Effects of app-based work on the labor market

This box analyzes the impact of the introduction of digital platforms for passenger transport and goods delivery services on the Brazilian labor market. The results of two separate exercises suggest that this phenomenon affected the labor force participation rate, the employment level, and the unemployment rate.

Introduction

The use of phone and Internet apps to hire personal transport and goods delivery services emerged about a decade ago and has since grown and become relevant to the Brazilian economy. For example, app-based transport was included in the Extended National Consumer Price Index (IPCA) – the inflation measure used as a reference in the Brazilian inflation-targeting system – starting in 2020, reflecting the results of the 2017/2018 Household Budget Survey (POF). In August 2025, the weight of the sub-item "app-based transport" in the IPCA was 0.3%, while, for comparison, the weight of "airfare" was 0.6%. As that weight still reflects consumption estimates from the 2017/2018 POF, its current relevance may be even greater.

This box uses data from the Continuous National Household Sample Survey (PNAD Continuous) to understand the implications of this phenomenon for the Brazilian labor market. After estimating the number of app-based workers, two separate analyses are presented. The results of both exercises suggest that this phenomenon contributed to an increase in the employment level and labor force participation and helped reduce the unemployment rate.

Estimate of the number of "app-based workers"

The term "app-based workers" used in this box refers to occupational categories that have grown significantly with the advent of digital platforms, although not all of them are working through those platforms. As a starting point, only self-employed workers are considered in terms of occupational status.[1] Workers on digital passenger transport platforms are estimated by cross-referencing the activity "Road passenger transport" from the National Classification of Economic Activities adapted for household surveys (Household CNAE) with the occupations "Motorcycle drivers" and "Taxi and van drivers" from the Brazilian Classification of Occupations adapted for household surveys (Household CBO). Home delivery platform workers are estimated by cross-referencing "Road passenger transport" and "Courier and delivery activities" (Household CNAE) with the occupation types "Pedal- or hand-powered vehicle drivers"[2], "Motorcycle drivers", and "Taxi and van drivers" (Household CBO).

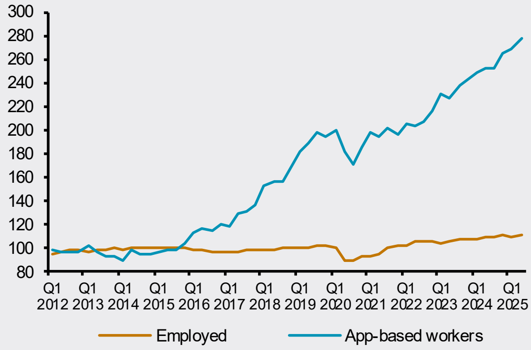
The number of app-based workers has grown strongly. This expansion has been driven by the emergence of new technologies and the low entry cost of this type of activity.[3] According to PNAD Continuous data, from 2015 to 2025Q2, while the employed population in the country grew nearly 10%, the number of app-based workers – comprising those on passenger transport and home delivery platforms – increased 170%, rising from around 770,000 to 2.1 million.

1/ For example, other types of occupational status include formal employees, informal employees, and employers, among others.
2/ This household CBO is cross-referenced only with "Courier and delivery activities".
3/ The app-based transport service Uber, for instance, began operating in Brazil in 2014, initially offering passenger transport in high-end cars. In 2015, it began serving other segments and quickly expanded in the following years.

Despite this significant growth, the share of these workers is still relatively small. It rose from 0.8% to 2.1% of the employed population (EP) from 2015 to 2025, and from 0.5% to 1.2% of the working-age population (WAP) in the same period. One can observe that, from 2015 to 2017, growth was stronger in passenger transport services. From 2017 to 2021, dynamism was stronger in home delivery services (Figure 2).

Figure 1 – App-based workers

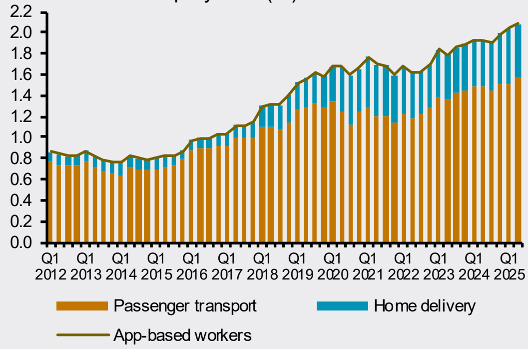
2015=100



Sources: IBGE and BCB

Figure 2 – App-based workers

Share of total employment (%)



Sources: IBGE and BCB

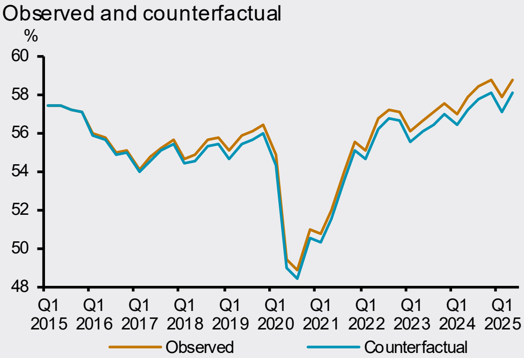
Counterfactuals without extraordinary growth in app-based employment

The first exercise uses the temporal dimension of Brazilian labor market variables viewed in aggregate terms – that is, without exploring differences between locations. The goal of this exercise is to estimate counterfactual values for the employment level (EL)[4], participation rate (PR),[5] and unemployment rate (UR) under a hypothetical scenario in which the accelerated growth of app-based workers – far above historical patterns – had not occurred.

To this end, the EP was segmented into two groups: app-based employed population (EP-app) and other employed individuals (EP-non-app). A counterfactual EP was then calculated as the sum of these two groups, assuming that the app-based workers group had grown at the same rate as the EP-non-app group, starting from 2015Q1 – when the accelerated growth of app-based workers began. Based on this counterfactual EP, a counterfactual EL was estimated, showing a progressive distancing from the observed values. In 2025Q2, the counterfactual EL was 0.8 p.p. below the actual observed EL (Figure 3).

Figure 3 – Employment level

Observed and counterfactual



Sources: IBGE and BCB

To estimate the counterfactual unemployed population (UP) and the population out of the labor force (POLF) – and thereby calculate the counterfactual participation and unemployment rates – it is necessary to

4/ Ratio between EP and WAP.
5/ Ratio between the labor force population and the WAP.

make assumptions about the destination of the extraordinary, employed population (extra EP), which is the difference between the observed EP and the counterfactual EP. In other words, it should be considered what would have happened to this group if they had not been employed. Three scenarios are analyzed: two extreme ones used as benchmarks and an intermediate one that aims to realistically reflect labor market dynamics:

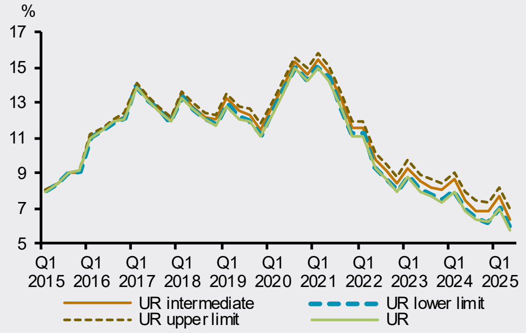
- Scenario 1 (Maximum UP): It is assumed that all individuals in the extra EP would have sought work, but without success, became unemployed.

- Scenario 2 (Maximum POLF): In this case, it is assumed that these individuals would not have sought work, moving directly out of the labor force.

- Scenario 3 (Intermediate UP and POLF): It is assumed that part of the extra EP would have become unemployed, and part would have left the labor force, reflecting an intermediate and more plausible situation. The split was calibrated based on the observed proportion of transitions from UP and POLF to EP-app.[6]

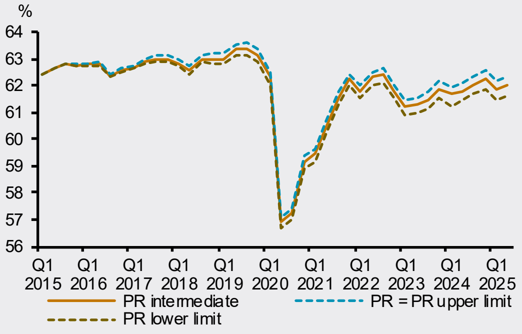
In Scenario 1 (Maximum UP), the unemployment rate gradually diverges from the observed rate, reaching 1.2 p.p. above it in 2025Q2. In this scenario, the PR remains identical to the actual rate, since all extra EP is considered unemployed, leaving the labor force size unchanged. In Scenario 2 (Maximum POLF), the unemployment rate remains nearly unchanged, but the PR declines, ending up 0.8 p.p. below the observed rate. Finally, in Scenario 3 (Intermediate UP and OLF), considered the most plausible, the results for UR and PR are intermediate, as expected. In 2025Q2, the UR would be 0.6 p.p. above the observed rate – half the impact seen in Scenario 1, which represents the upper bound for UR. The PR, in turn, would be 0.2 p.p. below the actual value (Figures 4 and 5).

Figure 4 – Unemployment rate
Observed and counterfactuals



Sources: IBGE and BCB

Figure 5 – Participation rate
Observed and counterfactuals



Sources: IBGE and BCB

Estimating labor market impacts using regional dispersion

This exercise leverages regional heterogeneity in the growth of app-based workers since 2015 to estimate the relationship between this growth and changes in employment level (EL), participation rate (PR), and unemployment rate (UR).[7] Panel data models were estimated, relating each labor market variable of interest to the share of app-based workers in the working age population (WAP). Fixed effects for location and time were included as controls. The locations correspond to the 146 strata of the PNAD Continuous (IBGE), and the sample covers the period from 2015 (the year before the growth of this type of worker began, as shown in Figures 1 and 2) to 2024. Formally,

6/ With paired data, it is possible to segment the app-based EP into three groups, depending on their previous status in relation to the labor force: employed, unemployed, and out of the labor force. By excluding those who were previously employed, the share of individuals who were unemployed and out of the labor force can be calculated in each quarter.

7/ The article "The labor market impacts of ridesharing on American cities", by Tucker Omberg, published in Labour Economics (2024), explores the staggered introduction of the Uber ridesharing service in U.S. cities to estimate the labor market impact of this new form of employment. The author estimates that Uber's entry into a city reduces the local UR by between 0.2 p.p. and 0.5 p.p. In the absence of similar data for Brazil, this box adopts an alternative strategy.

$$Y_{it} = \beta \text{App}_{it} + \alpha_i + \tau_t + \varepsilon_{it},$$

where $Y_{it} \in \{\text{EL}, \text{PR}, \text{UR}\}$ is the labor market variable of interest i in year t, App_{it} is the share of app-based workers (as previously defined) in the WAP, α_i and τ_t are fixed effects of location and time, respectively, and ε_{it} is the error term. β is the coefficient of interest, capturing the impact of app-based employment on the labor market variable.

It is worth noting that this coefficient may be biased in relation to the true causal effect, due to the possible existence of alternative mechanisms linking app-based work to key labor market variables. For example, it is plausible that the share of app-based workers is influenced by the UR, with higher uptake in times and places of higher unemployment. The existence of this reverse causality mechanism would make the estimated coefficient less negative than the true causal effect.

Table 1 presents the estimated coefficients, along with 95% confidence intervals using robust standard errors for heteroscedasticity and serial autocorrelation.[8] In addition to the baseline model (labeled Model 1), the table also includes results from an alternative model, to be presented later.

According to Model 1, a 1 p.p. increase in the share of app-based workers in the WAP is associated with a 1.12 p.p. increase in EL. The confidence interval includes the reference value of "one" – suggesting that the rise in app-based employment did not replace other forms of employment. Moreover, the one-off estimate for the association between the increase in app-based workers and the PR (0.87 p.p.) indicates that most individuals entering this type of work came from outside the labor force. This suggests that the new form of employment enables some people to engage more actively in the labor market. Finally, a 1 p.p. increase in app-based workers is associated with a 0.41 p.p. reduction in the UR – a one-off estimate that is not statistically significant, though economically relevant. According to this model, the 0.66 p.p. increase in the share of app-based workers in the WAP from 2015 to 2024 (Figure 2) would be associated with a 0.27 p.p. drop in the UR (Table 2). It is also possible to estimate the change in the UR indirectly through the models for EL and PR. The indirect estimate is 0.33 p.p., very close to the direct estimate from the UR model, suggesting consistency across the three models (Table 1).

Table 1 – β coefficient estimates

Regressor	Model[1]	
	1	2
Dependent variable: Employment level		
App-based	1.12 [0.36; 1.88]	
Transport		0.98 [0.10; 1.87]
Delivery		1.65 [-0.04; 3.35]
Dependent variable: Participation rate		
App-based	0.87 [0.15; 1.60]	
Transport		0.73 [-0.13; 1.58]
Delivery		1.46 [-0.34; 3.27]
Dependent variable: Unemployment rate		
App-based	-0.41 [-1.00; 0.19]	
Transport		-0.49 [-1.20; 0.23]
Delivery		-0.08 [-1.54; 1.38]

1/ Bracketed values indicate the 95% confidence interval at a 5% significance level. Variables were used in level.

8/ Robust errors to heteroscedasticity and to intra-location serial autocorrelation, with residuals clustered by location.

Furthermore, Model 2 explores potential heterogeneity in the impact of different types of apps (transport vs. delivery). The results suggest that the effect on the UR is proportionally greater for transport apps, while the effects on EL and PR are stronger for delivery apps.

Considering the change in the share of app-based workers from 2015 to 2025, the labor market impacts estimated by each model are summarized in Table 2.

Table 2 – Effect on rates associated with the apps
Variation 2024 - 2015 (p.p.)

	Observed	Models		
		1	2	Average
EL	0.71	0.74	0.79	0.76
PR	-0.46	0.58	0.63	0.60
UR (direct)	-1.81	-0.27	-0.24	-0.25
UR (indirect)	-1.81	-0.33	-0.33	-0.33

In summary, the estimates presented in this exercise suggest that new app-based jobs were not created at the expense of other occupations, that most app-based workers came from outside the labor force, and that the impact on the UR would be around -0.3 p.p. (although not statistically significant). It should be emphasized that these estimates may not represent the true causal effect of app-based employment growth on the labor market – due to likely alternative mechanisms linking the variables, such as reverse causality. Therefore, these estimates should be interpreted with caution.

Conclusion

Taken together, both exercises suggest that the emergence of platform-based work represents a structural shift in the labor market, which has contributed to a greater entry of individuals into the labor force and employment, with positive effects on key indicators. The extraordinary growth in the number of app-based workers led to an increase in the EL and PR, as well as a reduction in the UR. Under scenario 3 of the first exercise, the estimated impacts by 2025Q2 were +0.8 p.p. in the EL, +0.2 p.p. in the PR, and -0.6 p.p. in the UR. Comparatively, the results from the panel data models of the second approach suggest similar effects on the EL (+0.7 p.p.), stronger effects on the PR (+0.6 p.p.), and slightly smaller effects on the UR (-0.3 p.p.).