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Reducing Poverty and Inequality during the Coronavirus Outbreak:

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Abstract

While developing countries have been dramatically affected by the COVID-19 pandemic, most of them have set out social policies to counter its major negative impacts. Brazil implemented one of largest emergency cash transfer programs in Latin America, the Emergency Aid Transfer (EAT). In this paper we use new household panel data to compare the evolution of poverty and inequality indicators before and during the Pandemic with and without the EAT, perform inequality decompositions and characterize the dynamics of the Brazilian labor market, examining the demographic groups most affected by social distancing. We find that poverty rate declined from 12% in 2019 to 8% during the pandemic and extreme poverty dropped from 3% to about 1%. The poverty difference between blacks and whites also dropped significantly. The Gini index was reduced from 0.53 to 0.47, remaining below 0.50 for the first time in Brazilian history. Descriptive analysis suggests that poverty and inequality would have been much higher during the pandemic without the EAT. An inequality decomposition also indicates a major role for the EAT in explaining the decline in inequality between 2019 and 2020. As for the labor market, regression analysis comparing transitions between 2018 and 2019 with those between 2019 and 2020 indicate that women, the younger and older workers were particularly affected by the pandemic, displaying higher transition rates from work to inactivity. The sectors with the highest increase in the probability of job loss were accommodation and food services. The end of the EAT in December 2020 coupled with the Covid-19 second wave should throw millions of Brazilians back in poverty.

Keywords: Cash transfers; COVID-19; poverty; inequality; labor market.

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1. Introduction

The COVID-19 pandemic has generated unprecedented crisis, with potentially greater macroeconomic impacts than the international financial crises of 2008-2009 (Addison, Sen and Tarp, 2020; Loayza, 2020). Lower and Middle-income countries (LMIC) were particularly affected. Initially, LMICs have suffered an external demand shock, especially among commodity-exporting countries, as the disease spread across China and developed countries (Loayza, 2020; ECLAC, 2020a). With the arrival of the first cases of COVID-19, LMICs governments adopted non-pharmacological measures that cause a supply shock and a direct reduction in economic activity (Shadmi et al., 2020; Benítez et al., 2020; Addison, Sen and Tarp, 2020).

LMICs might suffer disproportionately more with the pandemic, as they have specific challenges, such as an overcrowded health system (Danquah, Schotte and Sen, 2020), a relevant portion of the population living in informal settlements and slums, with restrictions on sanitation, space and access to the health system (Corbun et al., 2020; Tampe, 2020), and the prevalence of comorbidities (Corbun et al., 2020; Pablos-Méndez et al., 2020). Moreover, LMICs usually have a large informal sector, whose workers do not have unemployment insurance, health insurance or paid leave, work in occupations that are not compatible with isolation measures, and most of them are self-employed with daily incomes and who directly face the trade-off between preserving health and maintaining livelihoods (Loayza, 2020; Gerard, Imbert and Orkin, 2020; Nogueira, Amaral and Jones, 2020). In addition, the high levels of social inequality in these countries tend to be aggravated by the pandemic (Benítez et al., 2020; Blundell et al., 2020). In Latin America, the first cases of COVID-19 occurred between the end of

February and March 2020, a time of economic fragility, as the region has been experiencing low levels of GDP growth and growing fiscal deficits (ECLAC, 2020a).

Brazil has one of the largest public health systems in the world (Paim et al., 2011; Castro et al., 2019) and a well-structured primary care strategy (Rocha and Soares, 2010). However, in October 2020 Brazil was the third country with the largest number of confirmed cases of COVID-19 and the second with the largest number of confirmed deaths in the world (Dong, Du and Gardner, 2020), despite being the sixth most populous.

Despite the importance of a national leadership and coordination with local governments in the responses to the pandemic (Pablos-Méndez, 2020), in Brazil there were controversies and conflicts between the president, the minister of health and local governments about the strategies to cope with the sanitary crisis (Benítez et al., 2020; Shadmi et al., 2020; Fonseca et al., 2020; Dyer, 2020). The Brazilian president decided not to follow the World Health Organization (WHO) protocols and took a denialist approach (Fonseca et al., 2020; Shadmi et al., 2020; Dyer, 2020). Brazil was the only country in the region that did not implement a systematic suppression policy or strategies of detection and tracing at the national level (González-Bustamente, 2020). State and municipal governments, however, have enacted measures to suppress the pandemic (Fonseca et al., 2020; Petherick et al., 2020).

In contrast with the absence of coordination around measures to mitigate the pandemic spread, Brazil has implemented one of largest emergency cash transfer programs in Latin America, with transfers reaching 38.2 million households (ECLAC, 2020b). Cash transfers can effectively mitigate inequalities in consumption due to the pandemic and allow people to adhere to lockdowns (Braun and Ikeda, 2020).

To mitigate the effects of the crisis on this population, the Emergency Aid Transfer (EAT) was instituted in April 2020. The monthly benefit amount was about US$ 120 (R$ 600) and could cover up to two people from the same family. In families where a woman is the household head, the amount paid was double the regular value (US$ 240 or R$ 1200). Initially, the proposal was for it to last for three months, but it was followed by an extension of another 2 months in June 30 and allocated more than US$ 20.2 billion (R$101 billion) to the program. A new extension of the EAT was implemented between October and December, but with new restrictions on access criteria and a benefit value reduced by half.

In this paper we examine the behavior of poverty, inequality and labor market indicators in Brazil during the pandemic using household panel data covering the period before and during the pandemic including and excluding income from the EAT. We also characterize the dynamics of the labor market in Brazil during the pandemic by following a panel of individuals over time to examine which groups were most affected by the pandemic in terms of transitions to inactivity and job loss.

We find that poverty rate declined from 12% in 2019 to between 7% and 9% during the first months of the pandemic and extreme poverty dropped from 3% to about 1%. The Gini index was reduced from 0.53 to 0.47, remaining below 0.50 for the first time in the Brazilian history. Descriptive analysis suggests the poverty and inequality would be much higher during the pandemic without the EAT. Our descriptive analysis shows that without EAT, if agents did not change their behavior, the poverty rate would have been between 18% and 19% in 2020, while extreme poverty would have been between 1% to 2%. The Gini coefficient without the EAT would be around 0.53. We additionally performed a decomposition of the reduction in the Gini index observed between 2019 and 2020 and

estimate that EAT was responsible for about 86% of the reduction, mostly due to the relatively high value of EAT in relation to the average per capita household income.

As for the labor market outlook, our results indicate that there was a reduction of 6 percentage points in the labor force participation between 2019 and the pandemic, from 62% in 2019 to 56% in May 2020. This reduction occurred more strongly among the blacks. The outflow of workers to inactivity originating from work and from unemployment status was so intense that, although the proportion of employed persons decreased significantly between 2019 and May 2020 (from 55% to 51%), the unemployment rate also decreased (from 12% to 9%), in contrast with the increase in unemployment rate observed in other developing countries.[4] Moreover, the share of workers working from home increased significantly between 2019 and 2020.

Our econometric results show that, controlling for other characteristics, women, younger and older workers were particularly affected by the recession brought about by social distancing, as they experienced a higher probability of losing their jobs or transitioning to inactivity between 2019 and 2020, as compared to the 2018-2019 period, than prime-age males. Moreover, the effects on young people entering the labor market in this period of recession may have long-term consequences on their lifetime career earnings (von Wachter, 2020). Self-employed workers also experienced an increasing probability of leaving work.

The main contribution of this paper is to the growing literature on the effects of the COVID-19 pandemic and of the social protection measures on poverty and labor market outcomes. Many studies on this topic were published recently, but most investigate the macroeconomic impacts of the pandemic, showing that reducing per capita income could

[4] For example, in India, the unemployment rate rose from 8.4% in March to 27% in April (Dev, 2020).

generate the first increase in global poverty since 1990 (Sumner et al., 2020; Mahler et al., 2020). Other studies use a bottom-up approach, estimating the effects of the pandemic and the social protection measures from microsimulations with household survey data (Martin et al., 2020; Lustig et al., 2020). We contribute to these studies by using panel data following the same individuals and households over time between 2019 and 2020, when people were already receiving the ECT.

Studies on the effects of the pandemic in developing countries have raised concerns that already disadvantaged groups have been more severely affected and show that new inequalities interact with existing inequalities (Blundell et al., 2020; Danquah, Schotte and Sen, 2020). We contribute to this literature by using individual panel data to show that women, younger and older workers were more affected by the pandemic.

In addition to this introduction, this paper is divided into four sections. Section 2 details the Emergency Aid. In section 3, we describe the data and methodology used in all empirical exercises. In section 4, we present the results for poverty and inequality, and the results for the labor market. We also present the econometric results for the assessment of the groups most affected in the pandemic period. Finally, we present some conclusions in section 5.

2. Emergency Aid Transfers in Brazil

Due to the COVID-19 outbreak and the non-pharmacological measures adopted by the Brazilian governmental sub-national units, many of the informal workers and the country's vulnerable population were left without income or with reduced income levels, having lost their jobs in the commerce and services. In order to mitigate the effects of the crisis on this population, the Emergency Aid Transfer ("Auxílio Emergencial") was instituted by Law in April 2nd and the Provisional Act was approved on May 25, opening

a credit of more than US$ 6 billion (R$29 billion) to the Ministries of Health and Citizenship to provide the resources to implement it. The EAT was intended exclusively for low-income informal workers and those unemployed who met certain criteria, as discussed below. The monthly benefit amount was about US$ 120 (R$ 600) and could cover up to two people from the same family. In families where a woman is the household head, the amount paid was double the regular value (US$ 240 or R$ 1200). Initially, the proposal was for it to last for three months, but it was followed by an extension of another 2 months in June 30 after the approval of Provisional Act that opened a new credit and allocated more than US$ 20.2 billion (R$101 billion) to the Ministries of Health and Citizenship to pay the aid.

ECT recipients can be divided into two groups. The first is composed of individuals registered in the Unified Registry for the government social programs (*Cadastro Único*) by March 20, 2020.[5] The government automatically replaced the Bolsa-Família benefit (PBF) for the EAT for those participants to whom the latter is more advantageous, for as long as the EAT lasts. For those who are not PBF recipients, in order to receive the Emergency Aid, they have to meet the requirements: 1) being of legal age (18 years) or a mother with less than 18 years of age; 2) not having a formal job; 3) not being a beneficiary of any other federal income transfer program other than the PBF; 4) per capita family income up to half a minimum wage (R$ 522.50 or approximately US$ 104.40) or total monthly family income up to R$ 3.135.00 (about US$ 627.00); 5) not having

[5] The Unified Registry is a government dataset on Brazilian families that are in a situation of poverty or extreme poverty. The government uses its data to determine the beneficiaries of the Bolsa Família Program (PBF), which is the federal government's largest direct income transfer program, for all families with a per capita income of up to R$ 89, or for families with a per capita income of up to R$ 178 and with children and young people up to 17 years of age. In addition to the criteria of income and presence of children, to receive the benefits of the PBF, participants must meet certain health and education conditionalities. In August 2020, the PBF covered 14.3 million families.

received annual taxable income above R$ 28,559.70 (about US$ 5711.80) in 2018; 6) to be unemployed or to be a worker under the MEI (registered individual entrepreneur) regime, or to be an individual or optional contributor to the Federal government pension system (the General Social Security System – RGPS), or to be an informal worker registered in Unified Registry.

The second is the group that meets the eligibility requirements but were not registered in the Unified Registry. They should enter the EAT program by registering on the website or mobile phone app of a major state bank that distributes the EAT (CEF). This group must also meet the criteria listed above to receive the transfers and, if approved, the aid is available through a personal account at CEF. By April, approximately 66 million people were included, and almost R$46 billion (nearly US$ 9.2 billion) were transferred (Brazil, 2020).

A Provisional Act of September 2nd introduced a new change in the ATE, extending its payment until the end of the year with a value reduced by half (R$ 300 or US$ 60), after receiving the installments established by the previous rules. In addition, that Provisional Act also introduced additional restrictions on receiving the transfer, excluding among others those who obtained formal employment after receiving the ATE, have received retirement, pension, unemployment insurance or other federal transfer (except the PBF) after receiving the ATE, are resident abroad, or do not meet criteria for income and possession of assets in 2019.

3. Data

To conduct the empirical analysis, we merge data from two types of household surveys, both collected and made available by the Brazilian Census Bureau (IBGE). The first is a rotating panel that collects socioeconomic and labor market information from a

representative sample of the Brazilian households since 2012 (“PNAD-Contínua”). Data are available at the individual and household levels on a quarterly basis plus an annual supplement. The quarterly data are composed of labor market indicators and the annual supplement additionally surveys income from all sources, as government pensions and cash transfer programs, household labor, and the use of information and communication technology. The sample is designed as a rotating panel, so that each household is followed through five quarterly interviews and a new sample of households in introduced in the sample every quarter. The annual survey is applied only to households who were in their first and fifth interviews during the year. We use data collected in the first quarters of 2018 and 2019.

The second dataset comes from the National Covid-19 Domestic Sampling Survey (PNAD COVID), which represents an effort made by IBGE to document and monitor the incidence of symptoms from the disease caused by the new coronavirus and its impacts on the labor market. The survey started on May 2020 and data is collected weekly through telephone calls to 48 thousand households every week, covering the entire national territory. The sample of households is fixed, based on the sample interviewed by the “Pnad Continua” in the first quarter of 2019, which means that the households interviewed in first month will be interviewed again monthly until the survey ends.

To identify the information from the EAT transfers, we use the PNAD COVID question about income receipt from emergency aid. Since the question also includes earnings of other emergency aid related to the COVID-19 pandemic (implemented by some States and municipalities or the federal program), we identify as beneficiaries of EAT only individuals who receive multiples of the basic benefit amount, R$ 600, up to a maximum of R$ 2,400.

The PNAD COVID sample was based on the "PNAD Continua" sample of households in the first quarter of 2019, so that it is possible to observe the same households in both surveys. We work out the matching procedures in two stages. In the first stage, we matched data from the first quarter of the 2019 Continuous PNAD with data from the May and June PNAD COVID at the household level, to identify the households that remain in the sample for the whole period. In the second stage we identify the same individuals over time by assuming that individuals who were in the same household in the two surveys, had the same gender and birth date were the same person.[6]

Our final sample is a panel of people interviewed in the first quarters of 2018, 2019 and in May 2020, and who may have responded to PNAD COVID interviews from June to November. According to "PNAD Contínua" rotating panel, these people were necessarily in households that answered their first interview in 2018 and the fifth interview in 2019. In the first quarter of 2018, a total of 37,815 households were interviewed for the first time, of which 91.5% were also interviewed for the fifth time in the first quarter of 2019 and 54% were interviewed again in May 2020. Of the total of 37,029 households interviewed for the fifth time in the first quarter of 2019, 93.5% had been interviewed in the first quarter of 2018 and 55% had also been interviewed in May 2020. In relation to the data for May 2020, a total of 118,758 households were interviewed. Of these, almost all had been interviewed in any of the 5 interviews during the first quarter of 2019, 19.6%

[6] If there was more than one person in a household, in the same period with the same sex and date of birth, we considered them to be twins and excluded them from the sample. Additionally, as the information is self-declared, it is possible that there will be a refusal to answer about the date of birth. For this reason, for those in 2020 with unreported birth date the criteria used for pairing with those in 2019 were to be in the same household, to have the same position in the household (reference person or their spouse), same sex, age in years one or two years higher than that presented in 2019, and the level of education, equal to or higher than that presented in the sample of 2019.

had been interviewed for the fifth time in that period, and 17% had also been interviewed in the first quarter of 2018.

Table 1 compares descriptive statistics of socioeconomic characteristics of paired samples of the "PNAD Contínua" in the first quarter of 2019 of those who were in the first interview. The first column presents the mean values for the overall sample, the second column shows the values for the sample of people who were also in the first quarter of 2018, and the last column shows the statistics for the final sample, composed of those were interviewed in the first quarters of 2018 and 2019, and in May 2020.

Table 1 – Characteristics of Paired Observations – 1st Quarter of 2019

	Total	Paired with 1Q2018	Paired with 1Q2018 and May 2020
Primary School comp.	0.054	0.052	0.042
Middle School inc.	0.298	0.304	0.286
Middle School comp.	0.090	0.088	0.087
Highschool inc.	0.078	0.071	0.067
Highschool comp.	0.280	0.278	0.286
College inc.	0.055	0.055	0.058
College comp.	0.145	0.152	0.175
Women	0.528	0.531	0.538
Black and Indigenous Ppl.	0.562	0.546	0.517
14 to 19 years	0.112	0.105	0.099
20 to 29 years of age	0.177	0.156	0.143
30 to 39 years of age	0.192	0.186	0.187
40 to 49 years of age	0.173	0.176	0.182
50 to 59 years of age	0.149	0.161	0.168
60 to 69 years of age	0.111	0.120	0.126
70 or more years of age	0.088	0.096	0.094
Tr. to poverty	0.034	0.037	0.057
Tr. to Inactivity	0.122	0.136	0.211
Job loss	0.131	0.143	0.220

Source: PNAD Contínua, PNAD COVID19.

As we can see, the final sample has slightly higher school achievement and age, a smaller proportion of black or indigenous people, and greater proportions of people who

transition to poverty, to inactivity or who lose their jobs, but the differences were not noticeably large, so that the final sample still seems representative of the Brazilian population.

Table 2 shows mean of income by source of income in the first quarters of 2018 and 2019 and in May 2020. The main component of household income in all periods is labor income, followed by government pensions and income from other sources, but income from all sources declined between 2019 and 2020. In 2020 household started receiving the Emergency Aid Transfer and other Emergency transfers from States and municipalities, however. And Table 2 shows that the EAT is very significative, with an average per capita value of R$105, almost seven times the value of other social programs, such as the Bolsa Familia program, in 2020. This means that total income declined by 15%, which is less than the drop in each of its sources. Inequality was also reduced by 10.4% between 2019 and 2020, suggesting a possible redistributive effect of the EAT, as detailed below.

Table 2 – Average Household per Capita Income by Income Source

	2018	**2019**	**2020**	**Δ2019-2018**	**Δ2020-2019**
Job	1287	1235	985	-4%	-20%
Pension	367	372	305	1%	-18%
Other	95	85	53	-10%	-38%
Social Programs	20	21	15	3%	-29%
Emergency Aid	0	0	106	-	-
Other Em. Aids	0	0	4	-	-
Total	1769	1713	1466	-3%	-14%
Gini	0.540	0.534	0.478	-1.0%	-10.5%

Source: PNAD Contínua; PNAD COVID; IPCA. Note – values at constant prices of July 2020.

4. Results

4.1. Poverty and Inequality

We now examine the behavior of poverty and inequality during the pandemic. To compute poverty rates, we use the poverty lines proposed by Rocha (2006), which proposes extreme poverty lines based on the minimum nutritional consumption and poverty lines based on the minimum consumption related to all basic needs. Due to big differences in consumption and prices across Brazilian regions, Rocha (2006) constructs 25 regional poverty lines for urban and rural areas in Brazilian States from regional consumption information obtained from the Family Budget Survey (POF) of IBGE. These lines reflect the cheapest food consumption basket in each region that includes the necessary caloric amount for a person's vital functions according to FAO recommendations, plus a consumption basket for seven categories of non-food products (Rocha, 2006). We updated the values of the lines using the Extended National Consumer Price Index (IPCA) (IBGE, 2020b) from the lines calculated by Rocha, Franco and IETS (n.d.).

In Figure 1, we show the poverty rate before and during the pandemic and present an additional poverty rate withdrawing the income from the EAT for the households that received it. In the first quarter of 2019, the poverty rate was around 12%. From May to September 2020, it reduced from 9% to 7%. In contrast, without the EAT, the poverty rate would have been around 18% from May to September 2020, if agents did not change their behavior. In September to November, the value of the EAT transfers was halved, and therefore the observed poverty rate starts to increase, reaching 11% by November. Noticeably, the poverty rate calculated without the EAT starts to decrease from September onwards, which suggests that, as the value of that transfers is reduced, households start looking for other sources of income.

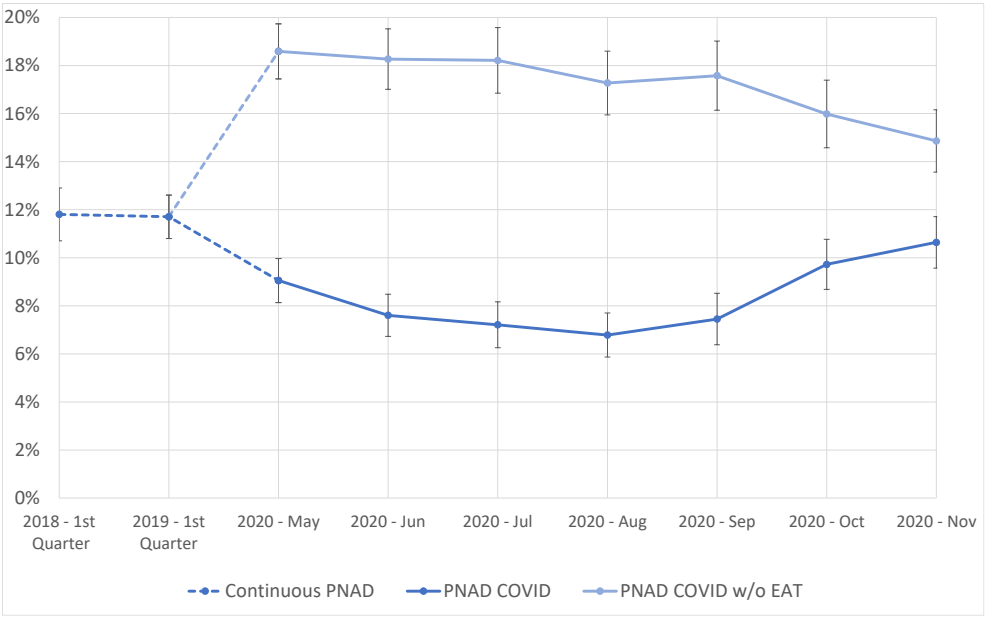


Figure 1 – Poverty Rates With and Without the ECT

Note – poverty rates estimated using the observed usual household per capita income, the household per capita income without the Emergency Aid, and Rocha, Franco and IETS (n.d.) poverty lines. All values are at July 2019 prices.

In Figure 2, we show the evolution of the observed extreme poverty rate and that without the income from the EAT. We observe that the pattern of evolution is similar to that of Figure 1. In 2018 and in 2019, there was about 3.5% of the population in extreme poverty. From May to September 2020, this percentage decreased fluctuating between 1% and 2%. Without the EAT, extreme poverty would have increase to between 7% and 8%, if the agents did not change their behavior. We also observe that from September onwards the extreme poverty rate starts increasing with the decrease in the EAT value, reaching 2% in November.

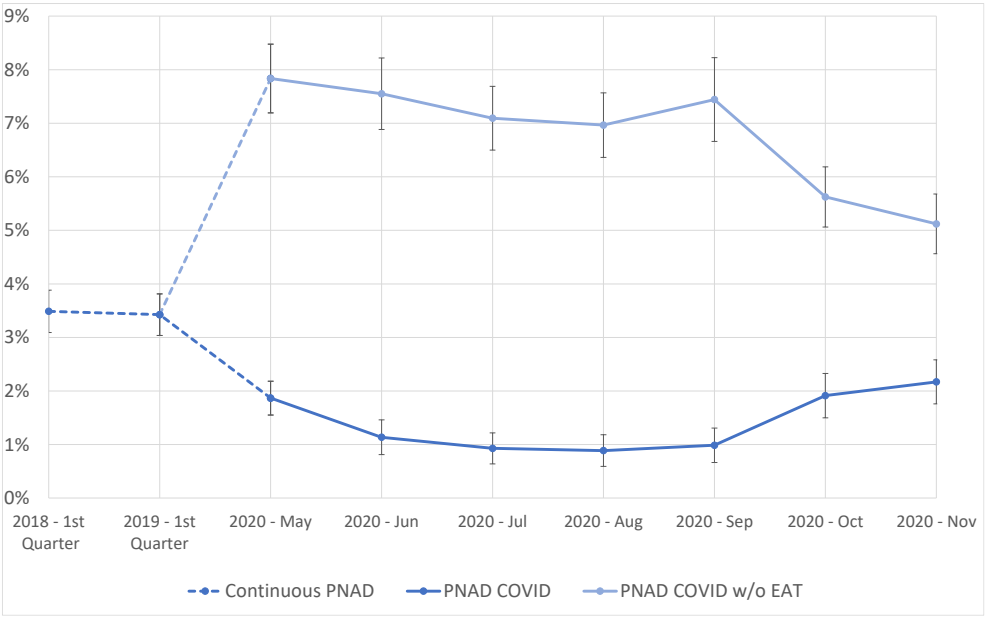


Figure 2 – Extreme Poverty Rates With and Without the ECT

Note – poverty rates estimated using the observed usual household per capita income, the household per capita income without the Emergency Aid, and Rocha, Franco and IETS (n.d.) extreme poverty lines. All values are at July 2019 prices.

In the Figures 3 and 4, we describe the evolution of poverty rates for different demographic groups. Figure 3 shows the evolution of the poverty rate by race. We see that the difference between the poverty rates calculated without the EAT and the actual rates are greater among blacks and indigenous, reaching 14 pp., while for whites and Asians the difference is about 6 pp. Importantly, the observed difference in poverty between the two groups, that was about 8 pp. before the pandemic, dropped to between 2.5 pp. and 5 pp. during the pandemic, becoming statistically insignificant. Figure 4 describes poverty rates by education levels, showing that the EAT seem to make more difference among the less educated. The differences in poverty rates between the two education groups, which was 9 pp. in 2019, dropped to around 3 pp. in 2020.

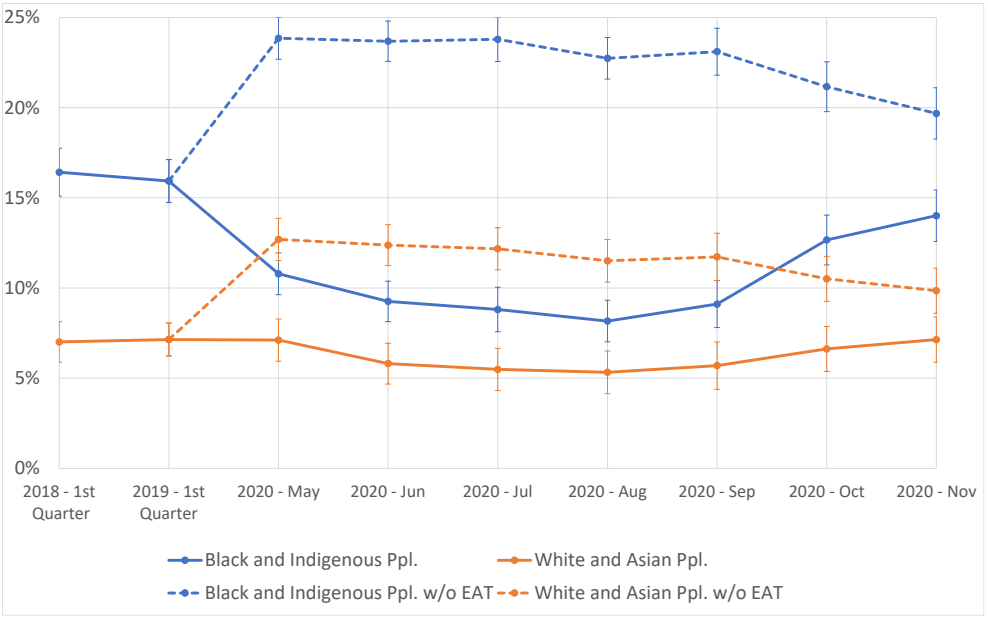


Figure 3 – Poverty Rate by Race

Note – poverty rates estimated using the observed usual household per capita income, the household per capita income without the Emergency Aid, and Rocha, Franco and IETS (n.d.) poverty lines. All values are at July 2019 prices.

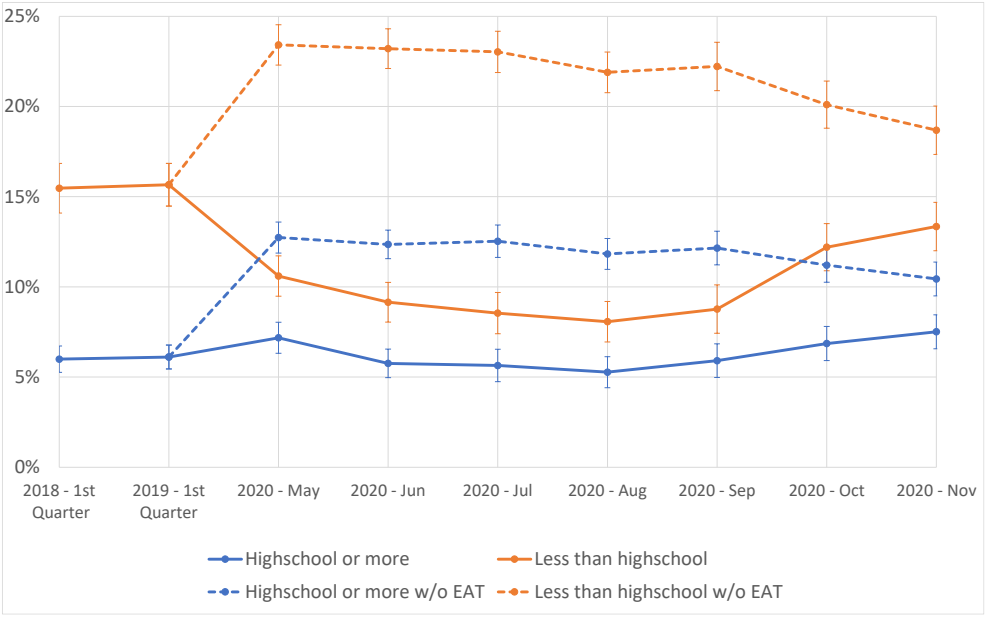


Figure 4 – Poverty Rate by Education

Note – poverty rates estimated using the observed usual household per capita income, the household per capita income without the Emergency Aid, and Rocha, Franco and IETS (n.d.) poverty lines. All values are at July 2019 prices.

Income inequality has also decreased during the Pandemic. Figure 5 shows that the Gini coefficient of household income per capita decreased from around 0.54 in 2018 and in

2019 to 0.48 in the first week of May 2020, a 10% reduction. In contrast, when we calculate the Gini index without the EAT, we observe that it remains relatively stable over time, fluctuating around 0.53 from May to September. From October onwards, when EAT transfers were reduced, inequality starts rising. Interestingly, the Gini index calculated without the EAT started decreasing in October, as households with lower levels of income start looking for other income sources.

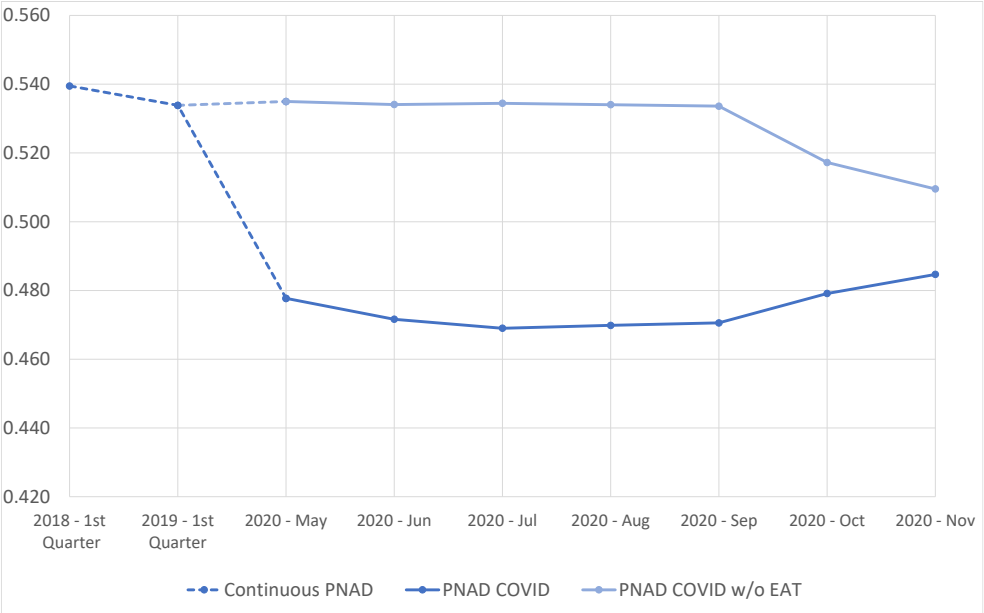


Figure 5 – Gini Index of Household per Capita Income

Note – Gini index estimated using the observed usual household per capita income, the household per capita income without the Emergency Aid.

4.2. Gini Index Decomposition

To deepen the discussion of the role of the EAT, we perform a decomposition of the Gini Index to describe the relative contribution of each source of household earnings to changes in inequality, as proposed by Hoffmann (2009). We write the Gini index of period t (G_t) as an average of the concentration ratio of each source, weighted by the percentage of each source in total income:

$$G_t = \sum_{i=1}^{k} \varphi_{it} C_{it} \quad (1)$$

Where φ_{it} the share of source i in the total household income in period t, C_{it} represent the concentration ratio of the income source i in time t.[7] We write the variation of the Gini index over time in the components of the total income for a given time interval:

$$(\Delta C)_{it} = (\overline{C_{it}} - \overline{G_t})\Delta\varphi_{it} + \overline{\varphi}_{it}\Delta C_{it} \quad (2)$$

Where $(\Delta C)_{it}$ represents the variation of the Gini index for component i for the interval t, $\overline{C_{it}}$ represents the simple average between C_{it} and $C_{i,t-1}$, $\overline{G_t}$ represents the average between the Gini index in t and in $t-1$, and $\Delta\varphi_{it}$ represents the variation of the share of component i of the total income between $t-1$ and t. The term $(\overline{C_{it}} - \overline{G_t})\Delta\varphi_{it}$ represents the composition effect of source i, which can be interpreted as the change in the Gini index due to changes in the share of source i. Its sign depends on the difference between the average concentration ratio and the average Gini index. If source i is more concentrated than Gini index, as increase in its share will have a contribution to increase the Gini index. The term $\overline{\varphi}_{it}\,\Delta C_{it}$ in equation 2 is the income effect, which represents how much of the variation of the Gini index is due to changes in the concentration of the income source i. The term $\overline{\varphi}_{it}$, denotes the average contribution of component i between t and $t-1$ and the term ΔC_{it} represents the variation of concentration ratio of i, between $t-1$ and t. A negative sign in this term means that there was a reduction in concentration of income source i, which contributes to the reduction of inequality.

It is possible to calculate the total composition effect and the total income effect by adding the correspondent terms all income parcels. The composition effect represents how much

[7] C_{it} is not the Gini index directly calculated considering only the income source i, but by sorting the data on the basis of the total household income and counting the income source i.

of the variation of inequality is explained by the variation in the composition of total income by source of income. The income effect represents the change in inequality explained by the changes in the concentration of each income source.

We perform the analysis of the Gini index decomposition for the period between the first quarter of 2019 and May 2020. We decompose income into six sources, namely: 1) labor income, which contains earnings of all the jobs of individuals; 2) retirement income and government pensions, which contains income from retirement and pensions from the government social security; 3) government programs, which represents the income from government cash transfer programs, such as the "*Bolsa Família*" Program; 4) EAT, which contains the proceeds from the government's income transfer program for the pandemic; 5) other emergency programs related to the COVID-19 pandemic; 6) other sources of income, which comprises income from scholarships, pensions, and pensions paid by insurance entities, income from savings accounts, patents and copyrights, unemployment insurance, leases and rents, donations from non-residents, alimony or cash allowance received from non-residents.

In Table 3, we show the results of the decomposition of the variation of the Gini index between 2019 and 2020 described in equation (2). The Table shows that that the main factor behind the reduction of income inequality was the EAT (86%), mainly through its composition effect (76%), but also through an income effect, as the value of the transfer is large. As the EAT is mostly received by the poorest families, an increase from zero to a significant proportion of total income contributed strongly to a reduction in total inequality. In addition, the income effects of government pensions and other sources of income also contributed significantly (respectively 14% and 11%). In both cases, the concentration of these sources was reduced during the pandemic.

Table 3 – ΔGini Decomposition (%) by Income Source – 2019-2020

	Composition Ef.	Income Ef.	Total
Job	3.1	-10.9	-7.8
Pension	0.3	14.3	14.5
Other Social Programs	3.1	8.1	11.2
Emergency Aid	-2.9	-2.6	-5.5
Other Em. Aids	75.6	10.7	86.3
Total	1.8	-0.4	1.4
	80.9	19.1	100.0

Source: Continuous PNAD/IBGE; PNAD COVID/IBGE; IPCA/IBGE.

There are also factors that have acted to increase income inequality. These include the income effect of labor income and transfers from social programs. Labor income became more concentrated in this period, probably due to the transitions out of the labor force among families with lower per capita household income. Other social programs have decreased in the period, as most were replaced by the EAT and have become relatively less concentrated in the poorest families, which made their income effect negative. Despite this, its average concentration is still lower than the total Gini index and for this reason, the reduction in the share of social programs in total income made the composition effect negative, contributing to an increase in inequality.

4.3. Labor Market Impacts of Covid19

We also examine changes in labor market indicators during the pandemic. Figure 6 shows the evolution of the labor force participation rate (LFP) in the first quarters of 2018 and 2019, and from May to November 2020. It shows that there is a big reduction LFP from 2018/2019 to 2020. While in 2018 and 2019 LFP was between 62% and 63%, in May 2020 LFP dropped to between 56%. From August 2020 on, the LFP started to increase again and reached 58% in November.

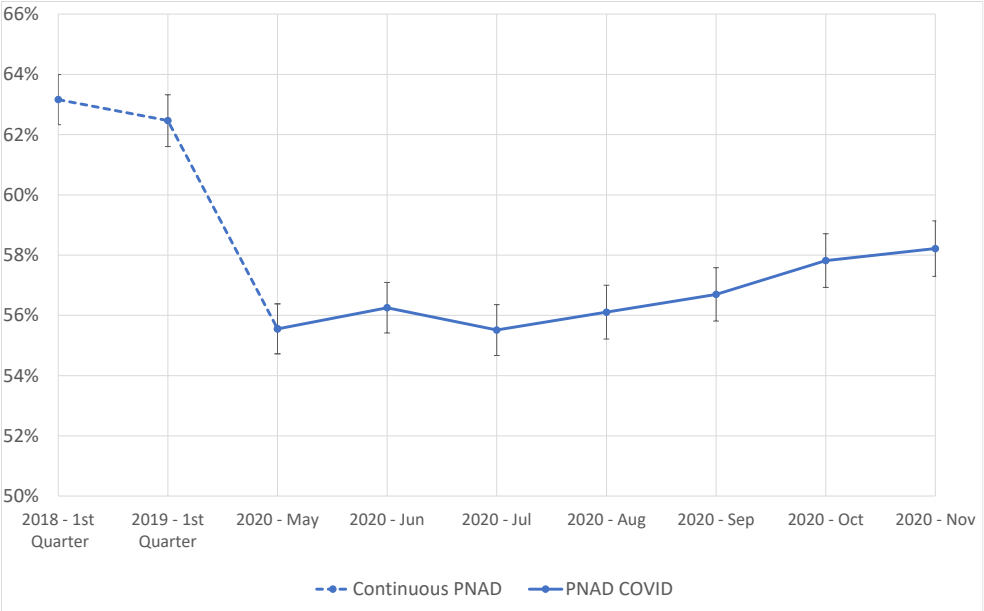


Figure 6 – Labor Force Participation

Note – Labor force participation rate is calculated as the population in the labor force over the overall population with 14 year of age or older.

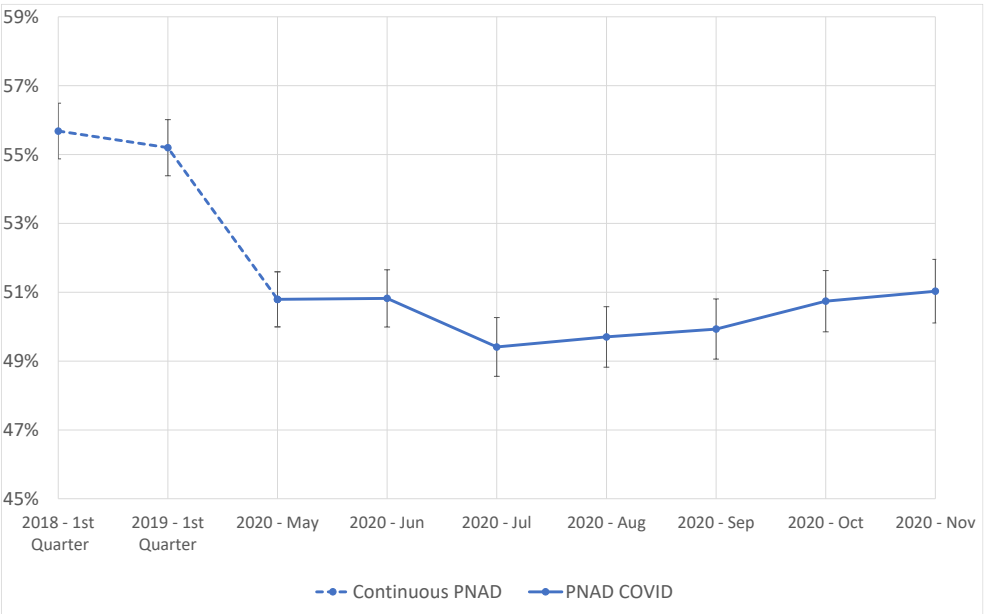


Figure 7 – Working Population

Note – Working population is measured as a proportion of the overall population with 14 year of age or older.

The movements in the LFP rate mostly reflect changes in the proportion of employed people in the population, as shown in Figure 7. We observe that in the first quarters of 2018 and 2019, employment levels were slightly above 55%. In May 2020,

that level dropped to 51%. Between May and July, the point estimate of the proportion of employed persons decreases to 49%, and starts to increase from then on, to 51% in November.

Despite the reduction in employment described in Figure 7, the transitions to inactivity prevented the unemployment rate from increasing between the first quarter of 2019 and May 2020, as described in Figure 8. On the contrary, the unemployment rate fell from around 11% in the first quarter of 2019 to 8.5% in May 2020. However, after the initial reduction, the unemployment rate gradually increased overtime, reaching around 12.5% in November, above the level of 2019.

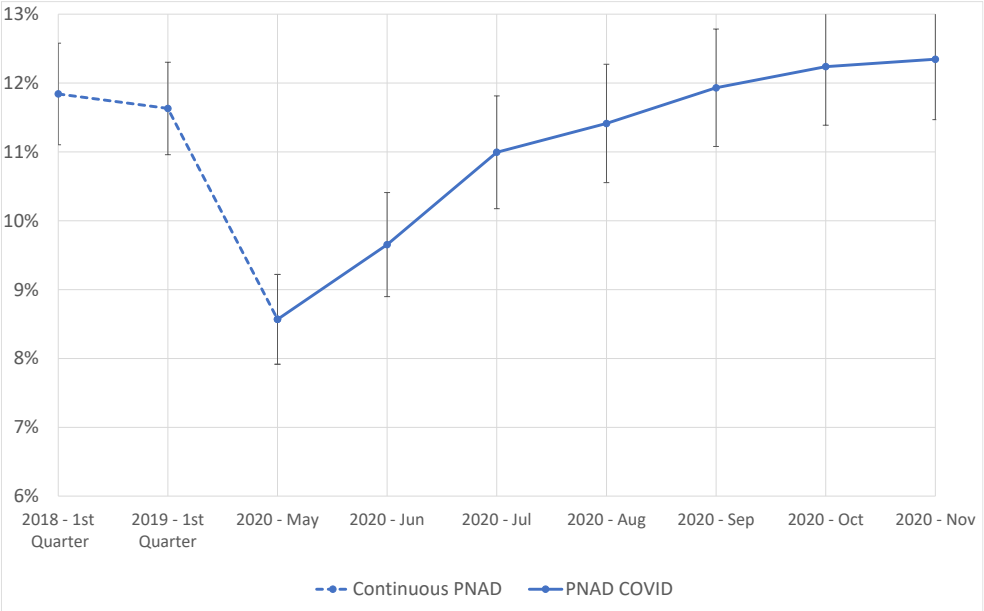


Figure 8 – Unemployment Rate

Note – unemployment rate is calculated as the population who did not have any work in the week of reference and took a concrete action to look for a job, as a proportion of the labor force.

Figure 9 shows the proportion of the working population people on leave, including those working from home. Between 2018 and 2019, the proportion of working people on leave was stable at just under 5%, but this share increased to 22% in May 2020, steadily decreasing since then to reach around 6% in November, as firms decide to go back to presential activities.

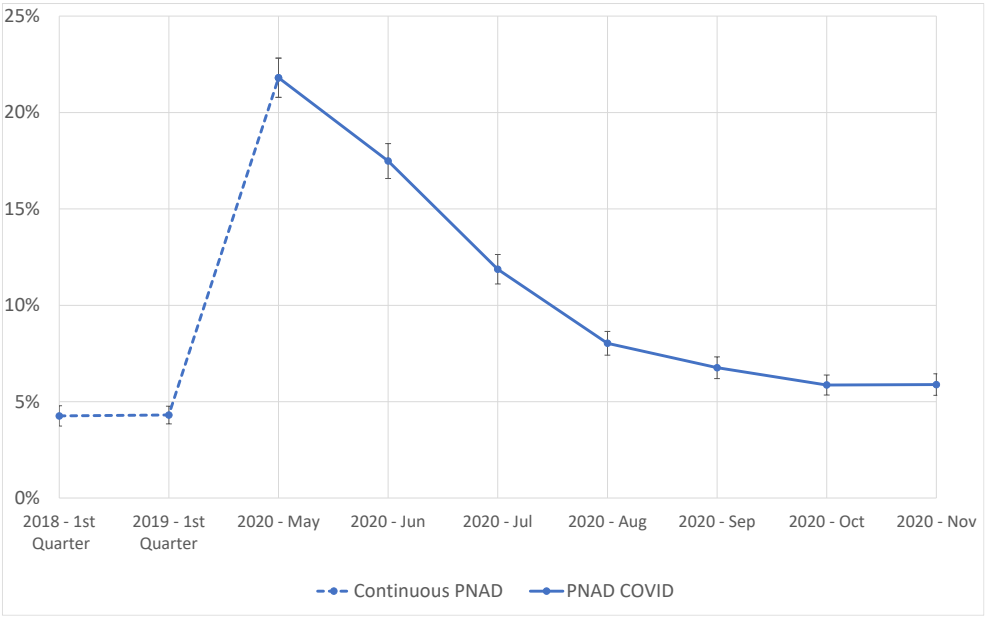


Figure 9 – Working Population on Leave

Source: Continuous PNAD/IBGE; PNAD COVID/IBGE. Note – data is working population on a leave as a proportion of the working population.

Figure 10 depicts the ratio of total earnings received by individuals in each period and earnings usually received (in normal times) among workers who remained employed, to describe the income reduction brought about by the pandemic among the employed. This ratio drops from just above 1 in the first quarters of 2018 and 2019 to close to 0.9 in May 2020. Without the EAT, the ratio would have dropped to 0.86 in May on the assumption that workers would not have changed their behavior during the pandemic without the EAT. From May to November, the ratio of actual to normal earnings increases again and converge to the same number as the value of the EAT transfers is halved, but it does not return to the previous level of 2019.

To examine how different socioeconomic groups were affected by social distancing, Figures 11 to 13 depict the evolution of LFP rate disaggregated by race, schooling, and gender. Figure 11 compares the LFP of black or indigenous people with that of the white or Asian. Despite the remarkably similar levels between the two groups in 2018 and in 2019, in 2020 the estimates for the white are consistently higher than those for black.

Black or indigenous people thus seem to have been more affected in the labor market than white or Asian people. They also might have been more affected by the EAT, which represents a non-labor income. This difference, however, is reduced over time (from 4 pp. in May to 1.5 pp. in November).

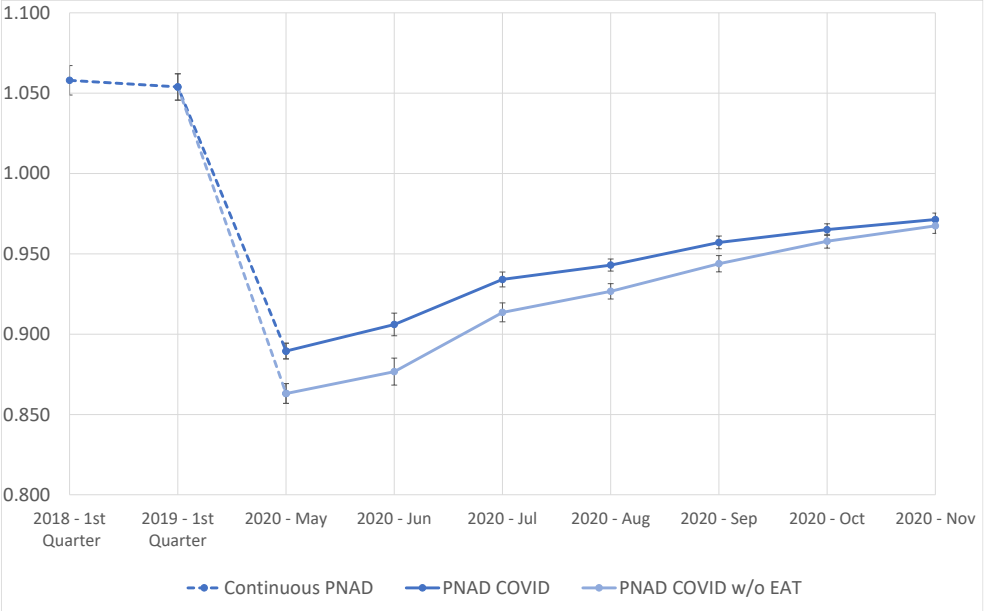


Figure 10 – Ratio of Effective to Usual Household per Capita Income

Source: Continuous PNAD/IBGE; PNAD COVID/IBGE.

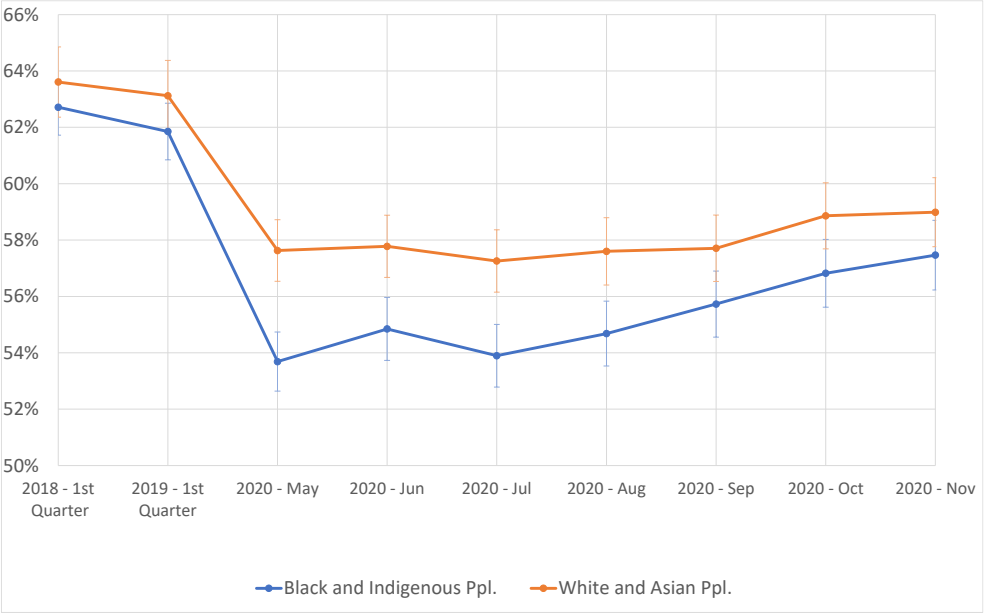


Figure 11 – Labor Force Participation Rate by Race

Note – labor force participation rate is calculated as the population in the labor force over the overall population with 14 year of age or older.

In Figure 12, we show the participation rate for the individuals who did not complete high school as compared to those with a high school degree or more. We observe that even in periods prior to the COVID-19 pandemic, people with less schooling had a much lower level of participation in the labor market than those with more schooling (about 50%, compared to 77% among the more schooled group). In May 2020, the level of participation of people with secondary education or more drops to 68% (9 pp. relative to 2019) while the participation the unskilled drops to 41% (8 pp. relative to 2019). The difference in participation rates between the two groups remains roughly at the same level in 2020 as compared to 2019.

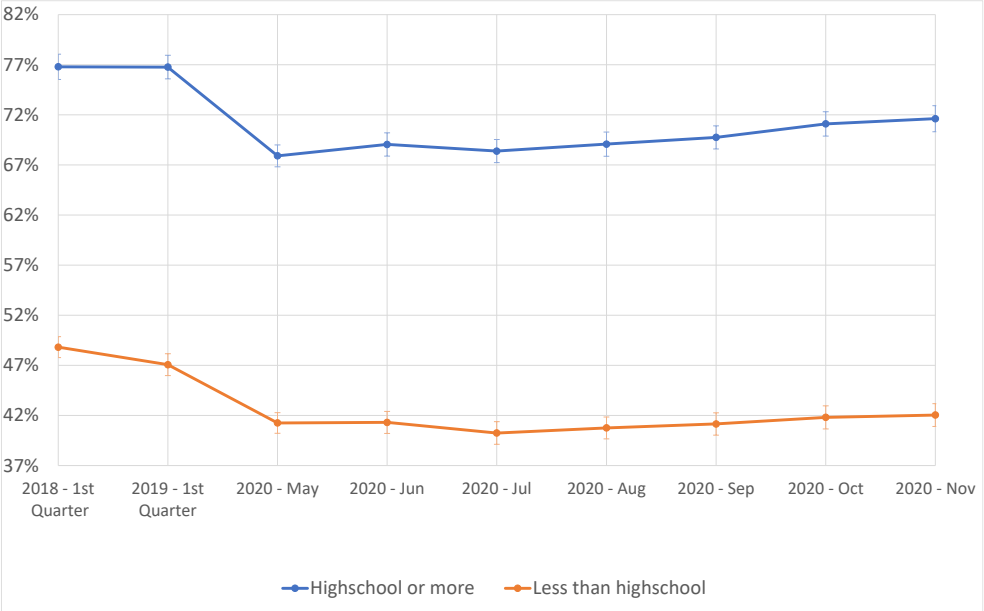


Figure 12 – Labor Force Participation Rate by Schooling

Note – labor force participation rate is calculated as the population in the labor force over the overall population with 14 year of age or older.

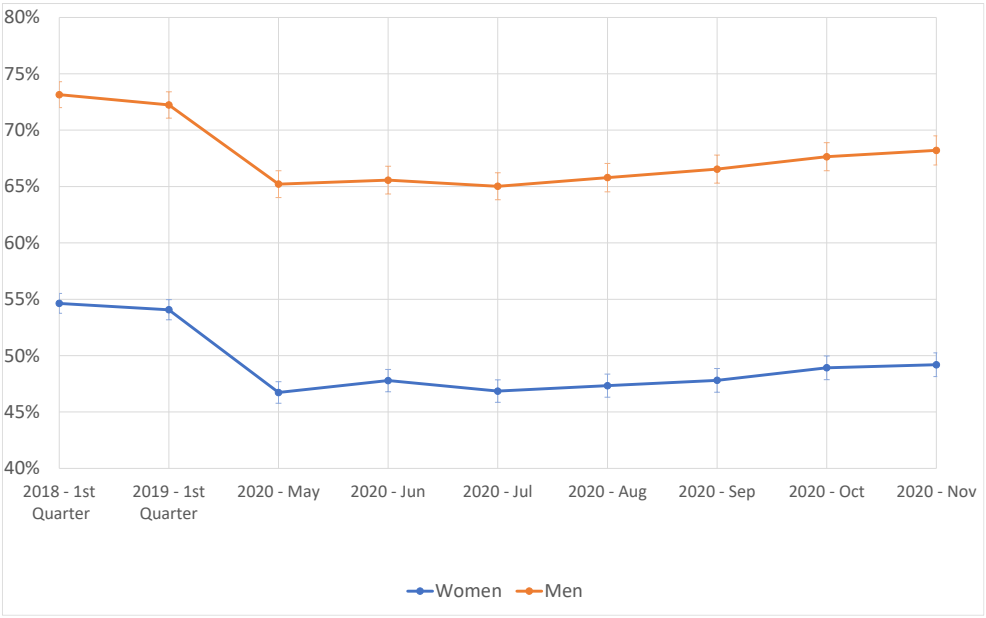


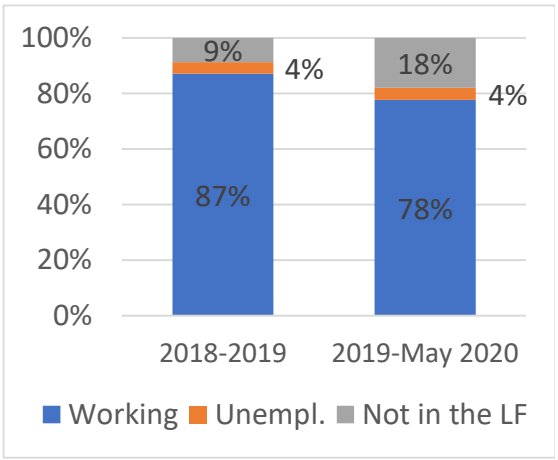
Figure 13 – Labor Force Participation Rate by Gender

Note – labor force participation rate is calculated as the population in the labor force over the overall population with 14 year of age or older.

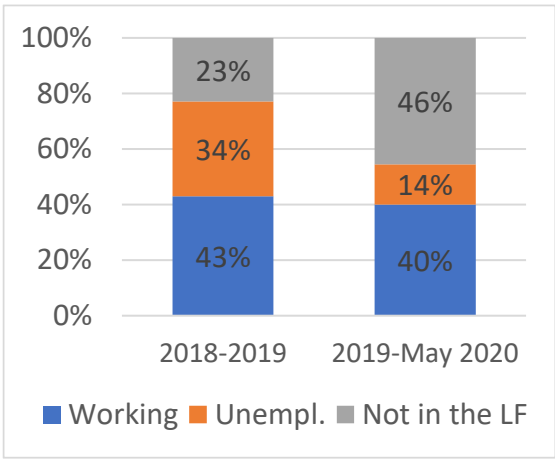
Figure 13 shows the behavior of labor force participation rates separately for men and women. Despite different levels, LFP of women and men show similar trends over time. The difference of 18 pp. between the participation rates of the two groups before the pandemic remained about the same over the weeks observed in 2020.

Figure 14 shows the probabilities of transitions in the labor market between work, unemployment, and inactivity, comparing the transitions that occurred between the 1st quarter of 2018 and the first quarter of 2019, with those that happened between the first quarter of 2019 and May 2020. Panels (a), (b) and (c) depict the probabilities of transition for people who were initially working, unemployed and economically inactive, respectively, showing that between 2019 and 2020 workers were more likely to move to inactivity. The share of workers who transitioned from work to inactivity increased from 9% in 2018-2019 to 18% in 2019-2020, while the proportion of workers who moved from unemployed to inactivity increased from 23% to 46%.

a) From Employment



b) From Unemployment



c) From OLF

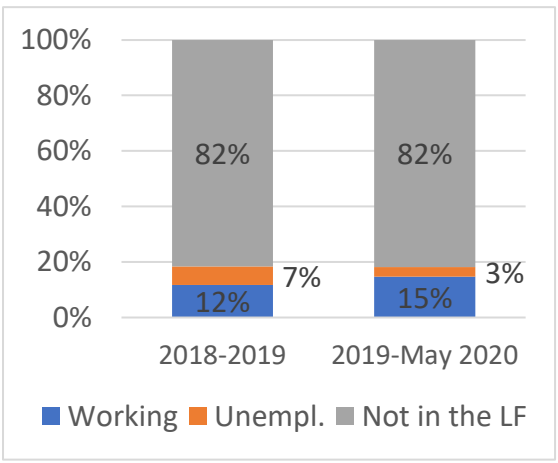


Figure 14 – Transitions Between Labor Market Situations

Note – unemployment rate is calculated as the population who did not have any work in the week of reference and took a concrete action to look for a job, as a proportion of the labor force.

As for the initially inactive people, the proportion of those who started looking for a job was reduced from 7% in 2018-2019 to 3% in 2019-2020. It seems, therefore, that the pandemic is causing people to leave the labor market, so that unemployment is not increasing in the first few months, as observed in other developing countries.

4.4. Econometric Results

In this section, we will analyze factors determining the transitions between situations in and the labor market. We also carry out statistical analysis to assess the associations

between socioeconomic characteristics and the probabilities of transition between situations of poverty, income, and the labor market between the years studied. In these exercises, we work with data from individuals who remain on the panel in the first quarters of 2018, 2019 and in May 2020. The dependent variables in the analysis indicate transitions out of the initial situation between year t and year $t + 1$. For each individual i, the dependent variable is described as:

$$Transition_{it} \equiv 1\big(y_{i,t+1} = 1 \mid y_{it} = 0 \big), \qquad (3)$$

where y_{it} is the dependent variable in period t. We examine transitions from inactivity and work status, estimating the following equation:

$$Transition_i = \alpha + Educ_i'\beta + \gamma Female_i + \delta BIP_i + Age_i'\xi + \varepsilon_i, \qquad (4)$$

where $Educ_i$ is a vector of education dummies, $Female_i$ is a female dummy, BIP_i is a dummy for black or indigenous people, Age_i is a vector of age group dummies and ε_i is the error term. We do not use the panel structure to control for fixed effects of individuals and for this reason we omit the time index t in equation 4.

Table 4 shows the results of transitions to inactivity among those who were economically active. In column 1, the results for the period 2018-2019 indicate that people with more schooling were less likely to transition to inactivity, while the likelihood between those aged up to 20 (omitted category) and those aged 60 or older is also higher than among those of intermediate age. Women are also more likely to transition to inactivity, and black or indigenous people have no significant difference at the 10% level in transition probability. In column 2, the results for 2019-2020 are relatively similar between the two periods, except for the estimates for the age groups and for women, which have higher magnitudes between 2019 and 2020. These differences are significant at 1% level, as shown in column 3.

Table 4 – Transitions from LFP to OLFP

Independent Variables	Dep. Var.: In the labor force - Not in the labor force		
	2018-2019	2019-2020	Diff. (2) - (1)
	(1)	(2)	(3)
Middle School inc.	-0.0846***	-0.0682**	0.0165
	(0.0255)	(0.0285)	(0.0382)
Middle School comp.	-0.102***	-0.0902***	0.0118
	(0.0268)	(0.0305)	(0.0406)
Highschool inc.	-0.140***	-0.0928***	0.0472
	(0.0271)	(0.0324)	(0.0423)
Highschool comp.	-0.152***	-0.132***	0.0202
	(0.0254)	(0.0285)	(0.0382)
College inc.	-0.141***	-0.132***	0.00876
	(0.0269)	(0.0320)	(0.0418)
College comp.	-0.184***	-0.217***	-0.0329
	(0.0255)	(0.0288)	(0.0384)
Women	0.0820***	0.116***	0.0337***
	(0.00531)	(0.00704)	(0.00882)
Black and Indigenous Ppl.	0.00682	0.00771	0.000887
	(0.00582)	(0.00784)	(0.00976)
20 to 29 years of age	-0.0911***	-0.193***	-0.102***
	(0.0146)	(0.0232)	(0.0274)
30 to 39 years of age	-0.113***	-0.257***	-0.143***
	(0.0145)	(0.0226)	(0.0268)
40 to 49 years of age	-0.116***	-0.291***	-0.176***
	(0.0145)	(0.0223)	(0.0266)
50 to 59 years of age	-0.0794***	-0.231***	-0.152***
	(0.0153)	(0.0229)	(0.0276)
60 to 69 years of age	0.0220	-0.0218	-0.0438
	(0.0196)	(0.0265)	(0.0330)
70 or more years of age	0.0973***	0.159***	0.0619
	(0.0329)	(0.0387)	(0.0508)
Constant	0.282***	0.493***	-
	(0.0287)	(0.0363)	
State Fixed Effects	Yes	Yes	-
Observations	23,065	23,259	-
R-squared	0.065	0.110	-
Average Dep. Var.	0.117	0.226	-

Source: Continuous PNAD/IBGE; PNAD COVID/IBGE; Rocha, Franco and IETS (n.d.); IPCA/IBGE.
Note – regression of the transition from not in poverty to poverty on socioeconomic variables. Sample is the panel observed in the 1st quarters of 2018 and 2019 in the Continuous PNAD, and in May 2020 in PNAD COVID. Regressions further controlled for state level fixed effects. Robust standard errors in parenthesis. Significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.10$.

Table 5 –Transitions from Working to Not Working

Independent Variables	Dep. Var.: Working - Not working		
	2018-2019	2019-2020	Diff. (2) - (1)
	(1)	(2)	(3)
Middle School inc.	-0.0906***	-0.106***	-0.0156
	(0.0294)	(0.0305)	(0.0423)
Middle School comp.	-0.109***	-0.117***	-0.00862
	(0.0311)	(0.0329)	(0.0453)
Highschool inc.	-0.113***	-0.128***	-0.0150
	(0.0325)	(0.0344)	(0.0473)
Highschool comp.	-0.139***	-0.139***	-0.000252
	(0.0299)	(0.0309)	(0.0431)
College inc.	-0.121***	-0.125***	-0.00413
	(0.0323)	(0.0351)	(0.0477)
College comp.	-0.159***	-0.185***	-0.0256
	(0.0308)	(0.0326)	(0.0449)
Women	0.0656***	0.0950***	0.0294***
	(0.00720)	(0.00858)	(0.0112)
Black and Indigenous Ppl.	0.0125*	0.0267***	0.0142
	(0.00696)	(0.00875)	(0.0112)
20 to 29 years of age	-0.109***	-0.186***	-0.0765**
	(0.0230)	(0.0272)	(0.0357)
30 to 39 years of age	-0.153***	-0.240***	-0.0870**
	(0.0226)	(0.0266)	(0.0349)
40 to 49 years of age	-0.152***	-0.265***	-0.114***
	(0.0226)	(0.0263)	(0.0347)
50 to 59 years of age	-0.128***	-0.218***	-0.0906**
	(0.0231)	(0.0269)	(0.0355)
60 to 69 years of age	-0.0445*	-0.0337	0.0107
	(0.0262)	(0.0301)	(0.0399)
70 or more years of age	0.0139	0.133***	0.119**
	(0.0373)	(0.0408)	(0.0553)
Unreg. employee in the private sec./HH.	0.0923***	0.0887***	-0.00359
	(0.0114)	(0.0136)	(0.0178)
Reg. employee in the public sec.	-0.0157	-0.0637***	-0.0481*
	(0.0152)	(0.0218)	(0.0265)
Unreg. employee in the public sec.	0.0952***	0.0472	-0.0480
	(0.0219)	(0.0331)	(0.0397)
Military and civil servants	-0.0136	-0.0587***	-0.0451**
	(0.0114)	(0.0169)	(0.0204)
Employer	-0.0216**	-0.0460***	-0.0244
	(0.0106)	(0.0138)	(0.0174)
Self-Employed Worker	0.0573***	0.0888***	0.0315**
	(0.00868)	(0.0113)	(0.0142)
Auxiliary worker in family business	0.173***	0.187***	0.0138
	(0.0253)	(0.0267)	(0.0368)

Table 5 – Regression of the Transitions from Working to Not Working (continued)

Independent Variables	Dep. Var.: Working - Not working		
	2018-2019	2019-2020	Diff. (2) - (1)
	(1)	(2)	(3)
Agriculture, forestry and fishing	-0.0203	-0.0394**	-0.0191
	(0.0136)	(0.0157)	(0.0208)
Construction	0.0122	-0.00293	-0.0152
	(0.0166)	(0.0184)	(0.0247)
Wholesale and retail trade, repair of vehicles	-0.0380***	-0.0155	0.0226
	(0.0123)	(0.0141)	(0.0187)
Transportation and storage	-0.0362**	-0.0332*	0.00294
	(0.0143)	(0.0181)	(0.0231)
Accommodation and food services	-0.0556***	-0.00150	0.0541**
	(0.0165)	(0.0217)	(0.0272)
Info., commun., financ., insur., real est., prof., scient., tech., adm. and support services	-0.0384***	-0.0309**	0.00750
	(0.0129)	(0.0155)	(0.0202)
Public adm., defence, compulsory social sec.	-0.0406**	-0.0270	0.0136
	(0.0159)	(0.0216)	(0.0268)
Educ., human health, social work	-0.0619***	-0.0547***	0.00726
	(0.0131)	(0.0182)	(0.0224)
Other services	-0.0530***	-0.0569***	-0.00387
	(0.0173)	(0.0207)	(0.0269)
Activities of household as employers	-0.0409**	-0.00396	0.0370
	(0.0195)	(0.0237)	(0.0307)
Technicians, clerical sup. workers, services and sales workers, and armed forces occupations	0.00936	0.0135	0.00413
	(0.00911)	(0.0124)	(0.0154)
Skilled agricultural, forestry and fishery workers, craft workers, plant and machine operators	-0.00736	0.00356	0.0109
	(0.0122)	(0.0154)	(0.0196)
Elementary occupations	0.0203	0.0150	-0.00536
	(0.0147)	(0.0181)	(0.0233)
Constant	0.338***	0.486***	-
	(0.0388)	(0.0431)	
State Fixed Effects	Yes	Yes	Yes
Observations	20,472	20,700	-
R-squared	0.080	0.116	-
Average Dep. Var.	0.139	0.235	-

Source: Continuous PNAD/IBGE; PNAD COVID/IBGE; Rocha, Franco and IETS (n.d.); IPCA/IBGE.
Note – regression of the transition from not in poverty to poverty on socioeconomic variables. Sample is the panel observed in the 1st quarters of 2018 and 2019 in the Continuous PNAD, and in May 2020 in PNAD COVID. Regressions further controlled for state level fixed effects. Robust standard errors in parenthesis. Significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.10$.

In Table 5, we show the transitions from work to non-work. In these regressions, we additionally control by job characteristics, such as the employment status, the sector of

activity and the occupation. The results for 2018-2019 shown in column 1 indicate that the people most likely to lose their jobs are those with less education, women, and people who are at the extremes of the age distribution. The reference category for the employment status is that of registered employees in the private sector or households. Relative to that position, employment statuses without registration (unregistered employees) or with a higher probability of informality (self-employed or auxiliary workers in family business) are more likely to leave work. Public sector employees, civil or military servants are less likely to lose their jobs, as civil servants or military personnel cannot be dismissed in the same way as employees in the private sector. As for the sectors of activity, industries are the reference category and relative to it, those employed in most other sectors are less likely to be out of work in the following year.

Regarding occupations, managerial, supervisory and professional occupations are the reference category. Despite the differences between occupational categories, there are no differences between them regarding the likelihood of being out of work the following year. In column 2, the results for 2019-2020 shows that while the magnitudes of the estimates for women became more positive and differences in probabilities between age groups became more pronounced, as compared to results in column 1. In addition, the probability of losing job became relatively smaller among civilian and military servants, registered public sector employees and employers, which means that these employment status categories were relatively less affected during the pandemic period. Employers might be able to adjust the size of their firms' operations before they leave the market. On the other hand, own-employed became relatively more affected. All those differences are statistically significant, as show in column 3. As for the other job characteristics, the differences are not significant between the two periods.

Figures 15 to 21 show the predicted transition probabilities from working to non-working by socioeconomic and job characteristics. In Figure 15, we observe the predicted probabilities by education levels. The probability of losing work is higher among the less educated in the two periods, and they seem to increase similarly between those periods for all categories.

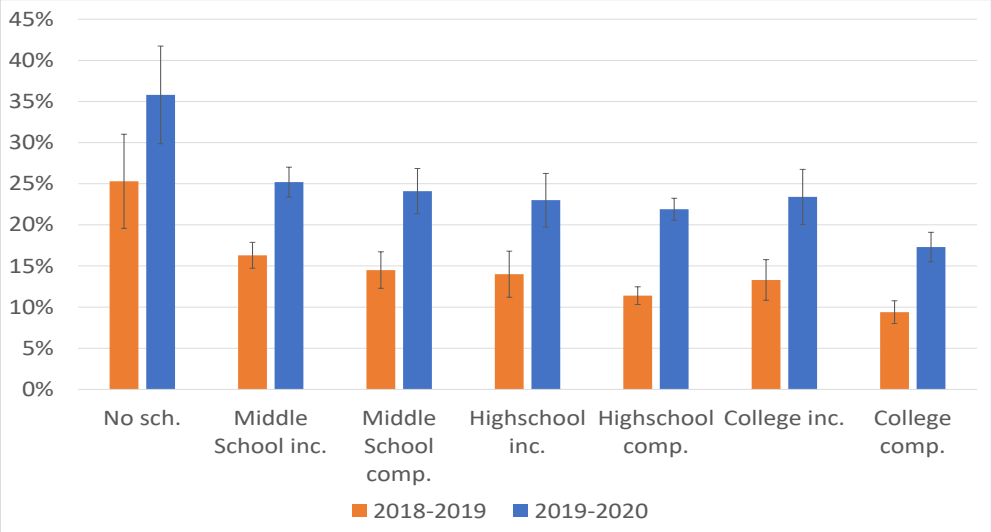


Figure 15 – Predicted Probabilities of Transitions to Unoccupied Status by Education

Note –predicted probabilities are calculated from the estimates in columns 2 and 3 of Table 4. Vertical bars are the 95% confidence interval.

In Figure 16, we show the transition probabilities of losing job by sex. Between 2018 and 2019, this probability was already higher among women (16%, compared to 10% of men). This difference grew further in the period from 2019 to 2020 and the probability of women losing their job reached 27%, while that of men was 18%.

Figure 17 shows the probabilities of job loss by race. In both periods, this probability is slightly higher among black or indigenous people. The growth in probability in the second period is also similar between the two groups.

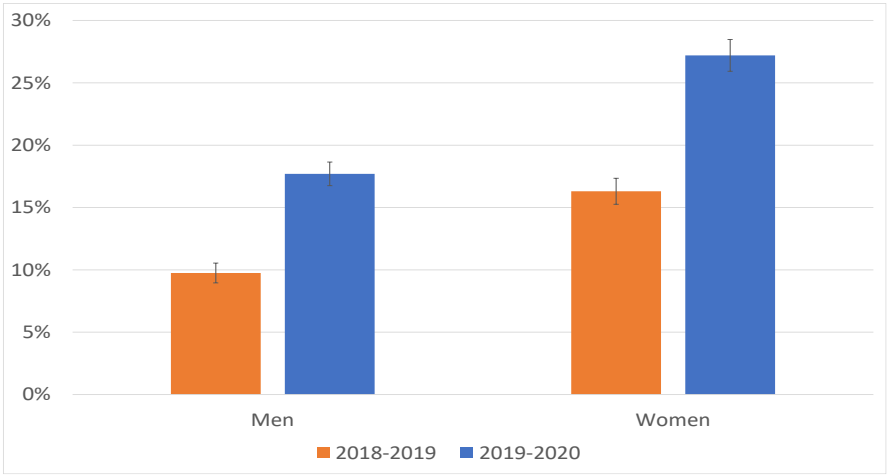


Figure 16 – Predicted Probabilities of Transitions to Unoccupied Status by Sex

Note –predicted probabilities are calculated from the estimates in columns 2 and 3 of Table 4. Vertical bars are the 95% confidence interval.

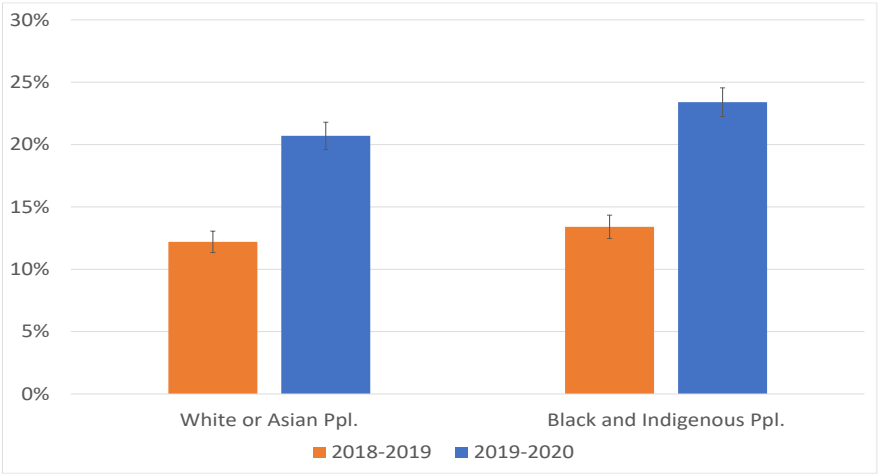


Figure 17 – Predicted Probabilities of Transitions to Unoccupied Status by Race

Note –predicted probabilities are calculated from the estimates in columns 2 and 3 of Table 4. Vertical bars are the 95% confidence interval.

In Figure 18, we show the probabilities of job loss by age groups. We observe that those probabilities are greater the more people move away from the group of 40 to 49 years of age. The most intense increase in probability also occurred in the most extreme age groups. Among those up to 20 years of age, the probability increased by 17 pp. (from 25% to 42%), while in the 60 to 69 years old and 70 years old or older, the increases were, respectively, 18 pp. and 29 pp. In contrast, the central age group of 40 to 49 years increased by 6 pp., Reaching 16% between 2019 and 2020.

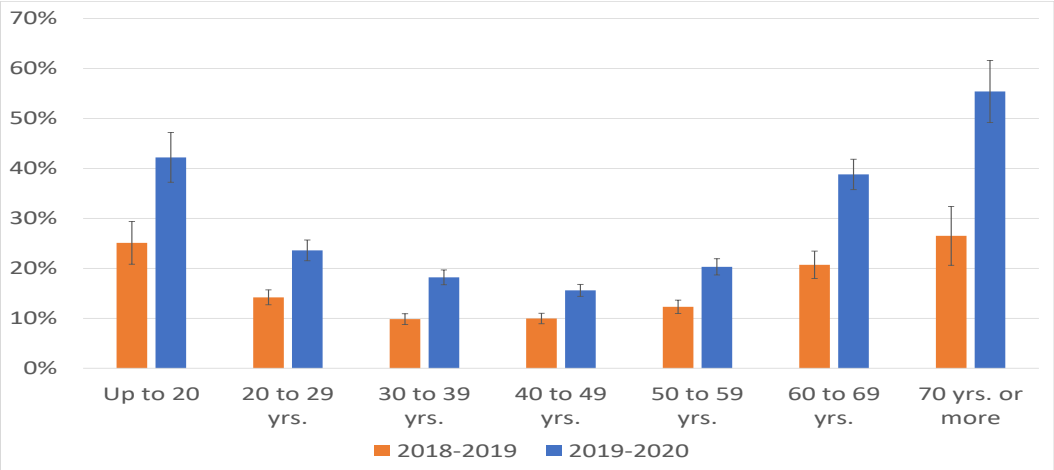


Figure 18 – Predicted Probabilities of Transitions to Unoccupied Status by Age

Note –predicted probabilities are calculated from the estimates in columns 2 and 3 of Table 4. Vertical bars are the 95% confidence interval.

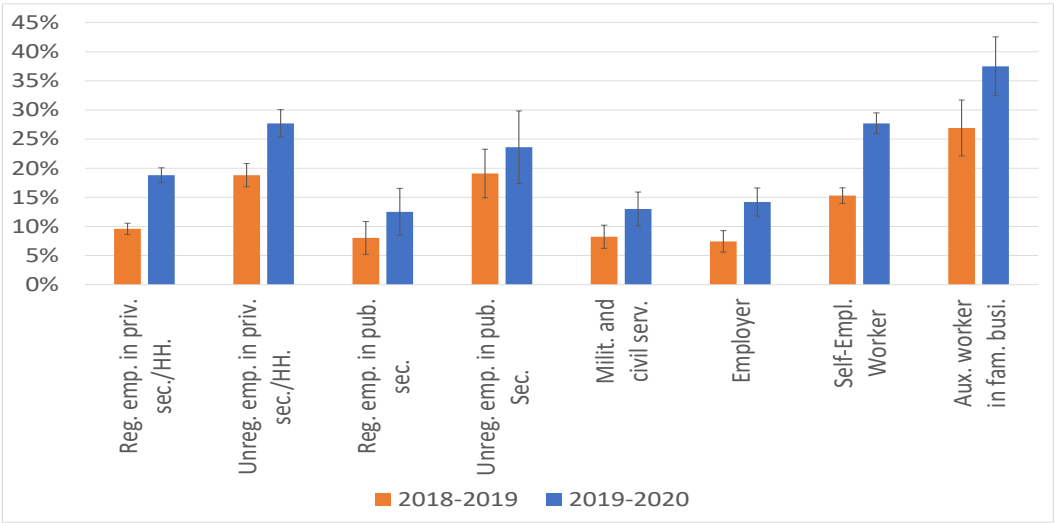


Figure 19 – Predicted Probabilities of Transitions to Unoccupied Status by Employment Status

Note –predicted probabilities are calculated from the estimates in columns 2 and 3 of Table 4. Vertical bars are the 95% confidence interval.

Figure 19 shows the probabilities of job loss by employment status. The highest probabilities in both periods are those of auxiliary family workers, unregistered employees in the private and public sectors, and of self-employed workers. Between the two periods, the probabilities did not increase significantly among workers in the public

sector. In contrast, they increased among employers, employees in the private sector, and more intensely among self-employed workers (by 12.4 pp.) and among auxiliary workers in family businesses (by 10.5 pp.). Despite the initial differences in level, in the private sector, the probability of job loss among registered employees increased as much as that of unregistered employees between the two periods (about 9 pp. for both).

In Figure 20, we present the predicted probabilities of job loss by economic activity. We observe that in the period from 2018 to 2019, the probabilities of the agricultural, industrial and construction sectors are slightly higher than those of the other sectors. Between the two periods, the sectors in which the probability of job loss increased the most were accommodation and food services (at 13.5 pp.), activities that have households as employers (at 12 pp.), trade and reparation of vehicles (10.5 pp.), and public administration, defense and social services (9.5 pp.). In this period, workers in industries, construction, accommodation and food services, and those who have household as employers have the highest probabilities of job loss, around 25%.

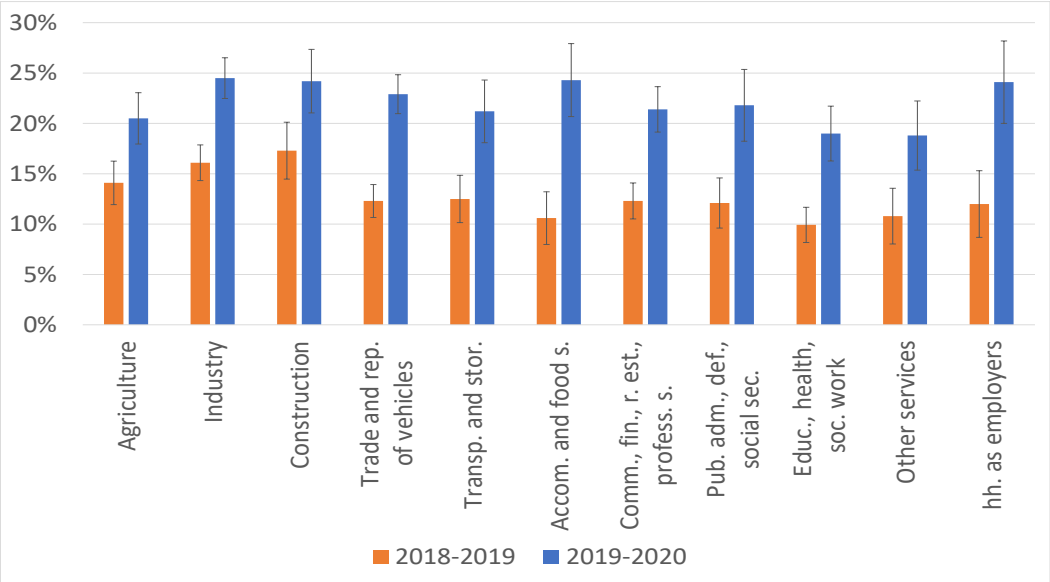


Figure 20 – Predicted Probabilities of Transitions to Unoccupied Status by Economic Activity

Note –predicted probabilities are calculated from the estimates in columns 2 and 3 of Table 4. Vertical bars are the 95% confidence interval.

Figure 21 shows the probabilities of job loss by occupation. We observed that the probabilities are very similar between occupations between 2018 and 2019, and the increase in these probabilities for the second period was also relatively homogeneous among occupations.

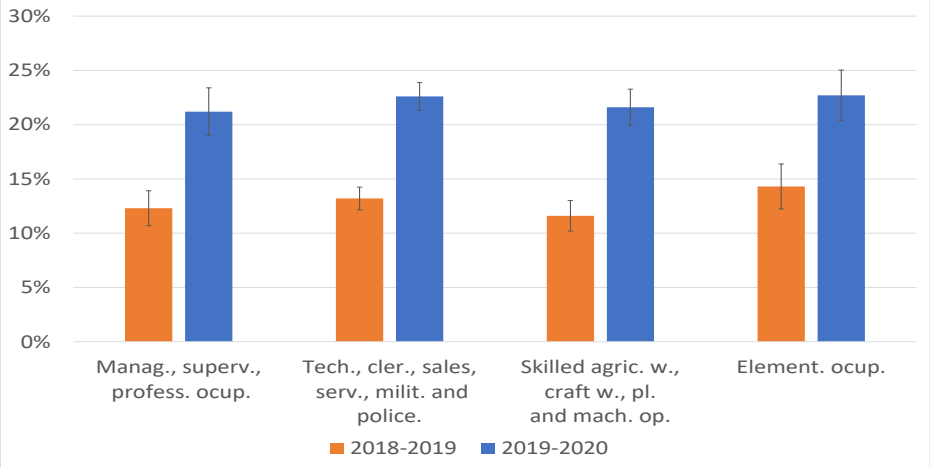


Figure 21 – Predicted Probabilities of Transitions to Unoccupied Status by Occupation

Source: Continuous PNAD/IBGE; PNAD COVID/IBGE; Rocha, Franco and IETS (n.d.); IPCA/IBGE.
Note –predicted probabilities are calculated from the estimates in columns 2 and 3 of Table 4. Vertical bars are the 95% confidence interval.

Results for the transitions in the labor market shows that, in the period 2019-2020, women and people in the extremes of the age distribution were relatively more affected and were more likely to transition to inactivity, comparing with the period 2018-2019. As for the probability of losing a job, the most affected groups in the pandemic period, compared to the situation in the previous year, were women, people in the extremes of the age distribution, and own-employed workers. Workers on the public sector were less affected. These results are consistent with some of the greatest concerns in the literature about the effects of the COVID-19 pandemic, the increase in attributions and violence against women (ECLAC, 2020a; Agüero, 2020; Sifat, 2020; Roesch et al., 2020). Our results

show that the likelihood of women leaving the labor market increased during the pandemic period, leading them to a situation where they may be more dependent on their partner's income. Differences in probabilities of young people to transition to inactivity or to lose their jobs, relative to those in the middle of the distribution, also increased from 2018-2019 to 2019-2020. The effects on young people entering the labor market in this period of recession might have long term consequences on their lifetime career earnings (von Wachter, 2020). Black or indigenous people, on the other hand, were no more affected than white or Asian people in the transition to inactivity when we control for other observable characteristics.

5. Conclusion

In this paper we examine the effects of the Emergency Aid Transfer in Brazil, a government transfer implemented to mitigate the effects of job and income loss resulting from the COVID-19 pandemic. We analyze poverty and inequality indicators of the income with and without the EAT using microdata. Our results show that poverty was reduced from 12% in 2019 to 9% in May 2020 and without that transfer poverty would have been around 19% if the agents did not change their behavior. Extreme poverty was also reduced from 3.5% in 2019 to values between 1% and 2% in 2020, and without the EAT it would have remained around 7% and 8%. These reductions impacted men and women equally, but they occurred with an especially greater magnitude among black or indigenous people and among people with less schooling. The differences observed between poverty rates for black or indigenous people and for white or Asian people have become very similar with EAT, which would not have happened without it. The same occurred for the difference between more and less educated people.

Our descriptive analysis also suggests that the EAT may have reduced the Gini index of per capita household income by 10% from May to September 2020, again assuming that agents would not change their behavior without the EAT. We also assessed the role of that program in the reduction of the observed Gini index between the first quarter of 2019 and May 2020 and find that the Emergency Aid was responsible for about 86% of the reduction in the Gini index in the period, mostly due to the relatively high value of the transfer in the total average household income.

We also examined the dynamics of the labor market from 2018 to 2020, tracking the same individuals over time. The results show that the labor force participation rate decreased sharply between 2019 and May 2020. The exit from the labor market in this moment of economic downturn may have been reinforced by the introduction of the EAT, as it increases non-work income and may discourage those who were dismissed from looking for another job during the recession. Transitions to inactivity, moreover, explain the reduction in the unemployment rate in a moment when the proportion of working people is decreasing. Black and indigenous people had a sharper reduction in the labor force participation rate between 2019 and 2020, compared to white or Asian people.

Among those who remained in the labor market, there was a sharp increase in the proportion of workers who were on a leave between 2019 and May 2020, from 5% to almost 22%. This movement occurred partly because the leave includes people in teleworking due to the COVID-19 pandemic. In the following months, this proportion systematically decreased.

The econometric results also show that when we control for schooling, race and age, women had an increased likelihood of transition to inactivity in 2019-2020, compared to 2018-2019. Women also had a greater increase in the likelihood of losing their job between the two periods. Despite this, the likelihood of transition to poverty has not

increased more among women than among men. These results are consistent with recent concerns about the increase in the attribution of women at home and that of domestic violence. It is possible that the loss of work means greater dependence on women in relation to a spouse who is still receiving income from work.

Furthermore, young people's probability to transition to inactivity or to lose their jobs relative to the group in the middle of the age distribution grew from 2018-2019 to 2019-2020. These effects might have long term consequences on their lifetime career earnings, as shown by a growing literature on the effects of entering the labor market in adverse conditions. Our results also show that self-employed, many of whom live on daily income, had an increase in the probability of losing job between that two periods. In this sense, informality in the labor market may play an important role making the impacts of the pandemic worse.

The EAT financial burden is heavy, having reached an estimated total cost of R$ 321.8 billion, leading to a total expenditure on pandemic responses of R$ 605 billion (8.4% of GDP) in 2020 (Brazil, 2020b). Starting from September, the amount of the transfer of the EAT for an increasing share of the recipients was reduced by half in September and should remain at that level until the end of the year, when it will be finished.[8] Given the evidence of low savings capacity among Brazilian families (Rodrigues, Menezes-Filho and Komatsu, 2018), it is hardly expected that the most vulnerable were able to constitute precautionary savings. The reduction in value and the end of the transfer, thus, may make the most vulnerable families suddenly have to return to the labor market to maintain their living conditions, even if this represents an increased risk of contracting COVID-19. It is

[8] According to Provisional Measure n. 1.000/2020.

necessary to plan a proper transition, or alternative basic income programs in order to avoid a negative income shock among the most vulnerable.

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