Population Research and Policy Review (2023) 42:22
https://doi.org/10.1007/s11113-023-09749-3

ORIGINAL RESEARCH

The Impact of Conditional Cash Transfers on Poverty, Inequality, and Employment During COVID-19: A Case Study from Brazil

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Received: 18 August 2021 / Accepted: 5 January 2023 / Published online: 2 March 2023

Abstract

The policy responses to the COVID-19 pandemic varied widely between countries. Understanding how effective these responses were is important to improve preparedness for future crises. This paper investigates how one of largest scale conditional cash transfer COVID relief policies in the world—the Brazilian Emergency Aid (EA)—impacted poverty, inequality, and the labor market amidst the public health crisis. We use fixed-effects estimators to analyze the impact of the EA on labor force participation, unemployment, poverty, and income at the household level. We find that inequality, measured by per capita household income, reduced to a historical low and was accompanied by substantial poverty declines—even as compared to pre-pandemic levels. Furthermore, our results suggest that the policy has effectively targeted those in most need—temporarily reducing historical racial inequalities—while not incentivizing reductions in labor force participation. Absent the policy, adverse shocks would have been significant and are likely to occur once the transfer is interrupted. We also observe that the policy was not enough to curb the spread of the virus, suggesting that cash transfers alone are insufficient to protect citizens.

Keywords Policy evaluation · Inequality · Poverty · COVID-19 · Conditional cash transfer · Emergency aid

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Introduction

In 2020, governments worldwide were faced with the decision of imposing restrictive lockdown measures to curb the spread of the COVID-19 virus while attempting to find strategies to mitigate the socioeconomic consequences that said measures would impose. The World Bank estimated that between 88 and 115 million additional people would be pushed below the extreme poverty line of $1.90 a day (World Bank, 2020). This was the first time in the last twenty years that extreme global poverty was predicted to increase, a factor with long-lasting consequences (Decerf et al., 2021). As such, the COVID-19 pandemic has exacerbated structural pre-existent inequalities between and within countries.

Many countries implemented income support policies, given the foreseen economic hardship that the pandemic would impose. However, the extent—both in terms of duration, value of compensation, and population targeted—varied considerably cross-nationally (Gentilini et al., 2020). In general, high-income countries were able to provide the most extensive support, with the African continent comprising the region with the highest number of countries without any income support policies (Hale et al., 2021). The capacity of populations to abide by lockdown measures also varied considerably by regional poverty intensity (Bargain & Aminjonov, 2021).

Latin America and the Caribbean were among the regions in the world most seriously affected by the COVID-19 pandemic (ECLAC, 2021). As of March 2021, the region accounted for roughly 19 percent of cases and 27 percent of deaths. The public health crisis in the region was exacerbated by its historically high levels of inequality, persistent extreme poverty, and extensive informal labor markets (Milanovic, 2015; Santos & Villatoro, 2018). Within Latin America, Brazil provides a relevant case to study the ability of policies to mitigate the socioeconomic impacts of calamities. By far the largest and historically the most unequal country in Latin America, Brazil was one of the hardest hit countries by COVID-19. Given global inequality in vaccine rollouts and the appearance of new and more contagious variants, Brazil became one of the epicenters of the pandemic. Despite accounting for roughly 2.7 percent of the world's population, Brazil reported approximately 10 percent of total COVID-19 cases and 13 percent of total deaths worldwide (as of August 2021).

The COVID-19 health crisis worsened in the country despite pre-existent institutional and policy infrastructures that in theory were expected to mitigate its effects. For example, in the 1990s, Brazil became home of one of the largest universal public health systems in the world (Castro et al., 2019). Additionally, early in the pandemic, Brazil approved one of the most generous emergency conditional cash transfer policies—the Emergency Aid (henceforth EA). The EA leveraged the pre-existing social protection structure to enable the quick transfer of money even to those in the most remote areas of the country. Approximately four percent of the country's 2020 GDP was spent on the EA, which translated into the provision of direct cash transfers to roughly 39 percent of Brazilian households (Masri et al., 2021).

Existing research on the EA's impact suggests significant poverty and inequality reductions, temporarily curbing the adverse effects on the most vulnerable populations (Lustig et al., 2020; Prates & Barbosa, 2020). However, many of these studies were carried out during the initial stages of the pandemic, when data available was limited to a pre-pandemic period. Therefore, most studies thus far for Brazil and many middle- and low-income countries, have focused on simulations techniques to predict the socioeconomic impacts of the pandemic (Brum & De Rosa, 2021). Fortunately, in early 2021, Brazil released data on seven waves of a nationally representative panel—the COVID National Household Sample Survey (PNAD COVID) that allowed us to directly observe and estimate the monthly impact of the pandemic and the EA on various socioeconomic indicators. Specifically, this study extends prior literature by focusing on two main questions. First, we ask how the pandemic affected Brazil in terms of inequality, poverty, unemployment, and labor force participation. Second, we evaluate how the EA policy impacted these indicators, controlling for household unobserved heterogeneity.

Similar to recent reports, we find that inequality reduced to a historical low and poverty declined substantially—even when compared to pre-pandemic levels (Masri et al., 2021; Menezes-Filho et al., 2021). Poverty rates also sharply reduced between racial groups, especially among Black and White children. As a novel finding, we show that the EA has effectively targeted those in most need while not significantly altering labor-related indicators at the household level. However, the extraordinary impact of the transfer on both poverty and inequality was not enough to curb the spread of the virus and the collapse of the health system, nor to tackle non-monetary vulnerabilities associated with poverty.

Our analysis is structured as follows. The next section provides a chronology of the COVID-19 pandemic in Brazil, the political instabilities, and the design of the main policy response: the EA. We, then, introduce our data and methods, followed by the results. Finally, we summarize and discuss our findings.

Background

COVID-19 and Emergency Relief Policies

Prior research on the socioeconomic effects of COVID-19 has been largely focused on high-income countries. These studies demonstrate that the effects of the pandemic varied greatly across socioeconomic groups. For instance, findings for the US show that employment declined more for Hispanics, younger workers, and those without a bachelor's degree (Montenovo et al., 2020). Black communities in the US were also disproportionally affected both in terms of mortality and contagion (Millett et al., 2020) as were foreign-born, particularly Latinos (Horner et al., 2021). Recent evidence suggests that the pandemic has furthered gender inequality in many countries, with women more likely to permanently lose their jobs and experience more pronounced wage losses than men (Dang & Viet Nguyen, 2021). Those with pre-existing health conditions, often associated with lower-income and education, are also more vulnerable to the effects of the health crisis (Wiemers et al., 2020).

Before vaccine rollouts, shelter-in-place and social distancing policies were the only effective measures against COVID-19 (Barberia & Piazza, 2021). However, compliance with such measures is highly correlated with poverty (Bargain & Aminjonov, 2021). The most economically vulnerable populations, quite simply, cannot afford to shelter-in-place. As such, social safety nets have been advocated as necessary conditions to enable lockdowns, particularly in countries with high poverty levels and where a substantial part of the workforce is informal (Soares & Berg, 2022).

Between March 2020 and May 2021, over three thousand social protection measures were adopted by 222 counties and territories, a fifth of which comprised cash transfer programs specifically (conditional or unconditional) (Gentilini et al., 2020). Latin America's pre-existing conditional cash transfer infrastructure enabled governments to rapidly target the lowest income households at the onset of the pandemic. As of 2015, approximately 0.33 percent of Latin America's GDP was spent on conditional cash transfer programs, benefiting roughly 20 percent of the region's population (Cecchini & Atuesta, 2017). As such, COVID-19 emergency measures enacted in the region were fairly effective in targeting households at the bottom quintile of the income distribution. However, income replacement rates and coverage varied considerably across countries and many lower-middle-income households were left uncovered (Brum et al., 2020; Lustig et al., 2021). Brazil is a notable exception to this pattern, with high replacement rates even among the low-middle classes (Brum et al., 2020).

As the effectiveness of lockdown measures to contain the spread of the virus are highly correlated with poverty levels, countries that implemented COVID-19 income relief programs and lockdown measures should have been more effective in curbing the spread of the virus by reducing geographic mobility. Bargain and Aminjonov (2021) analyze the effects of lockdowns considering the poverty composition of nine countries in Latin America and Africa. They find that, in general, changes in geographic mobility following lockdown mandates are more pronounced in areas with lower poverty. As exceptions, Brazil and Mexico are the only countries where poverty does not clearly predict mobility.

At least partially, the exceptionality of Brazil and Mexico is explained by lack of political coordination and leadership. While both countries had presidents that denied the seriousness of the pandemic (Dunn & Laterzo, 2021; Rosario et al., 2021), unlike Mexico, Brazil implemented cash transfers at the very onset of the virus outbreak (Beazley et al., n.d.; Lustig et al., 2021). Therefore, in principle, lockdown measures should have been more effective in Brazil than in Mexico, as cash transfers should enable the population—particularly the most disadvantaged—the means to shelter-in-place. However, as shown by Barberia and Piazza (2021), the Brazilian EA policy was not associated with decreases in physical mobility and, as such, Brazil did not have substantially better outcomes in managing the spread of the virus than Mexico (Ferreira et al., 2021).

While the long-term effects of social protection measures have still to be witnessed, studies have simulated the short and long-run impact of the COVID-19 pandemic on various inequality realms. Recent studies show that, while conditional cash transfer programs implemented during the COVID-19 pandemic were important to curb poverty increases, they were not enough, for example, to address schooling inequalities as a result of prolonged school closures (Engzell et al., 2021; Lustig et al., 2021; Zoido et al., 2020). Estimates suggest that in Latin America, the (typically

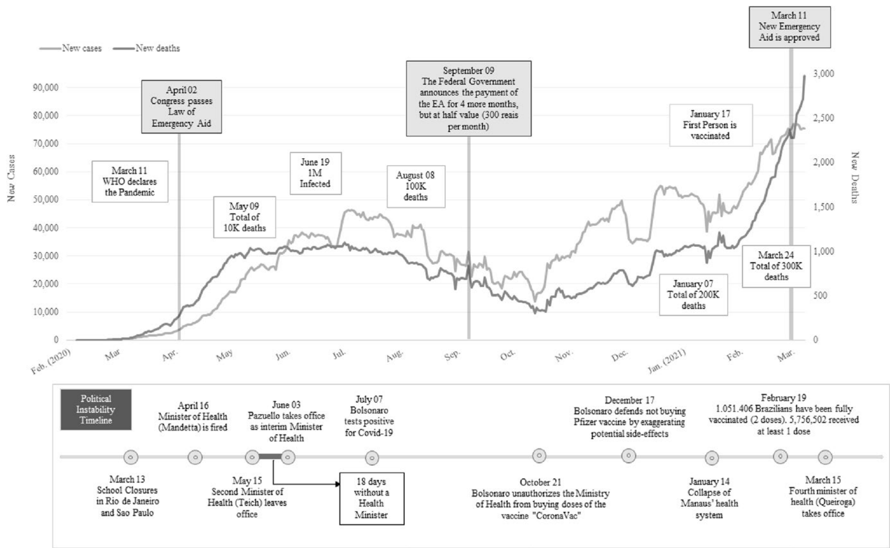

Fig. 1 Timeline of the pandemic in Brazil

high) school attainment levels of children with low-educated parents could fall by 20 percentage points (pp), and as much as 32 pp in Brazil (Neidhöfer et al., 2021).

The Brazilian Context and the Emergency Aid

On February 26, 2020, Brazil reported the first confirmed case of COVID-19. As of March 2021, over 12.7 million people had been infected, and confirmed deaths were above 320 thousand. Figure 1 summarizes trends in the number of cases and deaths during the first year of the pandemic, highlighting health and political benchmarks. The pandemic reached its first peak in mid-July 2020 and, from then until November, the number of cases and deaths receded. In December, the North region started to experience an increasing surge in cases and mortality that would reach the rest of the country around January. By March 2021, most public hospital ICUs were at critical capacity—defined as 80 percent or more.

Adding to the public health calamity, Brazil went through a political crisis (Prates & Barbosa, 2020). While President Bolsonaro was adamantly against lockdown measures throughout the pandemic,[1] various states and local governments adopted them—although in a non-coordinated manner and to varying degrees of strictness (de Moraes, 2020; Tavares & Betti, 2021). Since social confidence in institutions

[1] The Federal Government's expenditure on scientifically unproven drugs combined with the lack of investment on early purchases of vaccines were at the center of an inquiry mandated by Brazil's Federal Supreme Court during 2021.

negatively correlates with COVID mortality (Elgar et al., 2020), the political polarization and lack of a unified discourse between Federal and local governments contributed to the deteriorating trust of the population on public institutions.

Despite the political polarization, the National Congress approved one of the most generous social welfare responses in the country's history. The EA was a conditional cash transfer policy intentionally put in place to allow workers to stay at home, attempting to compensate the inevitable loss of income particularly for middle- and low-income families. This social protection is especially important given that roughly 40 percent of the workforce is employed in the informal sector (IBGE, 2020a).

The Federal Government's initial proposal was of a transfer of approximately 200 Brazilian Reais (roughly 88 $PPP—Purchasing Power Parity), developed as an alternative to the multiple aid proposals in discussion by legislators. However, this initial proposal was rejected by Congress, who deemed the amount too low. On March 26, 2020, Congress approved a law that stipulated a new EA at a much higher value. On April 2, the president ratified the Law. The policy implementation happened swiftly because Brazil is a country particularly well equipped for time-sensitive targeted policies due to the CadUnico—*Cadastro Unico* or Unique Register, an administrative register that gathers information on roughly one-third of the Brazilian population for the purposes of social assistance policies[2].

Initially, the EA Law determined a monthly payment of 600 Brazilian Reais (266 $PPP) for three months to informal adult workers whose family income totaled up to three times the value of the minimum wage or with per capita family income below half the minimum wage[3]. Single mothers qualified to receive twice the monthly amount, and no family could receive more than two payments per month. The EA substituted the conditional cash transfer *Bolsa Familia*[4] in situations in which the value of the latter would be lower than the former.

The EA was extended for two additional months in July 2020. On September 1, the Federal Government authorized another extension until December, however, at half of the initial value and with more restrictive rules[5]. On March 11, 2021, a third round of the EA—the "New EA"—was approved by Congress and ratified by the president on March 18. The New EA was much lower than the original, with transfers varying from 175 Brazilian Reais for singles, 250 for couples, and 375 for single mothers. Furthermore, to be eligible for the new EA, one should have received the 2020 EA and not have had their eligibility canceled for any reason. Therefore, besides the substantially lower value, families that fell into poverty in 2021 but were not in poverty in 2020 were not contemplated. The inability to dynamically adjust to changes in conditions faced by the individuals became one of the main points of

[2] The CadUnico is an administrative record established in 2001. Its main objective is to serve as an input for planning public policies in all spheres of government. Currently, registration in the CadUnico is necessary to access twenty different social programs of the Federal Government, targeted mainly toward low-income individuals and families.

[3] The monthly minimum wage in 2020 was 1,045 Brazilian Reais.

[4] Average monthly payments from Bolsa Familia are usually below 200 Brazilian Reais per family.

[5] For more details on changes in eligibility rules during the different phases of the EA, see World Bank (2021).

criticism to the program's design, partially explained by the false assumption that it would only last a couple of months (World Bank, 2021).

Preliminary reports on the effects of the Brazilian EA suggest that the policy curbed increases in poverty and inequality, actually decreasing both factors, even when compared to pre-COVID levels (Gonzalez & Barreira, 2020; Lustig et al., 2021; Masri et al., 2021; Menezes-Filho et al., 2021; Prates & Barbosa, 2020). Masri et al. (2021) estimate that the pandemic resulted in roughly 13 million job losses between December 2019 and August 2020, and labor income losses disproportionality affected households at the bottom of the income distribution. Without the EA, extreme poverty levels would have increased from a pre-covid level of 5–14 percent. However, considering the EA, poverty fell to four percent (Marsi et al., 2021). Inequality also declined in response to the aid: taking the EA into account, the Gini index fell to about 0.47, considerably lower than its pre-COVID level of 0.53 (Menezes-Filho et al., 2021).

Research Questions and Hypotheses

Our study joins the effort to evaluate the mitigating impacts that the EA had during the first months of the COVID-19 pandemic. While the focus is on Brazil, we place our discussion in the broader context of the role of cash transfers and social protection initiatives during moments of crisis. Our distinctive contribution has timing and methodological components. Timing relates to using a panel dataset gathered during the pandemic rather than simulations based on prior surveys. Methodologically, we combine distinct methods and units of analysis, which contributes to a better understanding of how families experienced the pandemic and how the policy eased adverse effects.

Our main objective is to understand how the EA policy affected inequality, poverty, and the labor market during the most uncertain months of the COVID-19 pandemic. Understanding the positive and negative effects of transfer programs in the population speaks to several current debates on social protection, such as the universal basic income and policy responses to disasters. While we bring evidence to advance these discussions, our results should not be interpreted in a causal fashion, as the dataset analyzed did not cover a pre-pandemic timespan, and the moment is unique on its own. Still, the use of fixed-effects estimators and panel data confers more robust estimates of the EA's impact within households compared to what a cross-sectional analysis would have allowed.

Given previous research and our focus in understating how the EA impacted social inequalities, we develop four main research questions and hypotheses:

1. *Did the EA benefit the most vulnerable?*

Leveraging the pre-existing social protection infrastructure, Latin American countries were able to rapidly implement emergency measures to curb income losses due to the pandemic (Brum et al., 2020). Brazil has an administrative registrar (CadUnico) that centralizes information on roughly one third of the population and 20 Federal social assistance programs, thus allowing for the rapid and efficient allocation of money to the most vulnerable and in the most remote locations in the country. The EA leveraged CadUnico to select about 40 percentage of its beneficiaries across all three phases of the program (World Bank, 2021). Given this infrastructure, *we expect the EA to have effectively target the non-privileged*.

2. *Did the EA impact labor market indicators (unemployment and labor force participation rates) within households?*

One of the objectives of the EA as a social protection policy was to allow individuals to stay in their homes. The most affected by the pandemic were precisely those who could not afford to stop working or to switch to remote work. By conferring money to lower-income populations, *we expect the EA to be associated with reductions in labor force participation within households*. Importantly, labor force participation reductions would have been "positive" outcomes given the specificities of the pandemic context.

The effect on unemployment is theoretically ambiguous. On the one hand, people who were unemployed may have stopped looking for work and left the labor force. On the other hand, the EA may have served as a cushion for those who became unemployed, enabling people to keep looking for employment. Likewise, employers may have felt more inclined/comfortable to lay off people by knowing they would be insured by the EA. While the overall employment rate in the country is estimated to have fallen by six pp (Soares & Berg, 2022), within-households dynamics as a response to the EA have not yet been fully investigated.

3. *How did the EA affect household's income dynamics?*

Previous studies report that the coverage and size of the EA in Brazil was so extensive that it decreased poverty and inequality to levels lower than pre-pandemic estimates (Lustig et al., 2021). The effectiveness of the Brazilian EA in replacing income losses during the COVID-19 pandemic was one of the highest among emergency transfers in Latin America (Brum et al., 2020).

Intuitively, households more likely to receive the EA are also those more likely to become unemployed or leave the labor force. As such, *we expect that, within households, the EA will be associated with reductions in per capita household income (exclusive of the EA)*. Consequently, the EA becomes a compensation mechanism in which households experiencing higher income losses would also be the ones receiving higher monthly transfers (EA). Relatedly, *we also expect the EA's compensatory household income mechanism to reduce the probability that families fall below the poverty line over the months.*

We note that the hypotheses outlined here follow from an expected adequate program targeting at its origin, and not over time. In other words, although we expect the EA to operate as a compensatory mechanism, this feature stems from the original design (namely, targeting the most vulnerable), and not by a dynamic adjustment to individuals' conditions. In fact, had the program had a dynamic adjustment mechanism to include new beneficiaries over time, the expected income compensating effects would have been even higher. However, in practice, the program determined that only those eligible at its conception would remain eligible in the following rounds, as long as they continued to meet the program criteria[6].

4. *How did the EA affect between-group inequality?*

Brazil is a country where race, class, and gender have historically interacted to form rigid slow-changing social stratification structures (Salata, 2020). As such, the non-White population comprisesthe majority of those at the bottom of the income distribution while the White population dominates elite positions (Monk, 2016). By redistributing income to the poorest, *we expect that the unprecedented scale of the monetary transfers conferred by the EA to drastically, albeit only temporarily, decrease between-group inequality*.

Data Source and Variables

Data

Our data source is the COVID National Household Sample Survey (PNAD COVID). PNAD COVID is a household survey produced by the Brazilian Institute of Geography and Statistics (IBGE), Brazil's primary data and statistics provider. PNAD COVID originated as an experimental survey in response to the COVID-19 pandemic, and as a subsample of the Continuous PNAD—the main household survey in the country.

PNAD COVID data collection began in May and continued until November 2020, covering questions related to the effects of the pandemic on households, including health, employment, and income. Of interest to this research, the EA was specified as a separate income source rather than coupled with other transfers. The survey is organized as a panel, in which each household is interviewed once per month. PNAD COVID's sample comprises 2.6 million individuals in 904 thousand households.

PNAD COVID is an unbalanced panel of households, for reasons that IBGE did not make explicit. Overall, 60 percent of the households show up in all seven months, and 19 percent in six months. We investigated whether the unbalance could be considered random based on selected characteristics of the householder (gender, race, and education), but did not find evidence of randomness. Therefore, we opted to work with an unbalanced but more representative panel of households, including those that showed up at least in four of the seven months. As such, we analyze the data for 94 percent of the sample.

[6] Monthly checks to verify if individuals continued to be eligible were introduced in EA round 2. As a result, the number of beneficiaries fell from 68 million in round 1, to 56 million in round 2 and 39.4 million in round 3 (World Bank 2021).

Variables

Dependent Variables

To answer our research questions and test their related hypotheses, we analyze the effects of the EA on four socioeconomic indicators, defined as such:

Equivalized per capita household income is a continuous variable, calculated by dividing total household income (before taxes and after transfers) by the equivalized household size (as in the OECD (2021)[7] equivalence scale).

Poverty status is a dummy variable equal to one if the equivalized household per capita income falls below the international poverty line for upper-middle-income countries ($5.50 or 375 Brazilian Reais) and zero otherwise.

Household labor force participation is defined as the sum of employed and unemployed individuals as a share of the adult population (age 14 and higher) in the household.

Household unemployment rate is defined the number of individuals who do not have a job but are actively looking for one as a share of the adult labor force in the household.

As we discuss in the Methods section, our analysis relies on different units of observation at the descriptive and inferential sections, respectively, individuals, and households. The above-mentioned definitions of household labor force participation and household unemployment rates correspond to the ones used in the inferential analyses. We adopt standard definitions *at the individual level* in the descriptive section[8].

[7] Following OECD (2021), the first adult received a unitary weight, children under age 14 receive a weight of 0.3, and each subsequent person aged 14 and over receives a weight of 0.5. Total income is deflated at November 2020 Brazilian Reais (R$) prices using IBGE's deflators. Zero incomes and the top 1 percent households in per capita income were removed from the analysis.

[8] In the descriptive section we define both variables as is standard in the literature. Labor force participation is the sum of employed and unemployed individuals as a share of the adult population. Unemployment rate is the number of individuals who do not have a job but are actively looking for one as a share of the labor force. These indicators are calculated for individuals aged 14 and older – the legal working age in Brazil.

Independent Variables

Per capita Emergency Aid is our key independent variable, defined as the total EA divided by the equivalized household size[9].

Race and gender of the head of the household are used to study heterogeneous effects of the EA on the dependent variables. Both gender and race[10] are coded as binary as follows: White men, White women, Black men, Black women.

Methods

Our empirical investigation begins with a descriptive analysis *at the individual level*, in which we summarize the socioeconomic scenario of Brazil in 2020 and carry a counterfactual analysis of income inequality had the EA not existed. In acknowledging the structural disparities that exist in Brazil, we also disaggregate the results by race and gender. Next, we turn to an inferential analysis to observe how the EA affected *household* dynamics during the pandemic.

Our choice for multiple units on analysis requires some explanation. We begin at the individual-level to assure comparability with the standard literature on work and employment. However, the bulk of analyses are carried at the household level as a direct acknowledgment that economic decisions (labor force participation inclusive) are often carried out by the family in considering all resources and constraints available (Blau & Robins, 1988; Blundell et al., 2016). Pandemic-related environmental constraints—such as school closures and shelter-in-place regulations—added further complexity to these decisions, making the investigation of household dynamics even more critical. To the best of our knowledge, our study is the first to focus on labor indicators at the household level in the context of the COVID-19 pandemic in Brazil.

[9] We note that all questions regarding income (including the EA) were asked in the present tense, whereas questions regarding employment status had the prior week as a reference. Interviews were administered throughout the month, but the specific week is not identified in the data. As a result, individuals interviewed during the first week of each month (about one fourth of the sample) have a mismatch between the income period (current month) and the labor force and unemployment information (prior month). Even though we cannot solve this problem, the fact that our analysis is at the household – in which it is unlikely that all members changed their employment status from one week to the next – partially mitigates it. Further, by design, this problem does not affect most of the sample, namely households interviewed after the first week of the month. However, to test how much this problem was driving our results, we ran our main models with one-month lag on per capita EA. The results remained consistent regardless of timing. We opted to use the non-lagged specification as our preferred one as the EA is more likely to affect immediate decisions, especially given the pandemic scenario and the expectation that the program would not last long.

[10] We code Black, Brown, and Indigenous populations as Black, and White and Asian and white following the common practice in the specialized literature (Bailey, 2008).

Overall Effects of the EA on Outcome Variables

We rely on fixed-effects models as our main specification, leveraging the panel component of the dataset to remove household-level unobserved heterogeneity. All models are carried at the household level, in which each observation represents one household, and each household shows up in the panel at least four (out of seven) times.

In Eq. (1), $Y_{i,t}$ represents the four different dependent variables: household labor force participation, household unemployment, per capita household income, and poverty status. The key independent variable is per capita EA ($EA_{i,t}$). We include lagged dependent variables as regressors to account for persistent time series and reduce reverse causality concerns. Interactions between state[11] and month capture common shocks, differences in local policy responses, and the pandemic severity alongside these space and time dimensions. Household fixed effects (α_i) tackle household unobserved heterogeneity.

$$\widehat{Y_{i,t}} = \alpha_i + \beta EA_{i,t} + \gamma Y_{i,t-1} + \delta(state_i \times month_t) \tag{1}$$

Specifications for all dependent variables are linear, except for the poverty model, in which we use a logistic regression. Consequently, in the fixed-effects model for poverty, only families that changed status across time—either by leaving poverty or falling below the threshold—remained in the regressions. We cluster the standard errors at the household level in all linear models, as suggested by Bertrand et al. (2004).

In addition to per capita EA, we investigate two other specifications: a dichotomous EA (received or not), and the EA as percentage of the total household income (exclusive of the EA). These additional models are reported in Table 5 in the Appendix.

Heterogeneous Impacts by Race and Gender

As discussed, the environmental changes imposed by the pandemic—such as school closures and shelter-in-place restrictions—may have altered gender and racial inequalities. Therefore, in our next set of analysis, we uncover whether the EA has unevenly impacted these groups. As per Eq. (2), the models herein differ from the prior ones by the inclusion of an interaction between the EA and race and gender of the head of household. To allow the model to capture non-linear relationships, this time we also include a quadratic EA.

$$\widehat{Y_{i,t}} = \alpha_i + \varphi(EA_{i,t}^2 \times \text{race}_i \times \text{gender}_i) + \gamma Y_{i,t-1} + \delta(\text{state}_i \times \text{month}_t) \tag{2}$$

[11] We adopt specifications at the state level as we only have more granular geographical identifiers for individuals living in capitals or metropolitan areas containing capitals (roughly 30 percent of the observations). Therefore, we preferred to focus on the entire sample.

Limitations

One of this paper's main limitations stems from the temporally brief data coverage—May to November 2020. Ideally, we would like to both extend our analysis backward and forwards. While the two-way fixed-effect estimation controls for household unobserved heterogeneity and most of the environmental and time shocks, the absence of a pre-treatment period prevents us from assessing causality[12]. Conversely, extending the data into the future would allow observing a period in which the EA was reduced and then eliminated, and in which the pandemic achieved its worst moment, reaching over 4 thousand deaths a day, and when shelter-in-place regulations were reinstated in many states[13]

Despite such limitations, the months for which we have data allow us to document how the EA policy influenced structural inequalities during the first moments of the crisis and how households responded to the transfer. Such findings contribute to evaluating the EA and advancing the literature on emergency responses and cash transfers in developing countries more broadly. We hope these lessons will be informative for future policy implementation in Brazil and elsewhere.

Results

Descriptive Analysis: General Impacts of the Emergency Aid

This section describes the socioeconomic conditions faced by Brazilians during the first months of the pandemic, with *individuals* as the unit of analysis. Table 1 provides estimates of inequality, poverty, unemployment, and labor force participation of the Brazilian population between May and November 2020. For inequality and poverty, we report estimates that reflect the actual scenario experienced by individuals (*with aid*) and counterfactual estimates where we deduct the contribution of the EA from total family income (*without aid*). We also include estimates of the predicted social indicators for the new EA that began in April 2021. The predictions are based on household characteristics in November 2020 (when our data ends), as only individuals who received the aid until it ended in December 2020 were eligible to apply for the new aid[14].

[12] While it is in theory possible to go back in time by linking PNAD COVID and the 2019 Continuous PNAD (Menezes-Filho et al., 2021), this cannot be done without important shortcomings such as a sizable sample size reduction and a final sample that is not necessarily nationally representative. Further, the rewording of some questions make both surveys not directly comparable in key measures, including income and unemployment (Duque et al., 2020; IBGE, 2020b).

[13] The release of the Continuous PNAD for the year 2021 has been postponed; therefore, we are also unable to provide estimated projections based on that dataset. Furthermore, the Continuous PNAD does not include information on the EA.

[14] These predictions likely represent a lower bound estimate for poverty and inequality, considering that we assume that families' socioeconomic condition remained stable from November 2020 to April 2021.

We observe that in the absence of the EA, the Gini coefficient would have remained above 0.50—in line with the historical pattern observed in Brazil (Souza, 2018). When we compare inequality estimates once the EA is factored into family's incomes, the results are quite striking. The Gini coefficient in all months remained below 0.50 for the first time in measurable Brazilian history. The Gini seems to have responded strongly to the implementation of the EA, staying at its lowest levels during the months for which the EA was given at its full value (600 Brazilian Reais) and increasing for the months the aid was cut by half. The predicted estimates for 2021 show that, even with a much smaller transfer, the new EA might keep inequality below 0.50.

Figure 2 illustrates the differences in Lorenz curves with and without the EA for the pooled sample (May–November). We observe a clear Lorenz dominance, with the curve representing the EA being much closer to the line of perfect equality than that without it. Figure 7 in the Appendix clarifies this shift further by plotting the difference in income distributions with and without the aid. The picture is clear: the poorest households received the largest income gains overall, and the difference between the two curves decreases as one moves up the income distribution.

Poverty levels also declined substantially. With the EA, extreme poverty—defined as 1.90 $PPP/day—affected less than 1 percent of the population between May and November of 2020 (Table 1). Without the aid, extreme poverty levels would have been much higher, varying between roughly eight and ten percent during the worst months of the pandemic (as shown in Table 1). The poverty reduction was also substantial in comparison to 2019 levels (pre-pandemic)[15]. A reduction in total poverty as compared to the scenario without EA is also observed when using a poverty line of 5.50 $PPP. Poverty decreased continuously until August, when the EA was readjusted to half of its initial value. Between August and September, the population living below 5.50 $PPP per day increased from about three to roughly six percent. The predicted values for April 2021 show that *extreme* poverty is likely to increase, while poverty levels measured at 5.50 $PPP/day will possibly remain stable—or decrease, as per our upper-bounded predictions.

Table 1 also reports estimates of the percentage of children—those aged 14 or younger—living below 1.90 $PPP and 5.50 $PPP a day by race. Two facts are worth pointing out here. First, children are overrepresented among the poor. This has important implications for society at large, given that the non-contemplation of basic needs during the early stages of development has important and often irreversible consequences that affect individual's life prospects (Heckman & Mosso, 2014; Hobcraft & Kiernan, 2001). Second, in the absence of the EA, a much higher proportion of Black children than White children would be living below the poverty line. Therefore, the policy functioned not only to decrease overall levels of child poverty but also to substantially close the racial poverty gap between children. For

[15] According to data from the 2019 Continuous PNAD, 6.5 percent of the population were living below 1.90 $PPP per day in that year (IBGE, 2020c). Therefore, the EA was enough to not only compensate for the number of people that would have fallen into extreme poverty, but to also lift out of poverty the majority of those already in that condition.

Table 1 Inequality, poverty, and labor market indicators by month-2020

Indicator	EA Scenario	Month							Predicted April 2021
		May	Jun	Jul	Aug	Sep	Oct	Nov	
Inequality									
Gini	Without aid	0.54	0.54	0.54	0.53	0.53	0.52	0.52	
	With aid	0.46	0.45	0.44	0.44	0.44	0.46	0.47	0.47
Income Share (90—100)	Without aid	0.41	0.41	0.41	0.41	0.40	0.40	0.40	
	With aid	0.37	0.37	0.37	0.36	0.36	0.37	0.37	0.38
p90/p50	Without aid	3.27	3.22	3.18	3.18	3.17	3.14	3.16	
	With aid	2.85	2.77	2.74	2.74	2.77	2.82	2.89	3.20
Poverty									
Population living below poverty (%)									
$PPP 1.90 /day	Without aid	8.99	9.76	8.92	8.46	8.19	7.20	6.85	
	With aid	0.48	0.28	0.23	0.21	0.21	0.55	0.63	1.44
$PPP 5.50 /day	Without aid	16.31	16.45	15.38	14.71	14.37	13.16	12.72	
	With aid	4.20	3.48	2.80	2.63	2.81	5.82	6.89	4.90
Children living below $PPP 5.50 /day (%)									
White	Without aid	17.00	16.71	15.58	14.90	14.64	13.59	13.07	
	With aid	5.14	3.97	3.47	2.86	3.17	6.24	7.08	4.43
Black	Without aid	30.15	30.72	29.28	28.32	28.11	25.59	24.99	
	With aid	6.84	6.19	5.20	4.92	5.51	12.39	14.51	8.66
Unemployment rate (%)	–	10.12	11.64	11.63	12.05	12.54	12.73	12.98	
Labor Force Participation (%)	–	56.81	57.50	57.75	58.51	58.99	59.57	59.87	

Data Source: PNAD Covid 2020

Gini and poverty lines calculated based on monthly household equivalized income in Brazilian Reais (R$) adjusted for inflation

Predicted values are based on the rules for eligibility for the New Emergency Aid that will begin in April 2021, with household characteristics in November 2020 used as benchmark

example, while without the EA an estimated 17 percent of White and 30 percent of Black children would be living at 5.50 $PPP a day or less in May 2020, with the EA these proportions went down to five and seven percent of White and Black children, respectively.

Regarding the workforce, we observe an upward trend in unemployment levels going from about 10–13 percent from May to November. Labor force participation has also continuously risen, even during the months in which the EA had its higher values, going from roughly 57–60 percent. With a growing labor force, part of the unemployment surge may have been driven by more individuals looking for jobs rather than purely by layoffs.

Figure 3 disaggregates the trends in labor force participation and unemployment rates by race and gender. Black women's unemployment rates suffered the fastest and most substantial surge, going from about 13 percent in May to roughly 19 percent in November. This increase was much higher than the increase in labor force participation rates for Black women, which went from roughly 46–49 percent. For all other racial-gender groups, unemployment rates increased by roughly 2 pp, in tandem with increases in labor force participation. White men's unemployment rates are the lowest at nine percent, and their labor force participation remained the highest at about 70 percent.

Regression Results

Table 2 presents the results of our main set of household-level analysis. We find that per capita EA reduces labor force participation and increases unemployment rates, although in small magnitudes: each additional per capita Brazilian Real is associated with decreases in household's labor force participation rates by 0.001 pp, and increases in household's unemployment rates by 0.002 pp. We interpret these numbers as significant statistically, but not economically. As such, concerns that cash transfers could translate into disincentives to work are not proven valid during the first months of the pandemic in Brazil.

Regarding income, each additional Real in aid decreases per capita income by 0.25, while also reducing the log-odds of households falling below the poverty line by 0.008 (a probability of roughly 50%)[16][17]. Therefore, strengthening the findings form the descriptive section, it seems that the EA turned into a mechanism that significantly compensated for income losses and benefited the most vulnerable, temporarily decreasing poverty and inequality. Finally, we observe a high persistency of intra-household economic conditions from one month to the following, as all lagged dependent variables exhibit positive and significant coefficients.

We tested the robustness of our findings by observing how the EA coefficients change as we add variables, and by studying alternative specifications. In the former case, Table 4 in the Appendix clearly shows that the inclusion of state-month fixed effects or the lagged dependent variables do not change our conclusions. Further, alternative operationalizations of our main independent variable (EA) in Table 3 reveal overall consistency across all models. However, two differences are worth noting in the labor force model: although receiving the EA does not lead to a difference in expected household labor force participation compared to not receiving it, as the importance of the EA relative to other income sources increases, we observe higher decreases in labor force participation. While in normal circumstances, negative cash transfers incentives on the labor force are considered undesirable, in a pandemic context we interpret this effect as beneficial: in practice, the EA granted those

[16] To convert the log-odds into probabilities we calculate: P = exp(log-odds)/(1 + exp(log-odds)).

[17] We interpret the poverty model with caution. Mechanically, the logistic model dropped all households that did not experience sufficient variation in poverty status over the period. Therefore, our results in column 4 reflect only families that either fell below the poverty line or that left it. Figure 8 in the Appendix provides a detailed sequence analysis of income brackets transitions.

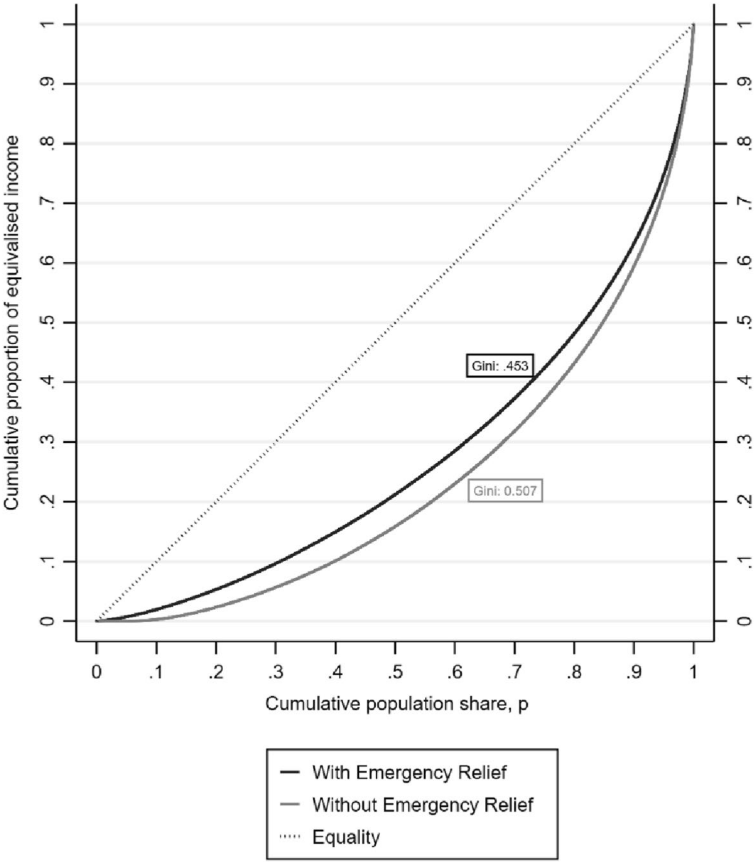

Fig. 2 Comparing Lorenz curves and Gini coefficients of monthly equivalized incomes with and without EA for pooled sample (May–November). *Note*: Calculations exclude families with total household incomes of zero in a given month

who typically could not afford working remotely the possibility of staying at home, which was one of the policy's objectives[18].

Furthermore, when operationalizing the EA as percentage of household income, its impact on the probability that family's fall below the poverty line is no longer negative, but positive. Hence, as the importance of the EA in the total household income increases so does the probability that families fall below the poverty line. We interpret this association as suggestive that the EA is on average acting as an effective compensatory household income mechanism, particularly for households

[18] Economic theory predicts that cash transfers could negatively affect labor market participation and prolong unemployment spells by increasing worker reservation wages. This includes unemployment insurance (Schmieder et al., 2016) and basic income programs (Alzúa et al., 2013).

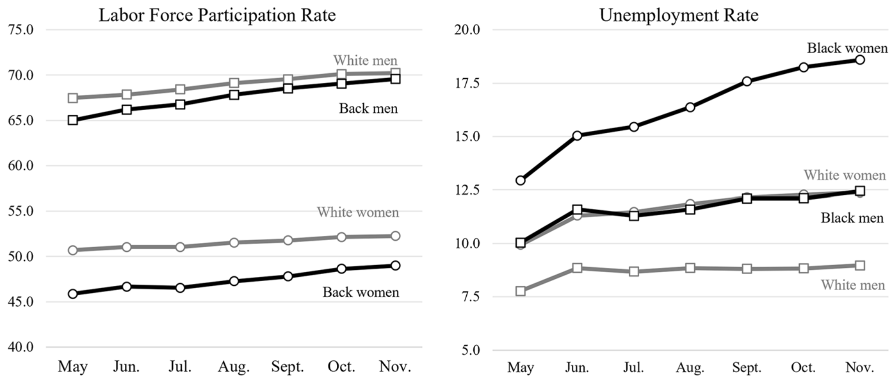

Fig. 3 Labor force participation and unemployment rates by race and gender. *Note*: Labor force participation rates are represented by continuous lines, while unemployment rates are given by the dashed lines. Fig 3 includes all adults aged 14 or more

in higher risk of poverty. Family's that are more likely to depend on the EA as their main source of income are also more likely to fall below the poverty line.

Table 5 in the Appendix reports the interactions between EA and gender and race of the head of the household. Based on the interaction effects, it seems that the EA has not been enough to reverse prior demographic inequalities. For a closer inspection of these differences, we plot predicted values and the contrasted differences for each demographic group by EA amount in Figs. 4, 5, 6. Figures 4 and 5 reveal stability of household labor force and unemployment rates across different values of the EA, once again highlighting that is has not substantially affected labor market behaviors. It also highlights that households headed by women have typically lower labor force participation and higher incidence of unemployment. Finally, Fig. 6 reveals that households headed by men typically have higher per capita income. More importantly, it shows an inverse relationship between EA amount and income from other sources for every group—a clear illustration of the compensation mechanism that we uncover.

Discussion and Conclusion

In 2020, the COVID-19 pandemic hit the world in an unexpected and unprecedented way. Beyond the numerous casualties, it highlighted structural differences in resilience across countries and triggered distinct responses. As we begin to foresee a closure for the pandemic with the (unequal) rollout of vaccines, investigating how effective the various responses were is necessary not only as a policy evaluation effort per se, but also as a forward-looking exercise for better preparedness for future crises.

Table 2 Effects of Per Capita EA on Households

Variables	Linear models			Logit
	(1)	(2)	(3)	(4)
	HH labor force participation	HH unemployment rate	HH per capita income	HH below \$5.50 poverty line
Per capita EA	−0.001***	0.002***	−0.245***	−0.008***
	(0.000)	(0.000)	(0.007)	(0.000)
HH LFP (t−1)	0.256***			
	(0.003)			
HH unemployment rate (t−1)		0.220***		
		(0.004)		
Per capita HH income (t−1)			0.166***	
			(0.005)	
Poverty status (t−1)				0.547***
				(0.029)
State*month	✓	✓	✓	✓
Observations	713,454	536,859	689,717	57,682
R-squared	0.082	0.056	0.041	
Number of households	135,658	109,394	133,682	11,089

All models are run at the household level

We restricted the sample to households that showed up in the panel at least four times, although most showed up all seven times. Observations reflect the number of appearances of households across all months

The logit model reflects only households that changed poverty status

Standard errors clustered at the household level in parentheses in all models, except the logit

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

In this paper, our main concern was to quantify the effect that the global pandemic and a large-scale emergency relief policy had on the resilience of families during the initial months of the crisis in Brazil. We argue that Brazil makes an interesting case study for several reasons. Besides being one of the pandemic hot spots, Brazil rather quickly implemented one of the most generous conditional cash transfer policies in the world. Additionally, as most of Latin America, the country suffers from high levels of income inequality and poverty and a large informal workforce such that lessons learned from it may provide insights into the regional context and beyond.

We focused on four indicators related to the socioeconomic condition of families: poverty, inequality, labor force participation, and unemployment rates. We add to the existing literature by taking advantage of a novel data source collected

Table 3 Alternative Specifications

Variables	Linear models									Logit models		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Labor force participation			unemployment rate			Per capita income			Below $5.50 poverty line		
Per capita EA	–0.001***			0.002***			–0.245***			–0.008***		
	(0.000)			(0.000)			(0.007)			(0.000)		
Received EA (dummy)		–0.052			1.122***			–141.823***			–1.273***	
		(0.125)			(0.140)			(4.466)			(0.042)	
EA as percentage of hh income			–0.129***			0.217***			-10.275***			0.014***
			(0.003)			(0.004)			(0.088)			(0.000)
HH LFP (t−1)	0.256***	0.256***	0.248***									
	(0.003)	(0.003)	(0.003)									
HH unemployment rate (t−1)				0.220***	0.220***	0.206***						
				(0.004)	(0.004)	(0.004)						
Per capita HH income (t−1)							0.166***	0.166***	0.156***			
							(0.005)	(0.005)	(0.005)			
Poverty status (t−1)										0.547***	0.733***	0.775***
										(0.029)	(0.027)	(0.028)
State*month	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	713,454	713,454	695,595	536,859	536,859	524,625	689,717	689,717	689,717	57,682	57,682	55,530
R-squared	0.082	0.082	0.094	0.056	0.057	0.093	0.041	0.041	0.089			
Number of households	135,658	135,658	134,089	109,394	109,394	108,155	133,682	133,682	133,682	11,089	11,089	10,862

All models are run at the household level

We restricted the sample to households that showed up in the panel at least four times, although most showed up all seven times. Observations reflect the number of appearances of households across all months

The logit model reflects only households that changed poverty status

Standard errors clustered at the household level in parentheses in all models, except the logit

***$p<0.01$, **$p<0.05$, *$p<0.1$

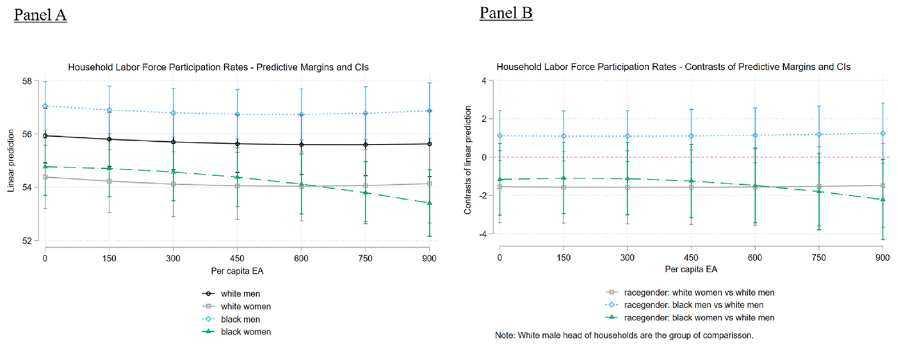

Fig. 4 Per capita EA effects on household labor force participation rates—predictive margins and contrasts marginal by gender and race of head of household

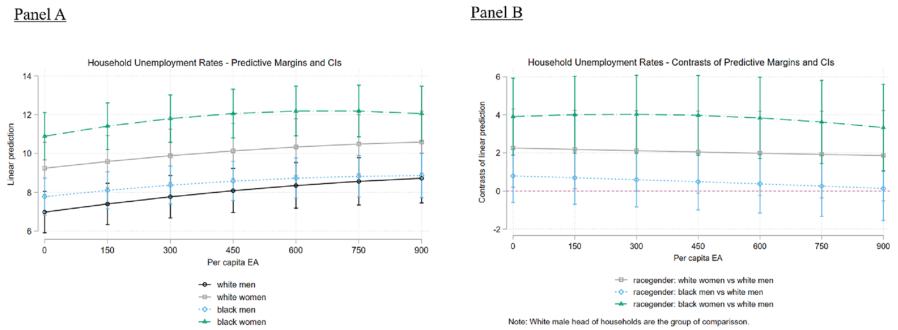

Fig. 5 Per capita EA effects on household unemployment rates—predictive margins and contrasts marginal by gender and race of head of household

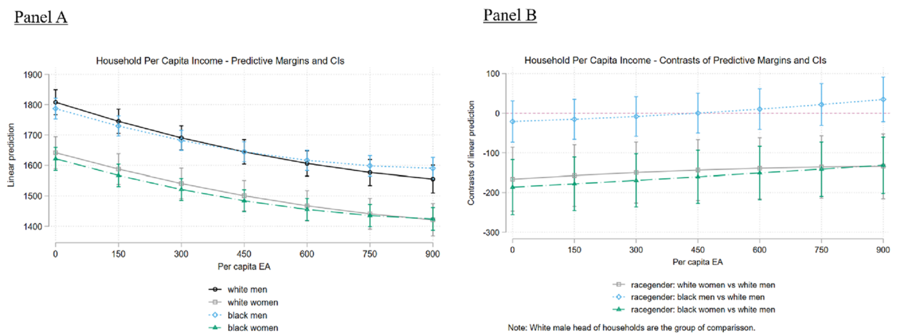

Fig. 6 Per capita EA effects on household per capita income—predictive margins and contrasts marginal by gender and race of head of household

during the pandemic, as well as diverse methods and units of analysis. Due to data limitations, most studies, particularly on low- and middle-income countries, focus on aggregate descriptions and individual dynamics. However, given the household panel nature of the dataset we used, we can rely on more robust inferential statistical techniques. Furthermore, we go beyond individual-level descriptive dynamics by analyzing household-level socioeconomic changes during the most uncertain months of the pandemic. By controlling for household-level unobserved heterogeneity, we can better weed out the direct effects of the EA on the resilience of families. Unfortunately, our dataset does not cover any pre-pandemic months, which hinders the causal interpretation of the dynamics in our models.

Policy-wise, in line with our first and third hypotheses, our fixed-effects regression models suggests that the EA has effectively targeted those in most need, functioning as a household income compensatory mechanism. Furthermore, we find that the EA is statistically associated with reductions in intra-household labor force participation rates and increases in unemployment. However, the coefficients of this association are rather small, which leads us to conclude, contrary to our second hypothesis, that the EA has not meaningfully affected labor force participation and unemployment dynamics at the household-level during the period analyzed.

Consistent with prior studies (Lustig et al., 2021; Masri et al., 2021; Menezes-Filho et al., 2021; Prates & Barbosa, 2020) and with our fourth hypothesis, we find that inequality reduced to a historical low and poverty declined substantially—even compared to pre-pandemic levels, with positive spillovers on reducing historical racial inequities, especially among children. Absent the policy, adverse income shocks would have been significant, and given its temporary feature, these impacts will likely be felt once the transfer ends.

Furthermore, our fixed-effects regression models do not identify changes associated with the EA and householder race and gender. These findings complement the descriptive individual-level analysis: although we observe increased unemployment, particularly for black women (Fig. 3), the regressions indicate that these differences are not associated with the EA (Figs. 4, 5, 6). Rather, the EA has reduced poverty and compensated for income losses without strong effects on intra-household labor dynamics.

Although we uncover a successful story of the EA policy during the first months of the pandemic, it is no standalone solution to the socioeconomic challenges imposed by the circumstances. Despite the extraordinary impact on poverty and inequality, the EA was not enough to curb the spread of the virus and the collapse of the health system, nor to tackle non-monetary vulnerabilities associated with poverty such as unequal access to services and living arrangements that favor the virus propagation. Thus, cash transfers are an important factor to attenuate the adverse socioeconomic effects of the health crisis but seem to be insufficient to curb the spread of the virus in the absence of political trust, a coordinated national effort, and strong leadership to enforce social distancing measures. Furthermore, cash transfers are insufficient to tackle non-monetary vulnerabilities associated with the pandemic. School closures in 2020, for example, are likely to have long-lasting effects, increasing pre-existing educational gaps (Lustig et al., 2020). These lessons are particularly valuable to developing countries, as they are likely to continue to experience pandemic-related stress for an extended period given the unequal access to vaccines (Schellekens, 2021), and their higher concentration of comorbidities.

Our research leaves some open questions that can provide fruitful avenues for further investigation. For instance, while we do observe small effects at the household unemployment and labor force participation rates, we do not cover intra-household changes in detail. As such, we do not investigate work-related transitions. Did people remain in the same types of industries and occupations? Did they take advantage of the cash transfer to invest in a career change or in human capital acquisition? Likewise, we cannot tell if there were changes in individuals' roles intra-households regarding who remains or leaves the labor force—perhaps young adults joined the labor force following school closures? Finally, uncertainties associated with the pandemic and the continuity of the EA prevents us from studying dynamic or long-term effects of this policy on our outcome variables. These are crucial questions to better understand how the pandemic has affected families, which fall beyond the scope of this paper.

Appendix

See Tables 4, 5 and Figs. 7, 8.

Table 4 Nested household fixed-effects regression models

Variables	Linear models									Logit models		
	Labor force participation			Unemployment rate			Per capita income			Below $5.50 poverty line		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Per capita EA	–0.002***	–0.001***	–0.001***	0.001***	0.002***	0.002***	–0.280***	–0.262***	–0.245***	–0.010***	–0.008***	–0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.008)	(0.007)	(0.000)	(0.000)	(0.000)
HH LFP (t-1)			0.256***									
			(0.003)									
HH unemployment rate (t-1)						0.220***						
						(0.004)						
Per capita HH income (t-1)									0.166***			
									(0.005)			
Poverty status (t-1)												0.547***
												(0.029)
State*month		✓	✓		✓	✓		✓	✓		✓	✓
Observations	713,454	713,454	713,454	536,859	536,859	536,859	689,717	689,717	689,717	57,682	57,682	57,682
R-squared	0.000	0.004	0.082	0.000	0.002	0.056	0.005	0.008	0.041			
Number of households	135,658	135,658	135,658	109,394	109,394	109,394	133,682	133,682	133,682	11,089	11,089	11,089

All models are run at the household level

We restricted the sample to households that showed up in the panel at least four times, although most showed up all seven times. Observations reflect the number of appearances of households across all months

The logit model reflects only households that changed poverty status

Standard errors clustered at the household level in parentheses in all models, except the logit

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5 Interactions of the EA with race and gender of the head of household

Variables	Linear models			Logit
	(1)	(2)	(3)	(4)
	Labor force participation	Unemployment rate	Per capita income	Below $5.50 poverty line
Per capita EA	−0.001	0.003***	−0.447***	0.017***
	(0.001)	(0.001)	(0.031)	(0.001)
Per capita EA squared	0.000	−0.000	0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
White women * EA	−0.000	−0.001	0.065	0.002
	(0.001)	(0.001)	(0.048)	(0.002)
Black men * EA	−0.000	−0.001	0.032	−0.002*
	(0.001)	(0.001)	(0.037)	(0.001)
Black women * EA	0.001	0.001	0.055	−0.002
	(0.001)	(0.001)	(0.038)	(0.001)
White women * EA^2	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Black men * EA^2	0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Black women * EA^2	−0.000*	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
HH LFP (t−1)	0.256***			
	(0.003)			
HH unemployment rate (t−1)		0.220***		
		(0.004)		
Per capita HH income (t−1)			0.166***	
			(0.005)	
Poverty status (t−1)				0.391***
				(0.030)
State*month	✓	✓	✓	✓
Observations	713,454	536,859	689,717	57,682
R-squared	0.082	0.057	0.042	
Number of households	135,658	109,394	133,682	11,089

All models are run at the household level

We restricted the sample to households that showed up in the panel at least four times, although most showed up all seven times. Observations reflect the number of appearances of households across all months

The logit model reflects only households that changed poverty status

Standard errors clustered at the household level in parentheses in all models, except the logit

***p < 0.01, **p < 0.05, *p < 0.1

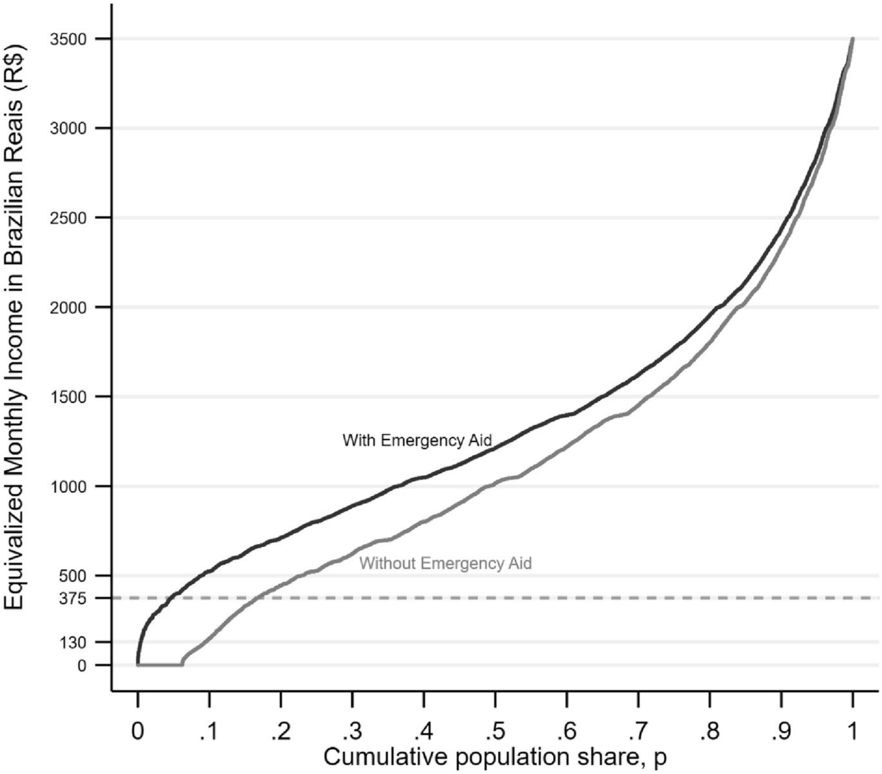

Fig. 7 Quantile Curve of Monthly Per Capita Equivalized Household Income with and without the emergency aid. *Note*: The BRL 375 line corresponds to the US5.50 poverty line.

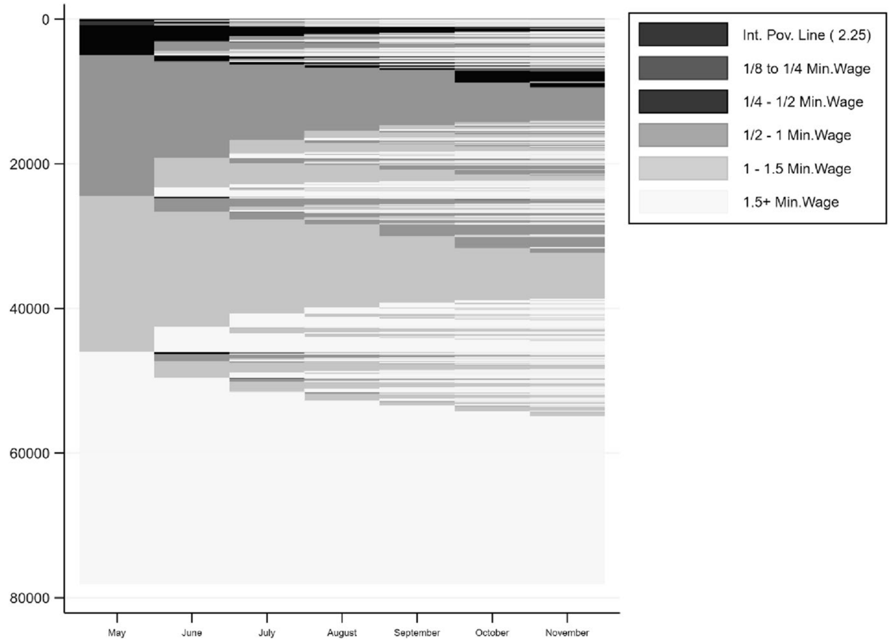

Fig. 8 Sequence analysis of income brackets transitions. *Note:* Darker to lighter colors indicate household monthly transitions from lower to higher equivalized per capita income brackets, defined as a proportion of the country's minimum wage in 2020. In 2020, the minimum wage was 1,045 Brazilian Reais per month.

Acknowledgements We thank the reviewers, Pedro Arruda, and participants at the CUNY's Stone Center Multidisciplinary Seminar Series for their helpful comments and suggestions.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability Our research used the COVID National Household Sample Survey (PNAD COVID) as the main data source. PNAD COVID data is publicly available at the Brazilian Institute of Geography and Statistics (IBGE) website: https://www.ibge.gov.br/en/statistics/experimental-investigations/experimental-statistics/27975-weekly-release-pnadcovid1.html?=&t=microdados

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