Who worked from home in Brazil? Inequalities highlighted by the pandemic

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Quem trabalhou remotamente no Brasil? Desigualdades evidenciadas pela pandemia

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Abstract

There is some consensus that the pandemic can widen pre-existing inequalities in the labor market and that an essential issue concerns the unequal possibilities of working remotely. This study analyzes inequalities in remote work in Brazil through descriptive analyzes and Probit regressions using PNAD COVID-19 microdata. We have found that workers with the least possibilities for remote work were the poorest, males, rural residents, non-whites, youngest, without college education, self-employed or wage workers from the private sector and agriculture workers. An important part of that stems from differences in selection into occupations; however, some variables maintained important independent effects, especially the college education and the labor income. The pandemic, regarding the possibility of remote work, had the effect of widening the existing inequalities, favoring the wealthier, more educated, and more formalized workers and imposing on the others the need to choose between employment and income versus risk of contagion.

Keywords: COVID-19; inequalities; labor market; pandemic; remote job

JEL Code: J21, J22, J23

Resumo

Existe certo consenso de que a pandemia pode ampliar desigualdades preexistentes no mercado de trabalho e que uma questão essencial são as possibilidades desiguais de trabalhar remotamente. Este estudo avalia as desigualdades no trabalho remoto no Brasil por meio de análises descritivas e modelos Probit aplicados aos microdados da PNAD COVID-19. Constatamos que os trabalhadores que menos trabalharam remotamente foram os mais pobres, homens, residentes rurais, não brancos, mais jovens, sem ensino superior, autônomos ou assalariados sem carteira de trabalho assinada e trabalhadores agrícolas. Uma parte importante disso decorre de diferenças na seleção nas ocupações; mas, algumas variáveis mantiveram efeitos independentes importantes, principalmente a educação superior e a renda do trabalho. Logo, quanto à possibilidade de trabalho remoto, a pandemia teve efeito de ampliar desigualdades existentes, favorecendo os trabalhadores mais ricos, escolarizados e formalizados e impondo aos demais a necessidade de escolha entre emprego e renda e risco de contágio.

Palavras-chave: COVID-19; desigualdades; mercado de trabalho; pandemia; trabalho remoto.

Códigos JEL: J21, J22, J23

1 Introduction

Covid-19's first case was confirmed in Brazil on February 26, 2020. At the beginning of April 2021, the country reached more than 13 million confirmed cases, with more than 330 thousand deaths (Brazil, 2021). The pandemic started when the country was slowly emerging from the deepest and longest recession since the Second World War (Oreiro, 2017) and, in the second quarter of 2020, Brazilian GDP fell 9.7% compared to the previous quarter, the biggest drop in the historical series, which started in 1996 (Brazilian Institute of Geography and Statistics - IBGE/National Accounts, 2020).

Worldwide, the current pandemic has caused the largest economic dislocation since the Great Depression (Campello et al., 2020). Because this is an unprecedented health and economic crisis, there is a new and rapidly growing literature dedicated to assessing the effects of Covid-19. Jonas (2013) points out possible demand and supply shocks associated with pandemics: avoidance reactions and measures of social distancing can lead to rapid and significant negative demand shocks and supply disruptions; contagion itself has direct and indirect costs, leading to loss of production due to death and illness of workers and other absenteeism related to the disease; and cascade impacts when these effects are combined.

The specific literature on socioeconomic consequences of Covid-19 has already demonstrated that social distancing and lockdown measures affect labor market issues, mental health and well-being, racial inequality and gender roles (Adams-Prassl et al., 2020; Brodeur et al., 2020; Campello et al., 2020; Montenovo et al., 2020).

Specifically regarding the effects on the labor market: they are likely to be deep and long-lasting (Campello et al., 2020). A highly active line of research in this context has been on the inequality of the effects of the negative shock related to Coronavirus; and it can be said that it is already agreed that this effect is uneven and can widen pre-existing inequalities (Adams-Prassl et al., 2020; Bartik et al., 2020; Brussevich et al., 2020; Crowley; Doran, 2020; Gallacher; Hossain, 2020; Gaudecker et al., 2020; Montenovo et al., 2020; Yasenov, 2020).

The results of Adams-Prassl et al. (2020), Gallacher and Hossain (2020), Gaudecker et al., (2020) and Montenovo et al. (2020) for the United States, Canada, United Kingdom, Germany, and Netherlands converge in pointing out that job losses were greater for

occupations that require interpersonal contact, which cannot be done remotely, and, considering the heterogeneous distribution of workers' characteristics among sectors, for workers in alternative labor arrangements and with less schooling.

Considering the difficulty of carrying out jobs that involve face-to-face contact – due to the Covid-19 spread characteristics – or the government definitions about essential activities, the central question behind the results is whether or not it is possible to do the job remotely. Yasenov (2020), Gallacher and Hossain (2020), Crowley and Doran (2020), Brussevich et al., (2020) and Bartik et al. (2020) focused specifically on this issue, covering the United States, Ireland, Canada and the Organization for Economic Co-operation and Development (OECD) countries. Up until now, the majority of studies analyzed developed countries. Among the authors who adopted this focus, we can mention Balde et al. (2020), Estupinan et al. (2021), Gottlieb et al. (2021) and Khamis et al. (2021). Although these studies have specificities, there is some convergence regarding the important inequalities in the probability of remote work, considering aspects of income, age, education, gender, and employment contract arrangements, with fewer possibilities for more vulnerable groups in the labor market.

The impact of the pandemic varies significantly among countries as there are many institutional differences between labor markets (Adams-Prassl et al., 2020; Brussevich et al., 2020). According to Brussevich et al. (2020), the heterogeneity in the possibility of remote work across countries stems from the different access to and use of technology, the sectoral distribution of the economy and the selection in the labor market, with a strong association between the level of economic development and the ability to work remotely. In this perspective, the current study aims to address the issue of inequalities in remote work specifically for Brazil.

The literature focused on Brazil has already identified that job losses were more intense for informal workers – with important negative effects on equity given the over-representation of more vulnerable groups in informality – and in industries that are more contact intensive (Al Masri et al., 2021; Corseuil et al., 2021; Bridi, 2020). Regarding tele-workability, the report by Góes et al. (2021) analyzed the composition of the "remote workforce", considering different attributes, and identified that it is predominantly composed

of formal-sector workers with complete college education, aged between 30 and 39 years, women and white people.

Our study aims to go into more detail regarding this issue, analyzing who are the workers who worked from home in Brazil and how unequal the probabilities of remote work are, considering different sociodemographic and work characteristics. We used PNAD COVID-19 data from May to August 2020 and descriptive as well as econometric analysis methods, by estimating Probit regressions.

Understanding how these impacts are distributed across the labor market is essential to guide the decisions of policy makers. The relevance of this analysis is amplified by the high degree of informality and presence of low-paid jobs as well as by the precarious living conditions of a large part of the population in the pre-pandemic scenario. In the first quarter of 2020, 19% of the employed population in Brazil were waged workers without a formal contract and 21% were employers, or self-employed, without registration with the National Registry of Legal Entities (CNPJ, in Portuguese) (Continuous National Household Sample Survey - IBGE/PNADC, 2020). In 2018, 25.3% of the population had incomes below US$ 5.50 PPP per day – a value suggested by the World Bank to classify people at poverty level in countries with medium-high income (IBGE, 2019).

This paper is structured as follows: in Section 2, we present the growing literature regarding the effects of Covid-19 on labor markets; in Section 3, we discuss our empirical model and the data sources that were used; and Section 4 shows the results and discussions. The final section presents our concluding remarks.

2 The growing literature on the pandemic's effects on the labor market

Because the health and economic crisis related to Covid-19 is an unprecedented crisis, there is a new and rapidly growing segment of literature dedicated to assessing its various effects. Regarding the effects on the labor market, a line of research that has been highly active addresses the uneven effects of the negative shock related to Coronavirus. There is already a consensus that this effect is uneven and may increase pre-existing inequalities.

Adams-Prassl et al. (2020) analyzed evidence for the UK, US and Germany and found that the probabilities of reducing hours worked, losing jobs and suffering earning reductions are greater for workers in alternative work arrangements and in occupations in which only a small share of tasks can be done from home, for those with less schooling and for women. The results of Montenovo et al. (2020) for the United States also show that job losses were greater for occupations that require interpersonal contact and, therefore, cannot be done remotely. Gallacher and Hossain (2020), analyzing the Canadian labor market, found that the most intense job losses between March and April were for workers with lesser possibilities for working from home.

Gaudecker et al. (2020), analyzing data from the Netherlands, have found that the total hours worked reduced more for the self-employed, because firms insure employees against transitory shocks, and for workers with less education, since workers with higher education may work more hours at home. These authors divided the economic sectors into two clusters: one dominated by office occupations with high participation of academics, hours of work at home and a reduced involvement of "essential" workers; and another in which manual tasks and social interactions are predominant, with low participation of academics and hours of work at home and a greater participation of "essential" workers (Gaudecker et al., 2020).

The results mentioned above highlight a central question: whether or not it is possible to do the different types of work remotely. Yasenov (2020), Gallacher and Hossain (2020), Crowley and Doran (2020), Brussevich et al., (2020) and Bartik et al., (2020) focused specifically on this issue.

Yasenov (2020) analyzed the US labor market and found that lower paid workers are up to three times less likely to be able to work from their homes; as a result, remote work is less possible for the least educated, the youngest, the ethnic minorities and immigrants. Also for the United States, the results of Bartik et al. (2020) corroborate that remote work is much more common in industries with better educated and better-paid workers.

Similarly, Gallacher and Hossain (2020), for Canada, found that 41% of the country's jobs could be done remotely and that workers with less chance of remote work were poorer,

younger, non-immigrant, single, male and/or without college education that worked in the private sector and in small firms and that were seasonal, contractual or part-time workers.

Brussevich et al. (2020) analyzed the feasibility to work from home for the OECD countries. Their results also suggest that the pandemic can exacerbate inequality because the workers least likely to work remotely tend to be younger and less educated, or those with atypical contracts and in smaller companies, or those located at the bottom of the income distribution.

Crowley and Doran (2020) performed a similar analysis for Ireland. They found that there is a wide variation of social distancing and remote working potential across occupations and within industries and that chances of remote work favor workers located in more affluent, larger, more densely populated cities, with better education and better broadband supply.

The literature developed so far on the topic highlights that the probabilities of reducing hours worked and earnings as well as of job losses are greater for workers in positions that cannot be fulfilled remotely and also highlights that there are important inequalities in the probability of remote work.

The vast majority of studies analyzed the circumstances in developed countries. Among studies that focus on developing countries, Gottlieb et al. (2021) measured the ability to work-from-home (WFH) in Armenia, Bolivia, China, Colombia, Georgia, Ghana, Kenya, Laos, Macedonia and Vietnam. They show that the ability to WFH is relatively low and strongly correlated with per capita income in these countries and that there is high heterogeneity across and within occupations and across characteristics of workers, with vulnerable groups less likely to work remotely.

Khamis et al. (2021) used high-frequency phone surveys to assess the early impacts of Covid-19 on the labor market in various developing countries. They found that 34% of respondents reported stopping work, with differences across regions: 21% in the East Asia and Pacific, 29% in Europe and Central Asia, 48% in the Latin America and the Caribbean region (LAC), 45% in the Middle East and North Africa region and 26% in the Sub-Saharan Africa region; within the LAC, 30% stopped working in Chile and 36% in Costa Rica, while 59% stopped working in Peru and 69% in Bolivia. They show that workers were more likely to stop working in services (38%) and industry (40%) than in agriculture (22%).

Balde et al. (2020) found that informal workers in sub-Saharan Africa were more likely to lose their jobs or to experience decrease in earnings, while Estupinan et al. (2021) found that workers in the non-essential industry and who were unable to work from home were the most affected in India.

Specifically, in Brazil, in terms of job losses, the impacts were severe. Between the quarters from January to March and April to June 2020, there was a drop of 8.9 million or 9.6% in the employed population, reaching the lowest level of the historical series (IBGE/PNADC, 2020). In May, out of the employed population of 84.4 million, 15.7 million or 18.6% were away from work due to social distancing; in June, the figure was 11.8 million (14.2%), in July, 6.8 million (8.3%) and, in August, 4.1 million, representing 5.0% of the employed persons.

The scientific and technical literature on the impacts of Covid-19 in Brazil grew rapidly in late 2020 and early 2021, with several perspectives being addressed. Among the first published studies in line with the objective of this analysis, that of Mattei and Heinen (2020), which used data from February to April 2020, found that the first dismissed workers or those with jobs that were not feasible in the face of the pandemic were the underemployed, generally in more flexible occupations.

Bridi (2020) concluded that job losses in Brazil in the second quarter of 2020 were significantly higher for informal workers; whether in comparison between salaried employees with and without a formal contract, or between entrepreneurs with or without CNPJ. Corseuil et al. (2021) also found that a relevant aspect of the current crisis was its magnified impact on informal occupation. Their studies showed that more vulnerable groups of workers tend to be over-represented in informality, which cause important negative effects on equity. Al Masri et al. (2021) found that the greatest reductions in employment occurred for informal, self-employed and younger workers in the second and third quarters of 2020; that the outflow of the workforce for men decreased as early as in the third quarter, while for women this outflow continued to increase; and that industries that are more contact intensive have experienced the largest job losses. None of this research specifically accessed remote work and its determinants.

Among the research focused on tele-workability in Brazil, we highlight the reports developed by investigators from the Institute of Applied Economic Research (IPEA). Using data from May to November of 2020, Góes et al. (2021) found that the "remote workforce" was predominantly composed of formal-sector workers with complete college education, aged between 30 and 39 years, women, and white people. These results are sensitive to the size of each group in the workforce.

3 Methodology

3.1 Data and sample

The IBGE has systematically investigated general characteristics of the population, education, labor, income, and housing by applying National Household Sample Surveys (PNADs) in Brazil since 1967. As of 2016, PNAD became Continuous PNAD, a quarterly survey to monitor labor force fluctuations and general socioeconomic indicators.

Due to the pandemic, IBGE carried out a special additional survey, PNAD COVID-19, which started on May 4, 2020. PNAD COVID-19 data collection was carried out by telephone in nearly 193 thousand households across the National Territory. The questionnaire had two parts, one for health and the other for labor issues.

We used monthly PNAD COVID-19 microdata from May to August 2020. For our purpose, we kept in our sample only workers who received labor income, aged between 16 and 65 and who did not attend school – to prevent conflicts between work and study decisions. Table 1 shows the filters applied to the initial sample and the final sample. Our variable of interest, worked-from-home, is equal to 1 if the respondent answered affirmatively to the question: "Last week, were you in remote work?". The value 0 was attributed for those who did not change their work routine activities[1]. Our final sample had 419,840 responses, of which 46,261 (11.02%) declared affirmatively that they were working from home.

Table 1 – Filters applied to PNAD COVID-19 sample and final sample

Filters	Excluded	Final sample

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[1] For details, see variables encoded C012 and C013 in the PNAD COVID-19 survey.

PNAD COVID-19 final sample (May-Aug)		1,501,262
Under 16 and over 65 years	473,861	1,027,401
Attending school	55,231	972,170
Undetermined or undeclared income	449,822	522,348
Occupation not defined	4,345	518,003
People who did not answer if they worked from home	98,163	419,840

Source: PNAD COVID-19.

3.2 Empirical strategy and selected variables

We first applied graphical and Kernel density analyses to investigate the work-from-home condition within all the selected socioeconomic, demographic and work characteristics indicated in Table 2 (for descriptive statistics, see Table A1).

As for the empirical model, we used *Probit* models to estimate the conditional probability of working from home for individual i given several observable characteristics $(y_i = 1|x_i)$. We used this class of models since OLS regressions ignore the discreteness of the dependent variable and there is no constrain for probabilities to be between zero and one. Following Cameron and Trivedi (2005), Probit model specifies $0 < p_i < 1$ as in eq. (1):

$$p_i = \Pr[y_i = 1|x_i] = \Phi(x_i'\beta) \tag{1}$$

where $\Phi(.)$ is the cumulative distribution function for the standard normal (so, $p_i = \int_{-\infty}^{\beta_1+\beta_2 x_i}(2\pi)^{-1/2}e^{-z^2/2}dz$) and x_i indicates the vector of covariates described in Table 2. The Probit model marginal effects are (2):

$$\frac{\partial p_i}{\partial x_{ij}} = \Phi(x_i'\beta)\beta_j = \phi(\Phi^{-1}(p_i))\beta_j \tag{2}$$

where $p_i = \Phi(x_i'\beta)$. Estimates were obtained by Maximum Likelihood Estimators (MLE) which are consistent by optimizing first-order conditions stated as $\sum_{i=1}^{N} w_i(y_i - \Phi(x_i'\beta))x_i = 0$ with the weight $w_i = \Phi(x_i'\beta)/[\Phi(x_i'\beta)(1 - \Phi(x_i'\beta))]$ (Cameron; Trivedi, 2005).

Table 2 – Selected variables for descriptive and empirical analyses

Variable	Description
Hourly earnings	Logarithm of hourly earnings from the main job.

No schooling	Schooling level. No schooling is the benchmark.
Elementary school	
High school	
Higher education	
Employer	Status in employment. Employee without a formal contract is the benchmark.
Self-employed	
Private sector (formal contract)	
Public sector (formal contract)	
Employee without a formal contract	
Age (16-19)	Age (in years). Age (16-19) is the benchmark.
Age (20-29)	
Age (30-39)	
Age (40-49)	
Age (50-59)	
Age (60-65)	
Agriculture	Economic sectors. Agriculture is the benchmark.
Industry	
Retail	
Services	
Rural	1 if the individual lives in a rural area, 0 otherwise.
Man	1 if the individual is a man, 0 otherwise.
White	1 if the individual is white, 0 otherwise.
F. U.	Federal Units (27 dummy variables, one omitted).
Month	Months (4 dummy variables, one omitted).
Types of work	Categories of types of work, position, or function (36 dummy variables, one omitted).

Source: authors, based on PNAD COVID-19

The variables in Table 2 were chosen in line with the objective of our study, to investigate inequalities in the probabilities of remote work in view of different socioeconomic and work characteristics. Also, those variables were selected according to: i) classical studies that addressed labor market issues as in Mincer (1962) for labor force participation decisions, Heckman (1974) for shadow prices and market wages, and Mincer (1974) and Willis (1986) for earnings functions; and ii) recent empirical works on labor

issues associated with COVID-19 – see Bridi (2020), Mattei and Heinen (2020), Pouliakas (2020), Yasenov (2020), Al Masri et al. (2021), Corseuil et al. (2021) and Góes et al. (2021).

To interpret our results, marginal effects of change in a regressor on the conditional probability that $y = 1$ were obtained at means of the variables. Our results for the Probit models also accommodate the sample weights of the PNAD COVID-19.

4 Results and discussions

According to data from PNAD COVID-19, the percentage of employed (and not on leave) people working remotely in the total employed and not on leave population reached 13.3% in May, decreasing to 12.7% in June, 11.7% in July and then 11.1% in August. In absolute numbers, the number of remote workers in Brazil was 8.7 million in May and 8.4 million in August.

The pandemic created the need for different remote work regimes for a large part of the employed population in Brazil and the ability to remain working under these circumstances depended on the occupation. Therefore, considering that the type of task performed at work is an essential determinant of the possibility of remote work, the analysis of the results starts from this characterization. Figure 1 shows the share of workers who worked from home by categories of types of work, position, or function.

The difference between the upper and lower values of the shares (Figure 1) is notable. The category with the highest share of remote work, close to 80% on average for the period, was that of kindergarten, elementary and high school teachers or college professors. This category also stood out with significant potential for remote working in the study by Crowley and Doran (2020) for Ireland.

Also with participation of remote work above 40%, there were: pedagogues and other teachers (languages, arts, music) and other professions with higher education, such as lawyers, engineers, accountants, and journalists. These categories fit well with the general "sector" in which the hours of remote work are high, as defined by Gaudecker et al. (2020), this being predominantly composed of personnel with higher education and office occupations.

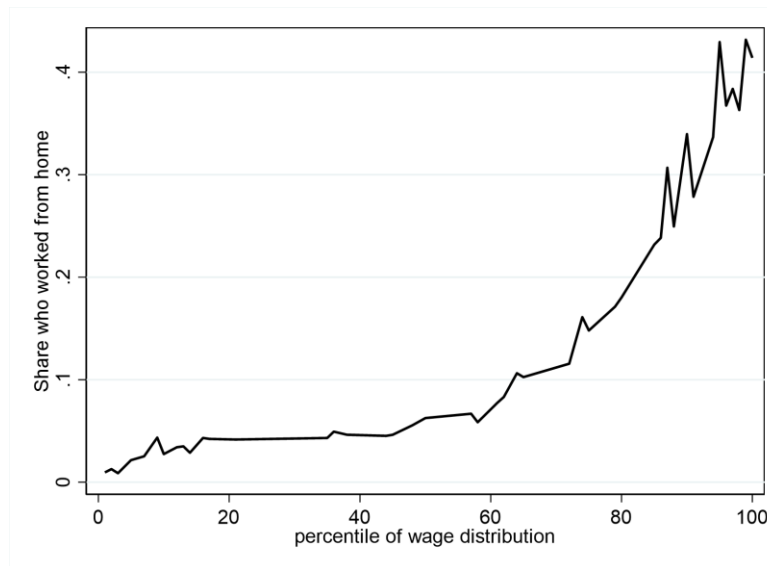**Figure 1** - Share of workers that worked from home, by types of work, position, or function
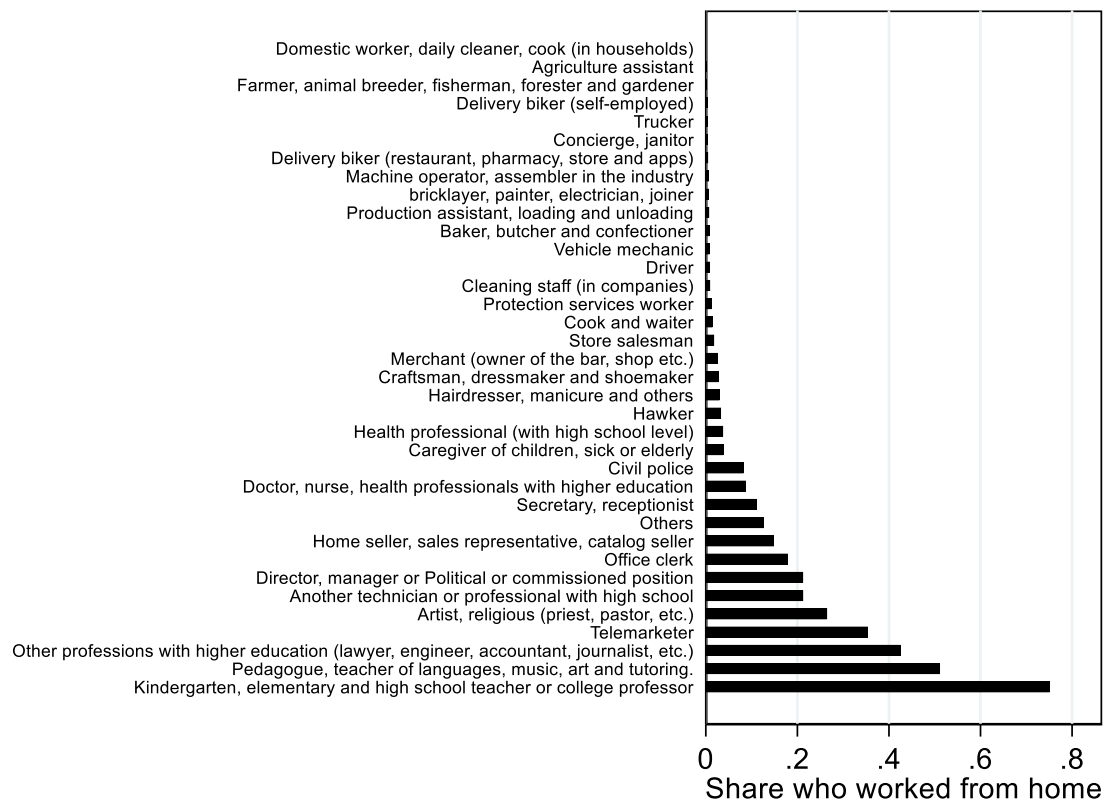
Source: authors, based on PNAD COVID-19

At the other extreme, with an unexpressive portion of remote work were the following categories: domestic workers, daily cleaners, cooks (in households); agriculture assistants and farmers and animal breeders in general; delivery bikers; truck drivers; janitors; bricklayers, painters, electricians, and joiners; machine operators and production assistants; bakers, butchers and confectioners; vehicle mechanics; drivers; among others. In the latter cases, the tasks performed are clearly not compatible, by definition, with remote work.

This unequal ability to work from home in different types of work, position, or function raises concerns about inequality, due to the systematic difference between these categories with respect to the representativeness of socially vulnerable groups of workers. The evidence in Figure 1 preliminarily suggests that low-income workers faced the difficult decision about employment versus health risks while higher-income workers were more likely to be able to choose remote work. To further explore this result, we present Figure 2, the share of remote work by location in the earnings distribution.

Figure 2 - Share of workers that worked from home by location in the wage distribution

Source: authors, based on PNAD COVID-19

Figure 2 is straightforward, with a clearly monotone pattern. The share of workers that worked from home increases more rapidly mainly from the 60th percentile and even more rapidly from the 80th. Therefore, the consequences of the pandemic reinforced the pre-existing inequality in the Brazilian labor market, as workers with higher wages were more likely to have the option of working from home.

Similar results were found by Yasenov (2020), for the United States, and by Gallacher and Hossain (2020), which analyzed Canada. And an analogous result is also true when comparing between countries. Brussevich et al. (2020), for the OECD countries, and Gottlieb et al. (2021), for a wide group of developing countries, all found that there is a strong association between the level of economic development, or the per capita income, and the ability to work remotely.

The labor market is made up of very heterogeneous workers regarding general characteristics (observable or not); and, workers of different demographic types, or sub-populations of workers, are differentially sorted into jobs across sectors and occupations. That said, the inequalities in probability observed so far are probably reflected in other types of sociodemographic inequalities.

To explore this issue, **Erro! Fonte de referência não encontrada.** shows the share of workers that worked from home by gender, race, levels of schooling, household location

(urban/rural), status in employment, age, and economic sector. These shares are calculated within each attribute.

There is evidence that participation in remote work is higher for women (15.88%), white (14.26%) and non-young workers, workers living in urban areas (12.95%) and working in the service sector (16.8%). Analogously, participation in remote work is lower for men (7.56%), non-white (8.14%) and younger workers and for those working in agriculture (1.37%), industry (3.9%) and retail (4.53%) (Figure 3).

Figure 3 - Share of workers that worked from home by gender, race, levels of schooling, household location (urban/rural), status in employment, age and economic sector
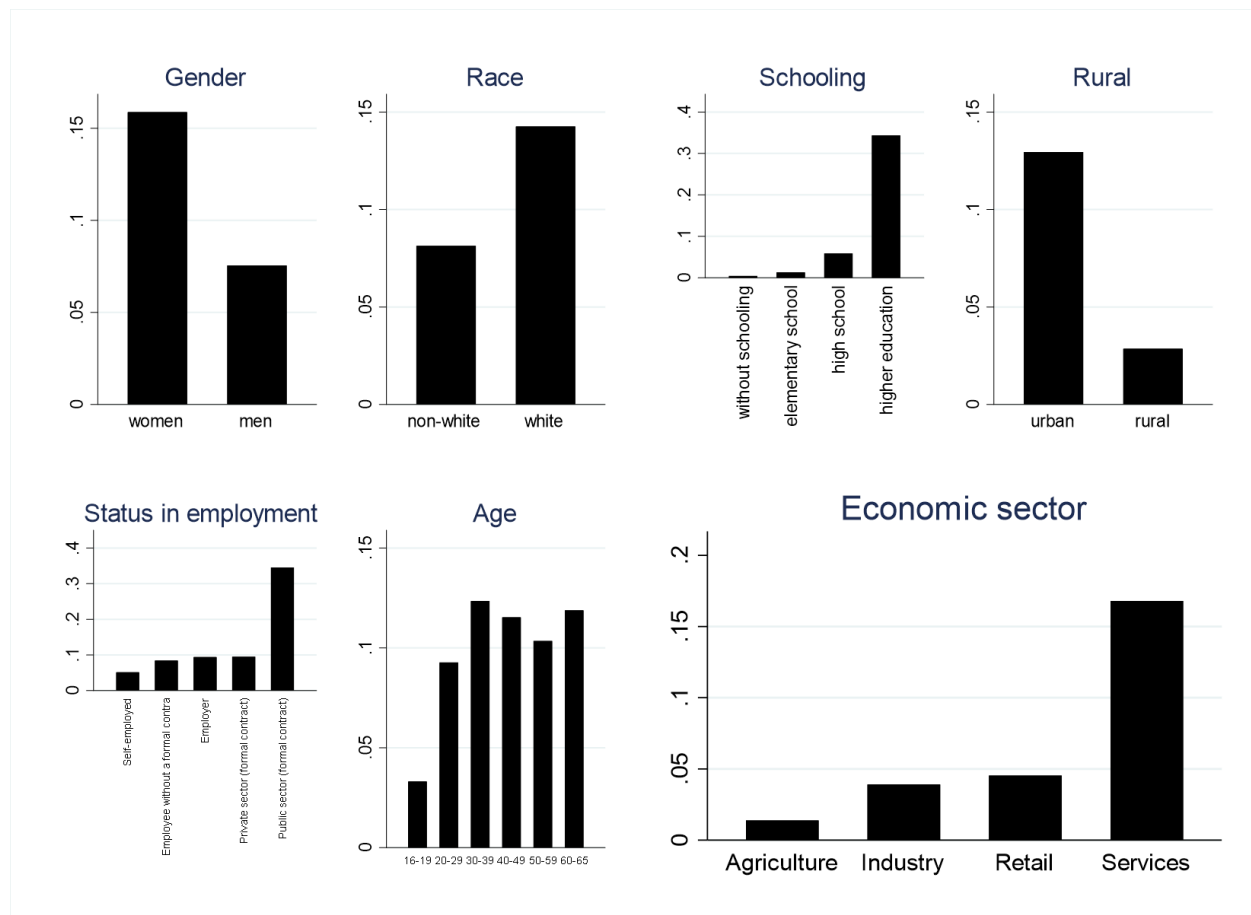
Source: authors, based on PNAD COVID-19

The results for gender are similar to those of Yasenov (2020), Gallacher and Hossain (2020) and Brussevich et al. (2020), and the results for race agree with Yasenov's (2020). Regarding age, expressive difference was found only for those aged 16 to 19 years. The result

that participation in remote work is lower for young workers is quite consensual in the literature (Brussevich et al., 2020; Gallacher; Hossain, 2020; Yasenov, 2020).

As for the economic sectors, the results of Crowley and Doran (2020) for Ireland are that those with less potential for remote work are: agriculture/forestry/fishing, construction, transportation and storage, and mining and quarrying. For industries in which these types of jobs predominate, the workers decision is between stopping production or taking on the health risk to continue in business, with no possibility of remote work (Bartik et al., 2020).

Although relevant, these latter differences in remote work participation are not as expressive as the ones regarding the different employment statuses – with 34.58% participation for public sector and 5.15% for the self-employed – and the schooling levels – with 0.45% participation for those without formal education and 34.38% for those with college education. In the case of schooling, the great leap in participation in remote work occurs with the achievement of higher education.

The result that more educated workers are more able to perform remote work is also consensual (Bartik et al., 2020; Gallacher; Hossain, 2020; Yasenov, 2020); and specifically for Brazil, Góes et al. (2021) found that more than 70% of the remote workforce had at least completed college education. Bartik et al. (2020) found that the level of participation of workers with higher education in an industry has almost the same predictive power of the possibility of remote work as the measure of Dingel and Neiman (2020), which has done a remarkably good job in predicting the industry level of remote work. According to these authors, this result shows the strength of the link between being an educated worker and being able to work remotely. Yasenov's (2020) results for the US and Gallacher and Hossain's (2020) results for Canada also indicate that the main difference occurs when completing a college education.

Regarding employment status, the difference that stands out is in the public sector. Therefore, inequalities in participation in remote work between salaried workers in the formal and informal sectors seems to actually reflect the difference between the public and private sectors (with the public sector over-represented in the "formal" sector). In the private sector, the difference in remote work participation between those with (9.52%) and without a formal contract (8.42%) was small.

It is important to highlight that job losses in Brazil were significantly higher for employees without a formal contract. According to Bridi (2020), the number of workers in the private sector decreased 8.9% among those with a formal contract and 21.6% among those without a formal contract, between the first and the second quarter of 2020. But, among informal workers who have not lost their jobs, participation in remote work was close to that of the formal private sector (Figure 3).

It is expected that the results presented so far for the different attributes of workers are strongly influenced by the sectoral and occupational composition of the workforce. Our last analysis focuses on assessing whether there are any independent effects of these attributes on the chances of remote work, after controlling for the types of work, position, or function.

This analysis is implemented by estimating Probit models of remote work, the results of which, expressed in marginal effects for conditional probabilities, are shown in

Table 3. In column (1) the model was estimated without controls for the federation units, for the months and for the 36 categories of labor activities; from column (2) to (4), fixed effects for these variables are added sequentially, with the model in the column (4) controlling all those fixed effects. Probit estimates are shown in Table A2.

The first result to be highlighted refers to the fact that almost all coefficients are significantly reduced by including the Types of work F. E., or the labor activities fixed effects – see column (4). This result shows that the composition effect in the labor force participation rate across labor activities accounts for a relevant part of the differences in the probabilities of remote work.

In this context, the most interesting aspect concerns the significant reduction in the public-sector effect when controlling the types of work. The descriptive analysis showed that the participation of remote work among public sector workers is significantly higher than that in all other employment statuses; in turn, evidences in Table 3 – comparing columns 3 and 4 – show that this results from a composition effect, or from the types of task prevalent in the public sector. Still on employment status, the self-employed workers' case stands out, with a lower probability of remote work compared to salaried employees without formal contract even if controlled for observable characteristics.

Table 3 – Probit results: marginal effects for conditional probabilities

	(1)	(2)	(3)	(4)
Hourly earnings	0.0545*	0.0525*	0.0523*	0.0420*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Elementary school	0.0107*	0.0107*	0.0106*	0.0096*
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
High school	0.0649*	0.0637*	0.0635*	0.0511*
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Higher education	0.2270*	0.2231*	0.2233*	0.1178*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Employer	-0.0216*	-0.0223*	-0.0218*	-0.0204*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Self-employed	-0.0529*	-0.0521*	-0.0521*	-0.0475*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Private sector (formal contract)	0.0064*	0.0032*	0.0033*	-0.0098*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public sector (formal contract)	0.0315*	0.0347*	0.0349*	0.0015*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age (20-29)	-0.0224*	-0.0211*	-0.0194*	-0.0022*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age (30-39)	-0.0392*	-0.0392*	-0.0360*	-0.0127*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age (40-49)	-0.0404*	-0.0414*	-0.0383*	-0.0179*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age (50-59)	-0.0388*	-0.0413*	-0.0380*	-0.0164*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age (60-65)	-0.0099*	-0.0144*	-0.0109*	0.0118*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Industry	0.0031*	-0.0004*	0.0002***	-0.0128*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Retail	0.0087*	0.0055*	0.0062*	-0.0116*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Services	0.0646*	0.0579*	0.0579*	0.0336*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Rural	-0.0372*	-0.0286*	-0.0283*	-0.0305*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Man	-0.0302*	-0.0303*	-0.0304*	-0.0219*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
White	0.0174*	0.0166*	0.0165*	0.0123*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Federal Units F. E.	No	Yes	Yes	Yes
Time F.E.	No	No	Yes	Yes
Types of work F. E.	No	No	No	Yes

Source: authors, based on PNAD COVID-19. Note: Standard errors in parenthesis. * $p<0.01$.

A reduced, but counterintuitive effect was estimated for private sector workers with a formal contract, who were 0.98 p.p. less likely to be in remote work compared to the benchmark, the private sector worker without a formal contract. This negative effect appears when the fixed effects for types of work are included, showing that the greater probability of remote work for formalized employees also arises from a composition effect. In fact, the literature dealing with the issue of informality in the labor market in the context of Covid-19 points out: first, that these jobs are more vulnerable and the losses were relatively greater in the informal market (Balde et al., 2020; Bridi, 2020); and second regarding the lower possibility of remote work, they point out that this is due to the type of tasks prevalent in informality, in which physical, manual and contact-intensive work are over-represented (Hatayama et al., 2020; Garrote Sanchez et al., 2021). After the Types of work F. E. were included, our result shows that the presence of a formal contract slightly reduces the likelihood of remote work.

The positive effect of hourly earnings on the probability of remote work was also maintained in column (4); therefore, for similar workers, the higher the income, the greater the chance of being able to work from home. And the effect that remained the highest in the column (4) model was that of college education. A worker with college education has an increase of 11.78 p.p. on the probability of doing remote work, compared to the worker with no education. This effect fell by almost half when controlling for labor activities, indicating that the greater participation in remote work for workers with higher education also reflect the occupation selection in the labor market. According to Gaudecker et al. (2020), the important role of education after controlling income may indicate that the possibility of working from home is driven mainly by the composition of tasks rather than the availability of home office resources.

As pointed out by Gottlieb et al. (2021), the result that more educated and salaried employees (other than self-employed or employers) are more likely to work from home, even when specific types of work are controlled, means that the propensity to remote work varies between occupations, but that there is also important heterogeneity within these occupations.

Regarding age, the models indicate that the probability of remote work is higher for the workers aged 16 to 19 years, except when comparing to those aged 60 to 65. Although the marginal effects related to age are of small magnitude, this result is noteworthy for, at

first glance, contrasting with those of Figure 3. Younger workers are somewhat more likely to work remotely than older workers when all other observable characteristics are the same (Table 3) – although young worker's participation in remote work was lower than for other age categories, when the other attributes are not controlled (Figure 3). As pointed out in Yasenov (2020) and Gallacher and Hossain (2020), the lower participation of young workers in remote work, compared to the total number of young workers, must be related to the fact that young people are concentrated in jobs that are less possible to be performed from home. Indeed, 41% of workers aged 16-19 were performing the following types of work, all with a very low remote work share: store salesman, farmer/gardener, office clerk, bricklayer and others and production assistant – see Figure 1. In addition, only 1.2% of young workers worked in the public sector. Therefore, the result in Figure 3 reflects the sorting of young workers in certain occupations, and not an age effect.

As for gender, the control of labor activities also led to some reduction in the coefficient; however, there is an independent effect, in which men are 2.19 p.p. less likely to do remote work compared to women. Brussevich et al. (2020) also find that men, on average, are less likely to be engaged in work activities that can be performed remotely compared to women, and that this result is mainly related to difference in selection into occupations and sectors between male and female workers. Even so, the existence of a negative independent effect for men may reflect the fact that, in Brazil, the gender division in domestic work – family assistance and child rearing – still mainly affects women. According to Duarte and Spinelli (2019), in 2017, women worked about 20.9 hours per week in domestic activities and in the sphere of care, and men, 10.8 hours; with the greater dedication to household chores by women occurring regardless of the level of education.

5 Concluding remarks

The objective of this study was to analyze who were the workers who worked from home in Brazil and how unequal the probabilities of remote work were, considering different sociodemographic and work characteristics. For this, we used descriptive graphical and Kernel density analyzes and Probit regressions based on PNAD COVID-19 microdata.

The results of the descriptive analysis showed that, in the months from May to August 2020, the subgroups of workers with the smallest participation (within their own subgroups)

in remote work were the poorest, males, rural residents, non-whites, youngest (16 to 19 years old), without college education, self-employed or salaried workers from the private sector and agriculture workers.

The relatively high participation in remote work for workers with complete college education and from the public sector stood out, with a very significant difference compared to other levels of education and to the other employment statuses. The direct, strong and monotonic relation between participation in remote work and labor income also stood out: the remote work share increases rapidly from the 60th percentile and even more rapidly from the 80th.

The results of the empirical model showed that an important part of the pattern found in the descriptive analysis reflects differences in selection into occupations and sectors, because almost all coefficients were significantly reduced when fixed effects for types of work, position, or function were included. There was a significant reduction in the public sector-effect, showing that the very high participation of remote work among public sector workers visualized in the descriptive analysis results from a composition effect, or from the types of task prevalent in the public sector.

Some variables maintained important independent effects after controlling for types of work fixed effects. We can highlight the positive effects on the probability of remote work of college education, salaried employment (other than self-employed or employers) and labor income – indicating that the propensity to remote work varies between occupations but also within these occupations. Furthermore, everything else kept constant, younger, female and white workers are somewhat more likely to work remotely.

Therefore, the pandemic, regarding the possibility of remote work, had the effect of widening the existing inequalities, in favor of wealthier, more educated, and more formalized workers in the labor market and imposing on the others the need to choose between employment and income versus risk of contagion. The results of the study provide insights that should be considered by policy makers, since the effects of the pandemic on the labor market will remain, at least to some extent, after the return of economic activity.

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About the article

Contributions

Nicole Rennó Castro: literature review, result analysis, text writting and final reviews;
Gustavo Carvalho Moreira: Data collection and analysis, construction of the empirical model and methodological description.

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APPENDIX

Table A1 – Descriptive statistics by categories of types of work, position, or function (continued)

	Gender (%)		Race (%)		Rural (%)		Schooling (%)				Status in employment (%)					Inc.	Age
	W	M	N-W	W	U	R	WS	ES	HS	HE	S-E	EM	PrS	PuS	ENC		
Domestic worker, daily cleaner, cook (in households)	92.9	7.1	68.0	32.0	79.3	20.7	43.0	23.5	31.8	1.8	0.0	0.0	29.1	0.0	70.9	1.8	43.3
Cleaning staff (in companies)	70.3	29.7	69.9	30.1	83.2	16.9	32.1	23.7	39.7	4.6	0.0	0.0	55.1	26.1	18.8	2.0	42.6
Office clerk	63.6	36.4	49.3	50.7	93.7	6.3	2.1	6.6	54.8	36.5	0.0	0.0	65.3	21.7	13.0	2.3	35.9
Secretary, receptionist	87.6	12.4	52.5	47.6	91.9	8.1	2.6	8.0	61.6	27.8	0.0	0.0	60.7	20.5	18.8	2.1	36.7
Telemarketer	74.9	25.2	61.3	38.7	95.5	4.5	1.1	5.6	76.5	16.9	0.0	0.0	92.6	1.2	6.2	2.0	29.8
Merchant (owner of the bar, shop etc.)	42.9	57.1	51.3	48.7	88.9	11.1	20.4	17.7	45.0	17.0	71.9	28.1	0.0	0.0	0.0	2.2	44.5
Store salesman	63.1	36.9	57.2	42.8	91.4	8.6	6.3	13.9	70.4	9.4	0.0	0.0	80.4	0.1	19.5	1.9	32.6
Home seller, sales representative, catalog seller	51.0	49.0	51.4	48.6	91.7	8.3	11.1	14.8	54.2	19.9	67.1	1.2	22.3	0.1	9.3	2.3	40.7
Hawker	42.4	57.6	69.1	30.9	88.8	11.2	33.4	21.7	39.9	5.0	89.4	1.7	2.4	0.1	6.5	1.8	42.0
Cook and waiter	67.4	32.6	62.8	37.2	86.4	13.6	23.7	24.6	46.5	5.2	19.6	1.8	48.7	6.8	23.2	2.0	39.7
Baker, butcher and confectioner	42.0	58.0	57.7	42.3	86.8	13.3	26.7	22.0	45.4	5.9	43.7	2.7	40.2	0.2	13.2	2.0	39.2
Farmer, animal breeder, fisherman, forester and gardener	20.0	80.0	52.0	48.0	22.5	77.5	55.9	19.0	22.2	2.8	78.9	2.3	9.0	0.2	9.7	1.7	44.0
Agriculture assistant	13.2	86.8	71.4	28.6	27.3	72.7	62.5	19.9	16.9	0.7	25.0	0.1	33.9	0.1	40.9	1.7	39.0
Driver	4.8	95.2	62.8	37.3	89.0	11.0	19.7	19.7	53.4	7.3	51.1	0.5	28.2	10.2	10.1	2.2	42.8
Trucker	1.6	98.4	51.4	48.7	84.3	15.7	29.7	27.5	40.4	2.4	28.6	1.0	58.1	2.5	9.8	2.3	42.9
Delivery biker (self-employed)	2.8	97.2	67.0	33.0	93.7	6.3	18.5	22.2	56.1	3.3	52.4	0.4	28.2	0.6	18.5	2.0	34.0
Delivery biker (restaurant, pharmacy, store and apps)	5.3	94.7	65.9	34.1	90.0	10.0	20.2	25.0	49.5	5.3	33.9	1.0	36.0	1.9	27.3	1.9	34.4
Mason, painter, electrician, joiner	1.8	98.2	66.5	33.5	84.7	15.4	41.7	25.3	30.8	2.3	65.5	1.6	18.9	1.5	12.6	2.0	41.6
Vehicle mechanic	2.8	97.2	58.3	41.7	88.9	11.1	24.4	25.7	45.6	4.3	40.7	5.8	38.8	1.2	13.6	2.2	39.2
Craftsman, dressmaker and shoemaker	79.4	20.6	52.1	47.9	87.3	12.7	24.3	22.9	44.4	8.4	67.5	1.7	22.3	0.1	8.4	1.8	43.5
Hairdresser, manicure and others	79.5	20.6	61.7	38.3	92.7	7.3	13.2	20.6	57.2	9.1	86.6	2.5	2.6	0.0	8.3	2.1	37.3

Note: W: Women; M: Men. N-W: Non-white; W: White; R: Rural; U: Urban; WS: without schooling; ES: elementary school; HS: high school; HE: higher education; S-E: self-employed; EM: employer; PrS: private sector (formal contract); PrS: public sector (formal contract); ENC: employee without a formal contract. Inc: Logarithm of hourly earnings from the main job; Age: mean age in years.

Table A1 – Descriptive statistics by categories of types of work, position, or function

	Gender (%)		Race (%)		Rural (%)		Schooling (%)				Status in employment (%)					Inc.	Age
	W	M	N-W	W	U	R	WS	ES	HS	HE	S-E	EM	PrS	PuS	ENC		
Machine operator, assembler in the industry	11.8	88.2	54.8	45.2	81.1	18.9	22.2	20.4	53.3	4.1	0.0	0.0	88.2	3.9	7.9	2.3	38.0
Production assistant, loading and unloading	24.1	75.9	58.6	41.4	82.5	17.5	24.0	23.6	48.9	3.5	5.7	0.3	80.8	0.7	12.5	2.0	34.8
Kindergarten, elementary, high school or higher education teacher	79.3	20.7	51.7	48.3	87.6	12.4	0.4	0.9	11.0	87.8	0.0	0.0	17.6	66.2	16.2	2.9	42.6
Pedagogue, teacher of languages, music, art and tutoring.	74.7	25.3	44.7	55.3	91.3	8.7	0.8	2.6	25.9	70.8	26.3	0.6	21.7	35.6	15.8	2.7	41.0
Doctor, nurse, health professionals with higher education	72.8	27.2	37.0	63.0	96.3	3.7	0.0	0.0	0.0	100.0	19.3	5.3	23.0	35.3	17.1	3.2	40.0
Health professional (with high school level)	78.6	21.4	60.8	39.3	86.7	13.3	0.0	0.0	80.2	19.8	3.1	0.3	32.6	49.9	14.2	2.3	41.0
Caregiver of children, sick or elderly	93.2	6.8	62.5	37.5	88.1	11.9	18.6	17.6	51.6	12.2	32.0	0.3	28.2	13.3	26.2	1.9	41.0
Protection services worker	9.3	90.7	67.2	32.8	88.2	11.8	15.1	15.9	56.3	12.8	3.3	0.1	55.9	28.6	12.1	2.3	42.0
Civil police	25.4	74.6	50.6	49.4	96.9	3.1	1.3	4.3	25.6	68.9	0.0	0.0	0.0	97.7	2.3	3.4	43.7
Concierge, janitor	23.9	76.1	66.3	33.7	88.0	12.0	27.9	22.9	45.1	4.2	0.0	0.0	75.8	14.7	9.5	2.1	44.5
Artist, religious (priest, pastor, etc.)	23.5	76.5	54.1	45.9	93.5	6.5	7.8	9.8	46.5	35.9	61.0	1.3	7.8	1.4	28.6	2.7	42.9
Political or commissioned position (Director, manager)	38.2	61.8	35.7	64.3	92.6	7.4	4.5	6.7	35.6	53.2	9.3	24.7	38.8	14.5	12.7	3.0	43.3
Other professions with higher education (lawyer, engineer, etc)	47.1	52.9	32.9	67.2	97.2	2.8	0.0	0.0	0.0	100.0	25.6	5.3	37.5	22.4	9.3	3.2	39.8
Other technician or professional with high school	33.3	66.8	50.1	49.9	94.3	5.7	0.0	0.0	70.3	29.8	15.8	1.1	48.0	26.2	8.9	2.6	39.0
Others	36.4	63.6	54.0	46.0	87.2	12.8	16.0	14.6	45.8	23.7	27.0	2.8	41.5	14.1	14.6	2.3	39.0

Note: W: Women; M: Men. N-W: Non-white; W: White; R: Rural; U: Urban; WS: without schooling; ES: elementary school; HS: high school; HE: higher education; S-E: self-employed; EM: employer; PrS: private sector (formal contract); PuS: public sector (formal contract); ENC: employee without a formal contract. Inc: Logarithm of hourly earnings from the main job; Age: mean age in years.

Table A2 – Probit estimates results

	(1)	(2)	(3)	(4)
Hourly earnings	0.3651*	0.3569*	0.3566*	0.3180*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Elementary school	0.2418*	0.2346*	0.2326*	0.1144*
	(0.0010)	(0.0010)	(0.0010)	(0.0011)
High school	0.8397*	0.8204*	0.8194*	0.4993*
	(0.0008)	(0.0008)	(0.0008)	(0.0009)
Higher education	1.6240*	1.6073*	1.6103*	0.9346*
	(0.0008)	(0.0008)	(0.0008)	(0.0009)
Employer	-0.1520*	-0.1582*	-0.1554*	-0.1522*
	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Self-employed	-0.4171*	-0.4118*	-0.4136*	-0.3829*
	(0.0007)	(0.0007)	(0.0007)	(0.0008)
Private sector (formal contract)	0.0418*	0.0214*	0.0218*	-0.0712*
	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Public sector (formal contract)	0.1934*	0.2138*	0.2153*	0.0104*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Age (20-29)	-0.1356*	-0.1288*	-0.1197*	-0.0161*
	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Age (30-39)	-0.2463*	-0.2494*	-0.2309*	-0.0941*
	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Age (40-49)	-0.2546*	-0.2651*	-0.2467*	-0.1348*
	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Age (50-59)	-0.2435*	-0.2641*	-0.2447*	-0.1234*
	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Age (60-65)	-0.0582*	-0.0866*	-0.0660*	0.0829*
	(0.0012)	(0.0013)	(0.0013)	(0.0014)
Industry	0.0273*	-0.0034*	0.0016***	-0.1088*
	(0.0008)	(0.0009)	(0.0009)	(0.0010)
Retail	0.0749*	0.0462*	0.0528*	-0.0984*
	(0.0008)	(0.0009)	(0.0009)	(0.0010)
Services	0.4627*	0.4144*	0.4167*	0.2513*
	(0.0008)	(0.0008)	(0.0008)	(0.0009)
Rural	-0.2491*	-0.1941*	-0.1927*	-0.2309*
	(0.0007)	(0.0007)	(0.0007)	(0.0008)
Man	-0.2004*	-0.2041*	-0.2050*	-0.1644*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
White	0.1162*	0.1126*	0.1123*	0.0933*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Constant	-3.2155*	-3.2882*	-3.2235*	-2.4347*
	(0.0016)	(0.0022)	(0.0022)	(0.0025)
Federal Units F. E.	No	Yes	Yes	Yes
Time F.E.	No	No	Yes	Yes
Types of work F. E.	No	No	No	Yes

Note: Standard errors in parenthesis. * $p<0.01$.

This preprint was submitted under the following conditions: