Impact of Job Loss on Household Income during the COVID-19 Pandemic: Results of a Quasi-Experimental Analysis in the Republic of the Congo

Ted Cléophane Ngassa
Marien Ngouabi University
Republic of the Congo
ted.ngassa@umng.cg

This study evaluates the average monthly income loss associated with COVID-19-related job losses in households in the Republic of the Congo (ROC). Firstly, the propensity score matching (PSM) method is used for the estimates. Secondly, endogenous switching regression accounts for the unobserved effect. The data used are from the survey on the impact of the COVID-19 pandemic on the living conditions of Congolese households conducted in 2020 by the National Institute of Statistics of the ROC. The results show, on the one hand, that the PSM method underestimates the assessed impact and, on the other hand, that the increase in household income loss attributed to job loss due to COVID-19 is 232,432.9 XAF on average per month. These results imply several measures (reducing the costs imposed on employers, subsidies, etc.) and the adaptation of labour market regulations to the new realities.

Key Words: job loss, household income loss, COVID-19, propensity score matching, endogenous switching regression, Republic of the Congo
JEL *Classifications:* C21; O15; O55; R20

Received 2025/08/19 · Revised 2025/10/23 · Accepted 2025/11/16

Published online 2026/03/31 https://doi.org/10.26493/1854-6935.24.5-31

Introduction

The COVID-19 pandemic has caused unprecedented losses of income and jobs in both developed and developing countries (Nafula et al. 2020). The International Labour Organisation (ILO) estimates income losses at USD 3.7 trillion and job losses at 144 million in 2020 compared with 2019 (International Labour Organization (ILO) 2020a). The same source indicated that the most affected sectors were services, particularly wholesale and retail trade, accommodation, catering, transport, and tourism. These job losses have resulted in significant losses in household income, with the corollary of increased unemployment, food insecurity and deterioration in household living conditions (Teachout and Zipfel 2020). A report on the world of work and COVID-19 reports a 60% decrease in income for informal-sector workers worldwide (ILO 2020b).

In Africa, this figure is around 80% (ILO 2020c). These statistics underscore the significance of assessing the impact of job losses on household incomes in African countries, particularly in the Republic of the Congo (ROC). These job losses could jeopardise the achievement of Sustainable Development Goals 1, 2, 8, and 10 – eradicating poverty, combatting hunger, promoting decent employment and economic growth, and reducing inequalities. This threat is particularly urgent for self-employed and informal workers, who represent the highest percentage of the working population in African countries and occupy the majority of precarious jobs (ILO 2020c).

The ILO's conclusions concur with those of the ROC. Strict lockdown for 46 days and the suspension of non-essential activities were the main measures taken by the Congolese government to curb the spread of COVID-19. These measures have not been without consequences for the Congolese economy. According to the results of a 2020 survey on the impact of COVID-19 on Congolese households conducted by the Institut National de la Statistique du Congo/National Institute of Statistics of the Republic of the Congo (INS-CG), job losses were observed in approximately 25% of households with at least one employed or salaried member (Institut National de la Statistique du Congo (INS-CG) 2020). This alarming statistic underscores the need to evaluate the impact of job losses on Congolese household incomes, particularly in a context where the informal sector is the leading provider of jobs on the labour market.

The objective of this study is to assess the impact of job loss on income loss during the COVID-19 period in the ROC. Specifically, the aim is to evaluate the difference between the average income lost by households where job loss was observed and those where job loss was not recorded. Secondly, it is a question of verifying whether this difference in average incomes lost is significant and associated with job loss due to COVID-19.

The contribution of this work can be considered at four levels. Firstly, on the construction of the job loss variable. Most studies (Assefa et al. 2022; Bundervoet et al. 2022; Gelo and Dikgang 2022) on Sub-Saharan Africa that analyse job loss and use telephone survey data employ a single question to capture this job loss.1 The present study extends this earlier work by considering a second question.2 In this way, our approach to job loss (which is based on these two questions) reduces the potential bias generated by households with members who were not employed before COVID-19 and who were entirely dependent on the transfers received.

Secondly, the data and methodology used. To our knowledge, this research is one of the few in sub-Saharan Africa to study the impact of job loss on income during a period of COVID-19 by combining two sources of data (telephone surveys and Ministry of Health data, i.e. the number of deaths and the number of infections linked to COVID-19). This combination of data sources makes it possible to take into account the potential selection bias generated by the psychosis (psychological factors) related to the health situation (psychosis affecting job loss during the COVID-19 period).

Third, while the extensive literature often explores measures to combat the COVID-19 pandemic (such as containment, teleworking, reduced working hours, and border closures) that affect employment, this study develops an analytical framework of a potential channel (often overlooked in the economic literature on COVID-19) through which psychological factors influence employment. This broader perspective enriches our understanding of the factors underlying job loss during the COVID-19 pandemic.

Fourth, this study is the first in the ROC to analyse the impact of job loss on household income lost during the COVID-19 pandemic. As such, it is the first to provide empirical evidence of the relationship between job loss and household income loss during COVID-19 in the ROC.

The rest of the paper is organised as follows. Section 2 presents the main government measures implemented in the ROC during the COVID-19 pandemic and their consequences on employment and income. Section 3 presents the selective literature review. Section 4 describes the methodology used in this study. Section 5 presents the results. Section 6 concludes the paper.

Measures to Combat COVID-19 in the Republic of the Congo and Its Consequences on Employment and Incomes

In this section, we present the main measures implemented by the Congolese government to combat the COVID-19 pandemic and their effects on employment and income.

The Republic of the Congo was one of the first African countries south of the Sahara to rapidly implement response measures against COVID-19, just days after confirming positive cases in its territory. After the first positive cases of COVID-19 were identified, the Congolese government introduced, among other measures, strict confinement for 46 days nationwide, the closure of economic activities deemed non-essential, and the shutdown of borders, schools, and markets. While these key measures have reduced the spread of COVID-19 in the ROC, they have also directly impacted employment and household income.

In June 2020, the Congolese government mobilised $50 million from the World Bank to provide an emergency income supplement to households, including an unconditional one-off transfer of 50,000 XAF (Central African CFA Francs), or $82, to 231,546 urban households.

According to the results of a survey on the impact of the COVID-19 pandemic conducted in the ROC in June 2020 by the World Food Programme (WFP) in collaboration with the Ministry of Social Affairs, the average monthly household income fell from 385,545 XAF in 2014 to 107,500 XAF in the first half of 2020. Similarly, a rapid survey by the United Nations Development Programme (Programme des Nations Unies pour le développement (PNUD) 2020) on the economic and social impact of the pandemic in the ROC found that the monthly income of 62.5% of household heads declined significantly during the same period. The survey also showed that 58.4% of household heads could save before the pandemic, but due to the COVID-19 pandemic, 39.8% have lost this ability.

The people most affected by these income losses are those working in industries such as trade, services, and transport (PNUD 2020). Informal workers are the most represented (INS-CG 2011; Bureau International du Travail 2016). This suggests that self-employed workers have been the hardest hit by the income loss, mainly due to measures implemented to combat COVID-19 in the ROC without practical accompanying measures to help maintain income, particularly for those working in the informal sector, which accounts for approximately 80% of jobs in the ROC (INS-CG 2011).

The results of a survey on the impact of COVID-19 on Congolese households carried out by the INS-CG in 2020 showed that 60.8% of heads of households were unable to go to work as usual. Of the total number of employees and trainees, only 39.5% could telework. Other results indicate that in August 2020, around 82% of households in the ROC experienced a reduction in their income from work or other income-generating activities, compared to before the pandemic, while 23% of businesses closed temporarily or permanently in the second quarter (World Bank 2021).

Some Elements of the Relationship Between Job Loss and Income Loss in the Literature

This selective literature review covers the following three points: COVID-19 and job loss in the literature, job loss and income loss during the COVID-19 period in the literature, and some empirical work.

COVID-19 AND JOB LOSS IN THE LITERATURE

This relationship can be analysed in part based on the matching theory. According to this theory, labour markets are characterised by frictions (Mortensen and Pissarides 1994). These frictions lead us to spend more time and mobilise more resources to match workers with jobs. This theory aligns with the realities observed during the COVID-19 pandemic. The measures taken to combat COVID-19, such as confinement, increased uncertainty and friction. This increase in uncertainty and friction led to a reduction in job offers, redundancies and a slowdown in re-employment, resulting in a rise in unemployment (Ernst et al. 2022). An increase in mismatches has also been observed as demand has shifted from one sector to another (e.g. a decline in the hotel industry and an increase in logistics) (World Bank 2021).

Similarly, segmentation theory can be used as a framework for analysing job loss during the COVID-19 period. This theory states that labour markets are divided into primary segments (stable, well-paid) and secondary segments (unstable, low-paid) (Doeringer and Piore 1971). This segmentation assumes that in the event of a shock, workers in the secondary segment are more exposed to job loss. Contreras-Gonzalez et al. (2022) argue that during the COVID-19 pandemic, informal workers were more exposed to job and income loss due to limited access to social protection.

Another channel rarely mentioned in the economic literature, but which partly explains job losses during the COVID-19 period, is linked to psychological factors. The high risk of exposure to COVID-19 and the poor quality of care provided in health facilities during the COVID-19 period in large African cities, where most of the population is concentrated, led to psychosis among the population (Semo and Frissa 2020). On the one hand, this psychosis led to the abandonment of economic activities. On the other hand, there has been a significant migration from urban to rural areas (where the risk of exposure to this pandemic was relatively low) (Ouadika et al. 2022).

Warr and Yusuf (2024) have argued that many people left their jobs or migrated during the pandemic due to safety concerns, specifically to avoid contracting COVID-19. The arguments put forward suggest that psychological factors influenced the decision to participate in the labour market. For example, some people have had to make a compromise between their health and their work and have voluntarily ceased their activities (particularly people in their fifties3 and the self-employed). This cessation of activity affects not only employment but also income.

JOB LOSS AND INCOME LOSS DURING COVID-19 IN THE LITERATURE

According to the economic approach to income distribution, income results from participation in production (wages, profits, and rents) and redistribution (donations and social transfers) (Mas-Colell et al. 1995; Kalecki 1938). This thesis on income distribution shows that work or employment (wages, profits) is directly linked to income. It also corroborates the argument that COVID-19 has affected income through two main channels (Contreras-Gonzalez et al. 2022). In this regard, some authors (Dandonougbo et al. 2021; World Bank 2020b) present two main groups of channels through which the COVID-19 pandemic has affected the economy. Some channels have a direct influence, while others have an indirect impact.

The direct channel of influence, often highlighted in the literature, is wages. According to several authors (Lollivier and Verger 1996; Ouedraogo and Thiombiano 2017; PNUD 2020), most of a household's income is derived from wages or profits generated by its primary source of income. The rest comes from other sources, such as transfers received or profits from complementary activities. All other things being equal, this composition of income means that job loss deprives household members of their primary source of income. This, in turn, reduces household income (Fofana and Omolo 2023).

Many authors claim that the measures implemented to combat the COVID-19 pandemic led to a reduction in working hours and to redundancies, which in turn caused considerable losses and reductions in income for individuals and households (Contreras-Gonzalez et al. 2022; Kansiime et al. 2021; Dandonougbo et al. 2021; Paweenawat and Liao 2024).

Savings and transfers received are often cited as indirect channels of influence. According to the World Bank (2020a), the prolonged duration of the pandemic has led to redundancies and unemployment. Unemployment alters the level of household savings, as members of households who lose their jobs increasingly rely on their savings to meet their basic needs (Mahmud and Riley 2021; Ogisi and Begho 2021). Similarly, the reduction in working hours has led households to resort to savings. This regular recourse to savings in turn reduces the capacity of jobless households to invest in income-generating activities. The primary consequence of this is a decline in the household's previously achieved income level over time.

Regarding transfers received, this channel plays a crucial role in explaining poverty and the impact of job loss on household income, particularly in developing countries (Fragoso 2022; Fisher et al. 2017). During the COVID-19 pandemic, the joint measures adopted by many countries resulted in job losses (Miyamura 2021). These job losses resulted in a decrease in both the frequency and volume of transfers. Consequently, the reduction in the amounts sent and the frequency with which they were sent had an impact on the incomes of the households that received these transfers, insofar as the amounts received were generally lower than those obtained during the pre-pandemic period.

SOME EMPIRICAL RESEARCH

Several authors have empirically demonstrated that job loss affects household income. Dandonougbo et al. (2021) found that the job loss of the breadwinner increases the likelihood of a decline in household income. Similarly, Putra et al. (2023) revealed that income declines are more pronounced among men, young people, the self-employed and part-time non-agricultural workers. Mahmud and Riley (2021) indicated that a 60% drop in income was almost entirely linked to the cessation of profits from agricultural businesses and wages. Mahmud and Riley (2023) found that the income of relatively well-off households that owned a business before the pandemic fell by one-third due to the prolonged closure of businesses, even after the initial confinement restrictions ended. Identical findings of declining household incomes following job loss were also obtained by Aragie et al. (2021), Laborde et al. (2021), and Djiofack et al. (2020).

Although the results of the empirical work presented above show that job loss leads to an increase in income loss for households and individuals, maintaining a job does not prevent a consequent fall in income. Analysing data from a sample survey of 5,000 people in 12 Indian states, Kesar et al. (2021) found that those who could keep their jobs during COVID-19 reported a sharp fall in income. Ondoua Biwolé (2021) found that the COVID-19 pandemic did not generally have a significant influence on household work and remuneration.

On the one hand, considering this brief review of the literature and bearing in mind that in most sub-Saharan African countries, significant job losses were observed during the COVID-19 pandemic and on the other hand, that households have low savings capacities and often depend on transfers, this research supports the hypothesis that job losses led to an increase in the amount of household income lost during the COVID-19 period.

Methodology

This section describes the methods used for the estimates, the data sources and the analysis variables.

CHOICE, PRINCIPLE, AND ESTIMATION METHOD

In this work, the propensity score matching (PSM) method developed by Rosenbaum and Rubin (1983) is used to assess the impact of job loss on income. The PSM method is appropriate when data is available over a single period, generally after the programme has been implemented, and when individuals are not necessarily assigned randomly. Given the nature of the data available (cross-section or snapshot), the PSM method offers a relative advantage over panel regressions and the computable general equilibrium method as it does not require data between two periods or the availability of an up-to-date social accounting matrix. Instead, it relies on assumptions or conditions based on observable variables. The basic principle of the PSM method is to create the conditions for a randomised experiment to evaluate a causal effect, as in a controlled experiment.

If Y_{1i} is the income lost by people who have lost their job ($T_i = 1$) and Y_0 is the income lost by people who have not lost their job ($T_i = 0$), it is possible to observe the result of people who have lost their job ($E(Y_{1i} \mid T_i = 1)$) but not the result of those who have not lost their job if they had lost their job ($E(Y_{0i} \mid T_i = 1)$). By satisfying two hypotheses (conditional independence and existence of a common support), estimation by propensity score matching makes it possible to obtain the net treatment (job loss) effects (Rosenbaum and Rubin 1983).

The assumption of conditional independence (($Y \perp T \mid X$)) is based on the thesis that selection bias can be controlled if there is a set of observable variables for which treatment assignment can be verified. The common support hypothesis relates to the distribution of the propensity score. It ensures that the individuals in each analysis group are sufficiently similar for the comparison to be possible and meaningful. Thus, the conditional probability between the outcome variable (Y_I) and the job loss status (T_I) is statistically independent and defines the job loss propensity score $e(X_i)$ as follows:

$$e(X_i) = P_r(T_i = 1 \mid X_i), \tag{1}$$

where X_I represents the observed covariates, $T_i = 1$ represents the treatment (job loss), and $T_i = 0$ for the control (no job loss).

To apply the PSM method, it must be possible to obtain individuals who have not lost their jobs who have similar characteristics to those who have lost their jobs. The individuals being compared must then have the same probabilities of losing or not losing the job, such that $0 < e(X_i) < 1$. Satisfying the assumptions of conditional independence, existence of a common support and unit value, leads us to specify the estimator of the Average Treatment effect on the Treated (ATT) by the PSM as follows:

$$ATT = E\{Y_{i1} \mid T_i = 1, e(X_i)\} - E\{Y_{i0} \mid T_i = 1, e(X_i)\}. \tag{2}$$

This equation is estimated in several stages. First, the probability of losing the job is estimated using a probit (see Table A1 in the Appendix). The probit is used to obtain propensity scores for each individual. Next, each individual who has lost a job is matched with someone who has not lost a job and who has a similar propensity score. Finally, the ATT value is estimated by taking the difference between the job and non-job losers' results with similar characteristics. In this work, nearest neighbour with replacement is used as the matching technique. As covariates, the variables household size, gender, closure of borders, access to finance, transfer received, age, and having worked during confinement are used. Estimates are made without and with bootstrap.

The results' sensitivity is assessed using complementary estimates with the endogenous switching regression method. This method is appropriate for situations where the result of interest is subject to selection bias and endogeneity, as in this research. Indeed, the contextual elements presented in Section 2 show that the measures taken by the government, in particular the confinement and cessation of non-essential activities, have directly affected employment in the sense that these measures have increased the probability of job loss, particularly among the self-employed. Similarly, the country's two major cities (Brazzaville and Pointe-Noire) were the ones with the highest number of confirmed cases of COVID-19, including deaths. The 'alarming' health situation, particularly in these cities, led to the voluntary cessation of activities and migration of people from these two large towns to other departments where positive cases were not identified or identified in very low proportions (Ouadika et al. 2022).

These migrations can be seen as self-selection behaviour since they led to the voluntary cessation of activities and, consequently, job losses, particularly among self-employed workers living in the two major cities, which account for three-quarters of the country's jobs (INS-CG 2021). This scenario highlights the potential bias of omitted variables. It suggests that deaths and contaminations influenced job loss during the COVID-19 pandemic, as some workers chose to give up work in favour of their health (Demirkaya et al. 2022).

Two variables, the cumulative number of COVID-19 cases per department and the cumulative number of COVID-19 deaths per department, are used in this study to account for this unobserved heterogeneity. These two quantitative variables were taken from a report on the COVID-19 pandemic in the ROC published on 5 September 2020 by the Ministry of Health, Population, the Promotion of Women, and the Integration of Women in Development. Therefore, employing these variables may resolve or reduce the potential bias of omitted variables.

The endogenous switching regression method consists of two primary equations: the selection equation and the outcome equation. In mathematical terms, this can be presented as follows:

i. Selection equation

$$T_i^* = Z\gamma + \eta, \tag{3}$$

$$T_i = \begin{cases} 1, & if \quad T_i^* = 1 \\ 0, & Otherwise \end{cases} \tag{4}$$

with $T_i = 1$ means job loss, and $T_i = 0$ no job loss. T^* is a latent variable.

ii. Outcome equations

$$Y_i = \begin{cases} (X_{1i}\beta_1 + \varepsilon_1, & if\ T_i = 1 \\ (X_{0i}\beta_0 + \varepsilon_0, & if\ T_i = 0 \end{cases}. \tag{5}$$

Y_{1i} and Y_{0i} are the outcomes of interest. In these equations, Z and X represent vectors of explanatory variables, while γ, β_1 and β_0 denote corresponding parameter vectors. The error terms η, ε_0, and ε_1, are assumed to be correlated across equations. The selection equation determines which regime (or state) an observation belongs to. The outcome equation details the relationship between the independent variables and the outcome, which is conditional on the regime. It is typically assumed that the error terms have a joint trivariate normal distribution, with zero mean disturbances and a covariance matrix.

After estimating the model parameters, it is possible to calculate the conditional outcomes with correction for biases arising from observable and unobservable factors. These conditional outcomes are defined as follows:

$$E(Y_{1i} \mid T_i = 1) = \gamma_1 X_{1i} + \sigma_{\varepsilon 1\eta}\lambda_{1i} \tag{6a}$$

$$E(Y_{0i} \mid T_i = 0) = \gamma_0 X_{0i} + \sigma_{\varepsilon 0\eta}\lambda_{0i} \tag{6b}$$

$$E(Y_{0i} \mid T_i = 1) = \gamma_0 X_{1i} + \sigma_{\varepsilon 0\eta}\lambda_{1i} \tag{6c}$$

$$E(Y_{1i} \mid T_i = 0) = \gamma_1 X_{0i} + \sigma_{\varepsilon 1\eta}\lambda_{0i} \tag{6d}$$

where

$$\lambda_{1i} = \frac{\varnothing(Z\gamma)}{\Phi(Z\gamma)} \tag{7a}$$

and

$$\lambda_{0i} = \frac{\varnothing(Z\gamma)}{1 - \Phi(Z\gamma)} \tag{7b}$$

represent the inverse Mill's ratios used to control for endogenous switching and estimated by using the results of selection equation estimation. $\varnothing$ is the density function of the standard normal probability and Φ is the cumulative normal density function. $\sigma_{\varepsilon 1\eta}$ and $\sigma_{\varepsilon 0\eta}$ are, respectively, the estimated correlation coefficients between ε_1 and η_i, and between ε_0 and η_i. X_{1i} and X_{0i} represent vectors of explanatory variables. γ_1 and γ_0 are the parameter vectors.

The ATT is obtained by taking the difference between (6a) and (6c), i.e.:

$$\begin{aligned} ATT &= E(Y_{1i} \mid T_i = 1) - E(Y_{0i} \mid T_i = 1) \\ &= X_{1i}(\gamma_1 - \gamma_0) + (\sigma_{\epsilon 1\eta} - \sigma_{\epsilon 0\eta})\lambda_{1i}. \end{aligned} \tag{8}$$

Data

The data used for the estimates were obtained from a sample survey administered by telephone to 1,500 households representative of the Congolese population at the national level. This survey was conducted by the National Institute of Statistics of the Republic of the Congo in September 2020 to analyse the effects of the COVID-19 pandemic on the living conditions of Congolese households. The sample considers the population structure by department. The survey was conducted from 2 to 17 September 2020, with 1,397 respondents, yielding a response rate of 93%. This database was chosen because it is directly linked to the COVID-19 pandemic. Sections also exist that refer to pre-pandemic situations, such as the employment situation before the pandemic and the amount of income lost declared by households compared to the pre-pandemic period.

Variables

OUTCOME VARIABLE

This is the monthly amount declared by the head of the household or the respondent relating to the income lost per month because of COVID-19 compared with the situation before the COVID-19 pandemic. This variable was quantitative.

TREATMENT VARIABLE

Unlike other studies (Dandonougbo et al. 2021; Bundervoet et al. 2022) that used a single question on job loss during COVID-19, our construction considers a second question related to the employment status of household members before the pandemic. A household is considered to have suffered a job loss related to COVID-19 if the household head declared a job loss related to COVID-19 for at least one member of the household (including themselves) and if the household had at least one member employed before COVID-19. Combining these two questions reduces the potential bias generated by households that had no employed members before the pandemic and were dependent on transfers received. This variable is binary and equals 1 if there is a job loss linked to COVID-19 and 0 otherwise.

CONTROL VARIABLES

Based on the literature review and availability of variables in the database, the following variables were selected:

- *Household size*: Having many members of the household employed can be an important factor in mitigating the loss of household income during the COVID-19 pandemic, when job losses are increasingly observed. This variable was quantitative.
- *Gender*: Due to labour market discrimination often experienced by women, income losses are expected to be higher in female-headed households than in male-headed ones. This variable equals 0 if the head of the household is a man and 1 if a woman.
- *Closure of borders*: Given the Republic of the Congo's dependence on certain staple products coming mainly from neighbouring countries (e.g. Cameroon, Democratic Republic of Congo), this measure by the Congolese government has mainly impacted the employment of traders and their income. It is coded 1 if the respondent states that the measure has impacted the employment of a household member and 0 otherwise.
- *Access to finance*: based on the role of finance in entrepreneurship (job creation, investment to maintain level of activity, innovation, etc.), we consider people who could access finance during the COVID-19 pandemic as those who maintained their activity level and experienced relatively less loss of income than others. This variable is binary and equals 1 if at least one member was able to access finance and 0 otherwise.
- *Transfer received*: The fact that a household received a money transfer is a source of increased household income. This variable is dichotomous and equals 1 if the household has received a money transfer, and 0 otherwise.
- *Age*: The literature on the COVID-19 pandemic maintains that young people were the most affected by job losses, suggesting that being young increases the probability of household job losses. This varia-

ble equals 1 if the household head is aged between 15 and 35, and 0 if over 35. The 15–35 age range is the one used by the African Union to define young people. This definition of a young person is also used in the Republic of Congo.

- *Having worked during confinement*: people who worked during confinement were the most likely to retain their jobs and income. This means, on the one hand, that working during the COVID-19 pandemic seems to reduce the likelihood of losing one's job. On the other hand, it seems to reflect an increase in the possibility of maintaining income. This variable is dichotomous and equals 1 if a member of the household has worked during confinement, and 0 otherwise.

Results and Discussion

This section presents and analyses results obtained and sensitivity. It also discusses the results after estimations.

TABLE 1 Description of Samples Before or After Matching

		Mean		T-test	
		Treated	Control	t	p>|t|
Gender of head of household or respondent	Unmatched	0.8231	0.7393	2.90	0.004
	Matched	0.8218	0.8545	-1.04	0.298
Age of head of household or respondent	Unmatched	0.7112	0.7727	-2.14	0.032
	Matched	0.7163	0.7163	0.00	1.000
Household size	Unmatched	4.8592	4.666	1.16	0.246
	Matched	4.8545	4.7964	0.34	0.737
Transfer received	Unmatched	0.3538	0.4453	-2.75	0.006
	Matched	0.3564	0.36	-0.09	0.929
Having worked during confinement	Unmatched	0.2599	0.3692	-3.42	0.001
	Matched	0.2618	0.2764	-0.38	0.701
Access finance during the confinement	Unmatched	0.3285	0.3970	-2.09	0.036
	Matched	0.3309	0.36	-0.72	0.474
Closure of borders	Unmatched	0.3105	0.2746	1.18	0.237
	Matched	0.3054	0.2945	0.28	0.781

	Sample	
	Before matching	After matching
Untreated	1,118	1,078
Treated	279	277
Total	1,397	1,355

SOURCE Author's calculations based on the COVID-19 survey conducted by INS-Congo in September 2020.

DESCRIPTIVE STATISTICS

Table 1 presents some characteristics of the analysis sample before and after matching.

The data indicate that, before matching, there are significant differences in gender, age, transfer received, having worked during confinement, accessing finance during confinement, and job loss related to COVID-19 between the sample of the treatment group and the sample of the control group. On the other hand, there is no significant difference in household size and closure of borders. After matching, these two groups have no significant difference for all variables. Additionally, the average monthly income loss declared by households for the sample before matching was 135,856.8 XAF.

ECONOMETRIC RESULTS AND DISCUSSION

The results of the impact of job loss on the loss of monthly household income are presented in Table 2, which indicates that the mean value of the propensity score for the treatment group is 0.23980, and the mean value for the control group is 0.23985. The region of common support is [.0569; .5156]. The estimated propensity scores respect the balancing property, resulting in a common support area of 1,355 observations, or 96.9% of the total sample (see table 1 and fig. A1 in the Appendix). The

TABLE 2 Estimates of the Impact of Job Loss on Loss of Monthly Income Using the PSM Method

		PSM
Without Bootstrap	ATT (XAF)	93074.327***
	Standard errors	21218.811
	T-stat	4.39
With Bootstrap (n replications=1500)	ATT (XAF)	93074.33***
	Standard errors	29661.42
	T-stat	3.14
Mean tests for common support propensity scores	Mean treated group	0.23980
	Mean control group	0.23985
	%Bias	-0.1
	P>|t|	0.995
	V(T) / V(C)	1.00
Region of common support		[0.0569 ; 0.5156]

SOURCE Author's calculations based on the COVID-19 survey conducted by INS-Congo in September 2020.

NOTE: ***p <0.01.

distribution of the two groups' propensity scores (fig. A2 in the Appendix) confirms the balancing property. Furthermore, the results of the Rosenbaum sensitivity tests (table A2 in the Appendix) support that the estimates obtained are not very sensitive to unobserved factors. These diagnostic tests show that common support and conditional independence assumptions are verified and satisfied. Similarly, the estimates show that the results obtained can be analysed and discussed. If we examine the results in Table 2 obtained without bootstrapping, we see that there is, on average, a positive and statistically significant difference in terms of ATT. This difference is approximately 93,074.327 XAF.

When the bootstrap method was used to estimate the errors, the standard error values increased from 21,218.811 XAF to 29,661.42 XAF. The results were calculated with precision (significance at the 1% level). These results suggest that job loss increases the average amount of income lost by households by around 93,074.327 XAF for households where job loss was observed, compared with what their lost income would have been had they not experienced job loss.

These results indicate that some households are more vulnerable to health and socio-economic shocks than others. This supports the hypothesis that job loss had a significant impact on the loss of income of families, particularly those in which job loss due to COVID-19 was actually observed, compared with households whose members did not experience job loss.

To verify the sensitivity of our results, as outlined in the Methodology section, we estimated the impact using the endogenous switching regression (ESR) method. On the one hand, the aim is to verify whether the results obtained with the PSM method, which do not take unobserved factors into account, are sufficiently reliable. Secondly, we check whether the independent factors influence the results obtained with the ESR method when we take certain conditions into account (interaction effects).

In the base case (model without interaction terms but with all covariates), the results of the estimates obtained using the ESR method (Table 3) indicate a significant average difference at the 5% threshold between the observed result for treated households and the counterfactual result they would have obtained if they had not been treated, correcting for biases related to the endogeneity of job loss (non-random choice in the treatment). The magnitude of this impact is approximately 232,432.9 XAF per month. This value is much higher than that obtained using the

TABLE 3 Results of Estimations with Endogenous Switching Regression (ESR) Method

	ESR			
	ATT (XAF) [T-stat]	ATT (XAF) [T-stat]	ATT (XAF) [T-stat]	ATT (XAF) [T-stat]
Without interaction				
	232,432.9** [2.26]			
With interactions				
Transfer received*Closure of borders		282,225.5*** [2.96]		
Access to finance*Having worked during confinement			275,252.2*** [2.81]	
Job loss*Transfer received*Closure of borders				286,839.3*** [3.00]

SOURCE Authors' calculations based on the COVID-19 survey conducted by INS-Congo in September 2020.
NOTE: ***p <0.01 ; **p <0.05 ; [...] T-statistic.

PSM method presented in table 2. This suggests that the PSM method underestimated the average amount of income lost by households affected by job loss due to COVID-19. This underestimation was identified by taking into account the number of cases and deaths linked to COVID-19, variables used to capture psychological factors. This highlights the significance of psychological factors in explaining the substantial job losses observed and the connection between job loss and income decline during the COVID-19 pandemic.

When we consider the interaction between transfers received and the closure of borders, we find a significant increase of 282,225.5 XAF, or 49,792.6 XAF more, compared to the basic model (i.e. the model without interaction terms). This increase is 275,252.2 XAF for the interaction between access to finance and work during the confinement period. The highest impact (286,839.3 XAF) is observed when considering the interaction between job loss, transfers received, and border closure. Furthermore, the significance level has dropped from 5% (for the basic model) to 1% (for the models with interaction terms). This suggests that the impact is accurately estimated when interactions are taken into account, highlighting that lost income is sensitive to interaction terms, although the effects remain moderate. This sensitivity analysis suggests that the model is relatively stable in practical applications. It also shows that the ESR model reacts to parameter changes. This reinforces its usefulness for planning or simulating the potential impacts expected in terms of income lost by households during the COVID-19 period.

In view of these results, the findings obtained in this work, using both methods (PSM and ESR), point in the same direction. They predict an increase in the average amounts of income lost by households where job loss has been observed, compared with what their income would have been had they not experienced job loss. However, those obtained using the PSM method appear to be more sensitive to unobserved factors. Thus, our results suggest that the ESR model performs better and seems more appropriate than the PSM model in the presence of strong endogeneity. Furthermore, the results obtained with the ESR method are only slightly sensitive to the inclusion of interactions between independent factors. This indicates that our results are acceptable even when considering certain additional conditions compared to the basic model.

These results are consistent with those of Adams-Prassl et al. (2020). Other authors (Murakami 2022; Bundervoet et al. 2022) have also found that job loss leads to income loss. These results reflect an increase in income inequalities and the creation of new inequalities between households, as the estimated average monthly income loss (232,432.9 XAF) for families whose members lost their jobs due to COVID-19 represents 34% of the average household income in the ROC before the COVID-19 pandemic. However, our results differ from those of Ondoua Biwolé (2021), who found that job loss had no significant effect on household income. Furthermore, these results are not in line with those of Kesar et al. (2021), who report a substantial loss of income for households whose members were able to keep their jobs.

In the context of this study, two main factors may help to explain these results. First, a context marked by the absence of immediate support measures granted to households whose members have lost their jobs due to measures taken by the Congolese government to combat the pandemic and by a significant presence of self-employed workers, particularly in activities classified as non-essential, that is, not authorised during the 46 days of strict confinement imposed by the government (PNUD 2020; Bitsoumanou Nkounkou and Temple 2021). Suppose we consider the cessation of non-essential activities during this period. In that case, we can assume a more rapid and greater increase in household income loss for those members who lost their jobs due to the COVID-19 pandemic.

Second, the COVID-19 pandemic, which caused job losses globally, must have had indirect effects on household incomes, mainly in Africa, where the transfers received played a significant role in improving income and reducing poverty (Janssens et al. 2021; Devereux 2021). However, the statistics presented in the INS-CG (2020) report indicate that only 3.29% of households received transfers in cash or in kind during September 2020, compared to the usual rate (30.85%). The absence of immediate support measures for families whose members have lost their jobs and the dependence of some households on transfers received, combined with the low level of savings and poor access to credit to restart activities after the end of strict confinement, may partly justify the results obtained six months after the measures put in place by the Congolese authorities to combat COVID-19 were lifted.

Conclusion and Economic Policy Implications

This study aimed to analyse the impact of job loss on household income loss in the context of the COVID-19 pandemic in the Republic of the Congo. We hypothesised that job losses led to an increase in the amount of household income lost during the COVID-19 period. To test this hypothesis, we first used propensity score matching. Then, the endogenous switching regression (ESR) method was used to test the sensitivity of the results.

The main results show a statistically significant positive difference between the average amount of income lost by households where job loss was observed, compared with what their lost income would have been had they not experienced job loss. This result suggests that job loss linked to COVID-19 increases the loss of income for households where the job loss occurred, compared to what their income would have been had the job loss not occurred. The hypothesis that this study supported is confirmed by this outcome. The increase in lost income averages 232,432.9 XAF per month. This estimated loss of average income during the COVID-19 pandemic represents 34% of the average income of Congolese households before the COVID-19 pandemic.

In implementing targeted policies regarding Sustainable Development Goals 1, 2, 8, and 10, for example, the results imply future economic policy measures focusing on job protection, creation, and retention. Strupat (2022) has shown that the social assistance received by households during the COVID-19 pandemic did not compensate for the negative economic consequences of the pandemic. This could involve, for example, reducing the costs imposed on employers in the formal sector to encourage the growth of formal employment. In the informal sector, it may mean rethinking the measures that enable people to move from the informal to the formal sector, to allow informal workers to migrate to the formal sector to benefit from potential subsidies allocated in times of crisis. These subsidies are often intended for firms operating in the formal sector. Adapting Congolese labour market regulations to the new realities would also be important. On the other hand, programmes should be implemented to improve the labour supply and help workers access acceptable-quality jobs.

The results obtained in this work show that the trends in the estimates obtained from the two methods point in the same direction. However, the PSM method appears to have the weakest effect, undoubtedly due to the impact of unobserved characteristics.

Using the endogenous switching regression method, taking into account the number of deaths and the number of cases of contamination by department, enabled these biases to be corrected and reduced. This study's techniques (PSM, ESR) have several limitations, mainly related to the data used. These include the potential bias of memory and income declaration, and the bias associated with excluding households without telephone access. However, these limitations do not significantly affect the results obtained. In the Republic of the Congo, measures to combat COVID-19 took effect in April 2020 and were extended several times until July 2020. Data collection for the survey used in this study took place in September 2020 (from the 2nd to the 17th).

This assumes that in the space of a month, individuals were able to remember the facts and provide consistent income declarations. Similarly, 2020 data from the World Bank (World Development Indicators) shows that for every 100 people, mobile phone subscriptions amounted to 98. This implies that, in 2020, the probability of finding a household without access to a telephone was very low. All the arguments show that, despite some limitations mentioned, the results of this research remain valid and acceptable.

Although this research has yielded some interesting results, several limitations remain. The primary issue is that it does not allow us to assess the impact dynamically. This limitation presents new research opportunities. For countries where data collected over several periods is available, the effect studied in this research can be assessed by taking into account, mainly, the dynamics of psychological factors and measures to combat COVID-19.

Informed Consent Declaration

Consent was obtained by the National Institute of Statistics of the Republic of the Congo for all respondents during the survey.

Notes

1 Whether the household head reported a job loss related to COVID-19 for at least one household member.

2 If the household had at least one member employed before COVID-19.

3 Correlation between age and deaths linked to the COVID-19 pandemic.

References

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh. 2020. 'Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys.' *Journal of Public Economics* 189:104245.

Aragie, E., A. S. Taffesse, and J. Thurlow. 2021. 'The short-term economy wide impacts of COVID-19 in Africa: Insights from Ethiopia.' *African Development Review* 33 (51): 152–164.

Assefa, N., Y. Y. Abdullahi, E. C. Hemler et al. 2022. 'COVID-19 Preventive Practices, Psychological Distress, and Reported Barriers to Healthcare Access during the Pandemic among Adult Community Members in Sub-Saharan Africa: A Phone Survey.' *The American Journal of Tropical Medicine and Hygiene* 108 (1): 124–136.

Bitsoumanou Nkounkou, J., and L. Temple. 2021. 'Résilience du secteur alimentaire face à la crise Covid-19 et perspective pour les politiques agricoles en République du Congo.' *Cahiers Agricultures* 30 (39): 1–8.

Bundervoet, T., M. E. Dávalos, and N. Garcia. 2022. 'The short-term impacts of COVID-19 on households in developing countries: An overview based on a harmonized dataset of high-frequency surveys.' *World Development* 153: 105844.

Bureau International du Travail. 2016. *Transition vers le marché du travail des jeunes femmes et hommes en* République du Congo. Work4Youth Série de publication No. 39. Bureau International du Travail.

Contreras-Gonzalez, I., G. Oseni, A. Palacios-Lopez, P. Janneke, and M. Weber. 2022. *Inequalities in Job Loss and Income Loss in Sub-Saharan Africa during the COVID-19 Crisis*. Policy Research Working Paper 10143. World Bank.

Dandonougbo, Y., Y. Tossou, E.- H. Atake, and D. K. Ekouevi. 2021. 'Effets de la COVID-19 sur la variation du revenu et la sécurité alimentaire des ménages au Togo.' *African Development Review* 33(S1): 194–206.

Demirkaya, H., M. Aslan, H. Güngör, V. Durmaz, and D. R. Şahin. 2022. 'COVID-19 and Quitting Jobs.' *Frontiers in Psychology* 13:916222.

Devereux, S. 2021. 'Social Protection Responses to COVID-19 in Africa.' *Global Social Policy* 21 (3): 421–47.

Djiofack, Z. C., H. Dudu, and A. G. Zeufack. 2020. 'Assessing COVID-19's Economic Impact in Sub-Saharan Africa: Insights from a CGE model.' In COVID-19 in Developing Economies, edited by S. Djankov, and U. Panizza. CEPR Press.

Doeringer, P. B., and M. J. Piore. 1971. *Internal Labor Markets and Manpower Analysis*. D. C. Heath and Company.

Ernst, E., R. Merola, and J. Reljic. 2022. 'Labour Market Policies for Inclusiveness: A Literature Review with a Gap Analysis.' ILO Working Paper 78. International Labour Organization.

Fisher, E., R. Attah, V. Barca et al. 2017. 'The Livelihood Impacts of Cash Transfers in Sub-Saharan Africa: Beneficiary Perspectives from Six Countries.' *World Development* 99:299–319.

Fofana, I., and M. W. O. Omolo. 2023. 'Understanding the Economic Impact of COVID-19 in Kenya.' PEP Working Paper 5. Partnership for Economic Policy.

Fragoso, K. P. 2022. 'In-Cash Transfers: From Passive to Empowered Beneficiaries in the Global South.' *Social Policy and Society* 21 (3): 352–68.

Gelo, D., and J. Dikgang. 2022. 'Implications of COVID-19 Labour Market Shock for Child and Household Hungers in South Africa: Do Social Protection Programs Protect?' *PLOS ONE* 17 (7): e0269848.

International Labour Organization (2020a) *World Employment and Social Outlook: Trends 2020*. International Labour Organization.

International Labour Organization (2020b) *ILO Monitor: COVID-19 and the world of work. Fifth edition: Updated Estimates and Analysis.* International Labour Organization.

International Labour Organization (2020c) *ILO Monitor: COVID-19 and the world of work. Third edition: Updated Estimates and Analysis.* International Labour Organization.

Institut National de la Statistique du Congo. 2011. *Deuxième Enquête sur l'Emploi et le Secteur Informel (EESIC), Phase 1 "Rapport d'analyse".* Ministère du plan, de la statistique, de L'intégration régionale, des transports, De l'aviation civile et de la marine Marchande.

Institut National de la Statistique du Congo. 2020. *Enquête sur les effets socioéconomiques du coronavirus au Congo (EESC)*. Ministère du plan, de la statistique, de L'intégration régionale, des transports, De l'aviation civile et de la marine Marchande.

Institut National de la Statistique du Congo. 2021. *Recensement Général des Entreprises du Congo (REGEC): Principaux resultants*. Ministère du plan, de la statistique, de L'intégration régionale, des transports, De l'aviation civile et de la marine Marchande.

Janssens, W., M. Pradhan, R. de Groot, E. Sidze, H. P. P. Donfouet, and A. Abajobir. 2021. 'The short-term economic effects of COVID-19 on Low-Income households in Rural Kenya: An Analysis Using Weekly Financial Household Data.' *World Development* 138:105280.

Kalecki, M. 1938. 'The Determinants of the Distribution of National Income.' *Econometrica* 6 (2): 97–112.

Kansiime, M. K., J. A. Tambo, I. Mugambi, M. Bundi, A. Kara, and C. Owuor. 2021. 'COVID-19 Implications on Household Income and Food Security in Kenya and Uganda: Findings From a Rapid Assessment.' *World Development* 137:105199.

Kesar, S., R. Abraham, R. Lahoti, P. Nath, and A. Basole. 2021. 'Pandemic, Informality, and Vulnerability: Impact of COVID-19 on Livelihoods in India.' *Canadian Journal of Development Studies* 42 (1–2): 145–64.

Laborde, D., W. Martin, and R. Vos. 2021. 'Impacts of COVID-19 on Global Poverty, Food Security and Diets: Insights from Global Model Scenario Analysis.' *Agricultural Economics* 52 (3): 375–90.

Lollivier, S., and D. Verger. 1996. 'Patrimoine des ménages: déterminants et disparités.' *Économie et Statistique* (296–297):13–31.

Mahmud, M., and E. Riley. 2021. 'Household response to an extreme shock: Evidence on the immediate impact of the Covid-19 lockdown on economic outcomes and well-being in rural Uganda.' *World Development* 140:105318.

Mahmud, M., and E. Riley. 2023. 'Adapting to an aggregate shock: The impact of the Covid-19 crisis on rural households.' *Review of Economics of the Household* 21 (1): 19–36.

Mas-Colell, A., M. D. Whinston, and J. R. Green. 1995. *Microeconomic Theory*. Oxford University Press.

Miyamura, S. 2021. 'Turbulence Ahead: Labour and Struggles in Times of the Covid-19 Pandemic in India.' *Canadian Journal of Development Studies* 42 (1–2): 165–77.

Mortensen D. T., and C. A. Pissarides. 1994. 'Job Creation and Job Destruction in the Theory of Unemployment.' *The Review of Economic Studies* 61 (3): 397–415.

Murakami, E. 2022. 'Immediate Impacts of the COVID-19 Pandemic on Household Economic Activities and Food Security in Tajikistan.' *Economics of Disasters and Climate Change* 6 (2): 259–91.

Nafula, N., D. Kyalo, B. Munga, and R. Ngugi. 2020. 'Poverty and Distributional Effects of Covid-19 on Households in Kenya.' AERC Working Paper. African Economic Research Consortium.

Ogisi, O. D., and T. Begho. 2021. 'Covid 19: Ramifications for Progress Towards the Sustainable Development Goals (SDGs) in Nigeria.' *International Review of Applied Economics* 35 (2): 256–68.

Ondoua Biwolé, V. 2021. 'Impact de la Covid-19 sur l'emploi au Cameroun. Résultats d'une étude empirique.' *Mondes en développement* 4 (196): 27–47.

Ouadika, S. A. B., T. Ngassa, and Y. Anki. 2022. 'Inégalités spatio-territoriales du risque d'exposition au Covid-19 au Congo.' *Les Cahiers de l'Association Tiers-Monde* (36):101–110.

Ouedraogo, M., and T. Thiombiano. 2017. 'Déterminants socio-économiques des défrichements agricoles en zone sud-soudanienne du Burkina Faso.' *Économie rurale* 360:23–41.

Paweenawat, S. W., and L. Liao. 2024. 'Who Suffers the Most During the COVID-19 Pandemic? Evidence From Thailand.' *The Developing Economics* 62 (3): 238–68.

Programme des Nations Unies pour le développement. 2020. Évaluation *des impacts* économiques *et sociaux de la pandémie de Covid-19*. Les Nations Unies du Congo.

Putra, R. A. A., K. Ovsiannikov, and K. Kotani. 2023. 'COVID-19-Associated Income Loss and Job Loss: Evidence from Indonesia.' *Journal of Asian Economics* 87:101631.

Rosenbaum, P. R., and D. B. Rubin. 1983. 'The Central Role of the Propensity Score in Observational Studies for Causal Effects.' *Biometrika* 70 (1): 41–55.

Semo, B.-W., and S. M. Frissa. 2020. 'The Mental Health Impact of the COVID-19 Pandemic: Implications for Sub-Saharan Africa.' *Psychology Research and Behavior Management* 13:713–20.

Strupat, C. 2022. 'Social Protection and Social Cohesion in Times of the COVID-19 Pandemic: Evidence from Kenya.' *European Journal of Development Research* 34 (3): 1320–57.

Teachout, M., and C. Zipfel. 2020. 'The Economic Impact of COVID-19 Lockdowns in Sub-Saharan Africa.' Policy Brief. International Growth Centre.

Warr P., and A. A. Yusuf. 2024. 'Pandemic-Induced De-Urbanization in Indonesia: Urban and Rural Impacts.' *The Developing Economies* 62 (2): 139–74.

World Bank. 2020a. *Poverty and Shared Prosperity 2020: Reversals of Fortune*. World Bank Group.

World Bank. 2020b. *Assessing the Economic Impact of Covid-19 and Policy Response in Sub-Saharan Africa.* Africa's Pulse 21. World Bank Group.

World Bank. 2021. *Living in Times of COVID-19 in the Republic of Congo : What Do the Surveys Reveal About Households and Companies?* World Bank Group.

Appendix

TABLE A1 Probability of Losing the Job (used to obtain propensity scores)

Job loss	Coef.
Household size	0.475***
	(0.115)
Household size square	-0.041***
	(0.010)
Gender	0.456**
	(0.178)
Age	-0.372**
	(0.162)
Access to finance	-0.521***
	(0.149)
Having worked during confinement	-0.531***
	(0.155)
Transfer received	-0.357**
	(0.146)
Closure of borders	0.403**
	(0.157)
Constant	-2.182***
	(0.342)
Observations	1,365
Wald Chi2	65.74
Prob > Chi2	0.000

SOURCE Author's calculations based on the COVID-19 survey conducted by INS-CG in September 2020.

NOTES Standard errors in parentheses; *** p<0.01, ** p<0.05.

TABLE A2 Rosenbaum Sensitivity Tests

Gamma	Nearest neighbour	
	sig+	sig-
1	1.6e-08	1.6e-08
1.01	2.4e-08	1.1e-08
1.02	3.5e-08	7.1e-09
1.03	5.2e-08	4.7e-09
1.04	7.6e-08	3.1e-09
1.05	1.1e-07	2.1e-09
1.06	1.6e-07	1.4e-09
1.07	2.2e-07	8.9e-10
1.08	3.1e-07	5.9e-10

Gamma	Nearest neighbour	
	sig+	sig-
1.09	4.3e-07	3.9e-10
1.10	6.0e-07	2.5e-10
1.11	8.3e-07	1.7e-10
1.12	1.1e-06	1.1e-10
1.13	1.5e-06	7.1e-11
1.14	2.1e-06	4.7e-11
1.15	2.7e-06	3.0e-11
1.16	3.7e-06	2.0e-11
1.17	4.8e-06	1.3e-11
1.18	6.3e-06	8.4e-12
1.19	8.3e-06	5.4e-12
1.2	.000011	3.5e-12

SOURCE Author's calculations based on the COVID-19 survey conducted by INS-CG in September 2020.

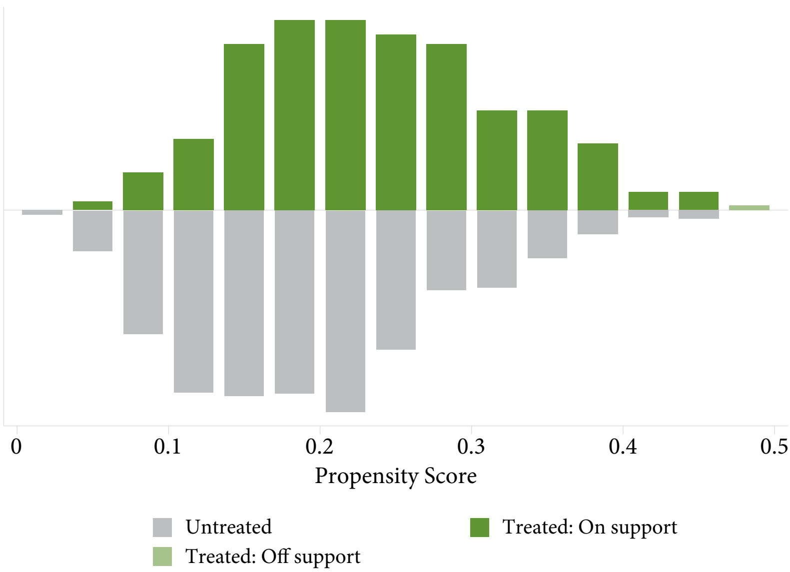

FIGURE A1 Balancing Propensity Scores

SOURCE Author's calculations based on the COVID-19 survey conducted by INS-CG in September 2020.

Nearest neighbour

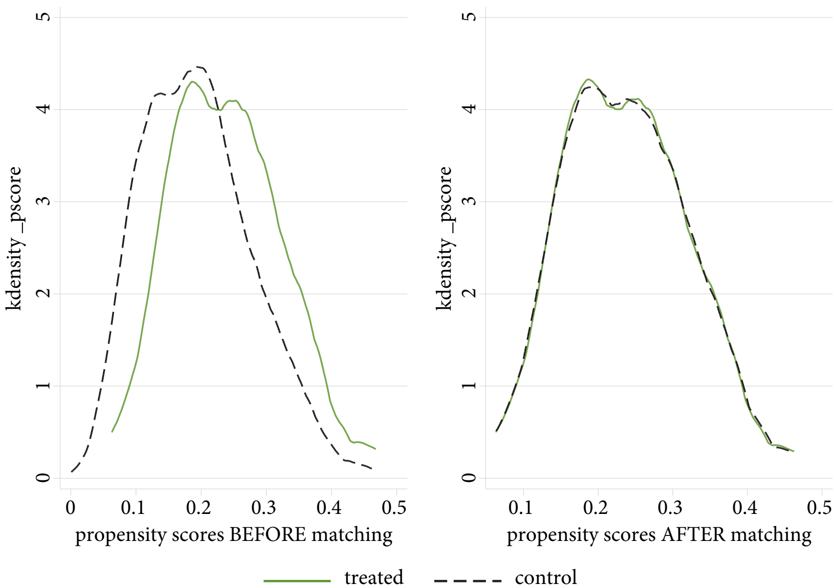

FIGURE A2 Distribution of Propensity Score Densities Before and After Matching
SOURCE Author's calculations based on the COVID-19 survey conducted by INS-CG in September 2020.