largest income drop, while, in the formal sector, this happens for workers in the third income group. Overall, however, the magnitude of the responses is similar across the two sectors, with median responses being less pronounced than the mean effect.

Figure 2: The effects of a 0.25 p.p. monetary policy surprise

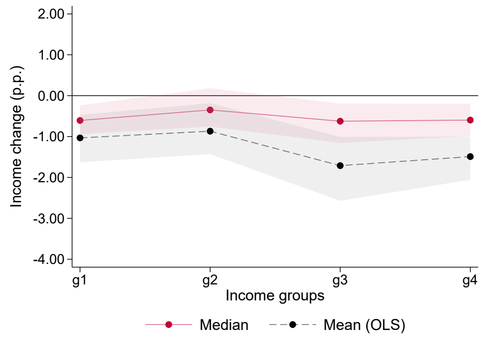
(a) On income growth – All workers



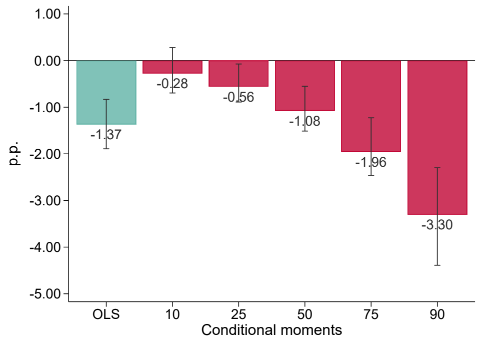
(b) On the income growth distribution – All workers



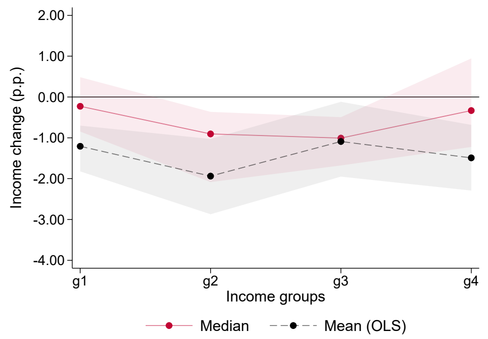
(c) On income growth – Formal workers



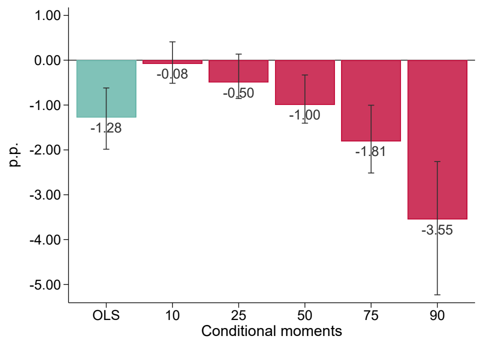
(d) On the income growth distribution – Formal



(e) On income growth – Informal workers



(f) On the income growth distribution – Informal



Notes: Panels (a), (c), and (e) show the mean and the median income responses to a 0.25 percentage point monetary surprise of the four quartiles of the income distribution when considering all workers, formal workers, and informal workers, respectively. Panels (b), (d), and (f) display the impact of a 0.25 percentage point monetary surprise on the different quantiles of the income growth distribution, once again considering the entire sample of workers, those in the formal sector and those in the informal sector. Shaded areas and dark vertical lines represent 68 percent confidence intervals calculated from bootstrapped standard errors with bias correction and clustered at the time dimension.

The right column of Figure 2 presents the results of our second exercise, described by Equation 4. It displays the estimates for β_h, that is, the impact on each given quantile of the income growth distribution from a 0.25 percentage point monetary policy surprise. Panel (b) exhibits the results when considering all workers. The estimates for β_h are all negative: when a 0.25 percentage point monetary policy surprise 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 0.21 percentage points, the 90th quantile declines by 2.64 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 surprise. The average income growth is reduced by 1.31 percentage points.

Panels (d) and (f) of Figure 2 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 is very similar between the two sectors, although slightly larger in the formal sector for all but the 90th quantile.

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, 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, without imposing income restrictions, as described in Appendix A.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 surprise, 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 surprises on the likelihood of a specific transition. For each indicator, $D_{i,t}$, we estimate the following equation using OLS:

$$D_{it} = \alpha_D + \beta_D surprise_t + \delta_D U_t + \varepsilon_{i,t}. \tag{5}$$

Once again, we normalize our surprise series such that β_D measures the change in the probability of transition $D_{i,t}$ occurring as a result of a 0.25 percentage point monetary policy surprise, given the level of unemployment (U_t).

Table 1: Transition rates across employment conditions

(a) Conditional on remaining employed

		Final	
		F	I
Initial	F	0.90	0.10
	I	0.13	0.87

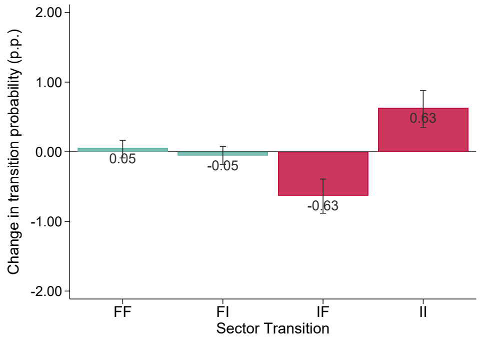
(b) With unemployment

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

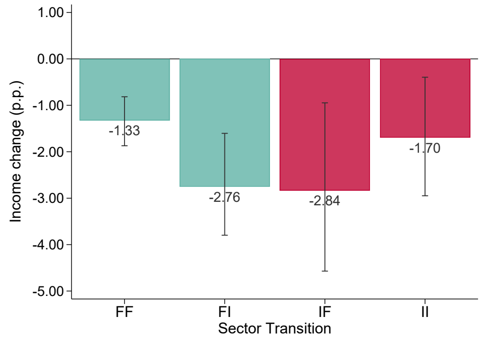
Notes: Panel (a) displays the one-year transition probabilities between the formal and the informal sectors for workers who were employed in both the initial and the final periods of the one-year comparison. Panel (b) displays the one-year transition probabilities between the two types of employment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

Figure 3: The effects of a 0.25 p.p. monetary policy surprise

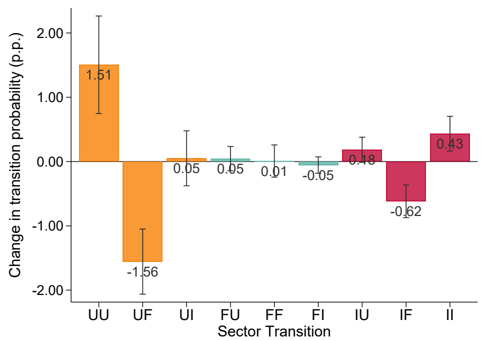
(a) On the probability of employed transitions



(b) On income growth by employment transition



(c) On the probability of all transitions



Notes: Panel (a) plots the impact of a 0.25 percentage point monetary surprise 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 surprise for workers who experienced each of the four possible employed transitions. Panel (c) shows the impact of the monetary surprise on the probability of transitioning between different employment statuses, including movements to and from unemployment. Dark vertical lines represent 68 percent confidence intervals calculated from bootstrapped standard errors clustered at the time dimension.

First, we focus on understanding how monetary policy affects transitions in the labor market between different formality statuses (employed in 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 3. A monetary policy surprise of 0.25 percentage points is associated with the probability of each transition becoming $\hat{\beta}_D \times 100$ percentage points higher, as estimated by OLS.

Monetary policy surprises have no significant impact on individuals who start in the formal sector. For those starting in the informal sector, however, the impact is larger: a 0.63 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.

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 (4) using OLS, considering only workers who experienced transition $D_{i,t}$ during the one-year window. The results are shown in Panel (b) of Figure 3. 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 surprise. Those remaining in the formal sector also see a decline, albeit smaller.

Next, we analyze the effect of monetary policy surprises 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.[7] We estimate equation (5) by OLS for each possible transition and report the results for each $\beta_D \times 100$ in Panel (c) of Figure 3.

A 0.25 percentage point monetary surprise leads to a 1.51 percentage point increase in the probability of remaining unemployed, a 1.56 decrease in moving from unemployment to a formal job, and a negligible impact on the transition to informality. Similarly, for those who begin the period in the informal sector, the 0.25 percentage point monetary surprise leads to a 0.62 percentage point drop in the probability of moving to a formal job and an increase in the probability of staying informal or becoming unemployed. Workers starting in a formal job, on the other hand, are essentially unaffected.

The job-flow effects we observe in the microdata are detectable within a time frame where aggregate unemployment has not yet shown economically or statistically significant responses. It is the cumulation of these effects over time that generates the pattern exhibited in Figure 1.

6 Concluding Remarks

This paper documents the distributional effects of monetary policy on labor income growth and employment transitions in Brazil, a developing economy

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

where informality is a significant phenomenon. 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 similar for workers in all income groups, with a real income drop of up to 1.5 percent in response to a 0.25 percentage point increase in interest rates. 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. A surprise increase in interest rates shifts the income growth distribution leftward, with a more pronounced movement in the right tail, indicating a reduction in high-income growth events. This effect is equally noticeable among formal sector workers and informal workers.

Furthermore, monetary contractions increase the persistence of informality and unemployment. Workers in the informal sector are less likely to transition to formal employment following a contractionary shock, and unemployment becomes more persistent. 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 policies 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

A Data

A.1 Sample Restrictions

Table A1 describes the sample restrictions applied to the microdata and the resulting number of observations dropped.

Table A1: Sample Restrictions

	Income Growth		Transition	
	Δ	N	Δ	N
Original number of observations		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	0	16,719,584	0	16,719,584
Age Selection				
Keep age between 18 and 65 years	-6,106,064	10,613,520	-6,106,064	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				
Observations with 1 year income growth		527,379		-
Formal sector		327,541		-
Informal sector		199,838		-
Observations in the labor force in both periods		-		696,662

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, when we restrict the surprise realization to the 2012-2019 period. For those individuals, we can calculate one-year income growth or employment status change.

Next, Table A2 presents some descriptive statistics on the resulting "Income Growth" sample.

Table A2: Descriptive Statistics of the (Income Growth) Sample

	All	By income groups			
		g1	g2	g3	g4
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%
% infomal (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

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

Table A3 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 A3: Real disposable income one-year growth (winsorized, p.p.)

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

A.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 A4: 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 A5: 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-mensal/tabela-de-contribuicao-historico.

B Monetary Policy Surprises

B.1 Estimation Details

In this appendix, we detail the estimation process of the monetary policy surprises. As described in the text, our monetary policy 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. A few points 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 when some of the meetings took place.[8] We use the minutes as the correct information. They also inform us that, before 2004, a few meetings ended while financial markets were still open. For those dates (listed below), we adjusted our surprise definition. Instead of comparing opening prices in $t+1$ to closing prices in t (which is what we do when the announcement happens on day t after markets have closed), we measure the price change between opening prices in $t+1$ and opening prices in t.

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 monetary authority meetings take place on the eve of a holiday, such that financial markets are not open the next day. In those cases, we use the next business day opening prices when calculating our monetary surprise.

[8] The summary table is available at Brazilian Central Bank (2024a). The official minutes of the meetings are available at Brazilian Central Bank (2024b).

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[9]
29/May/2013	31/May/2013
03/Jun/2015	05/Jun/2015

3. Finally, one needs to be careful about meetings that take place on the last business day of the month. The underlying future contract under the OD1 Comty security on the day after the meeting will be different from the one for which the closing price on the day of the meeting is shown. 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 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

We next present some descriptive statistics of our monetary surprise series when we aggregate it to a quarterly frequency and restrict it to the same horizon as our microdata in Table B1.[10] We are left with 29 events, which we show in Figure B1.

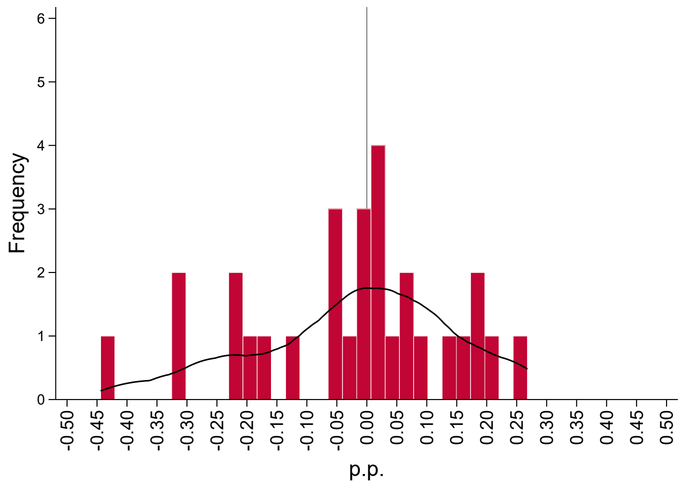
[9]Holiday followed by a weekend.

[10]Given the timing of our exercise detailed in the text, we measure the impact of a monetary surprise that occurs in period t on a one-year change (of income or employment status) between $t+3$ and $t-1$. Hence, as the microdata spans until 2019Q4, our last surprise in the sample is the one from 2019Q1.

Table B1: Quarterly monetary surprise series – 2012Q1-2019Q1 (p.p.)

	Percentiles	**Smallest**		
1%	-0.444	-0.444		
5%	-0.310	-0.310		
10%	-0.303	-0.303		
25%	-0.113	-0.224	**Obs.**	29
50%	0.005		**Mean**	-0.024
		Largest		
75%	0.071	0.191	**Std. Dev.**	0.170
90%	0.193	0.193	**Variance**	0.029
95%	0.199	0.199	**Skewness**	-0.545
99%	0.268	0.268	**Kurtosis**	2.864

Figure B1: Distribution of quarterly monetary surprises – 2012Q1 to 2019Q1



B.2 Robustness

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 sometimes can be predicted by 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.

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 the orthogonal monetary policy surprise series.

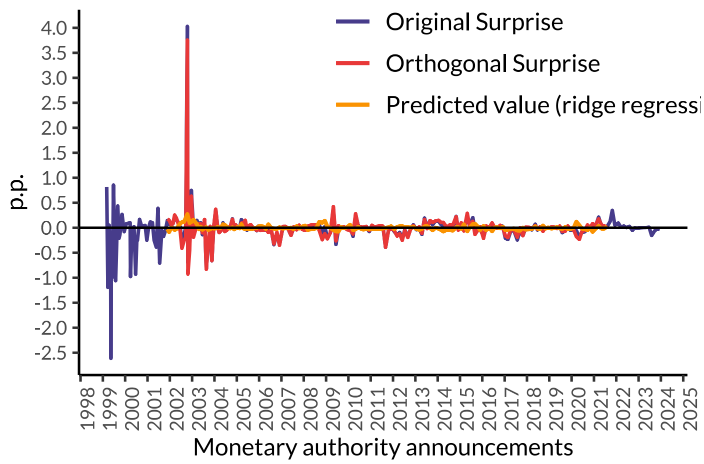
We collect market expectations from the *Boletim Focus* survey about the following list of economic variables (Brazilian Central Bank, 2024c): (i) interest rate (Selic) – 0 to 6 months forward; (ii) inflation rate (IPCA) – 0 to 6 months forward; (iii) industrial production – 0 to 6 months forward; (iv) 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. These set of market expectations is available for the time frame from Nov 2001 to August 2021, which restricts our orthogonal monetary surprise series.

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

$$L(\hat{\boldsymbol{\beta}}) = \sum_{t=1}^{T} \left(y_t - \mathbf{X}_t' \hat{\boldsymbol{\beta}} \right)^2 + \lambda \sum_{j=1}^{k} \hat{\beta}_j^2, \tag{B1}$$

where λ is called the shrinkage penalty. We set λ by k-fold cross-validation, obtaining the value $\lambda^* = 4.5$. Table B2 reports the estimated coefficients for our ridge regression.

Figure B2: Original, predicted, and orthogonal monetary surprises



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 B2. As would be expected given the small values estimated for the coefficients, the predicted component of the orthogonal surprise is practically irrelevant. For the overlapping horizon of the two series (2001-2021), the correlation between the original and the orthogonal monetary surprises is of 0.99. This 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 our original surprise, given that it allows us to cover a larger horizon when working with the microdata.

Table B2: Ridge Regression Coefficients

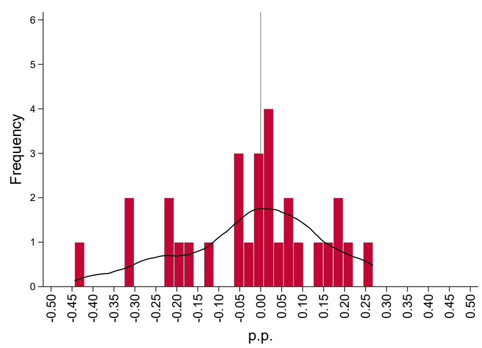
	Estimate	Estimate (Sc)	StdErr (Sc)	t-value (Sc)	Pr(>|t|)
Intercept	-0.0946	-6.2765	3.5350	-1.7756	0.0776 .
selic_0	0.0003	0.0249	0.0272	0.9172	0.3604
selic_1	0.0005	0.0348	0.0262	1.3286	0.1858
selic_2	0.0006	0.0397	0.0260	1.5267	0.1287
selic_3	0.0006	0.0426	0.0258	1.6500	0.1008
selic_4	0.0007	0.0491	0.0259	1.8969	0.0595 .
selic_5	0.0007	0.0463	0.0259	1.7867	0.0758 .
selic_6	0.0008	0.0506	0.0260	1.9432	0.0536 .
industry_0	0.0004	0.0244	0.0439	0.5558	0.5791
industry_1	0.0002	0.0127	0.0429	0.2952	0.7682
industry_2	0.0002	0.0075	0.0380	0.1975	0.8437
industry_3	-0.0002	-0.0087	0.0426	-0.2041	0.8385
industry_4	-0.0004	-0.0176	0.0424	-0.4149	0.6788
industry_5	-0.0007	-0.0224	0.0414	-0.5418	0.5887
industry_6	-0.0022	-0.0728	0.0505	-1.4424	0.1510
IPCA_0	0.0161	0.0626	0.0537	1.1662	0.2452
IPCA_1	0.0103	0.0240	0.0499	0.4806	0.6314
IPCA_2	0.0058	0.0123	0.0494	0.2488	0.8038
IPCA_3	0.0127	0.0271	0.0483	0.5604	0.5760
IPCA_4	0.0111	0.0223	0.0487	0.4580	0.6475
IPCA_5	-0.0121	-0.0253	0.0478	-0.5301	0.5967
IPCA_6	0.0279	0.0573	0.0507	1.1302	0.2600
USDBRL_0	-0.2298	-0.0733	0.0419	-1.7489	0.0821 .
USDBRL_1	-0.2454	-0.1025	0.0337	-3.0416	0.0027 **
USDBRL_2	-0.3134	-0.1566	0.0319	-4.9078	<2e-16 ***
USDBRL_3	-0.1903	-0.1078	0.0315	-3.4208	0.0008 ***
USDBRL_4	-0.1525	-0.0947	0.0318	-2.9756	0.0034 **
USDBRL_5	-0.1287	-0.0854	0.0319	-2.6792	0.0081 **
USDBRL_6	-0.1041	-0.0737	0.0324	-2.2737	0.0242 *
GDP_0	0.0007	0.0297	0.0438	0.6764	0.4997
GDP_1	0.0003	0.0081	0.0359	0.2248	0.8224
GDP_2	0.0000	0.0012	0.0417	0.0278	0.9778
netdebt_0	0.0002	0.0280	0.0504	0.5569	0.5783
netdebt_1	0.0002	0.0298	0.0496	0.6000	0.5493
primarydefict_0	0.0003	0.0142	0.0374	0.3790	0.7051
primarydeficit_1	0.0005	0.0145	0.0393	0.3683	0.7131

Notes: Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 ‘ ’ 1. “Sc” stands for scaled.
The number in the name of each regressor indicates the horizon for the forecast.

We conduct a second robustness exercise in the estimation of the monetary surprise series. Both monetary policy movements and market expectations tend to follow discrete movements of multiples of 25 basis points. Hence, to rule out the possibility of part of our identified surprises not corresponding to actual surprises, but rather to noise present in the variation of the future contract prices, we define an additional measure named the filtered surprise. We do so by imposing a threshold of 0.10 percentage points in absolute value to each surprise event. If a particular surprise in our series was smaller than this threshold, we changed it to zero. Then, analogously to the original strategy, we aggregated all filtered surprise realizations in a given quarter to obtain a series in quarterly frequency. Figure B3 compares our original surprise and the filtered surprise for the period between 2012 and 2019. Despite the filtering procedure reducing significantly the number of non-zero events, our results with the microdata are qualitatively and quantitatively robust to either definition of surprise, as we show in Figure B4.

Figure B3: Distribution of quarterly monetary surprises realizations – 2012Q1 to 2019Q1

(a) Original Surprise



(b) Filtered Surprise

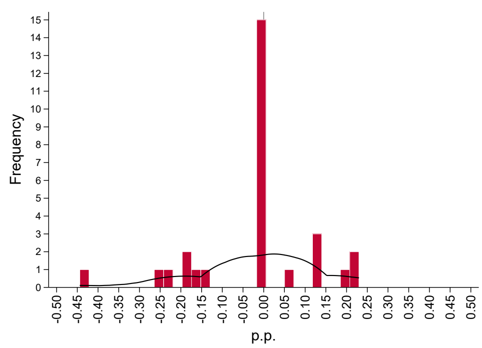
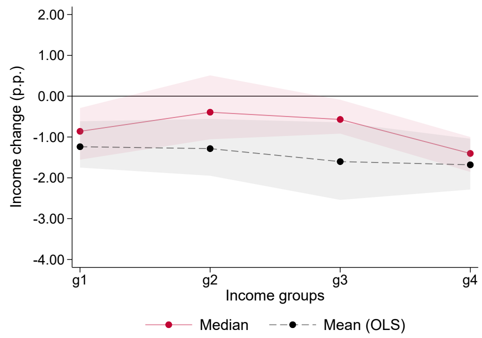
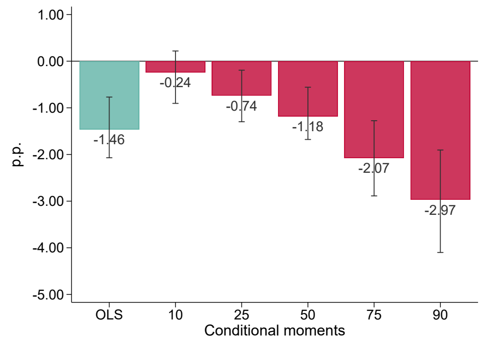


Figure B4: The effects of a 0.25 p.p. filtered monetary policy surprise

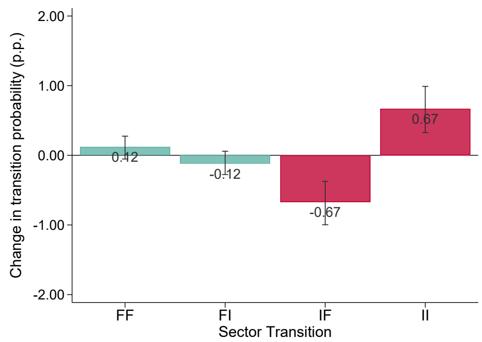
(a) On income growth



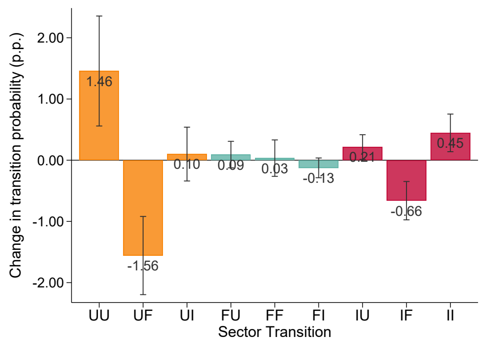
(b) On the income growth distribution



(c) On the probability of employed transitions



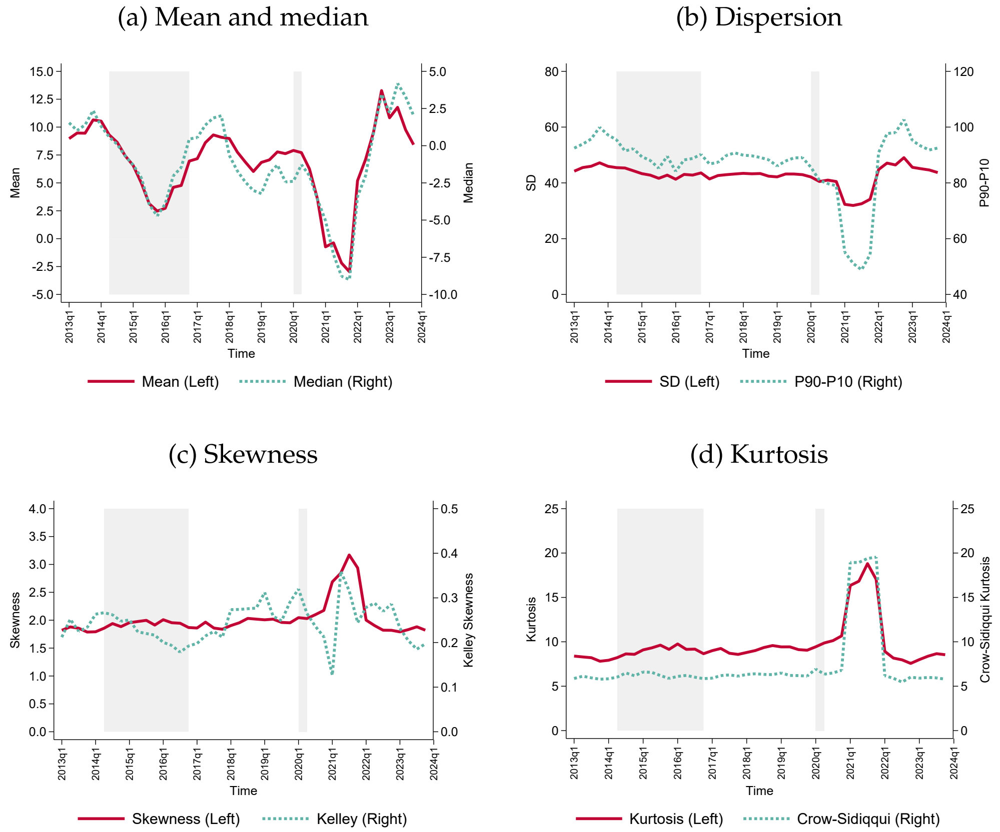
(d) On the probability of all transitions



Notes: Panel (a) shows the mean and the median income responses to a 0.25 percentage point monetary surprise of the four quartiles of the income distribution for all workers. Panel (b) displays the impact of a 0.25 percentage point monetary 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 surprise for workers who experienced each of the four possible employed transitions. Panel (d) shows the impact of the monetary surprise on the probability of transitioning between different employment statuses including movements to and from unemployment. Shaded areas and dark thin lines represent 68% confidence intervals calculated from bootstrapped standard errors with bias correction and clustered in the time dimension.

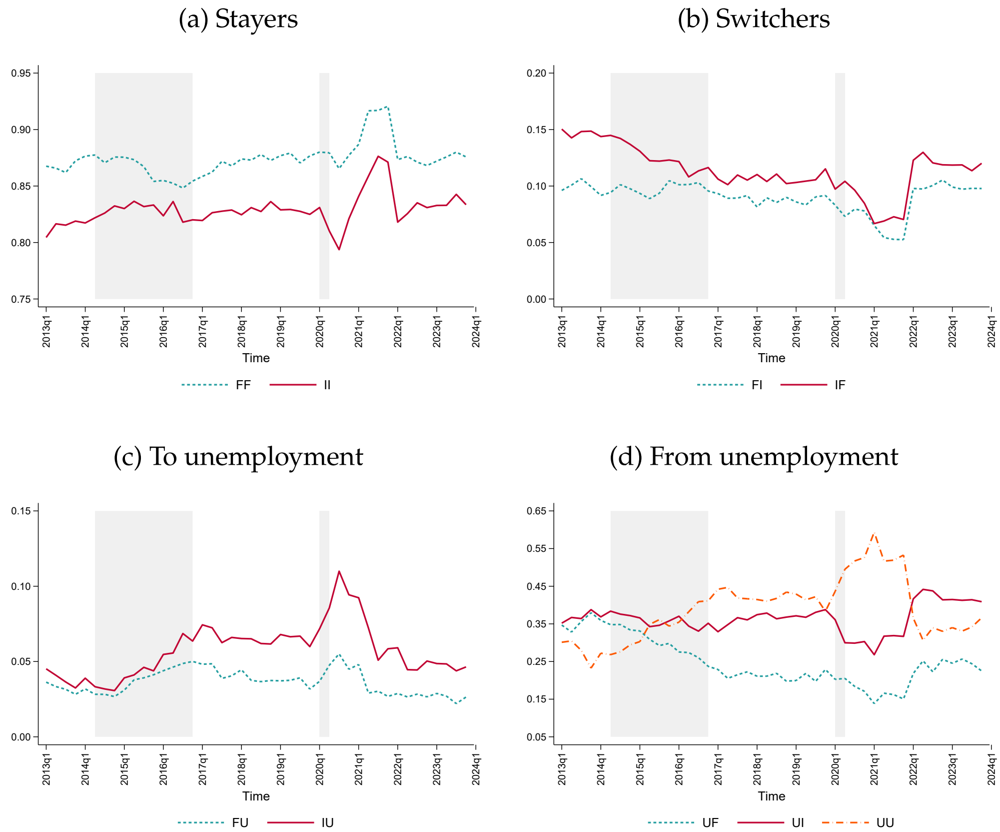
C Labor Markets During the Covid-19 Pandemic

Figure C1: Moments of the distribution of 1-year real disposable income growth



Notes: The figure shows measures of the four first 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 C2: Transition rates between employment statuses over time



Notes: The figure shows the evolution over time of the transition rates between t and $t-4$, 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).