Inflation and labour markets in the wake of the pandemic: the case of Brazil

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Abstract

This paper examines the behavior of the Brazilian labour market in the aftermath of Covid-19 and explores the relationship between labour market slackness indicators and real wages in Brazil. We propose seven different tightness indices and show that all of them had reduced predictive power in relation to real wages after the pandemic outbreak. Despite a heated labour market, we document a significant drop in real wages following the pandemic outbreak, and we find that more educated workers' real wages fell the most after the pandemic outbreak and have showed a slower recovery afterwards. These findings suggest that working from home amenities may be playing a role in releasing wage pressure during the post-pandemic recovery.

JEL classification: E24, E31, J21, J3, J63.

Keywords: real wages, Covid-19, inflation, labour market.

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1. Introduction

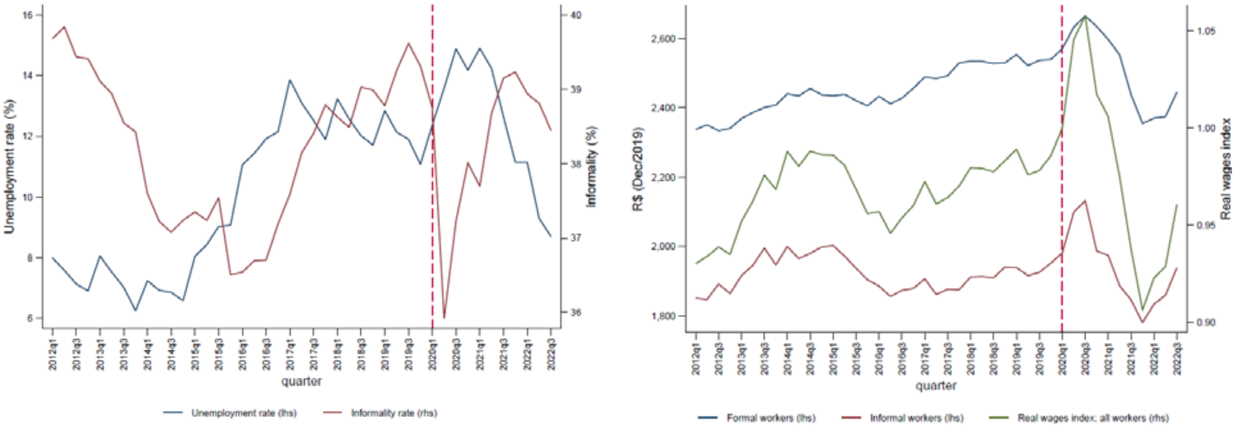
Most governments reacted to the Covid shock by adopting expansionary monetary and fiscal policies to prevent deep recessions in their local economies. It was a period of high correlation of expansionary policies both across countries, as well as within countries with the use of fiscal, prudential and monetary instruments. As the pandemic receded and there was a normalization of mobility, both inflation and economic activity rebounded faster than expected. This was due, in part, to stronger demand supported by expansionary policies. Core inflation reached record high levels across a wide array of countries and many countries faced the challenge of avoiding persistent and possibly entrenched inflation.

The Covid shock was very strong and complex in terms of its impact on the labour market. On the structural side, it had a large impact on how the labour market is organized, with relevant changes in participation rates and a sizable increase in contracts that provide for working from home (see Castro and Moreira (2021); Góes et al (2022)). On the cyclical side, understanding how slack in the labour market impacts inflation is paramount and is highly relevant for policymaking, especially in the wake of a large shock such as Covid-19.

Graph 1 provides a first view of the labour market in Brazil over the last 10 years. In a nutshell, Graph 1.A illustrates that the spike in unemployment after the Covid outbreak was completely reversed and the unemployment rate reached a level below the pre-Covid baseline by the end of 2022. Additionally, the large reduction in informality levels during the crisis period also reversed. Nonetheless, Graph 1.B shows that real wages reached their minimum by end-2021, when they started to recover. In the third quarter of 2022, real wages were still 4% below the level at the beginning of the pandemic, while the unemployment rate was more than 2 percentage points lower than prior to the pandemic. We start by examining how the labour market has behaved by looking at different dimensions: economic sectors, educational attainment, informality and occupation. Our measures show that the decrease in real wages is pervasive across different economic sectors, but quite heterogeneous across educational attainment. Moreover, the informal sector, which usually acts as a buffer in recessions, actually magnified the impact on the labour market during Covid. In respect of institutional changes, we discuss a labour market reform that was put in place before the pandemic. Finally, we discuss the role of inflation surprises when there is nominal stickiness.

Unemployment and informality Graph 1

A. Unemployment and informality B. Real wages



Real wages are deflated by the Extended National Consumer Price Index (IPCA), provided by Instituto Brasileiro de Geografia e Estatística (IBGE).

Source: Continuous PNAD – Continuous National Household Sample Survey, a survey conducted by IBGE.

After laying the groundwork, we evaluate a range of labour market indicators

and we construct new indices to assess the degree of tightness in the Brazilian labour market. As we discuss, each measure has its pros and cons that depend on its statistical quality, the dimension studied, as well as an assessment of structural changes in the labour market. We highlight three dimensions of the labour market: stocks, flows and expectations. Some of the measures are standard, such as the unemployment rate, while some were built in, such as the worker flow rate and quit-to-workers flow rate. The general profile that arises across these dimensions and measures is that the labour market is as tight or even tighter than before the pandemic although it has seen remarkable improvement following the pandemic.[2]

We then analyse the correlation of the labour market tightness to different measures of wage compensation from a time-series perspective. We find that (i) wage movements are less correlated with the labour market tightness than before the pandemic and (ii) the reduction of explanatory power is not due to a parametric change. We also examine the explanatory factors for such results. We discard the role of inflation surprises, productivity or institutional changes as major reasons for these results.

Our contribution to the literature is twofold. First, we show how educational attainment heterogeneity played an important role in determining labour market developments in the aftermath of the Covid shock in Brazil. The employment rate of college educated workers maintained its previous growth trend in the aftermath of the pandemic while experiencing the largest drop in real wages. This fact is suggestive of working from home amenities being offered as non-pecuniary benefits to the group of workers who are most likely to make use of them, according to the literature

2 Unfortunately, we do not have data on vacancies to build the traditional vacancies-to-unemployment measure obtained from the matching model literature and championed as the best tightness measure by Barnichon et al (2022) and Furman and Powell III (2021). We construct alternative measures based on the variables that we have.

(eg Castro and Moreira (2021); Góes et al (2022)). Second, we organize, classify and propose different labour market tightness indicators and demonstrate a reduction of the explanatory power of labour market tightness on wages in the aftermath of the pandemic.

The remainder of the paper is organized as follows. In Section 2, we present an overview of the main dimensions of the Brazilian labour market, and show how employment and wages responded to the Covid-19 shock. We also discuss the institutional changes that were implemented during the period close to the pandemic. Section 3 presents our measures of labour market tightness. We show the evolution of the main labour market indicators during the last 10 years and present different labour market tightness indicators. In Section 4, we assess the relationship between our tightness indicators and real wages (subsection 4.1) and the role of other educational attainment heterogeneity in explaining real wage variation (subsection 4.2). In Section 5, we investigate and dismiss alternative explanations that could impact the relationship between wages and slackness, such as the labour market composition effect, inflation surprises and productivity changes. In Section 6, we sum up the main results.

2. Descriptive analysis of the Brazilian labour market

In this section we describe the evolution of employment and wages in recent years across economic sectors, educational attainment levels and occupations. We also discuss the response of the informal market during the pandemic.

2.1 Economic sectors

We first describe the response of the labour market to the pandemic across 19 economic sectors. Overall, almost all economic sectors underwent some loss of jobs after the onset of the pandemic, according to Graph 2. The exceptions were the human health sector, in which the demand for jobs increased as a response to the pandemic, and public administration, which maintained the same number of employees. The recovery after the pandemic was also widespread. Only the water supply and sewerage sector showed a persistent drop in employment. Of the remaining sectors, only three have reached levels of employment close to pre-pandemic levels (accomodation and food services, admin and support activities, and electricity). Meanwhile, all other sectors now have levels of employment well above pre-pandemic levels.

With regard to real wages, they provide a different perspective (Graph 3). When compared with pre-pandemic levels 13 economic sectors have lower average wages, but with a recovery at the margin. Only three economic sectors have higher wages than before the pandemic.[3]

Summarising our results, by the third quarter of 2022 the locus of stronger employment and lower wages than before the pandemic is pervasive across sectors.

[3] We highlight the agriculture sector, which has reversed the previously declining employment trend with a significant recent rise in wages.

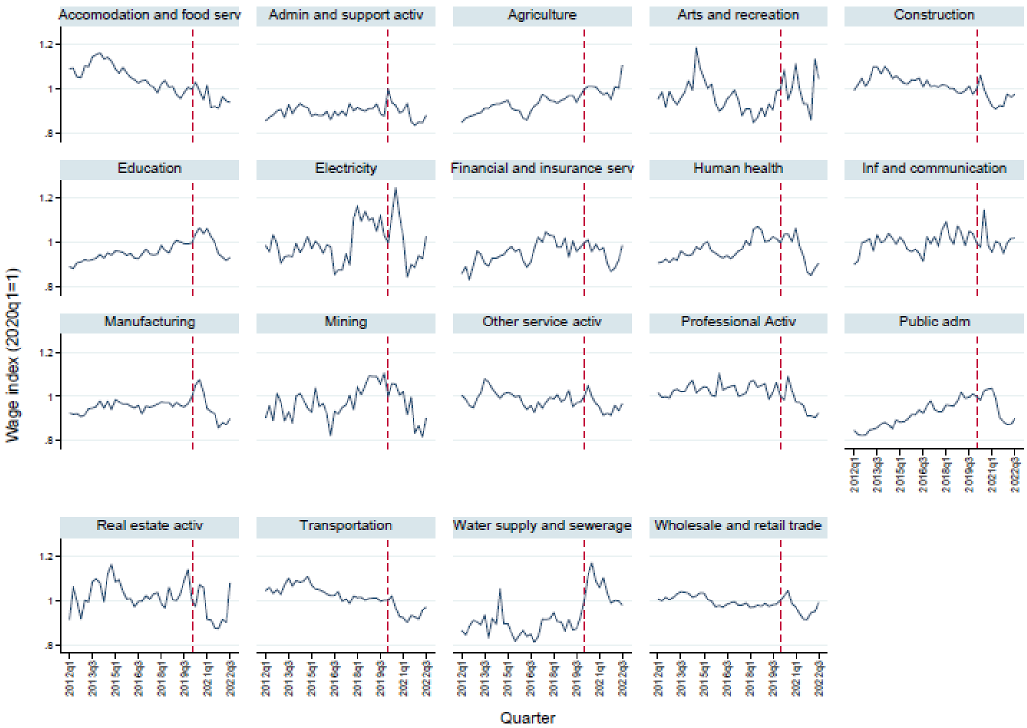
Jobs heterogeneity: economic sectors

Graph 2

Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC).

Wage heterogeneity: economic sectors

Graph 3



Real wages are deflated by the Extended National Consumer Price Index (IPCA), provided by IBGE.

Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC).

2.2 Educational attainment

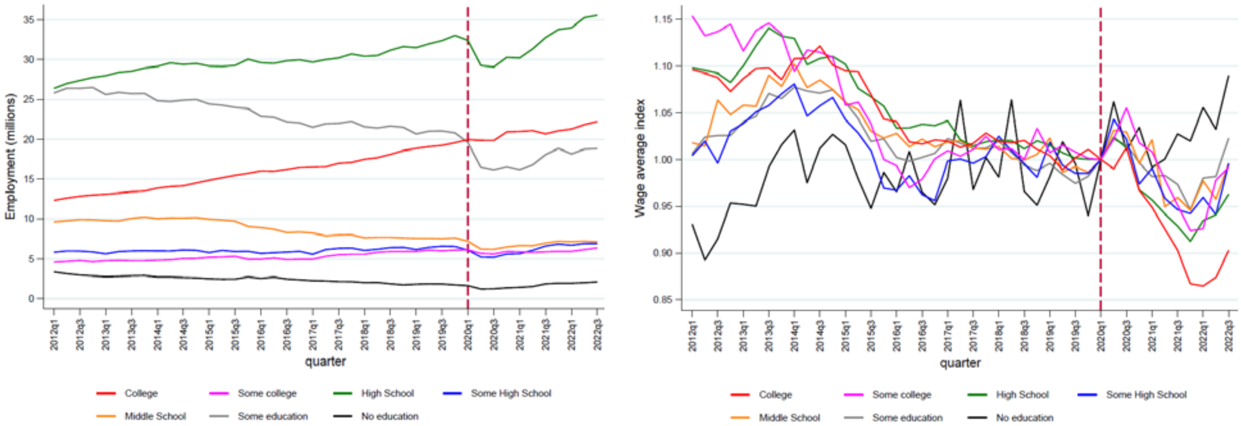
In contrast to the more homogeneous response to the pandemic across different economic sectors, we observe an intriguing pattern related to educational attainment classification. According to Graph 4, more highly educated workers were less impacted in terms of employment, but underwent larger real wage losses. While the employment level of college degree workers was unaffected by the pandemic,[4] high school workers experienced large losses in their jobs but had a fast recovery back to their pre-Covid trend. Nevertheless, workers with college degrees and those that had completed high school underwent the largest drops in real wages (Graph 4.B). The real wage losses of college educated workers reached 13% in the fourth quarter of 2021, compared with the pre-pandemic level.

Pandemic response by educational attainment

Graph 4

A. Employment trends

B. Real wage trends



Real wages are deflated by the Extended National Consumer Price Index – IPCA, provided by IBGE.

Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC).

These results are quite interesting because they can be related to the joint shock of the pandemic comprised of (i) mobility restrictions and (ii) working from home. Mobility restrictions had less impact on college workers than other workers because their services were less affected by changes in labour demand. Moreover, on the supply side, college workers may have found that working from home arrangements provided them with more flexibility and they may have, therefore, not bargained as much on wages. In fact, Castro and Moreira (2021) and Góes et al (2022) show that more educated workers, particularly college educated workers, were more likely to work remotely in the aftermath of the pandemic. Hence, contracts allowing for working from home by college educated workers may have lowered wage pressure, as Barrero et al (2022) have found in surveys.

4 College educated workers are now the second largest category of workers when we break down data into educational attainments. As at the first quarter of 2020, college educated workers represented 21% of total employed workers.

2.3 Occupations

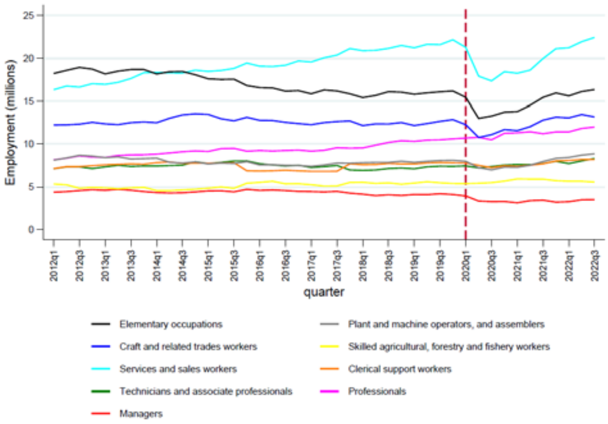
We now look into how employment and wages evolved by type of occupation. The three largest groups of workers by occupation type – services and sales workers, elementary occupations, and craft and related trades workers – experienced a large loss of jobs. On the other hand, professionals – around 80% of such workers have college degrees – continued on almost the same positive trend despite the negative economic shock. This corroborates the argument that more educated workers were less affected by mobility restrictions. We also notice a long-term decrease in elementary occupations, in line with the loss of importance of workers with no education previously shown. Moreover, we highlight the decrease in the number of managers in the aftermath of the pandemic, which remained stable during the recovery period.

Such results reinforce previous findings that college workers, or, more generally, workers that are more amenable to working from home arrangements, were less affected by the negative employment shock. However, they experienced lower wages during the pandemic.

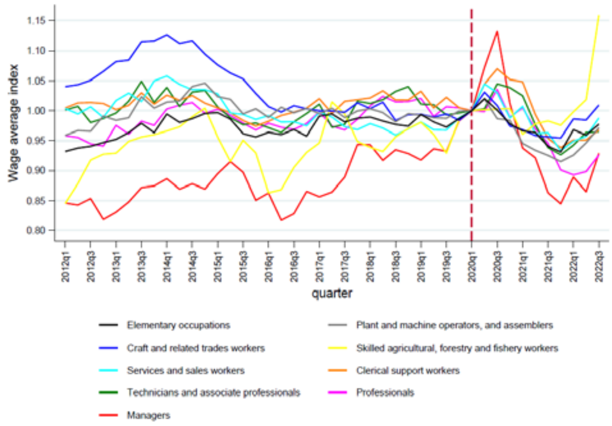
Pandemic response by occupation

Graph 5

A. Employment trends



B. Real wage trends



Real wages are deflated by the Extended National Consumer Price Index (IPCA), provided by IBGE.

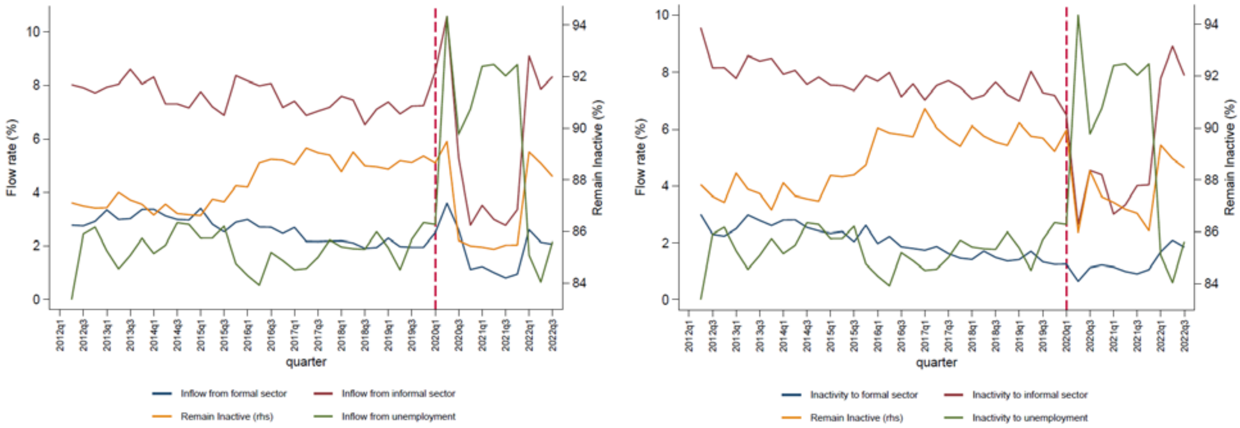
Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC).

2.4 Informality

The Brazilian labour market, as observed in many countries, responded with a large increase in inactivity in the aftermath of the Covid outbreak. According to Graph A.1, the pandemic shock yielded a large decrease in the inflows to employment from inactivity as well as a large outflow from employment to inactivity. In addition to the direct effects from mobility restrictions, in this section we highlight the role played by the informal sector during the unfolding of the Covid pandemic. Graph 6 depicts the relevance of the informal sector when we analyse the transitions from and into inactivity. The inflow rates to inactivity from the informal sector varies from two to four times the inflow rate from the formal sector during our sample period.[5] At the onset of the pandemic, there was also an increase in the inflows from the informal sector to inactivity that was even larger than the observed inflow from the formal sector. When we look into the outflow rates from inactivity, we also note the prominence of the informal sector, with outflows to the informal sector outsizing the ones to the formal sector by a margin of three to five times. Due to more flexibility, and lower hiring and separation costs, the informal sector has always played a key role as an employment buffer during recessions, despite the earning loss for workers who move from formal to informal jobs (Gomes et al (2020)). During the Covid recession, the informal labour market had a different role, contributing to the propagation of the negative labour market shock, a feature first documented by Leyva and Urrutia (2022). Another way of putting it is that the Covid shock, ie mobility restrictions, had a much larger impact on the informal sector than on the formal sector. Graph 7 describes the inflows and outflows of the informal sector and allows us to compare the Brazilian recession of 2015–16 with the Covid crisis. While we observe an increase in the inflows to the informal sector from unemployment in the 2015–16 recession, the inflow from unemployment to the informal sector reduced in the aftermath of Covid.

Inflows and outflows from inactivity — Graph 6

A. Inflows to inactivity — B. Outflows from inactivity



Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC).

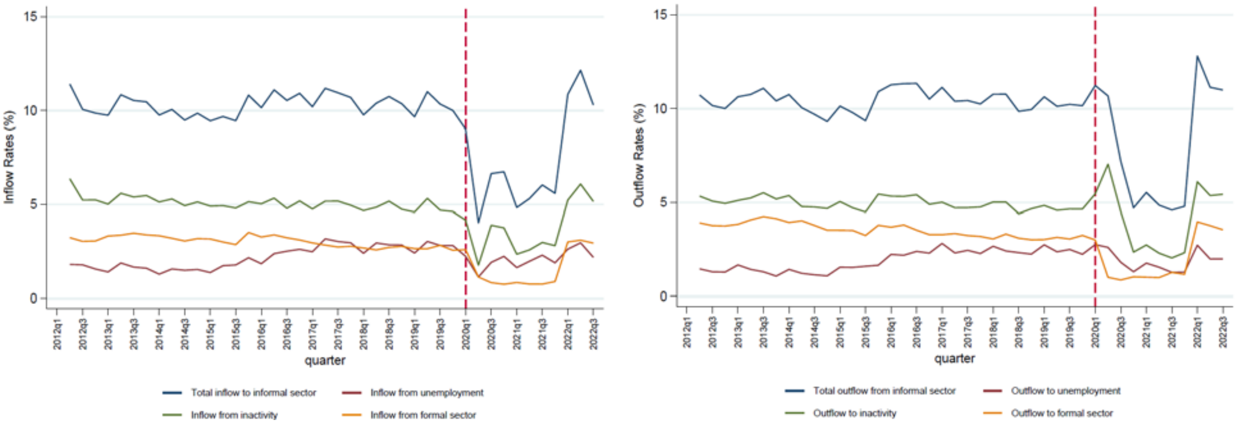
[5] In the year before the pandemic outbreak, the inflow rate to inactivity from the informal sector was more than three times the inflow rate from formal sector.

Inflows and outflows from the informal sector

Graph 7

A. Inflows to informal sector

B. Outflows from informal sector



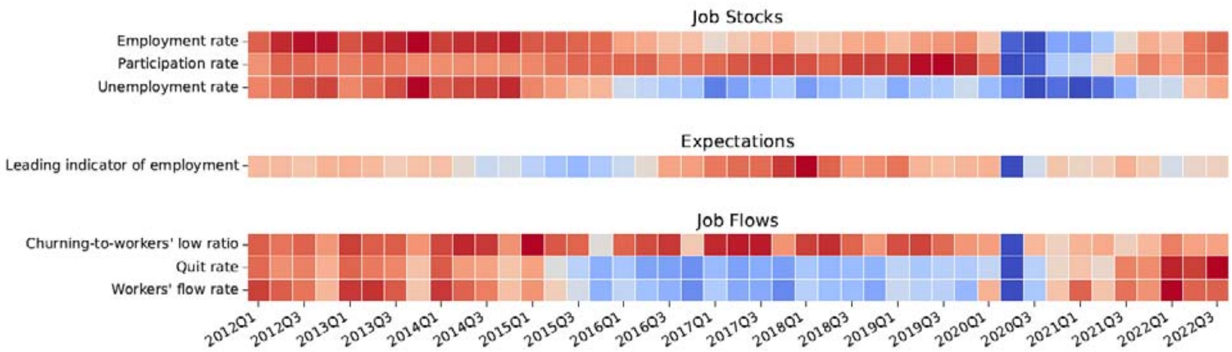
Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC).

3. Labour market tightness indicators

In this section we split our analysis of the labour market into three dimensions: stocks, flows and expectations. For each dimension, we discuss the construction of the respective tightness indices and the pros and cons of each. We provide a concise overview of all these measures by using a heatmap (Graph 8) in which each row displays how tight the labour market is relative to the historical sample. We further dig into each dimension to discuss some specific points about the appropriateness of using a given dimension to assess the labour market in Brazil.[6]

Brazilian labour market indicators

Graph 8



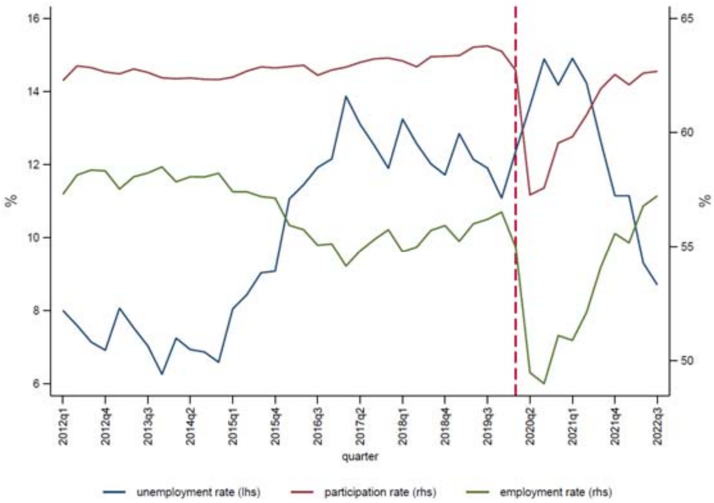
In each quarter, the heatmap displays how tight each index is compared with its historical values, ie from the first quarter of 2012 to the third quarter of 2022. The darker red the point, the tighter the index. We classify the indices as stock measures (employment rate, participation rate and unemployment rate), expectation measure (leading indicator of employment) and flow measures (workers flow rate, quit rate and churning-to-workers flow ratio).

Source: LIEmp index (provided by IBRE-FGV); PNADC/IBGE (employment measures); CAGED/MTE (flow measures).

6 We refer to Central Bank of Brazil (2022) for other measures of tightness using a spider chart.

Job stocks. The most common dimension to assess the labour market tightness is based on rates or stocks of employed and unemployed workers. Following the traditional literature,[7] we explore measures such as unemployment rate (the ratio of unemployed to the workforce), participation rate (the ratio of workforce to the working age population)[8] and employment rate (the ratio of employed workers to the working age population). These measures are based on publicly available information and are internationally comparable.[9,10] Additionally, most of them may be broken down among multiple dimensions such as economic sector, educational attainment, occupation and type of job (formal vs informal). The main concern is that these measures do not take into account structural changes of the non-accelerating inflation rate of unemployment (NAIRU). In the end, the appropriate measure of labour market tightness is the difference between the observed unemployment rate and the unobservable NAIRU. Graph 9 plots the three measures since 2012. By construction, the unemployment rate is negatively correlated with the other measures. All of them show a decrease in labour market tightness after the pandemic outbreak and also a subsequent recovery to pre-pandemic levels. While recent unemployment and employment rates indicate a tighter labour market in comparison with pre-pandemic levels, the participation rate still lies nearly 1 percentage point below its level in the fourth quarter of 2019.

Employment tightness measures Graph 9



Unemployment rate is the ratio of unemployed to the workforce, participation rate is the ratio of workforce to the working age population (ie persons aged 15 years and older) and employment rate is the ratio of employed workers to the working age population.

Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC), a survey conducted by the Instituto Brasileiro de Geografia e Estatística (IBGE).

7 See, for instance, Blanchflower et al (2022) and Domash and Summers (2022).

8 Our definition of working age population is persons aged 15 years and older.

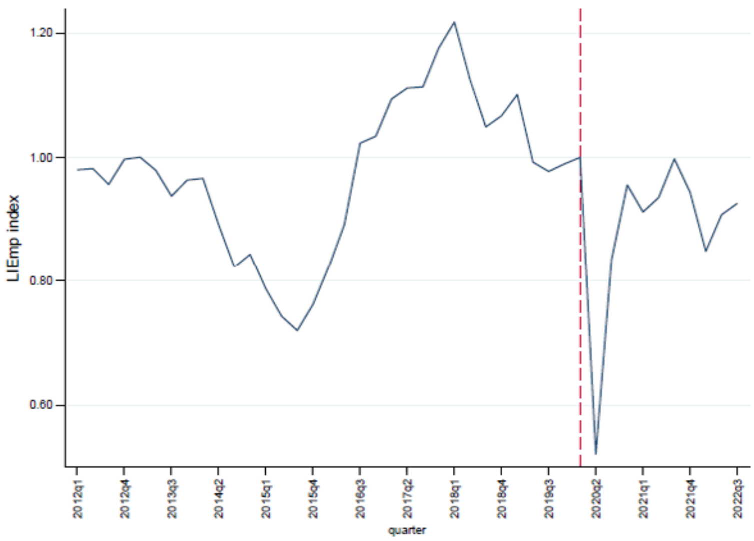
9 See Duval et al (2022) for a description of the main tightness measures employed in the literature.

10 Most countries faced problems in assessing the extent of the impact of mobility restrictions on labour markets due to the increase of non-response bias in household surveys (eg Dutz et al (2021); Rothbaum and Bee (2020)). In the Brazilian case, the household survey was impacted by pandemics, with a reduction in the response ratio and a wider discrepancy across different surveys (eg Central Bank of Brazil (2021); Corseiul and Russo (2021)).

Expectations. We employ the Leading Indicator of Employment (LIEmp) as our expectation measure for the labour market. LIEmp is an index based on data extracted from the Business and Consumer Surveys produced by FGV/IBRE. It measures consumer expectations for the labour market.[11] Such estimates could be leading indicators, but it should be borne in mind that they are based on soft data and perceptions. For instance, confounding effects, internal consistency issues and survey-based estimates make it harder to use it as a reliable measure for labour market tightness and compare it across time. Graph 10 shows the evolution of LIEmp. This measure shows a brisker response of the labour market to the pandemic than the previous tightness measures. After a deep drop in the second quarter of 2020, the index returned to a plateau below the pre-pandemic level in the following quarter and it has been fluctuating ever since.

Expectation tightness measures

Graph 10



Source: Business and Consumer Suveys conducted in seven Brazilian cities by IBRE/FGV.

Job flows. Our third set of tightness measures is based on job flows. We employ data from the General Registry of Employed and Unemployed (CAGED), an administrative database of the Ministry of Labour and Social Security (MTP). We rely on the traditional **quit rate**, defined as the share of workers who voluntarily leave their positions, and follow Burgess et al (2000) to build two other main measures from the job flows in the formal sector: (i) the **worker flow rate (WF)** measure, which comprises the ratio of the sum of hirings and separations to the employment level in a given quarter; and (ii) the **churning-to-workers flow** measure, which corresponds to the ratio of the excess of worker flows in a given quarter (churning)[12] to the total worker flow.

These measures of tightness that rely on job flow information share the same advantages as employment measures, such as the backing of publicly available information, and, for the quit rate, a widely known measure that is internationally

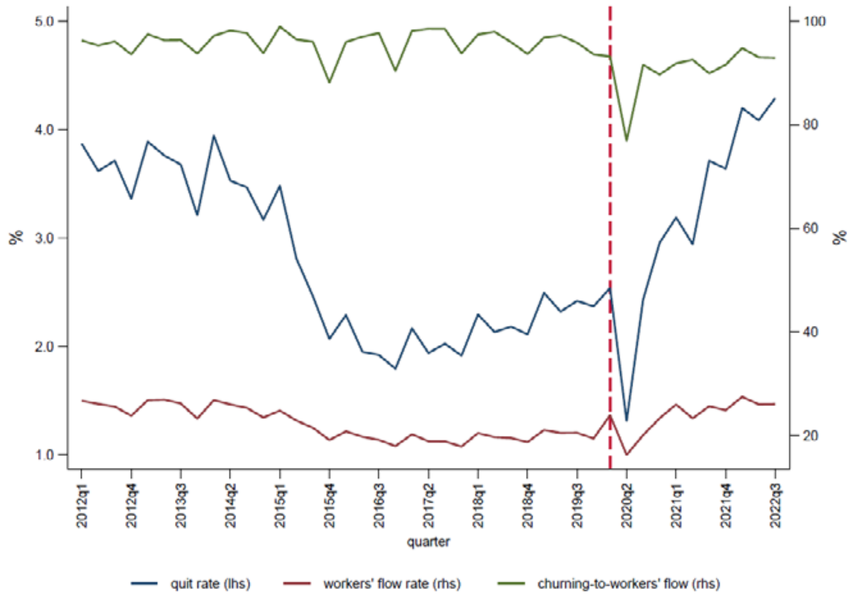
[11] See https://portalibre.fgv.br/en/leading-indicator-employment for more information.

[12] Churning is computed as worker flows minus the absolute value of variation in the stock of jobs.

comparable (eg Domash and Summers (2022)). However, and possibly the biggest caveat for using labour flow data in Brazil, it only includes the formal sector and does not take into account the large share of informal workers. Apart from these data, the analysis of the labour market flows across time disregards the labour market reforms that have introduced more flexibility and, hence, possibly increased flows for any given slack in the labour market.

Graph 11 displays the evolution of the three job flow measures for labour market tightness. It is evident that quit rates show more variation in our sample and had a more intense response to the Covid shock. Workers flow rate and churning-to-workers flow responded in the same direction as quit rates, but with lower magnitude.

Flow tightness measures — Graph 11



We construct the measures of tightness based on job flow using data from the General Registry of Employed and Unemployed (CAGED), an administrative database of the Ministry of Labour and Social Security (MTP). This dataset comprises all formal workers registered in Brazil. Quit rates is the share of workers who voluntarily leave their positions. Workers flow rate is the sum of hirings and separations divided by the (lagged) employment stock. Churning-to-workers flow is the ratio of churning (workers flow minus the absolute value of the variation in the stock of jobs) to workers flow.

Source: CAGED data.

4. Empirical analysis

In this section, we empirically assess the extent to which different labour market tightness indicators are associated with changes in aggregate real wages. We also conduct a panel data analysis at economic sector level to evaluate whether variation in tightness and educational attainment are related to changes in real wages.

4.1 Labour market tightness and wage inflation

In this subsection, we assess whether our different measures were effective indicators of labour market tightness in Brazil. We are particularly interested in the correlation between changes in real wages and variation in different labour market tightness indicators. To assess this in a simple and coherent way across tightness indicators, we evaluate whether the explanatory power of a simple linear statistical model that relates real wage changes to labour market tightness indicators and their lags was impacted after the onset of the Covid pandemic. Our baseline model is:

$$\Delta \log\left(wage_t\right) = \alpha + \Delta \log\left(wage_{t-1}\right) + \beta_1 tightness_{t-1} + \beta_2 tightness_{t-2} + \beta_3 tightness_{t-3} + \beta_4 tightness_{t-4} + u_t \quad (1)$$

We report the estimated coefficients in the appendix (Tables A1–A6). As shown in column (1) of the regression tables, despite the small sample available (our data cover the period from the first quarter of 2012 to the third quarter of 2022), we find statistically significant relationships at standard level between the changes in real wages and the following tightness measures:[13] employment rate and participation rate (employment tightness category), LIEmp (the expectation tightness measure) and churning to-workers flow (job flows tightness measures).

We then adjust the model to account for changes in the relationship between tightness measures and changes in real wages after the pandemic by adding interactions of a dummy indicator of post-Covid with the lag of the dependent variable and our tightness measures (and their lags). We report the results in columns (2) and (3) of Tables A1–A6. The more flexible form added some explanatory power to the previous model, except for quit rates and unemployment rate, as indicated by the Adjusted R^2.

The residuals of both models with their 95% confidence intervals are plotted in Graphs 12–14. The graphs show that the residuals and their confidence intervals increased considerably at the outset of the pandemic. Despite the increase in Adjusted R^2, the model with the post-Covid dummy interacted with the tightness measure did not succeed in reducing the residual dispersion after the first quarter of 2020 (Graphs 12B, 13B and 14B). Overall, these results indicate that: (i) the degree of labour market tightness is positively correlated with changes in real wages; (ii) there is no evidence of a change in the direction of this correlation after the pandemic outbreak; and (iii) other relevant aspects determined real wages at the outset of the pandemic. We investigate these other possible factors influencing real wages in the next sections.

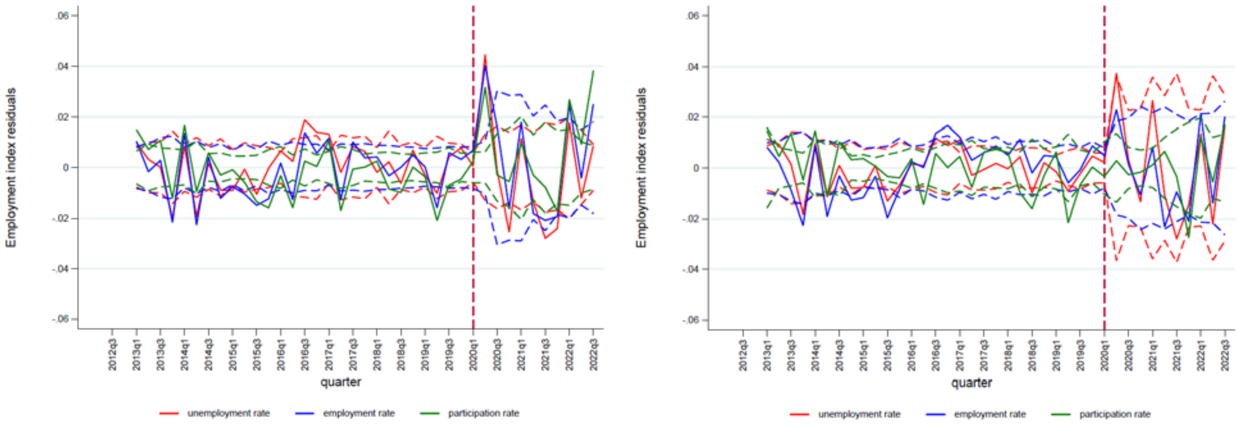
[13] We report the joint effect of the coefficients of the tightness measures and its respective p-value in each table. We name this joint effect, "total tightness".

Relationship between employment tightness indexes and wages

Graph 12

A. No changes in model parameters

B. Allowing changes in model parameters



The continuous lines represent the residuals from the linear regression of the change in real wages on the respective tightness measure and its lags (until the 4th lag). The dashed lines delimit 95% confidence intervals for each measure. In Graph 12.B, we allow the parameters related to the tightness variables to change after the onset of Covid (in the first quarter of 2020).

Relationship between flow tightness indexes and wages

Graph 13

A. No changes in model parameters

B. Allowing changes in model parameters

The continuous lines represent the residuals from the linear regression of the change in real wages on the respective tightness measure and its lags (until the 4th lag). The dashed lines delimit 95% confidence intervals for each measure. In Graph 13.B, we allow the parameters related to the tightness variables to change after the onset of Covid (in the first quarter of 2020).

Relationship between expectation tightness index and wages

Graph 14

A. No changes in model parameters

B. Allowing changes in model parameters

The continuous line represents the residuals from the linear regression of the change in real wages on the respective tightness measure and its lags (until the 4th lag). The dashed lines delimit 95% confidence intervals for each measure. In Graph 14.B, we allow the parameters related to the tightness variables to change after the onset of Covid (in the first quarter of 2020).

4.2 Panel analysis by economic sector

In this subsection, we aggregate data by economic sector and investigate the extent to which the degree of tightness and heterogeneity of educational attainment levels are associated with changes in real wages. First, we employ quit rates as our tightness measure and assess whether real wages are negatively related to quit rates.[14] In order to do so, we estimate the following model for sector i and quarter t :

$$\Delta \log\left(wage_{it}\right) = \alpha + \beta_1 \Delta \log\left(wage_{it-1}\right) + \beta_2 \, quit\, rate_{it-1} + u_{it} \quad (2)$$

Table 1 shows that there is a positive relationship between quit rates and real wages. The measured effect is economically relevant: an increase of one standard deviation in quit rates[15] is associated with an increase of real wage growth from 5.9 to 10.9 basis points (bp), which represents between 31% and 57% of the average quarterly aggregate real wage growth before the pandemic.[16] The result is statistically significant at standard levels and robust among all specifications.

Following the heterogeneity in wages graphically observed for educational attainment in our descriptive analysis, we also assess whether changes in real wages are associated with the share of college educated workers at the economic sector level. In order to do so, we estimate the following model:

[14] We chose quit rates as they are based on the administrative dataset (CAGED), which allows us to aggregate data at sector level. Moreover, quit rates are one of the best tightness measures for the labour market according to Domash and Summers (2022) and Furman and Powell III (2021), among others.

[15] The standard deviation is equal to 8.36 percentage points in our sample.

[16] From the first quarter of 2012 to the fourth quarter of 2010, the quarterly real aggregate wage growth measured by the Continuous PNAD was 19 basis points on average.

$$\Delta\log(wage_{it}) = \alpha + \beta_1 \Delta\log(wage_{it-1}) + \beta_2 pandemic_t + \beta_3 college_{it-1} + \beta_4 college_{it-1} pandemic_t + u_{it} \quad (3)$$

where the $pandemic$ is a dummy variable equal to 1 after the first quarter of 2020 and 0 otherwise, and $college_{it-1}$ indicates the share of workers with college degree in the economic sector i in the previous quarter (*t-1*).

Relationship between $\Delta\log(wage)$ and labour market tightness at economic sector level

Table 1

	(1)	(2)	(3)	(4)	(5)
$\Delta\log(wage_{t-1})$		–0.274***	–0.345***	–0.279***	–0.345***
		(0.051)	(0.038)	(0.052)	(0.038)
$quit\ rate_{t-1}$	0.007***	0.013***	0.011***	0.008***	0.009***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
$pandemics$			–0.647**	–1.427**	–1.380**
			(0.239)	(0.581)	(0.580)
$\Delta\log(wage_{t-1})\ x\ pandemics$			0.154		0.153
			(0.098)		(0.100)
$quit\ rate_{t-1} x\ pandemics$				0.270	0.265
				(0.201)	(0.194)
Constant	0.060	0.012	0.213**	0.212**	0.223**
	(0.054)	(0.066)	(0.083)	(0.078)	(0.082)
$quit\ rate_{t-1}(1+pandemics)$				0.278	0.274
P-value				0.182	0.174
Observations	840	820	820	820	820
Adjusted R^2	–0.001	0.071	0.079	0.075	0.080

This table shows the results of the estimation of equation 2, using data from the first quarter of 2012 to the third quarter of 2022. Heteroskedasticity-robust standard errors clustered at the economic sector level are shown in parentheses. The symbols *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

We report the results in Table 2. We first notice that the negative effect of the pandemic on real wages measured by the coefficient on the dummy pandemic in columns (1) and (2) loses its sign and statistical significance when we include the share of educated workers in the regression in column (3). This suggests that the negative change in the real wage level during the pandemic was driven by this category of workers. Before the pandemic, a larger share of college educated workers was associated with an increase in real wages. In that period, an increase of one standard deviation in college share (20.1 percentage points) was associated with an increase in wage growth of 18–20 bp, which represents 100% of the average quarterly real wage growth before pandemic. However, after the pandemic, the overall effect of college educated workers on wage growth was reversed. According to column (3), an increase of one standard deviation in the share of college educated workers is then associated with a decrease of 40 bp in wage growth. One could argue that sectors with more college educated workers would show greater labour market slack (ie lower labour tightness indicators), which would result in less pressure to adjust wages in the aftermath of the pandemic. In column (4), we add quit rate measures to assess whether the effect of college educated workers is related to the tightness level of the economic sector. The college share is robust to the inclusion of the tightness variable.

Relationship between $\Delta\log(wage)$ and college educated workers share at economic sector level

Table 2

	(1)	(2)	(3)	(4)
$\Delta\log(wage_{t-1})$	–0.279***	–0.345***	–0.346***	–0.347***
	(0.051)	(0.038)	(0.038)	(0.038)
$college\,share_{t-1}$			0.009**	0.010***
			(0.003)	(0.003)
$pandemics$	–0.691**	–0.657**	0.134	–0.478
	(0.246)	(0.238)	(0.286)	(0.754)
$\Delta\log(wage_{t-1})\,x\,pandemics$		0.153	0.152	0.153
		(0.098)	(0.097)	(0.099)
$college\,share_{t-1} x\,pandemics$			–0.028***	–0.026***
			(0.008)	(0.009)
$quit\,rate_{t-1}$				0.013***
				(0.002)
$quit\,rate_{t-1} x\,pandemics$				0.201
				(0.202)
Constant	0.241***	0.254***	0.049	–0.032
	(0.071)	(0.075)	(0.109)	(0.110)
$college\,share_{t-1}(1+pandemics)$			–0.020	–0.016
P-value			0.016	0.097
Observations	820	820	820	820
Adjusted R^2	0.075	0.080	0.081	0.080

This table shows the results of the estimation of equation 3, using data from the first quarter of 2012 to the third quarter of 2022. Heteroskedasticity-robust standard errors clustered at the economic sector level are shown in parentheses. The symbols *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

These results are in line with the findings from the survey conducted by Barrero et al (2022) that identified that the amenity value of working remotely would explain the absence of a bigger wage catchup effect when the labour market recovered after the Covid outbreak. According to Gottlieb et al (2021), educational attainment is one of the major determinants for the probability of working from home in developing countries following the outbreak of Covid. Castro and Moreira (2021) and Góes et al

(2022) highlight the particular relevance of college education for access to remote working during the pandemic in Brazil. Therefore, one possible explanation for the lower wage-growth pressure during the recent economic recovery is that more educated workers, who have a greater chance of working remotely, have accepted lower nominal wage growth in exchange for the amenity value of increased job flexibility.

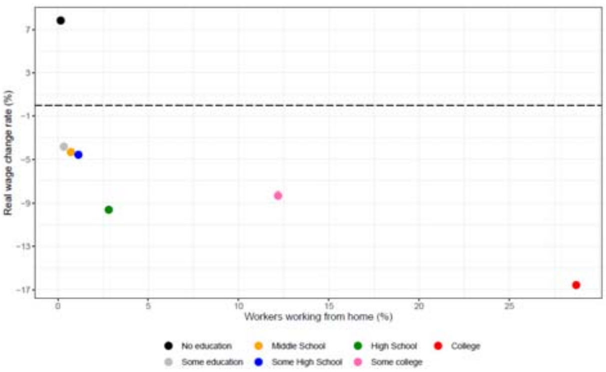
Graph 15 shows how real wages vary across two periods in our sample, and how this change relates to working from home adoption by educational attainment group. We computed the working from home share based on information from PNAD Covid, a survey conducted by IBGE between May 2020 and November 2020.[17] Graph 15.A shows the period from December 2019 to December 2021 when aggregated real wages reached their nadir, while Graph 15.B portrays the period from September 2021 to September 2022 when real wages started their recovery. The graphs illustrate the magnitude of the difference in adoption rates of working from home amongst college educated workers compared with other segments. Additionally, college educated workers experienced a larger real wage drop when aggregated wages fell and remained practically constant during the recovery period.

5. Alternative explanations

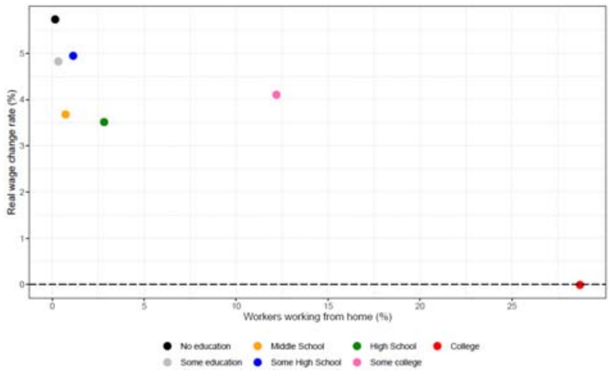
In this section we assess whether the response of wages to labour market tightness in the aftermath of the pandemic might be driven by changes in the composition of employment, inflation surprises, institutional changes or changes in firms' productivity.

Real wage variation and working from home adoption — Graph 15

A. December 2019 to December 2021



B. September 2021 to September 2022

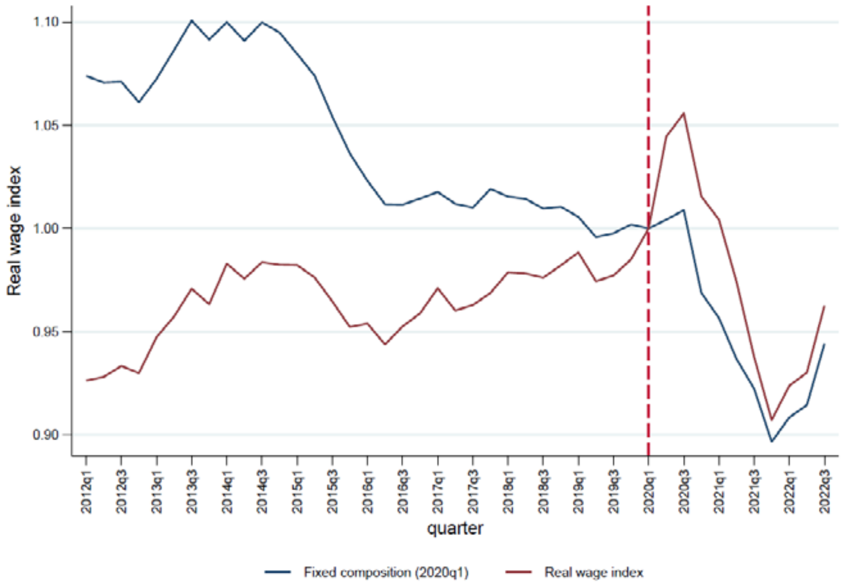


We compare the responses to the PNAD Covid survey related to working from home adoption in November 2020 with the variation in real wages by educational attainment. Graph 15.A displays the heterogeneity in wage variation during the fall in real wages, while Graph 15.B portrays the wage recovery. The PNAD Covid survey was conducted by telephone monthly from May 2020 to November 2020 with the sample of households interviewed by Continous PNAD survey in the first quarter of 2019. This is the only survey conducted by IBGE with the working from home question.

Source: PNAD Covid survey data (November 2020).

17 During this time, non-response bias was a major concern regarding the Continuous PNAD. Therefore, IBGE conducted a complementary survey with the sample of households that was interviewed in the first quarter of 2019 and that provided a telephone number.

Real wage variation Graph 16



5.1 Composition effect

As the previous analysis has shown that the impact of the outbreak of the pandemic on employment in Brazil was not homogeneous across economic sectors, educational attainment and occupations, we now assess whether the significant fall in real wages following the outbreak of the pandemic is mainly associated with changes in the composition of the pool of workers in our sample. Therefore, we compare actual real wages with the real wages that one would have observed if economic sector, informality and educational attainment levels were fixed as of the first quarter of 2020.[18] According to Graph 16, the composition effect was relevant in explaining wage changes at the beginning of the period (from 2012 to 2015). From 2016 until the pandemic outbreak, the composition effect was less relevant. After the outbreak of the pandemic, we observe similar behavior: average wages would be lower if we were to freeze the job composition as of the first quarter of 2020.

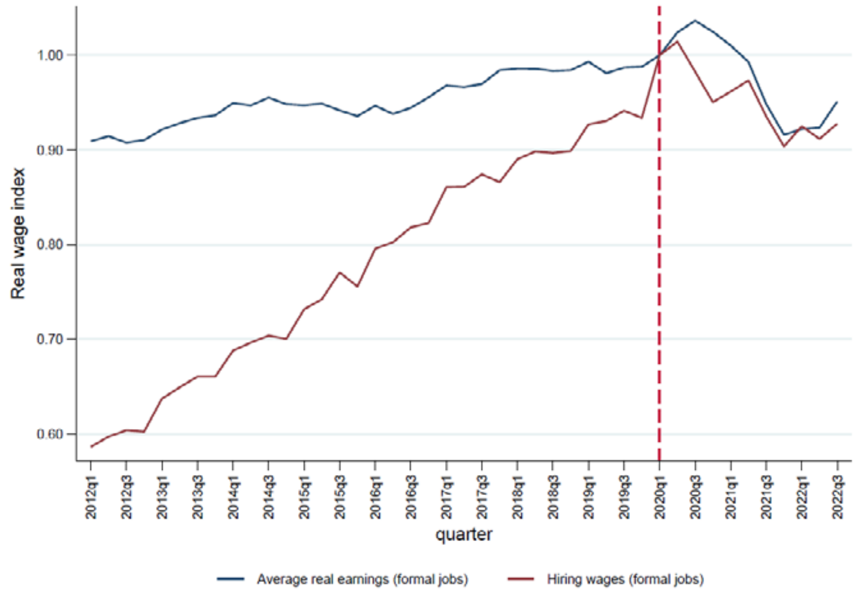
5.2 Inflation surprises

Another relevant concern when analyzing the fall in real wages following the pandemic is that the observed loss in workers' purchasing power is due to inflationary surprises. In this case, workers who have already agreed to a wage will have to wait until the next union convention for a wage reset. Therefore, if realised inflation was larger than expected during the period following the outbreak of the pandemic, a fall in real wages would be a mechanical response to this expectation error and not the result of a change in the labour market equilibrium. This would, in the end, entail the

18 We have undertaken the same exercise with occupation segment instead of informality rate with similar results.

observation that nominal wage rigidity may be even larger than price rigidity and real wages are affected by inflationary surprises.

Comparing average stock wages (PNAD measure) with newly hired wages (CAGED) — Graph 17



Real wages are deflated by the Extended National Consumer Price Index (IPCA), provided by IBGE.

Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC).

We address the effect of inflationary surprises by comparing the response of wages for new workers[19] with the average wage of the pool of formal workers. New workers would not be affected by the impact of an acceleration of inflation on workers with a wage fixed by a job contract agreed some time ago. After all, reset wages, by their nature, are flexible. Graph 17 shows that, although changes in the wages of newly hired workers were different from the average wage of all formal workers, the fall in wages observed for newly hired workers following the outbreak of the pandemic are similar (particularly during the economic recovery) to other employed workers. Therefore, in the aftermath of the pandemic, real wages were depressed both for workers who were already employed and for recently hired ones.

5.3 Institutional changes

It is important to notice that the Brazilian labour market underwent two relevant reforms in the last decade. The first labour reform was implemented in 2015 and aimed at reducing incentives to labour turnover by increasing the requirements for dismissed workers to enroll in the unemployment insurance (UI) programme.[20] According to Carvalho et al (2018), the adoption of stricter rules for UI eligibility led

[19] This information for formal workers is in the CAGED database.

[20] The law was enacted by Provisional Measure 665/2014, converted into Law 13.134/2015. See Carvalho et al (2018) and Van Doornik et al (2023) for more details about the change in the law and its impact on the labour market.

to a reduction of total layoffs of workers affected by the reform (ie those eligible for UI before the reform) of between 11 and 13%. Van Doornik et al (2023) suggest that before the change in the law, most workers were exploiting the UI system to extract rents . About 94% of the layoffs that were reduced by the reform were related to transitions from the formal to informal sector. The second relevant Labour reform took place in 2017. In March 2017, more outsourcing activities were permitted by Law 13.429/2017 and in July 2017 a series of measures that reduced the costs of labour litigation for firms were enacted (Law 13.467/2017).[21] Corbi et al (2022) found that firms' litigation costs have a negative impact on their hiring and wage decisions, as well as their likelihood of experiencing financial distress and survival rates. Additionally, based on a search-matching-bargaining model, the authors simulate the impact of the labour reform and estimate a reduction of 1.7 percentage points in the NAIRU due to a reduction in litigation costs.

Estimating and identifying the impact of a reform is always challenging, especially when it comes to an unobservable variable such as the non-accelerating inflation rate of unemployment. However, it is worth noting that this estimate aligns with the recent reduction in unemployment rates, without an increase in real wages, as the labour market recovers from the pandemic.

5.4 Productivity

We finally face the hypothesis that changes in firms' productivity induced by the pandemic explains the disconnection between wages and employment during the recovery from the pandemic. However, previous results show that the fall in real wages was not driven by changes in the composition of the sector, education, or informality. Therefore, one could argue that if it was a composition effect or an educational one, then it would have to be something observable on the firm level that affected productivity. But the firms' response to mobility restrictions was to implement the automation of tasks and increase the adoption of working from home schemes, both of which are associated with an increase in productivity (Barrero et al (2021)). However, any discussion of productivity during this period should be approached with caution as any productivity index, especially during the pandemic, may be heavily influenced by measurement errors.

6. Final remarks

This paper provides an overview of the Brazilian labour market, highlighting how different sectors and workers with different educational attainments were affected by the pandemic shock. We found that, besides a recovery of employment levels and wages overall remaining below pandemic levels, the real wages of college educated workers fell the most. A possible reason for that result is that the pandemic changed the labour market and allowed for more flexible working conditions. According to

[21] Corbi et al (2022) describes three channels through which they expect a reduction in firms' litigation costs: "(i) by increasing the set of employment practices deemed legal; (ii) by removing from procedural labour law its most noticeable incentives for excessive and groundless litigation; and (iii) by reducing the discretion of judges to decide in accordance to their views when these are in conflict with the law."

Barrero et al (2022), this new environment benefited more educated workers who would accept lower wages in exchange for more flexible working conditions. Therefore, our next step in this research consists of investigating the extent to which this hypothesis reconciles empirical results relating to the Covid-19 pandemic period with the wage-price literature.

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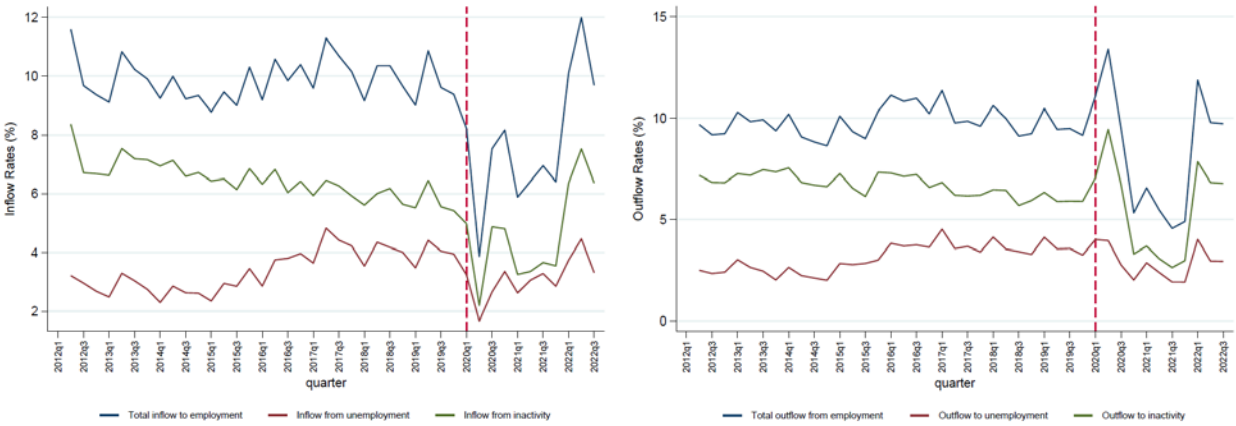
A Additional results

Job flows among employment, unemployment and inactivity — Graph A1

A. Inflows to employment

B. Outflows from employment



Employment in the above graphs comprises both formal and informal labour market.

Source: Continuous PNAD – Continuous National Household Sample Survey (PNADC).

Dependent variable: $\Delta \log(wage)$

Table A1

	(1)	(2)	(3)
$\Delta \log(wage_{t-1})$	0.484**	-0.025	0.074
	(0.183)	(0.296)	(0.248)
$unemployment\ rate_{t-1}$	-0.008**	-0.008***	-0.007***
	(0.003)	(0.003)	(0.002)
$unemployment\ rate_{t-2}$	0.005	0.003	0.006*
	(0.004)	(0.005)	(0.003)
$unemployment\ rate_{t-3}$	-0.002	0.000	-0.001
	(0.004)	(0.004)	(0.003)
$unemployment\ rate_{t-4}$	0.004	0.003	0.002
	(0.003)	(0.003)	(0.002)
$\Delta \log(wage_{t-1})\ x\ pandemics$			
$unemployment\ rate_{t-1} x\ pandemics$			
$unemployment\ rate_{t-2} x\ pandemics$	(0.238)	(0.286)	(0.754)
	0.153	0.152	0.153
$unemployment\ rate_{t-3} x\ pandemics$	(0.098)	(0.097)	(0.099)
		-0.028***	-0.026***
$unemployment\ rate_{t-4} x\ pandemics$		(0.008)	(0.009)
			0.013***
Constant	0.014	0.014*	0.008
	(0.009)	(0.008)	(0.008)
$\Delta \log(wage)_{t-1}(1 + pandemics)$		0.646	0.474
P-value		0.008	0.425
Total tightness	-0.001	-0.001	-0.000
P-value	0.201	0.225	0.539
Total tightness pandemic			-0.001
P-value			0.212
Observations	39	39	39
Adjusted R^2	0.284	0.332	0.309

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

Dependent variable: $\Delta\log(wage)$

Table A2

	(1)	(2)	(3)
$\Delta\log(wage_{t-1})$	0.397	-0.084	0.202
	(0.260)	(0.269)	(0.267)
$employment\ rate_{t-1}$	0.004	0.007*	0.012***
	(0.004)	(0.003)	(0.004)
$employment\ rate_{t-2}$	0.001	-0.000	-0.010**
	(0.005)	(0.005)	(0.005)
$employment\ rate_{t-3}$	-0.001	-0.005	0.004
	(0.004)	(0.004)	(0.005)
$employment\ rate_{t-4}$	-0.001	0.001	-0.002
	(0.003)	(0.003)	(0.004)
$\Delta\log(wage_{t-1})\ x\ pandemics$		1.009**	0.635
		(0.418)	(0.601)
$employment\ rate_{t-1} x\ pandemics$			-0.007
			(0.006)
$employment\ rate_{t-2} x\ pandemics$			0.013*
			(0.007)
$employment\ rate_{t-3} x\ pandemics$			-0.012
			(0.007)
$employment\ rate_{t-4} x\ pandemics$			0.006
			(0.005)
Constant	-0.145*	-0.103	-0.243*
	(0.073)	(0.076)	(0.121)
$\Delta\log(wage)_{t-1}(1+pandemics)$		0.925	0.837
P-value		0.018	0.121
Total tightness	0.003	0.002	0.004
P-value	0.050	0.172	0.053
Total tightness pandemic			0.005
P-value			0.051
Observations	39	39	39
Adjusted R^2	0.203	0.305	0.360

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

Dependent variable: $\Delta \log(wage)$

Table A3

	(1)	(2)	(3)
$\Delta \log(wage_{t-1})$	-0.024	-0.145	-0.325
	(0.247)	(0.223)	(0.263)
$participation\,rate_{t-1}$	-0.002	-0.000	-0.015
	(0.003)	(0.005)	(0.013)
$participation\,rate_{t-2}$	0.009***	0.008*	-0.001
	(0.003)	(0.004)	(0.011)
$participation\,rate_{t-3}$	-0.003	-0.004	0.021
	(0.003)	(0.003)	(0.014)
$participation\,rate_{t-4}$	0.004*	0.004*	0.011
	(0.002)	(0.002)	(0.014)
$\Delta \log(wage_{t-1})\, x\ pandemics$		0.320	0.637
		(0.533)	(0.489)
$participation\,rate_{t-1} x\ pandemics$			0.022
			(0.014)
$participation\,rate_{t-2} x\ pandemics$			0.008
			(0.012)
$participation\,rate_{t-3} x\ pandemics$			-0.026*
			(0.014)
$participation\,rate_{t-4} x\ pandemics$			-0.003
			(0.014)
Constant	-0.546***	-0.501***	-1.036***
	(0.089)	(0.118)	(0.142)
$\Delta \log(wage)_{t-1}(1+pandemics)$		0.175	0.312
P-value		0.736	0.482
Total tightness	0.009	0.008	0.017
P-value	0.000	0.000	0.000
Total tightness pandemic			0.017
P-value			0.000
Observations	39	39	39
Adjusted R^2	0.347	0.338	0.616

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

Dependent variable: $\Delta\log(wage)$

Table A4

	(1)	(2)	(3)
$\Delta\log(wage_{t-1})$	0.521***	0.269	0.220
	(0.186)	(0.267)	(0.318)
$quit\ rate_{t-1}$	-0.007	-0.003	-0.007
	(0.007)	(0.009)	(0.012)
$quit\ rate_{t-2}$	0.021**	0.019*	0.016
	(0.009)	(0.010)	(0.012)
$quit\ rate_{t-3}$	-0.021***	-0.022***	-0.008
	(0.007)	(0.007)	(0.007)
$quit\ rate_{t-4}$	0.010	0.010	0.003
	(0.007)	(0.007)	(0.006)
$\Delta\log(wage_{t-1})\ x\ pandemics$		0.362	0.582
		(0.436)	(0.396)
$quit\ rate_{t-1} x\ pandemics$			0.011
			(0.020)
$quit\ rate_{t-2} x\ pandemics$			0.005
			(0.018)
$quit\ rate_{t-3} x\ pandemics$			-0.029
			(0.020)
$quit\ rate_{t-4} x\ pandemics$			0.012
			(0.015)
Constant	-0.009	-0.010	-0.009
	(0.009)	(0.009)	(0.009)
$\Delta\log(wage)_{t-1}(1+pandemics)$		0.631	0.802
P-value		0.026	0.005
Total tightness	0.003	0.004	0.004
P-value	0.265	0.190	0.259
Total tightness pandemic			0.003
P-value			0.394
Observations	39	39	39
Adjusted R^2	0.304	0.299	0.275

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

Dependent variable: $\Delta\log(wage)$			Table A5
	(1)	(2)	(3)
$\Delta\log(wage_{t-1})$	0.459**	0.151	0.388
	(0.186)	(0.294)	(0.271)
$workers'\ flowrate_{t-1}$	-0.001	-0.000	-0.003**
	(0.002)	(0.002)	(0.001)
$workers'\ flowrate_{t-2}$	0.002	0.001	0.004**
	(0.002)	(0.002)	(0.002)
$workers'\ flowrate_{t-3}$	-0.003**	-0.003**	-0.001
	(0.001)	(0.002)	(0.001)
$workers'\ flowrate_{t-4}$	0.003**	0.003**	0.001
	(0.001)	(0.001)	(0.002)
$\Delta\log(wage_{t-1})\ x\ pandemics$		0.420	0.309
		(0.460)	(0.361)
$workers'\ flowrate_{t-1} x\ pandemics$			0.005
			(0.003)
$workers'\ flowrate_{t-2} x\ pandemics$			-0.004
			(0.003)
$workers'\ flowrate_{t-3} x\ pandemics$			-0.004
			(0.003)
$workers'\ flowrate_{t-4} x\ pandemics$			0.004
			(0.003)
Constant	-0.016	-0.019	-0.019
	(0.017)	(0.017)	(0.017)
$\Delta\log(wage)_{t-1}(1+pandemics)$		0.571	0.697
P-value		0.038	0.009
Total tightness	0.001	0.001	0.001
P-value	0.343	0.244	0.255
Total tightness pandemic			0.001
P-value			0.250
Observations	39	39	39
Adjusted R^2	0.246	0.248	0.317

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

Dependent variable: $\Delta\log(wage)$

Table A6

	(1)	(2)	(3)
$\Delta\log(wage_{t-1})$	0.374	0.185	0.179
	(0.247)	(0.216)	(0.269)
$churning\text{-}to\text{-}workers'\ flow_{t-1}$	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)
$churning\text{-}to\text{-}workers'\ flow_{t-2}$	0.002***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)
$churning\text{-}to\text{-}workers'\ flow_{t-3}$	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
$churning\text{-}to\text{-}workers'\ flow_{t-4}$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
$\Delta\log(wage_{t-1})\ x\ pandemics$		0.257	0.327
		(0.323)	(0.481)
$churning\text{-}to\text{-}workers'\ flow_{t-1} x\ pandemic$			0.001
			(0.001)
$churning\text{-}to\text{-}workers'\ flow_{t-2} x\ pandemi$			-0.000
			(0.001)
$churning\text{-}to\text{-}workers'\ flow_{t-3} x\ pandemi$			-0.001
			(0.001)
$churning\text{-}to\text{-}workers'\ flow_{t-4} x\ pandemi$			0.000
			(0.001)
Constant	-0.162**	-0.158*	-0.481**
	(0.075)	(0.079)	(0.187)
$\Delta\log(wage)_{t-1}(1+pandemics)$		0.442	0.507
P-value		0.167	0.222
Total tightness	0.002	0.002	0.005
P-value	0.035	0.050	0.016
Total tightness pandemic			0.005
P-value			0.018
Observations	39	39	39
Adjusted R^2	0.276	0.265	0.294

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

Dependent variable: $\Delta\log(wage)$

Table A7

	(1)	(2)	(3)
$\Delta\log(wage_{t-1})$	0.3653	-0.3232	-0.3341
	(0.2282)	(0.2289)	(0.2313)
$Iaemp_{t-1}$	-0.0001	0.0003	0.0007*
	(0.0002)	(0.0003)	(0.0004)
$Iaemp_{t-2}$	0.0006	0.0006	-0.0004
	(0.0004)	(0.0004)	(0.0006)
$Iaemp_{t-3}$	-0.0005	-0.0007**	0.0001
	(0.0004)	(0.0004)	(0.0007)
$Iaemp_{t-4}$	0.0004	0.0004	0.0002
	(0.0003)	(0.0002)	(0.0005)
$\Delta\log(wage_{t-1})\, x\ pandemics$		1.0376**	1.1762*
		(0.4542)	(0.5857)
$Iaemp_{t-1} x\ pandemics$			-0.0003
			(0.0008)
$Iaemp_{t-2} x\ pandemics$			0.0011
			(0.0007)
$Iaemp_{t-3} x\ pandemics$			-0.0011
			(0.0010)
$Iaemp_{t-4} x\ pandemics$			0.0002
			(0.0007)
Constant	-0.0320*	-0.0452**	-0.0508**
	(0.0166)	(0.0170)	(0.0190)
$\Delta\log(wage)_{t-1}(1+pandemics)$		0.7145	0.8422
P-value		0.0466	0.1305
Total tightness	0.0003	0.0005	0.0005
P-value	0.0526	0.0097	0.0105
Total tightness pandemic			0.0006
P-value			0.0189
Observations	39	39	39
Adjusted R^2	0.144	0.266	0.214

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