economies

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Underestimating the Pandemic: The Impact of COVID-19 on Income Distribution in the U.S. and Brazil

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Abstract: The COVID-19 pandemic has exposed individuals to various risks, including job loss, income reduction, deteriorating well-being, and severe health complications and death. In Brazil and the U.S., as well as in other countries, the initial response to the pandemic was marked by governmental underestimation, leading to inadequate public health measures to curb the spread of the virus. Although progressively mitigated, this approach played a crucial role in the impacts on local populations. Therefore, the principal aim of this paper is to evaluate the impact of COVID-19 and, indirectly, of the policies adopted by the U.S. and the Brazilian governments to prevent pandemic diffusion on income distribution. Utilizing available microdata and employing novel econometric methods (RIF-regression for inequality measures) this study shows that growth in COVID-19 prevalence significantly exacerbates economic disparities. Furthermore, the impact of COVID-19 on inequality has increased over time, suggesting that this negative impact has been intensifying. In the U.S., results indicate that working from home, the inability to work, and barriers to job-seeking significantly increase inequalities. Although further data are necessary to validate the hypothesis, this preliminary evidence suggests that the pandemic has significantly contributed to increased inequality in these two countries already characterized by increasing polarization and significant social disparities.

Keywords: inequalities; income polarization; Brazil; U.S.; COVID-19

JEL Classification: D63; N30; P36

Citation: Alfani, Federica, Fabio Clementi, Michele Fabiani, Vasco Molini, and Francesco Schettino. 2024. Underestimating the Pandemic: The Impact of COVID-19 on Income Distribution in the U.S. and Brazil. *Economies* 12: 235. https://doi.org/10.3390/economies12090235

Academic Editor: Sergio Scicchitano

Received: 27 May 2024
Revised: 7 August 2024
Accepted: 9 August 2024
Published: 3 September 2024

1. Introduction

Even though it is premature to draw definitive conclusions about the socioeconomic impact of COVID-19, it is widely acknowledged that its (pro-inequality) distributional impact has been significant, potentially initiating a process with consequences yet to fully emerge. Several studies have pointed out an increased concentration of income and wealth at the top percentiles of the distribution during the pandemic, yet research on the global middle class and poorer population remains limited. The lack of accurate information hinders a clear understanding of the economic loss and the enduring costs that may be incurred. Nevertheless, preliminary evidence suggests that those in vulnerable conditions, especially in countries with high infections and death rates, have experienced a rapid deterioration in their working and living conditions. Similarly, the progressive approach toward the poverty line by the lower middle class seems to have accelerated, a trend that has been developing for decades.

Some economic policy measures implemented to mitigate the impact of the pandemic may have had regressive effects, especially when considering the increase in the public debt that could disproportionally burden the less affluent in the future. Therefore, although expansionary monetary and fiscal policies were implemented to respond to an unprecedented crisis, they paradoxically contributed to exacerbating the existing divide between the wealthy and the poor in the long term.

Having said that, it is worth mentioning one important caveat of the analysis conducted in this paper. The distributive changes identified and associated with the pandemic in the analyzed countries (i.e., Brazil and the USA) cannot be solely attributed to COVID-19 or to the subsequent mitigation measures. Confounding factors prevent the establishment of a *direct* causal relationship; these distributional changes occurred during the pandemic crisis in a global context where inequalities were already on the rise (see Milanovic 2010; Piketty 2014, 2020).

The pandemic, rather than being exogenous, is, to some extent, a product of the recent capitalist development that strongly contributed to the significant biodiversity loss and deteriorating global ecosystem health (see, among others, Dushkova et al. 2024; Lawler et al. 2021). The policies employed to reduce the diffusion of the virus and mitigate its effect on global health have exacerbated pre-existing disparities. This hypothesis of the *endogenous nature* of COVID-19, therefore, poses several challenges to standard mainstream approaches that typically focus on identifying the *exogenous elements* destabilizing market forces and their theoretical equilibrium.

Instead, a more complex theoretical framework is required to disentangle the important distributive effects (also in terms of capital accumulation) attributable to COVID-19 from those resulting from the *structural* stagnation over the past two decades.

This article includes a preliminary empirical analysis describing the influence of COVID-19 on the income distributions of two of the most populated countries in the world: Brazil and the U.S. This choice is based on the profound impact of the pandemic despite the significant differences in GDP and other economic and social indicators, as reported by the World Health Organization. The U.S. and Brazil were the first and second countries in terms of cumulative deaths (1,088,854 in the U.S.; 695,088 in Brazil)[1], respectively. The common approach of Donald Trump and Jair Bolsonaro, which was characterized by underestimating or denying the pandemic, likely hindered their countries' institutional capacities to prevent the rapid spread of COVID-19. On October 6, 2020, President Trump tweeted: "Many people every year, sometimes over 100,000, and despite the vaccine, die from the flu ... we are learning to live with COVID-19, in most populations far less lethal". Similarly, President Bolsonaro repeatedly referred to COVID-19 as a "little flu" (*gripezinha*). Pre-existing socioeconomic disparities between classes and groups widened in both countries over the previous decades (see also Clementi and Schettino 2015; Schettino and Khan 2020) and created deeply divided societies with the election of the two far-rightist presidents.

The paucity of data available, however, presents a dilemma. While it is posited that COVID-19 was not an exogenous shock, data constraints limit the endogeneity bias correction. Consequently, the empirical analysis presented should not be interpreted as strictly causal, and the empirical estimates might be—to any extent—biased. Therefore, the implications of the COVID-19 pandemic on income inequality have been empirically evaluated using the regression method based on the notion of re-centered influence function (RIF). The influence function, as described by Cowell and Victoria-Feser (1996), reflects the influence of an individual observation on a given distributional statistic, such as a specific quantile. It also has properties that allow us to capture the effects of explanatory variables on the distributional statistic of interest. This way, this methodology has been employed to disentangle the income distribution changes that occurred during the highest diffusion of the COVID-19 pandemic, also providing a first and novel quantitative estimation of the "pure" impact of the virus and of the political choices of both governments.

This analysis represents a starting point for a more comprehensive reflection on the link between the pandemic and inequalities. As more data become available, the analysis can become more accurate, enhancing our understanding of the pandemic's distributional effects.

The rest of the paper is organized as follows: Section 2 reviews the recent literature on the pandemic's impact on inequalities. Section 3 describes the data used and empirical estimate findings. Section 4 concludes by proposing considerations for the future decisions of policy makers.

2. Literature Review

The socioeconomic effects of the COVID-19 pandemic are unprecedented. In addition to having a devastating impact on physical and mental well-being and the untimely death of millions, the pandemic has thrown entire economies into disarray and upended the livelihoods of many. At the time of writing, about 519 million cases of COVID-19 have been reported since the start of the outbreak, including more than 6 million deaths (European Centre for Disease Prevention and Control 2022). Despite the scarcity of updated information, the economic literature analyzing the impact of COVID-19 flourishes more and more every day.[2]

The pandemic has exposed people to different risks, increasing the likelihood of job and income loss, worsening well-being levels, and leading to serious health problems or death. Low-income countries where the population has unequal access to basic services, jobs, markets, and capital are more exposed to these risks, which can exacerbate inequality during crises (Hill and Narayan 2020; Berkhout et al. 2021). Some studies suggest that while the pandemic has affected all countries relatively evenly, the recovery has been less uniform, with the richest recovering on average nearly half of their 2020 losses and the poorest further losing on average 5% of their income (Deaton 2020; Hill et al. 2021).

Despite the scarcity of microdata after the pandemic started, several studies using regression methods have identified employment loss as a major channel of impact on household welfare (Josephson et al. 2020; Headey et al. 2020), exacerbating inequalities in the labor market. Informal workers, representing 60 percent of global employees, are not often covered by social protection schemes and are the most vulnerable to income loss and poverty during the COVID-19 crisis (ILO 2020).

Research on the labor market shows that the magnitude of the impact of the COVID-19 shock varies among countries, depending on institutional context, economic structure, and work schemes in place. It particularly affects tasks that cannot be carried out remotely or by less educated workers, youth, women, and the self-employed (Adams-Prassl et al. 2020; Alon et al. 2020; Bartik et al. 2020; Blundell et al. 2020; Bonacini et al. 2021; Dingel and Neiman 2020; Mongey et al. 2021; Montenovo et al. 2020; Palomino et al. 2020). The unequal access to health services in low- and middle-income countries, characterized by poorly funded public health systems with limited healthcare capacity, significantly increases the likelihood of dying from COVID-19 for poor and vulnerable people (Winskill et al. 2020). In the case of education, the global progress made in children's access to education in the last 20 years will likely be reversed by the effects of the pandemic (UNESCO 2020), resulting in increased educational inequality with a larger reduction in students' learning time for boys than for girls and no significant differences for parents from different educational backgrounds (Grewenig et al. 2021).

Among the poor, women are especially vulnerable, and COVID-19 is affecting women's labor market income and prospects more than men mainly due to their different participation rates in work industries and because women are disproportionately represented in sectors negatively affected by the crisis such as the accommodation and food services and the retail activities (Alon et al. 2020; Cajner et al. 2020; Dang and Viet Nguyen 2021; Madgavkar et al. 2020; UN Women 2020). While more men than women are dying from COVID-19, women are exposed to a higher risk of infection because they make up 70 percent of the health workforce and are more likely to be involved in the health sector, especially as nurses, midwives, and community health workers (Boniol et al. 2019). Within this framework, polls of economists supported the idea that the COVID-19 pandemic increases the level of inequality in terms of access to jobs and education for low-income household members, especially women.

Micro-simulation and calibration methods have also been employed to offset the limited availability of recent microdata. Using EUROMOD, several studies have simulated the impact of the pandemic on household incomes for different European countries, showing that the Gini coefficient would have increased due to the pandemic with an attenuation of relative inequality after the implementation of COVID-19 policy interventions (Almeida et al. 2020; Brewer and Tasseva 2020; Figari and Fiorio 2020). Other country-specific studies analyze the impact of welfare measures on household income focused on Ireland (O'Donoghue et al. 2020), Italy (Brunori et al. 2020), Germany (Bruckmeier et al. 2020), Australia (Li et al. 2020), Belgium (Marchal et al. 2021), and France, Germany, Italy, Spain, and Sweden (Clark et al. 2021).

Although not including specific questions on income level, high-frequency data collected by many statistical agencies offer a suitable way to analyze the socioeconomic impacts of the pandemic, especially in some less developed countries where the availability of data was already scarce before COVID-19. Findings from the COVID-19 High-Frequency Survey Global Dashboard, which produces 93 harmonized indicators on 14 topics, allow users to compare and analyze how COVID-19 impact varies across countries over time and by industry sector and regions, providing 96 harmonized indicators across 50 countries. This shows that widespread impacts amplify pre-existing inequalities between rich and poor countries and between haves and have-nots within countries (Sánchez-páramo and Narayan 2020). Several country-level impact monitoring reports have been produced based on high-frequency surveys that were fielded in the aftermath of the pandemic. These studies showed that women, youth, and workers with lower education levels are more likely to lose their income due to COVID-19 as they are disproportionately engaged in informal activities that shut down because of confinement, demonstrating that mitigation measures are limited in scope and insufficient to avoid significant increases in poverty and inequality (Bundervoet et al. 2021; Alfani et al. 2021; Egger et al. 2021).

The available evidence about the effects of past public health crises also confirms that past pandemics such as the SARS, MERS, H1N1, Ebola, and Zika, although smaller in scale than COVID-19, tend to reduce economic growth and increase inequality (Barro et al. 2020; Furceri et al. 2020; Jordà et al. 2020; Ma et al. 2021; Saadi-Sedik and Xu 2020). With reference to the latter, the net Gini coefficient shows an increase of about 1.2 percent in the medium term (Furceri et al. 2020; Saadi-Sedik and Xu 2020), and the output loss is immediate, with a 2.6 to 4.6 percent decrease in output in the same year of the pandemic (Ma et al. 2021; Saadi-Sedik and Xu 2020). The negative effects of crises and external shocks on growth tend to persist in the medium term, generating a vicious circle that exacerbates social unrest and inequality, impacting the labor market and the most vulnerable categories (Rodrik 1999; de Haan and Sturm 2017).

3. COVID-19 in Brazil and the U.S.

The impact of the pandemic, in terms of deaths and cases, has been profoundly heterogeneous, as highlighted above. It depended on a vast number of countries' characteristics whose relative importance has not always been clear. For instance, it is commonly accepted that the existence and quality of national health systems played a pivotal role in reducing both cases and deaths, as seen in the case of Cuba. However, what happened in sub-Saharan African (SSA) countries seems to contradict this common-sense observation: despite the low quality or absence of structured (public or private) health systems and the existence of the world's highest level of poverty and vulnerability in the majority of the considered territories, the data collected depict Africa as the continent that suffered the lowest number of cases and deaths due to COVID-19.

The limited capacity to rapidly detect and report cases, probably playing an important role in underestimating the overall impact (see also Skrip et al. 2021), cannot be considered the sole reason for these surprising outcomes. In general, it is becoming clearer every day that the structural and elevated complexity of the phenomenon is the highest obstacle that worldwide researchers and scientists are facing in precisely defining which features predominantly can act to prevent the rapid spread of COVID-19, consequently limiting health injuries and deaths.

In the following paragraphs, by means of special additional national household surveys provided, respectively, by IBGE-PNAD for Brazil and IPUMS-CPS for the United States of America, the results of a novel statistical and econometric analysis aimed at decrypting the impact of the pandemic on income distribution in the sixth and the third populous countries in the world are presented.

3.1. Data

3.1.1. The Brazilian PNAD COVID-19 Survey

In order to quantify the impact of the pandemic on economic inequality during the first wave of COVID-19 infections in Brazil, microdata from the special additional survey PNAD COVID-19 was used. This survey was carried out from May to November 2020 by the Brazilian Institute of Geography and Statistics (IBGE, Instituto Brasileiro de Geografia e Estatística), which has systematically investigated the general characteristics of the Brazilian population—education, labor, income, and housing—through the National Household Sample Survey (Pesquisa Nacional por Amostra de Domicílios, PNAD) since 1967, in partnership with the Ministry of Health. Brazil was one of the first countries to provide a national survey that includes the effects of the pandemic on the work and health of its population; in this sense, the PNAD COVID-19 survey is pioneering, as it represented the first release of experimental statistics prepared in Brazil (Penna et al. 2020).

The data collection of the PNAD COVID-19 relied on telephone interviews with approximately 48,000 households per week, totaling nearly 193,000 households per month across the entire national territory. The resident who answered the telephone completed the questionnaire on behalf of household members. The probabilistic samples were designed to provide representative estimates for each of the 27 federative units and the five geographical macro-regions of the country.

The PNAD COVID-19 questionnaire includes two main sections, one focusing on health issues—specifically, flu-like symptoms—and the other on labor issues.

For health issues, the survey investigates the incidence of major COVID-19 symptoms among all household members during the reference period. Questions are asked to determine if any symptoms were relieved, whether medical attention was sought, and the type of health establishment visited.

On the other hand, labor issues aim to classify working-age people into employed, unemployed, and out-of-the-workforce groups. The survey also explores employment and activity status, work leave and reasons for absence, remote work, job search activities and reasons for not seeking employment, the number of hours worked effectively and usually, and earnings from work. Additionally, residents are asked whether they received any earnings other than wages from labor as part of the household earnings, such as retirement, assistance benefits from programs such as Bolsa Família and BPC (Benefício de Prestação Continuada), emergency COVID-19 aid, unemployment insurance, and rental income.

The main modules in the PNAD COVID-19 questionnaire are supplemented with questions detailing other resident characteristics, such as sex, age, skin color or ethnicity, education level, and household conditions.

While data on COVID-19 symptoms have been collected since the survey's inception in May 2020, data on the performance of diagnostic tests for the disease became available only from July 2020 onwards. Therefore, the analysis conducted in this study refers to the period from July to November 2020, which is considered the first wave of COVID-19 infections in Brazil.

Regarding data preprocessing before the analysis, attention is restricted to individuals aged 14 years or older, as this is the minimum working age in Brazil. In addition, observations with zero income are removed from the samples, as some inequality measures are only defined for positive values. The sampling weights used to produce estimates from the PNAD COVID-19 survey have been recalibrated to ensure that estimates from the five monthly samples after data deletion align with the initial population totals. The income variable that is used in this study is derived by summing all individual sources of income (both labor income and other incomes), and the corresponding real values—at average prices of November 2020—have been obtained by applying the deflator for the PNAD COVID-19 microdata, available from the official IBGE website and providing the index numbers for the entire time series of the survey.

The summary statistics of the variables used for Brazil are proposed in Table A1 in Appendix A.

3.1.2. The U.S. Current Population Survey (CPS) and COVID-19 Supplement

For the United States, inequalities are assessed using monthly data from the Integrated Public Use Microdata Series—Current Population Survey (IPUMS-CPS) (Flood et al. 2021). The IPUMS-CPS is a harmonized database containing over 50 years of data from the Current Population Survey (CPS), a monthly household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics. The CPS was initiated in the 1940s in the wake of the Great Depression to measure unemployment, and over time, it has become the primary data source for studying income inequality trends in the United States. For some examples of the use of CPS in measuring inequality trends in the United States, see Gottschalk and Danziger (2005) and Burkhauser et al. (2009). It is important to note, however, that to prevent identification of individuals with extremely high incomes, CPS public-use data on sources of income are subject to top coding, which can be a major limitation as it can restrict the survey's ability to observe income changes for those at the top of the distribution (see, for example, Levy and Murnane 1992; Slemrod 1996; Burkhauser et al. 2003; Piketty and Saez 2006; Burkhauser et al. 2009). U.S. Census Bureau's internal CPS data, used to produce official income distribution statistics, are also top-coded, though to a much lesser degree (e.g., Burkhauser et al. 2012). Thus, to the extent that income inequality changes are due to changes in the top-coded portion of the CPS, researchers using these data may mismeasure trends in income inequality. Burkhauser et al. (2011) review CPS top-coding practices and provide references to previous discussions. Jenkins et al. (2011) demonstrate how a multiple-imputation approach may be used to estimate consistent levels of inequality and trends from top-coded CPS income data.

The CPS is administered monthly by the U.S. Census Bureau to over 65,000 households. A battery of demographic and labor force questions called the "basic monthly survey" is asked every month to gather information on education, labor force status, demographics, and other aspects of the U.S. population. A series of supplemental inquiries covering special topics were also developed for specific months. Among these supplemental surveys, the Annual Social and Economic Supplement (ASEC) is most used by social scientists and policymakers. IPUMS-CPS is based on the ASEC and basic monthly data from the CPS.

The IPUMS-CPS is a collection of microdata where each record represents a unique individual with numerically coded characteristics. In most samples, people are organized into households, making it possible to study their characteristics in the context of their families or other co-residents. To facilitate comparisons over time and across samples using the CPS data, variables in IPUMS-CPS are coded identically or "harmonized" from 1962 forward. A data extraction system allows users to select only the samples and variables they need.

In May 2020, the Bureau of Labor Statistics started asking questions in the CPS to measure the effects of the COVID-19 pandemic on the labor market. Specifically, people were asked whether the following had been true in the past 4 weeks at any time: (i) they worked from home or teleworked due to the pandemic; (ii) their employers closed or lost business because of the pandemic; (iii) they were compensated for the missed work; or (iv) their job search activities were hampered by the pandemic. These supplemental questions will remain in CPS until further notice (Current Population Survey 2020). A fifth question captures whether the pandemic caused anyone in the household to need medical care for something other than coronavirus but not get it because of the pandemic. This question was removed from the CPS starting in November 2020 and, in the following analysis, will therefore be used as long as available in the selected samples.

To examine the extent to which economic inequality in the United States was impacted by the pandemic, the above new CPS questions on COVID-19 for the period of May 2020 through March 2022, which at the time of writing is the last month of data available in the IPUMS-CPS database, were used. Questions about household members' demographics, family interrelationships, ethnicity/nativity, work, education, and disability are also used as control variables in the regression analyses that follow. As for the variable to measure inequality, reliance was placed on the "annual family income" of all persons related to the household's head. This variable includes the income of all members of the household who are aged 15 years or older. Income includes money from jobs, net income from business, farm or rent, pensions, dividends, interest, Social Security payments, and any other monetary income received by family members.

Rather than reporting a specific amount for total income, respondents in the monthly CPS samples are asked to choose among 16 categorical income ranges, the category representing the total combined income during the past 12 months for all members of the family. For the bottom part of the income distribution, the income ranges are fairly small—below USD 15,000, there are five categories, and from USD 15,000 to USD 40,000, the intervals are USD 5000 wide—whereas income ranges in the upper end are larger, and the top income bracket is open-ended. To run the regression analyses, this categorical response is converted into a continuous measure by assigning each case to the midpoint of its bin and using a robust pseudo-midpoint for the top, open-ended income bracket. Details for this imputation procedure are provided in the methodological section, while the results of additional analyses for robustness check on the validity of the income measure from the monthly CPS samples are reported in Appendix A. The robustness checks performed consist mainly of comparisons to family income in the CPS ASEC, the supplemental CPS survey conducted every year—mostly in March. In particular, the continuous income variable *HHINCOME* is used by such additional analyses. This variable reports the total money income during the previous calendar year of all adult household members. The amount equals the sum of all household members' individual incomes.

In the following, focus is placed on what is called "equivalized" family income, i.e., the family income adjusted using an equivalence scale to reflect the needs of different family types. Here, the OECD-modified equivalence scale (Hagenaars et al. 1994) is applied to make income comparable across households of different sizes and needs. The OECD-modified scale assigns a weight of 1 to the first adult (person aged 14 or older) in the household, a weight of 0.5 to each additional adult, and a weight of 0.3 to each child (person aged 0–13). This scale is widely used worldwide in the regular release of income distribution statistics from institution-level organizations. The monthly Consumer Price Index (CPI) of all urban consumers in the U.S. from May 2020 to March 2022 is used to adjust dollar amounts to constant dollars. This index, constant within years, inflates or deflates monthly dollar amounts to the amount they would have represented in the reference base period 1982–1984. Finally, due to the complex sampling design for the CPS, the analyses apply the provided sampling weights to produce representative statistics.

The summary statistics of the variables used for the U.S. are proposed in Table A2 in Appendix A.

3.2. Methodology

The implications of the COVID-19 pandemic for income inequality have been empirically examined using the regression method based on the notion of re-centered influence function (RIF). The influence function, as described by Cowell and Victoria-Feser (1996), reflects the influence of an individual observation on a given distributional statistic, such as a specific quantile. It also has properties that allow us to capture the effects of explanatory variables on the distributional statistic of interest.

To see this, let us consider the popular Gini coefficient (Gini 1914) as the income inequality measure. Defining $\mu = \int_{-\infty}^{\infty} y f(y) \mathrm{d}y$ as the mean of the income distribution Y, and denoting the corresponding cumulative distribution function by F_Y, the Gini coefficient may be expressed as follows (e.g., Firpo et al. 2018):

$$\nu^G(F_Y) = 1 - 2\mu^{-1}R(F_Y), \tag{1}$$

where $R_Y = \int_0^1 GL(p)\mathrm{d}p$, with $p(y) = F_Y(y)$, and where $GL(p)$ is the generalized Lorenz ordinate given by $GL(p) = \int_{-\infty}^{F_Y^{-1}(p)} z \mathrm{d}F_Y(z)$. The generalized Lorenz curve tracks the cumulative total of y divided by the total population size against the cumulative distribution function.

Monti (1991) derives the influence function of the Gini coefficient as follows:

$$IF\left(y; \nu^G, F_Y\right) = A(F_Y) + B(F_Y)y + C(y; F_Y), \tag{2}$$

where $A(F_Y) = 2\mu^{-1}R(F_Y)$, $B(F_Y) = 2\mu^{-2}R(F_Y)$, and $C(y; F_Y) = -2\mu^{-1}\{y[1 - p(y)]\} + GL(p; F_Y)$, with $R(F_Y)$ and $GL(p; F_Y)$ as defined underneath Equation (1). The function (2) is theoretically unbounded from above, but in practice, it reaches its maximum at the upper bound of the empirical support of the income distribution. This implies that the Gini coefficient is not robust enough to measure errors in high incomes, as pointed out by Cowell and Victoria-Feser (1996).

A property shared by influence functions is that, by definition, the expectation is equal to zero:

$$\mathbb{E}\left[IF\left(y; \nu^G, F_Y\right)\right] = 0. \tag{3}$$

Firpo et al. (2009) propose a simple modification in which the distributional statistic of interest is added back to the influence function, resulting in what the authors call the re-centered influence function (RIF). In the case of the Gini coefficient, re-centering yields the following:

$$RIF\left(y; \nu^G, F_Y\right) = \nu^G + IF\left(y; \nu^G, F_Y\right) = 1 + B(F_Y)y + C(y; F_Y). \tag{4}$$

The importance of this transformation depends on the fact that the expectation of the RIF is precisely the Gini, i.e., $\mathbb{E}\left[RIF\left(y; \nu^G, F_Y\right)\right] = \nu^G$. With this result, Firpo et al. (2009) show that the conditional expectation of the Gini RIF can be modelled as a simple linear function of the explanatory variables:

$$\mathbb{E}\left[RIF\left(y; \nu^G, F_Y\right) \middle| X = x\right] = X' \cdot \beta. \tag{5}$$

Moreover, by applying the law of iterated expectations to Equation (5), the result is an expression that directly relates the impact of changes in the expected values of the covariates on the Gini coefficient:

$$\nu^G = \mathbb{E}\left[RIF\left(y; \nu^G, F_Y\right)\right] = \mathbb{E}\left[\mathbb{E}\left[RIF\left(y; \nu^G, F_Y\right) \middle| X = x\right]\right] = \mathbb{E}(X) \cdot \beta. \tag{6}$$

In practice, following Firpo et al. (2009), the RIF of the Gini coefficient for each income i can first be computed using Equation (4) above; subsequently, the coefficient β can be estimated by OLS through the following equation:

$$RIF\left(y_i; \nu^G, F_Y\right) = \alpha + \sum_{k=1}^{K} \beta_k \cdot x_{i,k} + \varepsilon_i,\ i = 1, 2, \ldots, N, \tag{7}$$

where α is a constant, $x_{i,k}$ denotes a realization of the k-th explanatory variable, β_k is the corresponding coefficient, and ε_i is the error term. The estimated model parameter $\hat{\beta}_k$ can be interpreted as the effect of a small change in the distribution of X_k on ν^G—when the distribution of other covariates remains unchanged—or as a linear approximation of the effect of large changes of X_k on ν^G (e.g., Firpo et al. 2018).

The RIF-OLS regression method can be extended to draw conclusions on the impact of a set of covariates on a variety of distributional functionals—analytical expressions for (re-centered) influence functions have been, in fact, derived for many distributional statistics (see, e.g., Essama-Nssah and Lambert (2012); Rios-Avila (2020), for a comprehensive list of formulas). In addition to the Gini coefficient, to assess the impact of the COVID-19 pandemic on the level of income inequality, the Theil index (Theil 1967) and the Palma ratio (Palma 2011) of income concentration (Cobham and Sumner 2013) are also used. The RIF for the Theil index of inequality is given by Cowell and Flachaire (2007) as follows:

$$RIF\left(y; I_E^1, F_Y\right) = I_E^1 + \frac{1}{\mu}(y \ln y - \nu) + \frac{\nu + \mu}{\mu^2}(y - \mu), \tag{8}$$

where $I_E^1 = \frac{\nu}{\mu} - \ln \mu$, with $\nu = \int y \ln y \, \mathrm{d}F_Y(y)$, denotes the Theil coefficient. For the Palma ratio—the measure of the capture of total income of the richest decile over the capture of the poorest 40 percent—the RIF can be expressed as follows (c):

$$RIF(y; Iqsr(p_1, p_2), F_Y) = Iqsr(p_1, p_2) + \frac{1}{L(p_1)}[-IF(y; L(p_2), F_Y) - Iqsr(p_1, p_2) IF(y; L(p_1), F_Y)], \tag{9}$$

with p_1 and p_2 equal to, respectively, 40 and 90. In the equation above, $Iqsr(p_1, p_2) = \frac{1 - L(p_2)}{L(p_1)}$ is the interquartile share ratio, where $L(p)$ denotes the Lorenz ordinate given by $L(p) = \mu^{-1} GL(p)$, and where

$$IF(y; L(p), F_Y) = -\frac{y}{\mu} L(p) + \frac{p\nu_p}{\mu} + \left(\frac{y - \nu_p}{\mu}\right) \mathbb{I}\{y < \nu_p\} \tag{10}$$

is the influence function of the Lorenz curve at the point p (e.g., Essama-Nssah and Lambert 2012). In the following empirical analysis of the impact of COVID-19 on income inequality, the RIF-OLS regressions are estimated by replacing the dependent variable in (7) with the estimated values of the RIFs in Equations (8) and (9).

As mentioned in the previous section, in the U.S. case study, the measure of family income is binned into 16 categories, which are derived from the responses to survey questions of the following form: "Which category represents the total combined income of all members of this family during the past 12 months?". To implement the RIF-OLS approach in this context, it is converted these categorical responses into a continuous measure by assigning each case to the midpoint of its bin, $m_b = (l_b + u_b)/2$, where l_b and u_b are the lower and upper bounds of income for bin b, $b = 1, 2, \ldots, B$.

The midpoint estimation is straightforward for the middle categories, but the open-ended nature of the first and last income intervals presents a challenge (see Heitjan (1989) for a review). To cope with this, a lower limit of USD 0 is assumed for the first interval, even though some respondents may have reported negative household incomes. This choice is expected to yield a negligible impact on the estimates since it is likely to affect only a tiny fraction of the data. On the other hand, identifying a reasonable upper-end value for the final class is more difficult, particularly for very rich income recipients. In this case, a pseudo-midpoint for the top bin is estimated by using the "robust Pareto midpoint estimator" described by Von Hippel et al. (2016, 2017). This approach assumes that the top two bins follow a Pareto distribution with shape parameter $\alpha > 0$. Under the Pareto distributional assumption, the harmonic mean of the top income bracket B, given by the following:

$$h_B = l_B\left(1 + \frac{1}{\alpha}\right), \tag{11}$$

is a simple function of α, and an estimate of it can be used in place of the midpoint.

An estimate of h_B can be obtained by plugging an estimate of α into the formula for h_B. The most popular estimator for α is the maximum likelihood estimator (Henson 1967; Quandt 1966):

$$\hat{\alpha} = \frac{\ln(n_{B-1} + n_B) - \ln n_B}{\ln l_B - \ln l_{B-1}}, \tag{12}$$

where n_B specifies the number of cases in the top bin. The h_B statistic is the least sensitive to α, as it does not get arbitrarily large for α getting close to 0, and that makes h_B a better candidate for robust estimation of the top bin's pseudo-midpoint than other statistics derived from the Pareto distribution, such as the arithmetic mean, the geometric mean, or the median.

Except for midpoint estimation, which is used in the routines implemented in the binequality package for R 4.4.1 (Von Hippel et al. 2016), all econometric computations are carried out using the software Stata, and especially its rifvar command introduced by Rios-Avila (2020) to create RIFs for a large set of distributional statistics.

3.3. Principal Results

Tables A2–A4 in Appendix A summarize the results derived from the PNAD COVID-19 microdata. RIF-regression models were estimated monthly from July to November 2020, controlling for the same covariates. To conserve space, detailed commentary on the covariate results is omitted but included in the tables. The reference level for categorical control variables is coded as zero. In the tables, the omitted dummy-coded reference levels are indicated by the categories for which the corresponding estimated regression coefficient is equal to 0. A variable indicating whether the respondent has tested positive for COVID-19 is the main-effect variable used in the analysis.

Two main findings emerge from this study on the impact of COVID-19 on inequality in Brazil. Firstly, the results of the tables show that a change from a negative to a positive negative to a positive COVID-19 test result is significantly associated with an increase in income inequality. Specifically, the results of the RIF (re-centered influence function) regressions suggest that this change would be associated with an average monthly increase of about 0.042 points in the Gini index, as shown in Table A2. Similarly, when applying the RIF method to the Theil index and the Palma ratio, the results robustly confirm the negative impact of the COVID-19 pandemic on inequality. On average, a positive COVID-19 test result is associated with a monthly increase of 0.093 in Theil's index and 0.501 in the Palma ratio, as detailed in Tables A3 and A4.

Secondly, the magnitude of the estimated coefficients for the COVID-19 variable increased over time, suggesting that pre-existing income inequality was exacerbated during the study period.

These results are consistent with those of other studies conducted globally. For example, a report from the International Labour Organisation (ILO 2020) found that the pandemic had a disproportionate impact on low-income and informal workers, contributing to increasing economic inequality in many countries, including those in Latin America. In particular, the ILO has highlighted that the loss of working hours and the reduction in wages have affected the least qualified workers the most, further aggravating income inequality.

A World Bank study (2020) observed similar trends, indicating that the pandemic has led to a significant increase in poverty and inequality in developing countries, with developing countries, with particularly severe effects in Brazil. This study estimated that the Gini index increased by approximately 0.05 points during the 2020s due to pandemic-related income losses.

Narayan et al. (2022) show the impact of disease on inequality and poverty both within and between countries. The short-term impact, while existing, appears to be limited, although the long-term consequences can be very significant.

Tables A5–A7 in Appendix A summarize the results for the U.S.

Regarding the U.S. context, the estimated impacts of the COVID-19 pandemic on income inequality are presented in Tables A4–A6. These tables contain the RIF-regression results for the Gini coefficient, the Theil index, and the Palma ratio, respectively. Due to space limitations, only results for selected "representative" months of CPS data are shown—specifically, September 2020, March 2021, and March 2022. The econometric results for the remaining monthly CPS samples used in this study are available upon request.

The results look very similar across the three distributional statistics, showing an overall negative impact of the pandemic on inequality. Focusing in particular on the variables for the special COVID-19 questions, RIF-regression results suggest that working from home because of the pandemic would lead—on average for the three months considered—to a statistically significant increase in the Gini index of about 0.05 points, while being unable to work and being prevented from seeking work because of the pandemic would increase the Gini for about, respectively, 0.02 and 0.04 points. The same considerations apply to the effects on the Theil index and the Palma ratio, for which RIF-regression results confirm that a positive shift in the three COVID-19 supplemental questions would be related to average significant increases ranging between 0.05 and 0.07 points in the case of the Theil index, and between 0.55 and 1.18 points for the Palma ratio.

Two additional points are worth emphasizing here, which help to gauge the effects of the Coronavirus pandemic on inequality. The first concerns the inability to look for a job, which, as can be observed, has the greatest impact, especially when the Palma index is employed. This further reinforces the belief that the pandemic has precisely affected those who were (and still are) in the most disadvantaged conditions, preventing—or making it very difficult—to (re-)enter the labor market. The second aspect concerns the temporal profile of the pandemic's impact on inequality: similar to the case of Brazil, the estimated coefficients on the variables for the special COVID-19 questions show increasing magnitudes over time, suggesting that the negative impact of the pandemic on inequality has intensified over the time span covered by the dataset.

The control variables show results that are in line with expectations. As in the case of the Brazilian regression tables, the omitted dummy-coded reference groups for categorical control variables are indicated by the categories for which the corresponding estimated regression coefficient is equal to zero. For instance, a higher level of education and being employed have a positive impact on decreasing inequality, as does being married compared to being single or divorced—this aspect may be related to the fact that the family plays a role in economic support, especially in times of crisis. Also of interest is the aspect regarding citizenship and race: belonging to minorities (Blacks and Native Americans) or not possessing U.S. citizenship has a negative impact on inequality.

The results are in line with other studies on the country. Tan et al. (2021) find that the association between income inequality and COVID-19 cases and deaths varied over time and was strongest in the summer months of 2020. Liao and De Maio (2021) show similar results, as well as pointing out how the impact of the disease is also influenced by racial/ethnic composition.

As a robustness check, all estimates in the main analysis were replicated using a continuous income variable drawn from the CPS ASEC, the supplemental CPS survey conducted in March every year. Results of this check from the March 2021 ASEC files—provided in Appendix A Table A1—highlight essentially the same conclusions of the main analysis, thus confirming its robustness.

4. Conclusions

In a recent article in the *Financial Times*, Michael Strain from the American Enterprise Institute (Strain 2022) reflects on the U.S. budget deficit and the ongoing debate on how and when to stabilize it. This deficit has various origins, among others, the fiscal expansion both Trump and Biden administrations have undertaken to offset the economic impact of COVID-19. The new phase, however, is characterized by the debate on how to reduce the negative side effects of the expansionary fiscal and monetary policies undertaken in the last two decades. And almost inevitably, it seems to suggest Strain, the biggest burden will be borne by the American middle class and then by the lower strata of the population.

It goes without saying that what is proposed is one political option, but even if one might not share the same political beliefs as the author, it is unlikely that fiscal consolidation and the tightening of monetary policies can be undertaken without seeing a further increase in inequality. This is because the middle and lower classes in the U.S., as in other countries, are relatively more indebted than the top classes, benefit more from public spending—in Europe more than elsewhere—and tend to use more public services such as public schools and hospitals. Higher interest rates and a reduction in the provision of public services or an increase in their cost clearly impact these classes more than top earners.

The aforementioned scenario looks particularly gloomy if it is considered that those who will likely pay the highest price of the post-pandemic recovery are those who had already paid a disproportionate price during the pandemic. Micro-level data on household income have only recently started to be re-collected, and most of the research has been conducted through telephone interviews; nonetheless, the picture that emerges from this preliminary evidence is quite clear. All those with precarious or informal jobs—without proper health insurance or some form of social protection—but also those who could not conduct their job from home were the most vulnerable to income loss and poverty during the COVID-19 crisis.

This study, using data from Brazil and the U.S., is one of the first attempts to *directly* estimate the impact of COVID-19 on inequality using household-level income data. A few findings are worth mentioning. In both countries, a positive shift in COVID-19 testing results significantly influences inequality, and the impact is robust to the choice of the inequality indicator. Secondly, the results concerning the temporal profile of the pandemic's impact on inequality are very interesting. In the U.S., as in Brazil, the impact of COVID-19 on inequality has increased over time, suggesting that this negative impact has intensified over the time span covered by the dataset.

For the U.S., since the questionnaire is more detailed, there are interesting responses regarding the labor market transmission channels from COVID-19 to inequality. The results suggest that working from home because of the pandemic would lead to a statistically significant increase in the Gini index of about 0.05 points, while being unable to work and being prevented from seeking work because of the pandemic would increase the Gini by about 0.02 and 0.04 points, respectively. This confirms the recent literature findings based on telephone interviews that the pandemic had negatively affected those who were in the most disadvantaged conditions, preventing them from re-entering the labor market or re-entering with worse work conditions.

This analysis represents the first building block of a more in-depth analysis of the impact of the COVID-19 pandemic on inequalities. More data of the type managed for Brazil and the U.S. need to be made available for both developed and developing countries to have a more exhaustive account of the contribution of the pandemic to inequality growth. Future research will be focused on disentangling the direct contribution of the pandemic from a number of confounding factors that also contribute to the observed increase in inequality. This continuous focus can have an effect in both academic and policy spaces. In academia, there is hope to see more attention being placed on the collection and analysis of data that can illuminate the nature, evolution, and consequences of the pandemic. This research agenda will be of interest to those in the policy sphere, too. Tackling the rising inequality is an increasingly central argument in the political debate, and the crisis has certainly accentuated the interest in thinking outside the box.

Author Contributions: Conceptualization, F.S., F.A. and V.M.; methodology, F.C. and M.F.; software, F.C., F.S. and M.F.; validation, F.A., V.M. and F.C.; formal analysis, F.S.; data curation, M.F.; writing—original draft preparation, F.A.; writing—review and editing, V.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used for statistical calculations are available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Additional Tables

Table A1. The Brazilian PNAD COVID-19 survey summary statistics.

	July	August	September	October	November
Positive for COVID-19	3.05	4.21	5.25	6.12	6.83
HH size	2.884	2.877	2.878	2.878	2.877
Worked in the last week	43.14	45.37	46.58	47.7	48.11
Race					
White	44.01	44.12	44.13	44.1	44.12
Black	9.35	9.45	9.34	9.39	9.35
Asian	0.81	0.79	0.77	0.77	0.78
White–Black	45.5	45.31	45.43	45.42	45.42
Indigenous	0.34	0.33	0.5	0.5	0.6
Area					
Capital	24.49	24.53	24.54	24.52	24.49
Metropolitan region, excluding the capital	16.46	16.40	16.43	16.51	16.44
Integrated economic development region, excluding the capital	0.79	0.79	0.79	0.79	0.8
Federation unit	58.27	58.27	58.25	58.18	58.27
Urban area	86.11	86.13	86.05	86.08	86.08
Rural area	13.89	13.87	13.95	13.92	13.92
Relationship with HH head					
HH head	40.22	40.31	40.27	40.26	40.6
Spouse	25.01	24.96	24.86	24.77	24.75
Child of the parent and spouse	14.19	14.20	14.22	14.25	14.35
Child only of the responsible person	10.92	10.93	11.07	11.14	11.19
Spouse's child only	1	0.99	0.99	0.99	0.96
Son-in-law or daughter-in-law	1.25	1.20	1.20	1.2	1.19
Father, mother, stepfather, or stepmother	1.59	1.56	1.55	1.55	1.54
Father/mother-in-law	0.56	0.58	0.39	0.28	0.29
Grandchild	2.24	2.23	2.26	2.25	2.27
Great-grandchild	0.02	0.03	0.03	0.11	0.03
Brother or sister	1.49	1.51	1.51	1.51	1.51
Grandfather or grandmother	0.27	0.26	0.36	0.46	0.47
Other relative	1.22	1.22	1.21	1.23	1.21
Age	41.283	41.321	41.337	41.377	41.396
Sex					
Male	48.39	48.39	48.38	48.38	48.38
Female	51.61	51.61	51.62	51.62	51.62
Education					
Lower middle level of education	46.96	46.96	46.99	46.99	46.95
Higher middle level of education	53.04	53.04	53.01	53.01	53.05
Housing condition					
Own—already paid	66.05	66.03	66.22	66.31	66.56
Own—still paying	7.38	7.42	7.37	7.34	7.33
Rented	15.66	15.62	15.43	15.46	15.17
Provided by employer	1.25	1.25	1.26	1.23	1.24
Granted by family member	8.38	8.41	8.47	8.42	8.45
Otherwise given	0.9	0.92	0.89	0.88	0.86
Other condition	0.38	0.35	0.35	0.34	0.39

Table A2. The U.S. Current Population Survey (CPS) and COVID-19 supplement summary statistics.

	Septmeber 2020	March 2021	March 2022
HH size	3.168	3.142	3.158
Age	39.667	39.819	39.76
Sex			
Male	48.75	48.74	48.98
Female	51.25	51.26	51.02
Race			
White	76.66	76.81	76.41
Black	13.05	12.81	12.94
American Indian	1.09	1.16	1.26
Asian	6.33	6.22	6.4
Multiracial	2.86	3	2.99
Marital status			
Married	59.57	59.38	59.01
Separated	1.39	1.39	1.34
Divorced	8.2	8.15	7.88
Widowed	4.78	4.77	4.85
Never married/single	26.07	26.31	26.92
Citizenship			
Born in U.S.	85.51	85.26	84.84
Born abroad of American parents	0.85	0.78	0.8
Naturalized citizen	7.13	7.15	7.03
Not a citizen	6.51	6.81	7.34
Veteran status			
No	94.68	94.62	94.71
Yes	5.32	5.38	5.29
Employment status			
Employed	63.92	64.31	66.18
Armed forces	0.31	0.39	0.3
Unemployed	3.72	3	1.86
Not in the labor force	32.04	32.3	31.67
Education			
Not in universe or blank	18.18	18.04	17.96
None or preschool	0.26	0.26	0.24
Primary	1.31	1.34	1.39
Secondary	32.12	31.77	32.59
Higher	48.13	48.58	47.82
Any physical or cognitive difficulty			
No difficulty	90.73	90.53	89.85
Has difficulty	9.27	9.47	10.15
Region			
New England division	4.51	4.56	4.55
Middle Atlantic division	12.35	12.02	12.38
East North Central division	14.57	14.33	14.32
West North Central division	6.58	6.53	6.63
South Atlantic division	19.92	20.35	20.22
East South Central division	5.8	5.88	5.82
West South Central division	12.3	12.35	12.35
Mountain division	7.68	7.82	7.75
Pacific division	16.28	16.16	15.97
COVID-19			

Table A2. *Cont.*

	Septmeber 2020	March 2021	March 2022
Worked remotely			
No	89.57	90.23	95.13
Yes	10.43	9.77	4.87
Unable to work			
No	94.07	96.51	99.24
Yes	5.93	3.49	0.76
Received pay for hours not worked			
No	99.38	99.64	99.88
Yes	0.62	0.36	0.12
Prevented from looking for work			
No	98.63	98.86	99.74
Yes	1.37	1.14	0.26

Table A3. RIF-regression for inequality measures of the U.S. family income distribution.

	Gini Coefficient	Theil Index	Palma Ratio
HH size	−0.00815 *** [0.001584]	−0.0108783 *** [0.0033827]	−0.12564 *** [0.022856]
Age	0.001797 *** [0.000573]	0.0024449 [0.0014952]	0.030224 *** [0.00817]
Age squared	−0.0000166 *** [0.00000616]	−0.0000183 [0.0000166]	−0.00029 *** [0.0000877]
Sex			
Male	0 [.]	0 [.]	0 [.]
Female	−0.00653 *** [0.002401]	−0.0109197 * [0.0056204]	−0.09288 *** [0.034329]
Race			
White	0 [.]	0 [.]	0 [.]
Black	0.046011 [0.006764]	0.0769323 *** [0.0158989]	0.653059 *** [0.098158]
American Indian	0.039386 *** [0.01497]	0.0614158 ** [0.0275475]	0.544394 ** [0.22183]
Asian	0.012905 [0.012303]	0.0217008 [0.0267455]	0.178721 [0.176497]
Multiracial	0.011604 [0.010733]	0.0137372 [0.0189764]	0.168973 [0.15657]
Marital status			
Married	0 [.]	0 [.]	0 [.]
Separated	0.041234 *** [0.010306]	0.0679596 *** [0.0203215]	0.640012 *** [0.150061]
Divorced	0.018071 *** [0.006643]	0.0311156 * [0.016222]	0.282264 *** [0.094675]
Widowed	0.018153 ** [0.007417]	0.0249584 [0.0192458]	0.281175 *** [0.106095]
Never married/single	0.01593 *** [0.006104]	0.0290203 * [0.0149742]	0.25472 *** [0.086846]
Citizenship			

Table A3. *Cont.*

	Gini Coefficient	Theil Index	Palma Ratio
Born in the U.S.	0 [.]	0 [.]	0 [.]
Born abroad to American parents	−0.00598 [0.01606]	−0.0383404 [0.030225]	−0.07999 [0.227661]
Naturalized citizen	0.020107 ** [0.008118]	0.0255147 [0.0179038]	0.268313 ** [0.116514]
Not a citizen	0.053406 *** [0.009109]	0.0866233 *** [0.0196663]	0.774836 *** [0.131741]
Veteran status			
No	0 [.]	0 [.]	0 [.]
Yes	−0.03456 *** [0.007199]	−0.0598934 *** [0.0180326]	−0.50792 *** [0.10224]
Employment status			
Employed	0 [.]	0 [.]	0 [.]
Armed forces	−0.02125 [0.014859]	−0.0238634 [0.0359497]	−0.36952 ** [0.207821]
Unemployed	0.051455 *** [0.008691]	0.0872279 *** [0.0196423]	0.742665 *** [0.124913]
Not in the labor force	0.068133 *** [0.004675]	0.1010882 *** [0.0115641]	1.001666 *** [0.066547]
Education			
None or blank	0 [.]	0 [.]	0 [.]
None or preschool	−0.08899 *** [0.019131]	−0.1503111 *** [0.0351639]	−1.2253 *** [0.285205]
Primary	−0.03461 [0.013693]	−0.0579251 ** [0.0278469]	−0.47562 ** [0.199911]
Secondary	−0.09514 *** [0.008995]	−0.138117 *** [0.022511]	−1.44216 *** [0.12833]
Higher	−0.11596 *** [0.009481]	−0.1838974 *** [0.0234096]	−1.71117 *** [0.135292]
Any physical or cognitive difficulty			
No difficulty	0 [.]	0 [.]	0 [.]
Has difficulty	0.024694 *** [0.00478]	0.0366356 *** [0.0112673]	0.378729 *** [0.068881]
Covered by health insurance			
Covered	0 [.]	0 [.]	0 [.]
Not covered	0.048943 *** [0.006076]	0.0904221 *** [0.0138452]	0.658334 *** [0.088358]
Region			

Table A3. *Cont.*

	Gini Coefficient	Theil Index	Palma Ratio
New England division	0 [.]	0 [.]	0 [.]
Middle Atlantic division	−0.01365 [0.013354]	−0.0316571 [0.0336348]	−0.18185 [0.18993]
East North Central division	−0.00742 [0.013289]	0.0010195 [0.0345961]	−0.12026 [0.188713]
West North Central division	−0.00652 [0.016109]	0.0103461 [0.0495176]	−0.10035 [0.227392]
South Atlantic division	−0.00482 [0.012468]	−0.0035884 [0.0322178]	−0.076 [0.177182]
East South Central division	0.006529 [0.013121]	0.0133189 [0.0329608]	0.067251 [0.18725]
West South Central division	0.003286 [0.013386]	0.0144821 [0.0342171]	0.053746 [0.190389]
Mountain division	−0.02071 [0.01321]	−0.0417687 [0.0330394]	−0.29021 [0.187907]
Pacific division	−0.00717 [0.013]	−0.019587 [0.0327385]	−0.11132 [0.18498]
COVID-19 VARIABLES			
Worked remotely			
No	0 [.]	0 [.]	0 [.]
Yes	0.066422 *** [0.009759]	0.0816084 *** [0.0288994]	0.969071 *** [0.137752]
Unable to work			
No	0 [.]	0 [.]	0 [.]
Yes	−0.00484 [0.008533]	−0.019589 [0.0177861]	−0.07369 [0.122773]
Received pay for hours not worked			
No	0 [.]	0 [.]	0 [.]
Yes	−0.03991 * [0.020726]	−0.0794891 ** [0.032875]	−0.55877 ** [0.298328]
Prevented from looking for work			
No	0 [.]	0 [.]	0 [.]
Yes	0.027493 ** [0.010943]	0.0443766 ** [0.0191796]	0.421258 *** [0.161135]
CONSTANT	0.483039 *** [0.017177]	0.4139996 *** [0.0444194]	2.923833 *** [0.244291]
Number of observations	106,228	106,228	106,228
Prob > F	0.0000	0.0000	0.0000
R-squared	0.0230	0.0099	0.0254

Notes: Standard errors (in brackets) are clustered at the household level, and estimates are computed with sample weights; reference groups for categorical control variables are indicated by the categories for which the corresponding estimated regression coefficient is equal to 0; star codes for statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: elaborations by the authors on March 2021 CPS ASEC data (extracts made before 15 April 2022).

Table A4. RIF-regression for the Gini coefficient of Brazilian total personal income.

	July	August	September	October	November
Positive for COVID-19	0.0358 *** [0.0133]	0.0370 ** [0.0173]	0.0515 *** [0.0156]	0.0439 *** [0.0138]	0.0412 *** [0.00942]
HH size	−0.00617 *** [0.000912]	−0.00618 *** [0.000957]	−0.00682 *** [0.000758]	−0.00402 *** [0.000759]	−0.00234 *** [0.000750]
Worked in the last week	−0.0293 *** [0.00260]	−0.0419 *** [0.00259]	−0.0468 *** [0.00249]	−0.0799 *** [0.00240]	−0.0999 *** [0.00241]
Race (reference category "White")					
Black	−0.0800 *** [0.00376]	−0.0835 *** [0.00386]	−0.0855 *** [0.00362]	−0.0737 *** [0.00360]	−0.0664 *** [0.00365]
Asian	0.0397 [0.0280]	0.0515 * [0.0305]	0.00359 [0.0174]	0.0376 [0.0282]	0.0313 [0.0281]
White–Black	−0.0680 *** [0.00273]	−0.0704 *** [0.00282]	−0.0682 *** [0.00268]	−0.0540 *** [0.00263]	−0.0515 *** [0.00252]
Indigenous	−0.0683 *** [0.00915]	−0.0781 *** [0.00904]	−0.0785 *** [0.00846]	−0.0591 *** [0.00911]	−0.0510 *** [0.00888]
Area (reference category "Capital")					
Metropolitan region, excluding the capital	−0.113 *** [0.00532]	−0.112 *** [0.00542]	−0.110 *** [0.00519]	−0.102 *** [0.00508]	−0.100 *** [0.00484]
Integrated economic development region, excluding the capital	−0.124 *** [0.00626]	−0.122 *** [0.00614]	−0.116 *** [0.00589]	−0.105 *** [0.00583]	−0.0910 *** [0.00585]
Federation unit	−0.132 *** [0.00427]	−0.129 *** [0.00432]	−0.127 *** [0.00403]	−0.114 *** [0.00385]	−0.113 *** [0.00378]
Urban area	0 [.]	0 [.]	0 [.]	0 [.]	0 [.]
Rural area	−0.00441 ** [0.00194]	−0.00420 ** [0.00183]	−0.00300 [0.00193]	0.0187 *** [0.00191]	0.0182 *** [0.00189]
Relationship with HH head (reference category "HH head")					
Spouse	−0.00123 [0.00389]	−0.00187 [0.00390]	−0.00138 [0.00371]	−0.00556 [0.00361]	−0.000167 [0.00355]
Child of the parent and spouse	−0.0140 *** [0.00484]	−0.0167 *** [0.00510]	−0.0172 *** [0.00479]	−0.0418 *** [0.00479]	−0.0441 *** [0.00477]
Child only of the responsible person	−0.0588 *** [0.00383]	−0.0589 *** [0.00405]	−0.0592 *** [0.00388]	−0.0737 *** [0.00413]	−0.0794 *** [0.00414]
Spouse's child only	−0.000617 [0.00757]	0.00909 [0.0128]	0.00327 [0.0106]	−0.0219 ** [0.0106]	−0.0204 * [0.0109]
Son-in-law or daughter-in-law	−0.0535 *** [0.0108]	−0.0646 *** [0.0104]	−0.0675 *** [0.0100]	−0.0836 *** [0.0101]	−0.0922 *** [0.00902]
Father, mother, stepfather, or stepmother	−0.0498 *** [0.00770]	−0.0466 *** [0.00791]	−0.0490 *** [0.00733]	−0.0424 *** [0.00820]	−0.0358 *** [0.00840]
Father/mother-in-law	−0.00986 [0.0171]	−0.00112 [0.0189]	−0.00674 [0.0180]	−0.00637 [0.0174]	−0.00312 [0.0180]
Grandchild	−0.108 *** [0.00511]	−0.107 *** [0.00733]	−0.113 *** [0.00521]	−0.168 *** [0.00534]	−0.179 *** [0.00583]
Great-grandchild	−0.152 *** [0.0126]	−0.142 *** [0.0171]	−0.153 *** [0.0170]	−0.208 *** [0.0173]	−0.228 *** [0.0165]
Brother or sister	−0.0578 *** [0.00792]	−0.0532 *** [0.00849]	−0.0554 *** [0.00759]	−0.0745 *** [0.00798]	−0.0694 *** [0.00798]
Grandfather or grandmother	−0.121 *** [0.0127]	−0.113 *** [0.0138]	−0.105 *** [0.0140]	−0.0988 *** [0.0137]	−0.0905 *** [0.0156]
Other relative	−0.0540 *** [0.00812]	−0.0639 *** [0.00851]	−0.0520 *** [0.00879]	−0.0830 *** [0.00668]	−0.0880 *** [0.00669]

Table A4. *Cont.*

	July	August	September	October	November
Age	−0.00154 *** [0.000339]	−0.00127 *** [0.000350]	−0.00122 *** [0.000326]	−0.00233 *** [0.000326]	−0.00270 *** [0.000343]
Age squared	0.0000153 *** [0.00000364]	0.0000111 *** [0.00000369]	0.00000934 *** [0.00000345]	0.00000763 ** [0.00000342]	0.00000743 ** [0.00000364]
Sex (reference category "Male")					
Female	−0.0185 *** [0.00279]	−0.0198 *** [0.00285]	−0.0178 *** [0.00267]	−0.0134 *** [0.00266]	−0.0131 *** [0.00262]
Education (reference category "Lower middle-level")					
Higher middle level of education	0.0919 *** [0.00228]	0.0920 *** [0.00229]	0.0890 *** [0.00221]	0.0753 *** [0.00220]	0.0732 *** [0.00222]
Housing condition (reference category "Own—already paid")					
Own—still paying	0.0211 *** [0.00816]	0.0121 * [0.00735]	0.0111 [0.00681]	0.00872 [0.00755]	0.00864 [0.00737]
Rented	−0.00531 [0.00416]	−0.00600 [0.00425]	−0.00659 * [0.00378]	−0.0125 *** [0.00383]	−0.0137 *** [0.00373]
Provided by employer	0.00528 [0.00450]	0.00640 [0.00478]	0.0137 [0.0119]	−0.00411 [0.00467]	0.00107 [0.00447]
Granted by family member	−0.0423 *** [0.00270]	−0.0424 *** [0.00311]	−0.0472 *** [0.00284]	−0.0358 *** [0.00335]	−0.0299 *** [0.00335]
Otherwise given	0.00679 [0.00692]	0.00803 [0.00686]	0.00828 [0.00787]	0.0152 ** [0.00704]	0.00949 [0.00707]
Other condition	−0.0677 *** [0.0101]	−0.0579 *** [0.0126]	−0.0724 *** [0.0102]	−0.0487 *** [0.0135]	−0.0510 *** [0.0122]
Constant	0.603 *** [0.00959]	0.610 *** [0.00994]	0.617 *** [0.00918]	0.694 *** [0.00938]	0.726 *** [0.00989]
Number of observations	297,349	299,668	300,448	294,930	295,179
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.0354	0.0352	0.0364	0.0308	0.0325

Notes: Standard errors (in brackets) are clustered at the household level, and estimates are computed with sample weights; reference groups for categorical control variables are indicated by the categories for which the corresponding estimated regression coefficient is equal to 0; star codes for statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: authors' elaborations using the PNAD COVID-19 monthly samples.

Table A5. RIF-regression for the Theil index of Brazilian total personal income.

	July	August	September	October	November
Positive for COVID-19	0.0700 ** [0.0346]	0.104 [0.0793]	0.114 *** [0.0415]	0.0961 ** [0.0375]	0.0791 *** [0.0230]
HH size	−0.00738 ** [0.00330]	−0.00779 ** [0.00343]	−0.0110 *** [0.00173]	−0.00661 *** [0.00182]	−0.00350 * [0.00181]
Worked in the last week	−0.0386 *** [0.00630]	−0.0646 *** [0.00614]	−0.0706 *** [0.00584]	−0.123 *** [0.00573]	−0.160 *** [0.00584]
Race (reference category "White")					
Black	−0.129 *** [0.0105]	−0.136 *** [0.0106]	−0.134 *** [0.00900]	−0.120 *** [0.00934]	−0.107 *** [0.00951]
Asian	0.0879 [0.0818]	0.122 [0.0912]	−0.0392 [0.0337]	0.0638 [0.0863]	0.0551 [0.0891]
White–Black	−0.113 *** [0.00740]	−0.117 *** [0.00783]	−0.110 *** [0.00638]	−0.0909 *** [0.00641]	−0.0853 *** [0.00624]
Indigenous	−0.123 *** [0.0147]	−0.136 *** [0.0162]	−0.133 *** [0.0133]	−0.114 *** [0.0148]	−0.0971 *** [0.0149]
Area (reference category "Capital")					

Table A5. *Cont.*

	July	August	September	October	November
Metropolitan region, excluding the capital	−0.203 *** [0.0140]	−0.200 *** [0.0141]	−0.195 *** [0.0126]	−0.185 *** [0.0128]	−0.183 *** [0.0122]
Integrated economic development region, excluding the capital	−0.210 *** [0.0135]	−0.205 *** [0.0140]	−0.193 *** [0.0125]	−0.182 *** [0.0121]	−0.160 *** [0.0123]
Federation unit	−0.235 *** [0.0119]	−0.230 *** [0.0119]	−0.222 *** [0.00996]	−0.206 *** [0.00982]	−0.208 *** [0.00984]
Urban area	0 [.]	0 [.]	0 [.]	0 [.]	0 [.]
Rural area	0.0132 ** [0.00539]	0.0125 ** [0.00493]	0.0124 ** [0.00505]	0.0460 *** [0.00498]	0.0462 *** [0.00501]
Relationship with HH head (reference category “HH head”)					
Spouse	−0.00198 [0.0105]	−0.00299 [0.0105]	−0.00112 [0.00916]	−0.0107 [0.00930]	−0.000417 [0.00926]
Child of the parent and spouse	−0.0648 *** [0.0118]	−0.0712 *** [0.0123]	−0.0659 *** [0.0104]	−0.111 *** [0.0110]	−0.119 *** [0.0113]
Child only of the responsible person	−0.124 *** [0.00908]	−0.128 *** [0.00924]	−0.121 *** [0.00806]	−0.151 *** [0.00897]	−0.165 *** [0.00935]
Spouse’s child only	−0.0345 ** [0.0144]	−0.0153 [0.0257]	−0.0165 [0.0211]	−0.0611 *** [0.0218]	−0.0641 *** [0.0231]
Son-in-law or daughter-in-law	−0.114 *** [0.0283]	−0.140 *** [0.0271]	−0.142 *** [0.0251]	−0.170 *** [0.0246]	−0.190 *** [0.0215]
Father, mother, stepfather, or stepmother	−0.108 *** [0.0165]	−0.107 *** [0.0171]	−0.107 *** [0.0148]	−0.0972 *** [0.0183]	−0.0854 *** [0.0193]
Father/mother-in-law	−0.0372 [0.0373]	−0.0229 [0.0397]	−0.0199 [0.0390]	−0.0252 [0.0408]	−0.0216 [0.0433]
Grandchild	−0.223 *** [0.0106]	−0.220 *** [0.0156]	−0.224 *** [0.00999]	−0.317 *** [0.0109]	−0.345 *** [0.0121]
Great-grandchild	−0.269 *** [0.0223]	−0.265 *** [0.0271]	−0.268 *** [0.0271]	−0.370 *** [0.0289]	−0.420 *** [0.0301]
Brother or sister	−0.118 *** [0.0191]	−0.108 *** [0.0197]	−0.109 *** [0.0171]	−0.144 *** [0.0191]	−0.139 *** [0.0194]
Grandfather or grandmother	−0.222 *** [0.0234]	−0.212 *** [0.0247]	−0.192 *** [0.0229]	−0.183 *** [0.0245]	−0.175 *** [0.0293]
Other relative	−0.120 *** [0.0250]	−0.135 *** [0.0264]	−0.107 *** [0.0261]	−0.177 *** [0.0122]	−0.191 *** [0.0125]
Age	−0.00506 *** [0.000801]	−0.00480 *** [0.000804]	−0.00444 *** [0.000721]	−0.00651 *** [0.000744]	−0.00777 *** [0.000840]
Age squared	0.0000489 *** [0.00000877]	0.0000435 *** [0.00000861]	0.0000386 *** [0.00000786]	0.0000385 *** [0.00000805]	0.0000446 *** [0.00000925]
Sex (reference category “Male”)					
Female	−0.0416 *** [0.00724]	−0.0440 *** [0.00749]	−0.0390 *** [0.00638]	−0.0322 *** [0.00661]	−0.0351 *** [0.00663]
Education (reference category “Lower middle-level”)					
Higher middle level of education	0.128 *** [0.00575]	0.129 *** [0.00549]	0.124 *** [0.00521]	0.107 *** [0.00531]	0.107 *** [0.00555]
Housing condition (reference category “Own—already paid”)					

Table A5. *Cont.*

	July	August	September	October	November
Own—still paying	0.0330 [0.0209]	0.0169 [0.0189]	0.00782 [0.0158]	0.0205 [0.0204]	0.0172 [0.0201]
Rented	−0.00334 [0.0135]	−0.00743 [0.0139]	−0.0140 [0.00888]	−0.0189 ** [0.00937]	−0.0213 ** [0.00932]
Provided by employer	−0.00530 [0.00746]	−0.00122 [0.00784]	0.0298 [0.0361]	−0.0138 * [0.00813]	−0.00650 [0.00809]
Granted by family member	−0.0688 *** [0.00535]	−0.0675 *** [0.00661]	−0.0743 *** [0.00576]	−0.0555 *** [0.00809]	−0.0463 *** [0.00820]
Otherwise given	0.0203 * [0.0116]	0.0205 * [0.0115]	0.0261 * [0.0159]	0.0272 ** [0.0124]	0.0231 * [0.0129]
Other condition	−0.115 *** [0.0152]	−0.0958 *** [0.0184]	−0.116 *** [0.0156]	−0.0845 *** [0.0204]	−0.0837 *** [0.0188]
Constant	0.734 *** [0.0222]	0.753 *** [0.0229]	0.753 *** [0.0199]	0.883 *** [0.0216]	0.954 *** [0.0245]
Number of observations	297,349	299,668	300,448	294,930	295,179
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.0136	0.0134	0.0155	0.0141	0.0138

Notes: Standard errors (in brackets) are clustered at the household level, and estimates are computed with sample weights; reference groups for categorical control variables are indicated by the categories for which the corresponding estimated regression coefficient is equal to 0; star codes for statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: authors' elaborations using the PNAD COVID-19 monthly samples.

Table A6. RIF-regression for the Palma ratio of Brazilian total personal income.

	July	August	September	October	November
Positive for COVID-19	0.400 *** [0.148]	0.404 ** [0.191]	0.579 *** [0.176]	0.548 *** [0.183]	0.572 *** [0.137]
HH size	−0.0607 *** [0.0100]	−0.0623 *** [0.0107]	−0.0667 *** [0.00862]	−0.0601 *** [0.0102]	−0.0304 *** [0.0109]
Worked in the last week	−0.290 *** [0.0290]	−0.435 *** [0.0293]	−0.491 *** [0.0283]	−1.277 *** [0.0324]	−1.662 *** [0.0353]
Race (reference category "White")					
Black	−0.895 *** [0.0417]	−0.951 *** [0.0434]	−0.983 *** [0.0410]	−0.949 *** [0.0485]	−0.959 *** [0.0532]
Asian	0.426 [0.311]	0.594 * [0.341]	0.0419 [0.202]	0.514 [0.372]	0.450 [0.402]
White–Black	−0.758 *** [0.0303]	−0.801 *** [0.0318]	−0.784 *** [0.0305]	−0.674 *** [0.0353]	−0.730 *** [0.0366]
Indigenous	−0.791 *** [0.0998]	−0.913 *** [0.0998]	−0.907 *** [0.0923]	−0.738 *** [0.126]	−0.724 *** [0.134]
Area (reference category "Capital")					
Metropolitan region, excluding the capital	−1.257 *** [0.0594]	−1.271 *** [0.0613]	−1.255 *** [0.0591]	−1.338 *** [0.0679]	−1.454 *** [0.0703]
Integrated economic development region, excluding the capital	−1.378 *** [0.0687]	−1.378 *** [0.0682]	−1.325 *** [0.0661]	−1.355 *** [0.0803]	−1.310 *** [0.0870]
Federation unit	−1.452 *** [0.0476]	−1.458 *** [0.0487]	−1.436 *** [0.0459]	−1.494 *** [0.0514]	−1.623 *** [0.0548]
Urban area	0 [.]	0 [.]	0 [.]	0 [.]	0 [.]
Rural area	−0.0472 ** [0.0213]	−0.0466 ** [0.0203]	−0.0342 [0.0217]	0.313 *** [0.0261]	0.332 *** [0.0279]
Relationship with HH head (reference category "HH head")					
Spouse	−0.00114 [0.0432]	−0.0116 [0.0440]	−0.00572 [0.0422]	−0.0591 [0.0481]	0.0350 [0.0514]

Table A6. *Cont.*

	July	August	September	October	November
Child of the parent and spouse	0.302 [0.526]	0.465 [0.690]	0.790 [0.699]	1.600 * [0.926]	1.335 [1.056]
Child only of the responsible person	−0.113 ** [0.0540]	−0.138 ** [0.0576]	−0.145 *** [0.0547]	−0.596 *** [0.0646]	−0.600 *** [0.0695]
Spouse’s child only	−0.613 *** [0.0426]	−0.619 *** [0.0458]	−0.623 *** [0.0442]	−1.035 *** [0.0560]	−1.133 *** [0.0606]
Son-in-law or daughter-in-law	0.0256 [0.0837]	0.136 [0.146]	0.0664 [0.121]	−0.344 ** [0.145]	−0.297 * [0.162]
Father, mother, stepfather, or stepmother	−0.541 *** [0.119]	−0.657 *** [0.116]	−0.699 *** [0.112]	−1.186 *** [0.134]	−1.330 *** [0.131]
Father/mother-in-law	−0.579 *** [0.0859]	−0.558 *** [0.0896]	−0.590 *** [0.0835]	−0.582 *** [0.110]	−0.570 *** [0.122]
Grandchild	−0.164 [0.193]	−0.0609 [0.215]	−0.135 [0.207]	−0.159 [0.235]	−0.162 [0.261]
Great-grandchild	−1.093 *** [0.0559]	−1.085 *** [0.0825]	−1.152 *** [0.0586]	−2.410 *** [0.0720]	−2.622 *** [0.0850]
Brother or sister	−1.470 *** [0.126]	−1.411 *** [0.181]	−1.573 *** [0.182]	−3.050 *** [0.231]	−3.471 *** [0.234]
Grandfather or grandmother	−0.634 *** [0.0879]	−0.579 *** [0.0957]	−0.603 *** [0.0859]	−1.039 *** [0.107]	−1.022 *** [0.116]
Other relative	−1.434 *** [0.135]	−1.312 *** [0.148]	−1.239 *** [0.150]	−1.388 *** [0.186]	−1.405 *** [0.221]
Age	−0.0165 *** [0.00377]	−0.0128 *** [0.00396]	−0.0127 *** [0.00371]	−0.0383 *** [0.00440]	−0.0415 *** [0.00499]
Age squared	0.000189 *** [0.0000406]	0.000138 *** [0.0000417]	0.000124 *** [0.0000393]	0.000131 *** [0.0000461]	0.000114 ** [0.0000529]
Sex (reference category “Male”)					
Female	−0.227 *** [0.0311]	−0.246 *** [0.0322]	−0.225 *** [0.0304]	−0.146 *** [0.0357]	−0.189 *** [0.0381]
Education (reference category “Lower middle-level”)					
Higher middle level of education	1.009 *** [0.0252]	1.028 *** [0.0258]	1.004 *** [0.0251]	0.923 *** [0.0297]	1.009 *** [0.0324]
Housing condition (reference category “Own—already paid”)					
Own—still paying	0.235 *** [0.0910]	0.142 * [0.0829]	0.135 * [0.0778]	0.103 [0.100]	0.134 [0.106]
Rented	−0.0562 [0.0460]	−0.0716 [0.0478]	−0.0719 * [0.0431]	−0.172 *** [0.0513]	−0.211 *** [0.0543]
Provided by employer	0.0352 [0.0496]	0.0507 [0.0541]	0.135 [0.133]	−0.0730 [0.0652]	−0.0264 [0.0685]
Granted by family member	−0.478 *** [0.0299]	−0.485 *** [0.0348]	−0.537 *** [0.0321]	−0.443 *** [0.0453]	−0.414 *** [0.0490]
Otherwise given	0.0716 [0.0769]	0.0763 [0.0778]	0.0883 [0.0895]	0.241 ** [0.0986]	0.150 [0.107]
Other condition	−0.702 *** [0.110]	−0.579 *** [0.143]	−0.765 *** [0.115]	−0.629 *** [0.188]	−0.770 *** [0.183]
Constant	4.019 *** [0.107]	4.112 *** [0.112]	4.182 *** [0.105]	6.068 *** [0.127]	6.628 *** [0.144]
Number of observations	297,349	299,668	300,448	294,930	295,179
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.0349	0.0352	0.0362	0.0309	0.0338

Notes: Standard errors (in brackets) are clustered at the household level, and estimates are computed with sample weights; reference groups for categorical control variables are indicated by the categories for which the corresponding estimated regression coefficient is equal to 0; star codes for statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: authors’ elaborations using the PNAD COVID-19 monthly samples.

Table A7. RIF-regression for the Gini coefficient of U.S. family income.

	September 2020	March 2021	March 2022
HH size	0.005594 *** [0.001267]	0.002949 *** [0.001264]	0.001796 [0.00135]
Age	0.001749 *** [0.000323]	0.002271 *** [0.000323]	0.001659 *** [0.000325]
Age squared	−0.0000173 *** [0.00000327]	−0.000025 *** [0.00000323]	−0.0000178 *** [0.00000323]
Sex (reference category "Male")			
Female	−0.00109 [0.001687]	−0.00248 [0.001684]	−0.00138 [0.00162]
Race (reference category "White")			
Black	0.041355 *** [0.004446]	0.031062 *** [0.004414]	0.035547 *** [0.004514]
American Indian	0.043588 *** [0.015333]	0.020953 * [0.012154]	0.050187 *** [0.010954]
Asian	−0.01117 * [0.006518]	−0.00018 [0.00677]	−0.007 [0.006655]
Multiracial	0.02483 *** [0.008789]	0.01673 ** [0.008475]	0.00362 [0.007317]
Marital status (reference category "Married")			
Separated	0.058732 *** [0.008949]	0.061155 *** [0.008963]	0.061924 *** [0.008609]
Divorced	0.025282 *** [0.004406]	0.023086 *** [0.0043]	0.034609 *** [0.00448]
Widowed	0.006089 [0.005124]	0.006217 [0.005113]	0.015129 *** [0.004972]
Never married/single	0.038972 *** [0.004085]	0.036583 *** [0.004083]	0.035091 *** [0.003865]
Citizenship (reference category "Born in U.S.")			
Born abroad to American parents	0.000503 [0.013886]	0.031243 ** [0.012919]	0.014425 ** [0.0142]
Naturalized citizen	0.022197 *** [0.004851]	0.023166 *** [0.004801]	0.021186 *** [0.004684]
Not a citizen	0.074587 *** [0.005783]	0.071512 *** [0.005411]	0.070237 *** [0.005327]
Veteran status (reference category "No")			
Yes	−0.02115 *** [0.004329]	−0.01861 *** [0.004134]	−0.02175 *** [0.004094]
Employment status (reference category "Employed")			
Armed forces	0.009455 [0.015358]	−0.00334 [0.012687]	0.00379 [0.01225]
Unemployed	0.051503 *** [0.005182]	0.062713 *** [0.005803]	0.072168 *** [0.007138]
Not in the labor force	0.043628 *** [0.002715]	0.05092 *** [0.002658]	0.046276 *** [0.002546]
Education(reference category "Not in universe or blank")			
None or preschool	−0.03944 [0.02152]	−0.03108 [0.019646]	−0.02812 [0.018511]
Primary	−0.0278 *** [0.010196]	−0.03238 *** [0.010219]	−0.013 [0.011341]
Secondary	−0.08023 *** [0.006725]	−0.08425 *** [0.006613]	−0.07325 *** [0.006401]
Higher	−0.10318 *** [0.006864]	−0.11117 *** [0.006746]	−0.10293 *** [0.006538]

Table A7. *Cont.*

	September 2020	March 2021	March 2022
Any physical or cognitive difficulty (reference category "No difficulty")			
Has difficulty	0.027938 *** [0.003364]	0.031923 *** [0.003344]	0.033688 *** [0.003115]
Region (reference category "New England division")			
Middle Atlantic division	0.005484 [0.007421]	−0.00363 [0.007472]	−0.00882 [0.00727]
East North Central division	−0.01313 * [0.006878]	−0.00829 [0.006987]	−0.01348 * [0.006947]
West North Central division	−0.0063 [0.007753]	−0.01326 * [0.007461]	−0.0132 * [0.007593]
South Atlantic division	−0.00457 [0.006717]	0.005978 [0.006666]	0.002563 [0.006695]
East South Central division	0.021226 *** [0.007516]	0.006027 [0.007262]	0.007306 [0.007399]
West South Central division	0.016122 ** [0.007125]	0.013386 * [0.007027]	0.014785 ** [0.007092]
Mountain division	−0.01144 [0.007268]	−0.00889 [0.007291]	−0.00849 [0.007395]
Pacific division	0.013864 * [0.007209]	0.008813 [0.007018]	−0.00152 [0.00699]
COVID-19			
Worked remotely (reference category "No")			
Yes	0.050598 *** [0.005055]	0.049904 *** [0.0051]	0.047001 *** [0.007299]
Unable to work (reference category "No")			
Yes	0.007915 [0.004872]	0.016675 *** [0.005995]	0.029035 ** [0.012276]
Received pay for hours not worked (reference category "No")			
Yes	−0.01263 [0.014048]	−0.03318 * [0.018676]	−0.04893 [0.037663]
Prevented from looking for work (reference category "No")			
Yes	0.022179 *** [0.007898]	0.034795 *** [0.008919]	0.04842 *** [0.017167]
Did not get medical care for a non-COVID-19 condition (reference category "No")			
Yes	0.017468 * [0.008631]	— —	— —
Constant	0.485149 *** [0.008457]	0.521287 *** [0.008416]	0.546077 *** [0.009054]
Number of observations	111,132	107,334	100,535
Prob > F	0.0000	0.0000	0.0000
R-squared	0.0299	0.0317	0.0371

Notes: Standard errors (in brackets) are clustered at the household level, and estimates are computed with sample weights; reference groups for categorical control variables are indicated by the categories for which the corresponding estimated regression coefficient is equal to 0; star codes for statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: authors' elaborations using IPUMS-CPS monthly samples (extracts made before 15 April 2022).

Table A8. RIF-regression for the Theil index of U.S. family income.

	September 2020	March 2021	March 2022
HH size	0.0057292 ** [0.0025454]	−0.000658 [0.0027235]	−0.0039014 [0.0031083]
Age	0.003203 *** [0.0006231]	0.0041546 *** [0.0006695]	0.0028179 *** [0.0007182]
Age squared	−0.0000299 *** [0.00000627]	−0.0000441 *** [0.00000667]	−0.0000295 *** [0.000000707]
Sex (reference category "Male")			
Female	−0.0003142 [0.0034476]	−0.0014374 [0.0036687]	0.0005713 [0.0036431]
Race (reference category "White")			
Black	0.0897122 *** [0.0083788]	0.0746557 *** [0.0090729]	0.0888121 *** [0.0097532]
American Indian	0.0999627 *** [0.0290721]	0.0566097 ** [0.025095]	0.1203011 *** [0.0234133]
Asian	−0.0456558 *** [0.0125741]	−0.0276881 * [0.0144521]	−0.0314893 ** [0.0150763]
Multiracial	0.0518196 *** [0.0169881]	0.0421298 ** [0.0177839]	0.0139563 [0.0162528]
Marital status (reference category "Married")			
Separated	0.1270413 *** [0.0176974]	0.1531806 *** [0.0188136]	0.1526043 *** [0.0187629]
Divorced	0.0703839 *** [0.0086103]	0.0738638 *** [0.0089438]	0.1013374 *** [0.0096758]
Widowed	0.0278146 *** [0.0100408]	0.0275235 ** [0.0107545]	0.0491712 *** [0.0107121]
Never married/single	0.0889268 *** [0.0079467]	0.0934215 *** [0.0084747]	0.0905557 *** [0.0083131]
Citizenship (reference category "Born in U.S.")			
Born abroad to American parents	0.0109246 [0.028158]	0.0602785 ** [0.0276892]	0.0311001 [0.031401]
Naturalized citizen	0.0540756 *** [0.0092886]	0.0554648 *** [0.0098935]	0.0563475 *** [0.0101893]
Not a citizen	0.1599625 *** [0.0112638]	0.1692001 *** [0.0110646]	0.1717154 *** [0.011786]
Veteran status (reference category "No")			
Yes	−0.0349153 *** [0.008273]	−0.0278908 *** [0.0083259]	−0.0355936 *** [0.0086096]
Employment status (reference category "Employed")			
Armed forces	0.045763 [0.0304945]	0.0321725 [0.0262847]	0.0374763 [0.0258739]
Unemployed	0.1008877 *** [0.0098125]	0.1347499 *** [0.0120487]	0.1625785 *** [0.0154066]
Not in the labor force	0.083628 *** [0.0051652]	0.1053439 *** [0.0054429]	0.1037226 *** [0.0054433]
Education (reference category "Not in universe or blank")			
None or preschool	−0.0849582 ** [0.0416539]	−0.0794584 * [0.0410254]	−0.0777796 * [0.0399449]
Primary	−0.0588486 *** [0.0193408]	−0.060232 *** [0.0207574]	−0.0173844 [0.0244108]
Secondary	−0.1515939 *** [0.0131787]	−0.1630433 *** [0.013842]	−0.1445294 *** [0.01405]
Higher	−0.2157216 *** [0.0133734]	−0.2467094 *** [0.0140552]	−0.2383545 *** [0.014319]

Table A8. *Cont.*

	September 2020	March 2021	March 2022
Any physical or cognitive difficulty (reference category "No difficulty")			
Has difficulty	0.0588142 *** [0.006408]	0.0721858 *** [0.0068193]	0.0788129 *** [0.0065235]
Region (reference category "New England division")			
Middle Atlantic division	0.0238743 * [0.0142492]	0.0057715 [0.0156282]	−0.0148614 [0.0161583]
East North Central division	0.0016503 [0.0131006]	0.0213831 [0.0146066]	−0.0015605 [0.0153301]
West North Central division	0.0163755 [0.0149213]	0.0087046 [0.0155836]	0.0010452 [0.0167348]
South Atlantic division	0.014350 [0.0129103]	0.039533 *** [0.0139199]	0.0280241 * [0.0148373]
East South Central division	0.0739536 *** [0.0141957]	0.0575792 *** [0.0149897]	0.0549912 *** [0.0160406]
West South Central division	0.0524142 *** [0.0136056]	0.0571499 *** [0.0145497]	0.0542295 *** [0.0156499]
Mountain division	0.0058426 [0.0139343]	0.0128473 [0.0151728]	0.0103712 [0.0163628]
Pacific division	0.0438654 *** [0.0139329]	0.0379049 *** [0.0146912]	0.0093812 [0.0155393]
COVID-19			
Worked remotely (reference category "No")			
Yes	0.0566538 *** [0.0100657]	0.0517689 *** [0.0108137]	0.0458256 *** [0.0160876]
Unable to work (reference category "No")			
Yes	0.0281759 *** [0.009364]	0.0451736 *** [0.0122318]	0.0720705 *** [0.0254885]
Received pay for hours not worked (reference category "No")			
Yes	−0.0214357 [0.0261926]	−0.0524728 [0.0390665]	−0.0832072 [0.0814507]
Prevented from looking for work (reference category "No")			
Yes	0.0392926 *** [0.014734]	0.0770644 *** [0.0179403]	0.1078523 *** [0.0353981]
Did not get medical care for a non-COVID-19 condition (reference category "No")			
Yes	0.0396184 ** [0.0164962]	— —	— —
Constant	0.3960299 *** [0.0166899]	0.46841 *** [0.0178375]	0.5275952 *** [0.0206941]
Number of observations	111,132	107,334	100,535
Prob > F	0.0000	0.0000	0.0000
R-squared	0.0349	0.0317	0.0371

Notes: Standard errors (in brackets) are clustered at the household level, and estimates are computed with sample weights; reference groups for categorical control variables are indicated by the categories for which the corresponding estimated regression coefficient is equal to 0; star codes for statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: authors' elaborations using the IPUMS-CPS monthly samples (extracts made before 15 April 2022).

Table A9. RIF-regression for the Palma ratio of U.S. family income.

	September 2020	March 2021	March 2022
HH size	0.070701 **	0.000567	0.022246
	[0.029923]	[0.034758]	[0.040353]
Age	0.044886 ***	0.070347 ***	0.064267 ***
	[0.007064]	[0.008578]	[0.009429]
Age squared	−0.00043 ***	−0.00075 ***	−0.00067 ***
	[7.14×10^{-5}]	[0.000086]	[9.37×10^{-5}]
Sex (reference category "Male")			
Female	−0.00146	−0.04641	−0.03851
	[0.036292]	[0.043583]	[0.045999]
Race (reference category "White")			
Black	1.08496 ***	0.903123 ***	1.194694 ***
	[0.103797]	[0.125941]	[0.142851]
American Indian	1.181797 ***	0.694208 *	1.646031 ***
	[0.366029]	[0.354386]	[0.353119]
Asian	−0.3957 ***	−0.24318	−0.24395
	[0.142073]	[0.182945]	[0.190358]
Multiracial	0.606859 ***	0.508989 **	0.113777
	[0.201898]	[0.240623]	[0.226973]
Marital status (reference category "Married")			
Separated	1.458869 ***	1.75382 ***	1.940761 ***
	[0.195814]	[0.235862]	[0.249148]
Divorced	0.628153 ***	0.697782 ***	1.054921 ***
	[0.09252]	[0.109197]	[0.124258]
Widowed	0.072223	0.136733	0.415067 ***
	[0.109564]	[0.130971]	[0.139347]
Never married/single	0.921743 ***	1.08198 ***	1.161567 ***
	[0.086679]	[0.104958]	[0.10926]
Citizenship(reference category "Born in U.S.")			
Born abroad to American parents	0.029079	0.843015 **	0.386177
	[0.282452]	[0.335166]	[0.391865]
Naturalized citizen	0.48881 ***	0.656912 ***	0.554208 ***
	[0.104924]	[0.127776]	[0.135683]
Not a citizen	1.778457 ***	2.069272 ***	2.110115 ***
	[0.130952]	[0.152345]	[0.161101]
Veteran status (reference category "No")			
Yes	−0.43178 ***	−0.48213 ***	−0.64981 ***
	[0.08935]	[0.104461]	[0.112666]
Employment status (reference category "Employed")			
Armed forces	0.300938	−0.26294	−0.0824
	[0.328714]	[0.333393]	[0.360597]
Unemployed	1.207317 ***	1.747777 ***	2.249202 ***
	[0.11639]	[0.159246]	[0.212809]
Not in the labor force	1.006354 ***	1.413616 ***	1.423349 ***
	[0.059036]	[0.070629]	[0.073934]
Education(reference category "Not in universe or blank")			
None or preschool	−0.8894 *	−0.63496	−0.68736
	[0.502435]	[0.546911]	[0.592171]
Primary	−0.54158 **	−0.86547 ***	−0.35842
	[0.23699]	[0.286404]	[0.343658]
Secondary	−1.89354 ***	−2.46683 ***	−2.34791 ***
	[0.146344]	[0.175483]	[0.187245]
Higher	−2.48087 ***	−3.20195 ***	−3.1122 ***
	[0.14929]	[0.178885]	[0.190837]

Table A9. *Cont.*

	September 2020	March 2021	March 2022
Any physical or cognitive difficulty (reference category "No difficulty")			
Has difficulty	0.673333 *** [0.074086]	0.908202 *** [0.089156]	0.958205 *** [0.091863]
REGION (reference category "New England division")			
Middle Atlantic division	0.121185 [0.160824]	−0.14261 [0.198053]	−0.1712 [0.209382]
East North Central division	−0.1665 [0.149734]	−0.16448 [0.185387]	−0.30902 [0.20032]
West North Central division	0.038675 [0.168057]	−0.27396 [0.197443]	−0.24366 [0.220626]
South Atlantic division	−0.05338 [0.145404]	0.195963 [0.176447]	0.10114 [0.191971]
East South Central division	0.618495 *** [0.166927]	0.229453 [0.196532]	0.2552 [0.216664]
West South Central division	0.4743 *** [0.155608]	0.467274 ** [0.188947]	0.512081 ** [0.205491]
Mountain division	−0.10946 [0.157644]	−0.14108 [0.194458]	−0.15717 [0.211799]
Pacific division	0.3296 ** [0.155463]	0.237254 [0.185428]	0.030212 [0.198737]
COVID-19			
Worked remotely (reference category "No")			
Yes	0.937473 *** [0.102109]	1.231106 *** [0.124753]	1.358905 *** [0.192518]
Unable to work (reference category "No")			
Yes	0.197439 * [0.105765]	0.50502 *** [0.161227]	0.945094 *** [0.356748]
Received pay for hours not worked (reference category "No")			
Yes	−0.14399 [0.297303]	−0.85445 ** [0.482331]	−1.34437 [1.043381]
Prevented from looking for work (reference category "No")			
Yes	0.515367 *** [0.18574]	1.090695 *** [0.252249]	1.542518 *** [0.547422]
Did not get medical care for a non-COVID-19 condition (reference category "No")			
Yes	0.3766479 ** [0.1862112]	— —	— —
Constant	2.868523 *** [0.186197]	3.647679 *** [0.223084]	3.895004 *** [0.258757]
Number of observations	111,132	107,334	100,535
Prob > F	0.0000	0.0000	0.0000
R-squared	0.0350	0.0317	0.0371

Notes: Standard errors (in brackets) are clustered at the household level, and estimates are computed with sample weights; reference groups for categorical control variables are indicated by the categories for which the corresponding estimated regression coefficient is equal to 0; star codes for statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Source: authors' elaborations using IPUMS-CPS monthly samples (extracts made before 15 April 2022).

Notes

1. https://covid19.who.int/data, (accessed on 17 January 2023).
2. A comprehensive literature review conducted by Alfani et al. (2023) offers valuable insight. These authors provide a thorough examination of the current body of literature on COVID-19 and inequalities, delving into various dimensions of inequality. They

explore the interplay between the pandemic crisis and not only income and consumption expenditures but also health, education, and well-being disparities, sex and ethnic/racial disparities, and "functional" disparities.

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