Impact of the COVID-19 Pandemic on Income Inequalities in Cameroon: The Influence of Employment Status

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Abstract

Due to interruptions and closures of activities resulting from social distancing measures implemented to limit the spread of the virus, individuals have seen their incomes reduced, increasing poverty and pre-crisis inequalities. These inequalities have been exacerbated by measures such as the increase in family allowances, which only benefit civil servants. The objective of this study is to analyse the contribution of the activity situation due to COVID-19 to household income inequalities in Cameroon. The data used are those collected from 604 households by CEREG as part of an IDRC-funded study on the impact of public policies related to the COVID-19 pandemic in Burkina Faso, Cameroon, Côte d'Ivoire and Senegal. The Gini and Theil inequality indices show increased income inequality in households where the head is not employed. The conditional quantile regression shows that employment status has a significant and higher effect during severe restrictions on the incomes of typical households in the 25th, 50th, 75th, and 90th percentiles. On the other hand, this increased the distribution of income inequalities within households in the first three quartiles, more than 70% of which can be explained by the change in behaviour resulting from the loss of employment by the heads of household. This result is confirmed by the fact that the share of employment in the formation of income inequalities fell during severe restrictions, according to the Shapley decomposition.

Key words: COVID-19, income inequality, employment, household, Cameroon.

JEL classification: D01, D63, I31, O15

1. Introduction

The scale of the spread of the COVID-19 pandemic led the WHO to declare the disease a Public Health Emergency of International Concern (PHEIC) on January 30, 2020, 30 days after it was identified in Hubei Province, China. This recognition presupposed a strategic plan coordinated at the international level to protect populations, particularly those in countries with fragile healthcare systems. However, government policy responses and containment measures have led to an economic slowdown that has particularly affected sectors that employ large numbers of salaried and self-employed workers (Webb et al., 2020). The impact on the economy was felt through several channels, the main ones being the epidemiological shock, the supply shock, the domestic demand shock, and the foreign demand shock. In addition, numerous studies have highlighted the consecutive job losses that have led to a fall in household incomes (Yasenov, 2021). These income losses are exacerbated, according to Yasenov (2021), by the fact that workers with low levels of education and fewer qualifications work in the informal sector without the option of working from home.

In Cameroon, the measures taken by the state have restricted the mobility of people and goods, resulting in unemployment and even a reduction in worker productivity due to the many restrictions put in place (both abroad and within the country) to combat the spread of the disease (Ngomba, 2020). From then on, the shock to labour supply became a shock to productivity and employment. This is how the GICAM (2020) report on the impact of COVID-19 on companies estimates that 87% of companies have either gone into technical unemployment or reduced their workforce.

In addition to the many sectors that have been affected by the restrictive measures taken[1], the wholesale, retail, and repair sectors, whose purchases are mainly made up of imported goods, have been the most affected (ILO, 2020). This sector is the largest, accounting for 28.1% of total business turnover in 2017[2], 51% of turnover in the informal sector in 2010[3], and around 16.8% of GDP over the period 2013-2018. Together with the "Business support activities" and "Transport and storage" branches, they account for 46.6% of the country's workforce. Most of this workforce is engaged in informal activities, which could result in a considerable number of households falling below the poverty line.

Indeed, most sub-Saharan African economies are characterised by the preponderance of the informal sector. While there are around 1.8 billion jobs in the informal sector worldwide, representing 60% of the workforce, informal economic activity outside the agricultural sector in sub-Saharan Africa accounts for threequarters of jobs[4]. Moreover, a high level of informality is associated with poor development performance. Countries with a large informal sector are characterised by lower per capita income, more widespread poverty, and greater income inequality. According to the OECD (2009), more than 700 million informal workers worldwide live in extreme poverty, on less than $1.25 a day, and some 1.2 billion on less than $2 a day.

Thus, the adaptation strategies put in place in crisis situations by informal production units lead either to a reduction in profits, diversification of activities, the search for another job, and/or abandonment of the activity for workers. Whichever adaptation option is chosen by workers in the informal sector to cope with this crisis, it is likely to lead to a significant drop-in activity and therefore in income (Fomba & Nda'Chi, 2022). However, most of the measures put in place by the state to deal with the economic consequences of the pandemic are aimed at formal businesses or their employees, which is likely to increase inequalities in the country[5]. Inequalities have been shown to have a significant impact on poverty, social outcomes, and public finances. For example, for a given level of average income, greater inequality generally implies higher levels of poverty. Moreover, Ravallion (1997) shows that high levels of inequality hamper poverty reduction policies.

Although significant empirical evidence exists in both developed and developing countries on the impact of COVID-19 on socio-economic indicators such as consumption, employment, and income (Baker et al., 2020; Coibion et al., 2020), none of these studies has looked at the increase in inequality resulting from the impact of the pandemic on employment. The aim of this research proposal is to fill this knowledge gap by assessing the impact on income inequalities of the employment situation of individuals following the health shock.

Furthermore, as the head of the household is the main provider of funds for the household, the objective of this study is to analyse the contribution of the activity status due to COVID-19 on the level and variation of household income inequalities in Cameroon. To do this, we began by assessing the level of household income inequality using the GINI and Theil indices, taking into account the employment status of the head of household. The effect of employment status on the level of household income and inequality is analysed using conditional and unconditional quantile regressions, taking into account the existing heterogeneity along the income distribution. The RIF decompositions allow us to examine the sources of the inequality differential between the two groups of households.

The results show that employment status had a significant and greater effect during the severe restrictions on the incomes of typical households in the 25th, 50th, 75th, and 90th percentiles. This was also reflected in an increase in the distribution of income inequalities within households in the first three quartiles, which can be explained mainly by the change in behaviour due to the loss of employment by the head of household. In addition, the Shapley decomposition confirms the reduction in the share of employment in the formation of income inequality during periods of severe retrenchment.

The rest of the paper is organised as follows: The second section presents the literature review, the third presents the study data and some statistics, the fourth presents the methodology; and finally, the last section presents the results of the study.

2. Literature review

The issue of income variation has been the subject of much research in the literature (Conceição et al., 2011; Olabiyi, 2020). From all this research, there is a consensus that shocks in the health sector generally have a negative and significant impact on economic activities, mainly in the short term (Woldemichael and Gurmu, 2018). The impact varies between an avoidance response due to social distancing measures, low direct costs, higher indirect costs, and offsetting effects (Martin et al., 2020).

To better understand the economic impact of COVID-19, it is important to understand the transmission channels through which shocks will affect the economy. According to Carlsson-Szlezak et al (2020), there are three main transmission channels. The first channel is linked to supply disruptions. Stopping production as a result of the pandemic will have a negative impact on supply chains, labour demand and employment, leading to prolonged periods of redundancy and higher unemployment. The second channel, which is the demand channel, assumes that the shock will pass through the reduction in consumption of goods and services because of the reduction in income. In addition, the prolonged duration of the pandemic and social distancing measures could reduce consumer confidence, making them more wary and pessimistic about the long-term economic outlook. As incomes fall, households will stop saving or draw on their assets to manage day-to-day living; hence the third channel, which is the indirect impact of financial market shocks on the real economy. In addition, the pandemic may create an anticipation shock that could lead economic agents to adopt a 'wait-and-see' attitude, resulting in a change in their transactions or consumption behaviour (Baldwin and Tomiura, 2020). However, given the poor development of financial markets in developing countries, particularly in Africa, we will only have demand and supply channels.

For Baldwin et al. (2020), the pandemic affects income by reducing the number of hours worked or stopping work. This contributes to a reduction in household consumption and savings. The work of Coibion et al. (2020) in the United States highlighted the fact that the measures put in place as part of the response led to a fall in consumption, employment and incomes among economic agents. However, as a precaution against future price rises due to shortages, Baker et al. (2020) found that households significantly increased their spending at the start of the pandemic in specific sectors such as retail and food expenditure. In Kenya and Uganda, on the other hand, Kansiime et al (2021) found that low-income and labour-dependent households were more vulnerable to income shocks and had lower consumption during the pandemic than other categories of workers.

In addition, Bisong et al (2020) highlighted the effect of the pandemic on the fall in consumption of households receiving remittances from migrants, who suffered a drop in income as a result of the containment measures and the cessation of work in the host country. According to Ozili (2022), this drop in income is the result of downtime, restrictions on international travel, and the internal movement of people. Considering the heterogeneity of the effects induced by the pandemic response measures, Diop et al (2021) showed that social distancing measures were productive in Europe and counterproductive in Africa. However, Bodewig et al (2020) found that the cash transfer programmes introduced helped to offset the loss of workers' income and mitigate the negative impact on vulnerable households.

Nevertheless, Bodewig et al (2020) do not take account of imperfections in household cash transfer programmes. In an environment undermined by the predominance of the informal sector and the lack of control over vulnerable populations, state aid that is restricted to part of the population will create inequalities rather than address the economic impact of the pandemic. It would therefore be vital, in order to put in place appropriate policies to reduce the consequences of the pandemic, to analyse its effect on household income inequalities through employment.

3. Data and statistics

Data

The data used in this study come from the survey on the impact of public policies related to the COVID-19 pandemic on businesses, women and young people, which took place in September 2021. The survey was carried out in Burkina Faso, Cameroon, Côte d'Ivoire and Senegal, with financial support from IDRC. In Cameroon, of the 604 households visited in the Centre and Littoral regions, 574 gave their consent. The two main regions chosen in Cameroon for this study are those that have suffered the most from the pandemic, both in terms of health, with the number of people infected, and in economic terms, with the number of production units that have been affected. The number of households was obtained from a stratified two-stage sampling. At the first stage, the Enumeration Zones (EZ) were drawn, respecting the representativeness between the Centre and Littoral regions, then the households were drawn at the second stage with a step of 3 using several entries to grid the EZ. All individuals aged 15 and over were interviewed in each household using a questionnaire consisting of 8 sections.

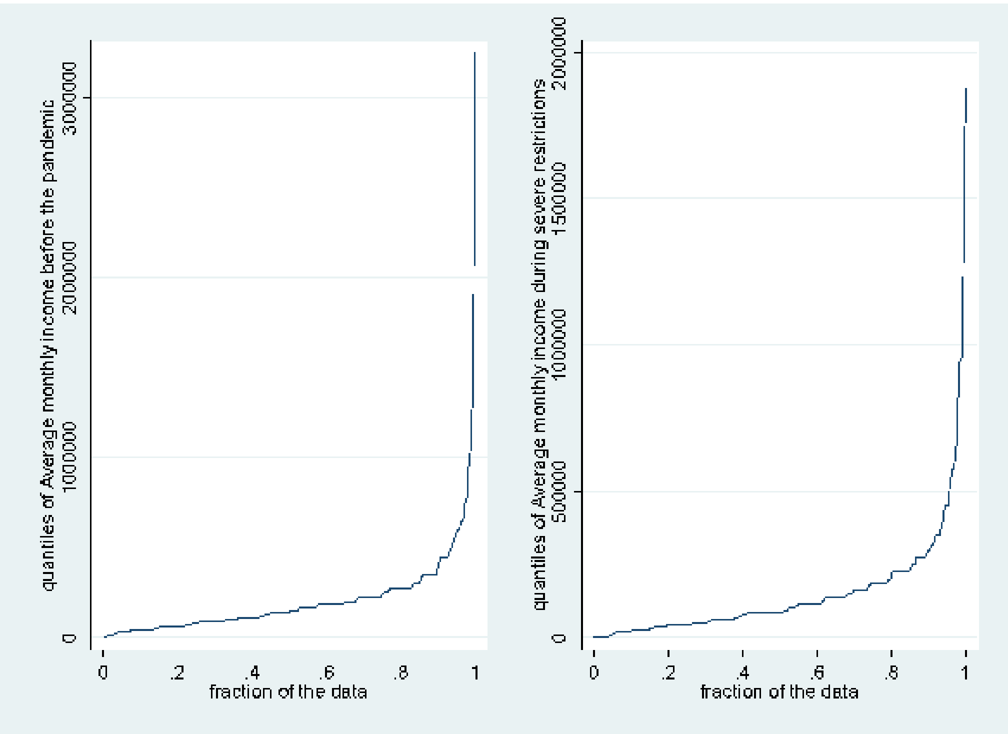
The first two sections were addressed to the head of household and concerned information and changes observed in the household. The heads of household first provided information on the location of the household and the assets owned by the household. They were then asked to indicate the changes observed in the household during COVID-19 in terms of illness, as well as the level of income and expenditure for the three periods selected[6]. Once the residents had been listed, a selection was made of those eligible to respond to the individual sections based on the minimum age criterion of 15 years. The head of household was also considered to be an individual in the household to whom the other six sections of the questionnaire were addressed.

Furthermore, residents were required to provide information about their personal characteristics. Specifically, in relation to the level of education (last attended class and diploma obtained), marital status, religion, main sector and field of activity, and socio-professional category. Questions about the experience with COVID-19 were addressed at the individual level in section 4, knowledge about the spread and public measures in section 5, and its effects in section 6. These effects were documented in terms of individual employment, violence (all types of violence experienced at all levels of life), and household task-sharing. A number of questions were used to obtain the necessary variables for our study.

Variables and descriptive statistics

Many studies use objective and subjective measures such as household income, expenditure, debt, assets and financial satisfaction to approximate economic well-being (Baye, 2013). However, although household income excludes several benefits, it remains a more comprehensive measure of economic well-being as it considers the incomes of all household members and those from related sources (Reimers, 2006). For this reason, this study uses household income to assess income inequality. It is obtained by asking the head of the household, "How much would you estimate your household's monthly income to be over the following periods?" Graph 1 below shows that household income fell between March and May 2020 after the government took several measures to reduce the spread of the disease.

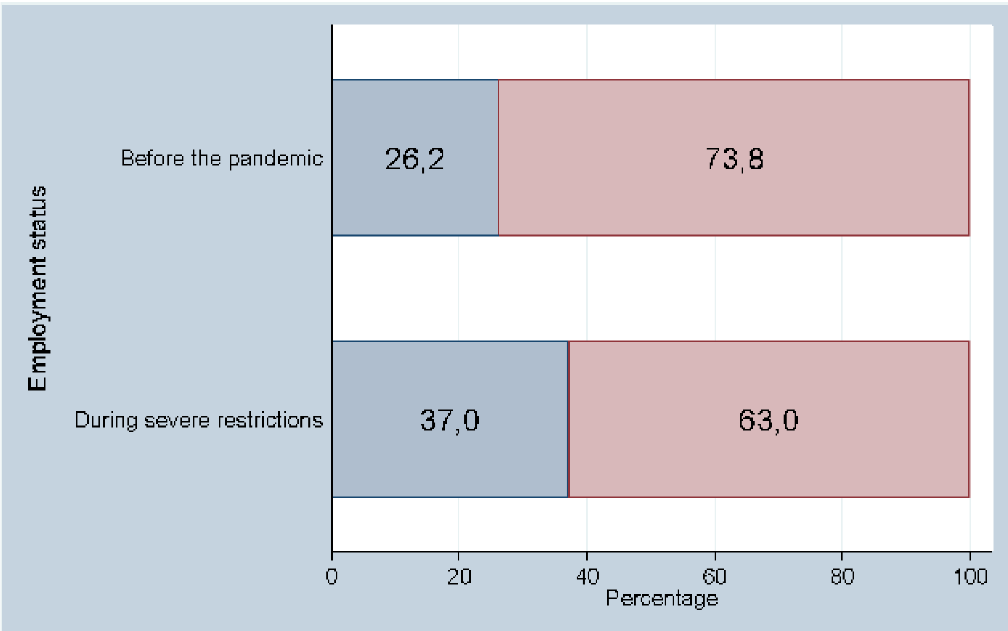
Graph 1: Household income by quantiles



Source: Based on data on the impact of COVID-19

The main variable of interest in the study is employment status. For a long time, the unitary household approach considered the head of household as the sole provider of household income (Donni and Ponthieux, 2011). However, this unitary consideration does not explain how individuals with a priori distinct preferences will behave once brought together under the same roof. This is why the collective household approach has made it possible to consider the behaviour of all the other members of the household from the point of view of optimal resource allocation. In our paternalistic environment, the head of the household remains the main provider of household income, which is essential for maintaining his authority. This is why the employment situation used in this study is that of the head of household. Before the pandemic, 73.69% of the heads of household in our sample had a job, as shown in graph 2, but only 62.89% responded positively during the severe restrictions, corresponding to a reduction of 10.8%. This figure conceals problems in terms of reduced working hours and technical leave.

Graph 2: Employment status of heads of household



Source: Based on data on the impact of COVID-19

The control variables refer to the household environment, the household and the head of the household. The environmental characteristics of the household are the region in which the household is located and the area of residence. Household characteristics include household size and ownership of land and property, which can be factors in alleviating pressure on household income in a crisis. The personal characteristics of the head of household refer to the gender of the head of household, age, marital status, level of education, professional training and sector of activity.

Table 1: Descriptive statistics for study variables

Variables	**Definition**	**min**	**max**	**Mean**	**Std. Dev.**
Environmental characteristics					
Region of household location	Takes the value 1 when the household is in the Centre region and 0 for the Littoral region.	0	1	0.489	0.5
Place of residence	Takes the value 1 when the household is in a rural area and 0 for an urban area.	0	1	0.251	0.434
Household characteristics					
Household size	The number of people living in the household at any one time.	2	20	6.053	2.992
Ownership of land and real estate	Takes the value 1 if the household owns land and real estate and 0 otherwise.	0	1	0.235	0.424
Personal characteristics of household head					
Age of household head	The age of the head of household on a continuous basis.	18	85	45.470	13.584
Sex of household head	Takes the value 1 if the head of household is a woman and 0 otherwise.	0	1	0.700	0.459
Secondary school level	Takes the value 1 if the head of the household has secondary education and 0 otherwise.	0	1	0.581	0.494
Higher level of education	Takes the value 1 if the head of household has reached a higher level and 0 otherwise.	0	1	0.228	0.42
Completed professional training	Takes the value 1 if the head of the household has undergone vocational training.	0	1	0.465	0.499
Matrimonial status	Takes the value 1 if the head of household is in a couple and 0 otherwise.	0	1	0.667	0.472
Formal sector	Takes the value 1 if the head of household works in the formal sector and 0 otherwise.	0	1	0.314	0.465
Informal sector	Takes the value 1 if the head of the household works in the informal sector and 0 otherwise.	0	1	0.482	0.5

Source: Based on data on the impact of COVID-19

Table 1 presents the descriptive statistics for the control variables used in the analyses. According to the environmental characteristics of the household, most households surveyed are in the Centre region, with 25.3% located in rural areas and mainly in agriculture. The households in our sample have between 2 and 20 people, with an average of 6 people per household. In addition, 23.5% of households own land and property. More than two-thirds of the heads of household are men, with an average age of 45. Around 80% of heads of household have at least secondary education, and almost 23% have higher education. The majority are married or cohabiting (66.7%), and 48.2% of them work in the informal sector, with 46.5% having completed vocational training.

4. Methodology

Although there are many indicators for measuring inequality within a distribution, this paper uses traditional measures, namely the Gini coefficient and Theil's entropy index. The coefficient of Gini (1921) is calculated from the curve of Lorenz (1905), which links the cumulative proportions of the population in classes (percentiles, deciles) with the cumulative percentages of the corresponding incomes. The specification used is based on that of Dagum (1997), which considers the two groups of households whose heads have a job *h* and those whose heads do not have a job *j*. The Gini coefficient $I_{gini}\left(Y\right)$ is formally equivalent to:

$$I_{gini} = \frac{1}{n_j n_h(\mu_j + \mu_h)} \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} \left| y_{ji} - y_{hr} \right| \tag{1}$$

Where y_j is the income vector for households whose heads are employed; y_h is the income vector for households whose heads are not employed; μ_j and μ_h are the average incomes for each of the groups *j* and *h* respectively; n_j and n_h are their size.

This index, in the range [0,1] , represents twice the area between the first bisector and the Lorenz curve. When it tends towards 1, this means that the distribution is unequal and the concentration is high; and at 0, the distribution is egalitarian, and the concentration is low. However, Sen (1976) shows that the Gini index is a linear function of a weighted sum of income shares, with the weighting depending on the individual's rank. The higher an individual's rank *i* in the income distribution, the lower the weight of the income share held by that individual, with a weight *n* for the poorest and a weight equal to unity for the richest. Many studies also use generalised entropy indices because they are regular, invariant to translation, and additively decomposable. However, only the first and second de Theil indices have a sum of intra-group weights equal to unity, allowing independence between the measurement of intra-group inequality and inter-group inequality.

The generalised entropy measure proposed by Theil (1967) is derived from thermodynamic measures of entropy. It measures the disorder of a thermodynamic system by linking the concept of disorder to the concept of inequality, and by using incomes instead of probabilities. Theil obtains his measure of inequality as follows:

$$I_{Theil} = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{\mu}\log\frac{y_i}{\mu} \tag{2}$$

With y_t the income of the individual i and μ the average income.

The non-decomposed approach makes it possible to compare different indices if they are standardised. We then evaluate the factors that explain inequality and decompose the results obtained from the Gini indices to assess income dispersion within and between sub-populations.

Conditional and unconditional quantile regressions

Because the composition of income differs between households (Lerman, 1999), differences in household income according to the employment status of the head of household vary throughout the income distribution (Melly, 2005). This heterogeneity is a source of heteroscedasticity, which would make the link between household income and the employment status of the head of household depend on an unobserved component υ. Conditional quantile regression can identify these heterogeneous effects by quantifying changes in the income distribution of typical households across quantiles if employment status were to change. Therefore, we regressed reported household income on a dummy variable of employment status and observed characteristics using Conditional Quantile Regression (CQR). Specifically, we model the logarithm of reported household income y_i as follows:

$$y_i = x_i\beta_\tau + u_{\tau i} \quad \text{with} \qquad Q_\tau\left(y_i \mid x_i\right) = x_i\beta_\tau \tag{3}$$

Where x_i denotes the vector of explanatory variables including a constant and β_τ the vector of corresponding coefficients. The function $Q_\tau\left(y_i \mid x_i\right)$ represents the $\tau - ième$ conditional quantile of income as a function of explanatory factors and $u_{\tau i}$ is an error term with $Q_\tau\left(u_{\tau i} \mid x_i\right) = 0$ (see Koenker and Hallock, 2001 for more details). The CQR is used to explain how the outcome of a household that is ranked above a specified quantile $(\tau\%)$ among typical households changes as a result of a change in their characteristics[7].

The conditional quantiles method does not allow interpretations to be made at the individual level since the position of the individual in the conditional distribution (τ) is unknown. Instead of trying to determine how employment status affects the incomes of households with specific characteristics, we might be interested in analysing the effect of households with a specific employment status on the unconditional income distribution. In this way, unconditional distributions are affected by changes in the distribution of other characteristics. Firpo et al. (2009) show that the effects of the unconditional quantiles can be calculated as a weighted average of all the partial effects of the conditional quantiles. Machado and Mata (2005) use a similar principle to simulate unconditional outcome distributions based on CQR to estimate the effects of unconditional quantiles. In principle, the procedure requires the estimation of a large set of quantile regressions to characterise the entire distribution of the dependent variable. Once the models have been estimated, simulation methods can be used to determine the effect of a change in the distribution of characteristics, for example, a change in the employment status of the head of household on the distribution of household income.

To solve this problem, Firpo et al. (2009) proposed a simpler strategy that uses the Recentered Influence Function (RIF) to provide a first-order approximation of the marginal effect of small, location-shifting changes in the distribution of independent variables on any unconditional quantile. In practice, as described in Rios-Avila (2020), these small shift changes should be understood as changes in the mean of the independent variables. Unlike CQR, RIF regressions in general, and Unconditional Quantile Regression (UQR) in particular, can only be used to draw inferences in terms of unconditional effects, the construction of which is derived from Influence Functions (IF).

Consider the random variable (Y) representing household income with a cumulative function F_Y and a density distribution $f_y = dF_Y$. All statistics of interest can be written as v[8], a function of the cumulative distribution function:

$$\nu_{F_y} = \nu\left(F_y\right) \tag{4}$$

Adding a new household with income Y_0 to the initial sample of size *η* gives a second distribution taking the form:

$$G_y^0 = \frac{\eta}{\eta+1} F_y + \frac{1}{\eta+1} \Delta\left(y \geq y_0\right) \tag{5}$$

$\Delta(\bullet)$ being the indicator function for whether the observation y_0 is below y. Using these two distributions, the change in the distribution statistic caused by the additional household is simply the difference between ν_{F_y} and $\nu_{G_y^0}$. If we rescale this difference by the relative change in population size, we obtain the Influence Function for that observation. Mathematically, for $\varepsilon = \left(\eta+1\right)^{-}$, the Influence Function (IF) of a household *i* with income y_i on the *v* statistic is defined as follows:

$$IF\left(y_i, \nu, F_y\right) = \lim_{\varepsilon \to 0^+} \frac{\nu\left(\left(1-\varepsilon\right)F_y + \varepsilon * \Delta\left(y \geq y_i\right)\right) - \nu\left(F_y\right)}{\varepsilon} \tag{6}$$

This expression represents a first-order (linear) approximation of the rate of change or influence of an observation with income y_i on the statistical distribution *ν*. From the influence function, Firpo et al (2009) linearly established the contribution of a single observation to the construction of the distributional statistic v by defining the Refocused Influence Function (RIF) as follows:

$$RIF\left(y, v, F_y\right) = v\left(F_y\right) + IF\left(y_i, v, F_y\right) \tag{7}$$

Although RIF functions can be used to analyse a large number of statistical distributions, RIF in the context of Unconditional Quantile Regression (UQR) is defined as follows:

$$\mathrm{RIF}\left(\mathrm{y_i}; Q_\tau(\bullet); F_y\right) = Q_\tau(y) + \frac{\tau - \Delta\left\{y_i \le Q_\tau(y)\right\}}{f_y\left(Q_\tau(y)\right)} \tag{8}$$

where $Q_\tau(y)$ is the unconditional quantile, τ is the rank or percentile of interest and $f_y(Q_\tau)$ represents the marginal density of y_i evaluated at $Q_\tau(y)$ (Firpo et al, 2009). Once the RIF has been obtained, the UQR can be estimated by means of standard linear regression (RIF-OLS) using the corresponding RIF as the dependent variable instead of Y. Assuming that income y of household i is a function of a set of variables x including the employment status of the head of household, we obtain the equation defined in (9), which will be estimated by Ordinary Least Squares (OLS):

$$RIF\left(y_i; Q_\tau(\bullet); F_y\right) = x_i\gamma_\tau + \upsilon_{\tau i} \tag{9}$$

γ_τ the vector of coefficients and $\upsilon_{\tau i}$ the error term with $E\left[\upsilon_{\tau i} \mid x\right] = 0$. The standard OLS regressions of equation (9) yield UQR coefficient estimates that can be interpreted as unconditional changes in the distribution of household income inequality since the indicator used will be the Gini index.

To obtain the unconditional partial effect on the statistic v, we first need to obtain the unconditional expectation on both sides of equation (9) as shown below:

$$v\left(F_y\right) = E\left[RIF\left(y_i; Q_\tau(\bullet); F_y\right)\right] = E\left(x_i\gamma_\tau\right) + E\left(\upsilon_{\tau i}\right) = \bar{x}\gamma_{\tau k} \tag{10}$$

$\bar{x}$ being the unconditional mean of x. From this, the unconditional partial effect is given by:

$$\frac{\partial v\left(F_y\right)}{\partial \bar{x}_k} = \gamma_{\tau k} \tag{11}$$

On the basis of (11), the interpretation of the unconditional partial effect is that if the distribution x changes so that its unconditional mean increases by one unit $\left(\Delta\bar{x}_k = 1\right)$, the statistical distribution v should change by $\gamma_{\tau k}$ units.

Decomposition of gaps by employment status using unconditional quantiles

To decompose the gap between households where the head has a job and those where they do not into the unconditional quantiles of household income, we apply the decomposition method proposed by Firpo et al (2009), which is based on RIF. One of the advantages of this approach, over others (for example, Machado & Mata, 2005a; Melly, 2005), is that it allows a detailed decomposition of the composition effect. In this way, we can also quantify the contribution of differences in the employment status of the head of household, for example on household size, along the unconditional distribution of household incomes.

We model the RIF specific to the group of households whose head has a job $(g=1)$ and those whose head does not have a job $(g=0)$ by again adopting a linear specification for the conditional expectation of RIF.

$$RIF\left(y_{gi};Q_{\tau g}\right)=x_i\gamma_{\tau,g}+\upsilon_{\tau gi} \text{ for } g=0,\ 1 \tag{12}$$

The vector of explanatory variables x_i does not include any dummy variables for the employment status of the head of household. After estimating equation (12) by OLS for the two groups, the overall difference between employment statuses at $\tau - ième$ quantile $\hat{\Delta}_0^\tau$ can be decomposed as follows:

$$\hat{\Delta}_0^\tau=\underbrace{\bar{x}_1\left(\hat{\gamma}_{\tau,1}-\hat{\gamma}_{\tau,0}\right)}_{\hat{\Delta}_U^\tau}+\underbrace{\left(\bar{x}_1-\bar{x}_0\right)\hat{\gamma}_{\tau,0}}_{\hat{\Delta}_E^\tau} \tag{13}$$

where $\hat{\gamma}_g$ represents the OLS coefficient vector and $\bar{x}_g$ the vector of means for each group. Consequently, the gross difference according to the employment status of the head of household at $\tau - ième$ quantile is decomposed into an unexplained part $\hat{\Delta}_U^\tau$ and the explained part $\hat{\Delta}_E^\tau$.

In order to interpret the explained and unexplained parts of the decomposition as an effect of income composition and structure, we must assume that for each quantile τ, the error term $\upsilon_{\tau g}$ is independent on average of the employment status of the head of household G, i.e.:

$$E\left[\upsilon_{\tau g}\mid x,G\right]=E\left[\upsilon_{\tau g}\mid x\right]=0, \qquad \forall\tau\in[0,\ 1],\ \ g=0,\ 1 \tag{14}$$

This requires conditioning with employment status on all variables that are correlated with the outcome variables. The analyses will take into account a wide range of explanatory variables that we have selected on the basis of economic reasoning and previous evidence on the determinants of household income inequality (Chameni and Miamo, 2012; Lerman, 1999). Although we do not have access to detailed controls for all underlying aspects of economic preferences and beliefs associated with both household income and employment status, satisfying assumption (14) would require only conditioning on variables that can represent these aspects to achieve conditional independence of group-specific outcomes.

On the basis of the conditional RIF expectations estimated between households whose head has a job and those whose head does not, we can estimate the Oaxaca Blinder-type decompositions at each unconditional quintile according to 2 effects, namely a *Pure Structural Effect* and a *Pure Composition Effect*, to which we add two error terms that can be used to assess the overall quality of the model. The first is the Reweighting Error used to assess the quality of the reweighting strategy, which should tend towards zero for large samples. The second is the Specification Error, which is used to assess the extent of disparities in the results when the linearity assumption is relaxed in the RIF approximation.

The Shapley decomposition of the contribution of employment status to income inequality

To assess the contribution of employment status to household income inequality, we will use the Shapley decomposition method borrowed from Chantreuil and Lebon (2015). It involves rewriting each household's income as the sum of the items related to each attribute. Given that COVID-19 turned into a pandemic that can modify the behaviour of individuals as well as the structure of economies through supply and demand shocks, we want to determine to what level the employment situation contributed to the variation in household income inequalities before the onset of the pandemic and during the severe restrictions. The method of analysis we propose has been used by Baye (2006) to analyse the evolution of poverty in Cameroon and by Azevedo, Sanfelice and Nguyen (2012) for welfare in Paraguay between 1999 and 2009.

Consider a function $f : C^n \rightarrow \sim$ which for all the attributes of the household or head of household $c_1, c_2, ..., c_n$ associates the total household income *R* such that:

$$R = f(c_1, c_2, ..., c_n) \tag{15}$$

Let *I* be the characteristic function that estimates the value of the game, evaluates the inequality in the distribution of household income such that:

$$I = I\left(R\right) = I\left(f(c_1, c_2, ..., c_i, ..., c_n)\right) \tag{16}$$

We want to decompose the change experienced by *I* between 2 periods $\left(t = 0, 1\right)$ into *n* contributions $\left(i = 1, ..., n\right)$ attributed to each of the n attributes considered as sources of household income. However, if we take only the first marginal change in *I* during the change in the distribution of the c_i component from the $t = 0$ period to the $t = 1$[9] period, there is no guarantee that in the end, the sum of all the *n* contributions is equivalent to the total change in *I* between the two periods. Shapley's decomposition addresses the problem by considering all possible *n*! ways of decomposing *I* by eliminating each component at a time, then taking the average of the contributions. Shapley (1953), in the context of game theory, establishes that the relationship between the sequential elimination of players and their final contribution is given by a weighted average. So, to decompose the evolution of an indicator into contributions attributed to each of its components individually, the final contribution of the c_i component when Shapley's decomposition is used will be determined by the following weighted average:

$$\sigma_i = \sum_{s=0}^{n-1} \sum_{C} \frac{s!(n-s-1)!}{n!} \left[I\left(f\left(c_i^{t=1}, C_{n-1,s+1} - \{c_i\} \right) \right) - I\left(f\left(c_i^{t=0}, C_{n-1,s} - \{c_i\} \right) \right) \right] \tag{17}$$

where s denotes the number of components that have already changed from the $t = 0$ period to the $t = 0$ period. C denotes all the combinations of the other $n = 1$ components that have already changed between the two periods. Equation (17) establishes the final contribution of the c_i component after all possible combinations have been formed.

In the case of a four-player game in which the main attributes representing the sources of household income are employment, age of head of household, marital status and degree, the contribution of the c_i attribute (employment status) is given by the following weighted average:

$$\sigma_1 = \sum_{s=0}^{3} \sum_{C} \frac{s!(4-s-1)!}{4!} \left[I\left(f\left(c_1^{t=1}, C_{3,s+1} - \{c_1\} \right) \right) - I\left(f\left(c_1^{t=0}, C_{3,s} - \{c_i\} \right) \right) \right] \tag{18}$$

The quantity $I\left(f\left(c_1^{t=1}, C_{3,s+1} - \{c_1\} \right) \right) - I\left(f\left(c_1^{t=0}, C_{3,s} - \{c_i\} \right) \right)$ measures the marginal contribution of the c_1 component representing employment status to the variation in income inequality between $t = 0$ and $t = 1$. More practically, it can be written as:

$$\begin{aligned} \sigma_1 = {} & \frac{1}{4}\left[I\left(f\left(c_1^1, c_2^0, c_3^0, c_4^0 \right) \right) - I\left(f\left(c_1^0, c_2^0, c_3^0, c_4^0 \right) \right) \right] + \frac{1}{12}\left[I\left(f\left(c_1^1, c_2^1, c_3^0, c_4^0 \right) \right) - I\left(f\left(c_1^0, c_2^1, c_3^0, c_4^0 \right) \right) \right] \\ & + \frac{1}{12}\left[I\left(f\left(c_1^1, c_2^0, c_3^1, c_4^0 \right) \right) - I\left(f\left(c_1^0, c_2^0, c_3^1, c_4^0 \right) \right) \right] + \frac{1}{12}\left[I\left(f\left(c_1^1, c_2^0, c_3^0, c_4^1 \right) \right) - I\left(f\left(c_1^0, c_2^0, c_3^0, c_4^1 \right) \right) \right] \\ & + \frac{1}{12}\left[I\left(f\left(c_1^1, c_2^1, c_3^1, c_4^0 \right) \right) - I\left(f\left(c_1^0, c_2^1, c_3^1, c_4^0 \right) \right) \right] + \frac{1}{12}\left[I\left(f\left(c_1^1, c_2^0, c_3^1, c_4^1 \right) \right) - I\left(f\left(c_1^0, c_2^0, c_3^1, c_4^1 \right) \right) \right] \\ & + \frac{1}{12}\left[I\left(f\left(c_1^1, c_2^1, c_3^0, c_4^1 \right) \right) - I\left(f\left(c_1^0, c_2^1, c_3^0, c_4^1 \right) \right) \right] + \frac{1}{12}\left[I\left(f\left(c_1^1, c_2^1, c_3^1, c_4^1 \right) \right) - I\left(f\left(c_1^0, c_2^1, c_3^1, c_4^1 \right) \right) \right] \end{aligned} \tag{19}$$

The RIF decomposition will enable us to assess the causes of the inequality differential between households whose heads have jobs and those whose heads do not. However, the Shapley decomposition will enable us to assess the effects on inequality of job losses in the main branches of activity most affected.

5. Results[10]

Changes in income inequality before and during the period of severe restrictions

The mechanisms put in place to halt the spread of the pandemic were at the root of the shocks through which COVID-19 affected the economy and led to a loss of income within households. This reduction in income, which does not affect all households equally, is at the root of the exacerbation of inequalities. Household income inequality, which stood at almost 46% before the outbreak of the pandemic, rose to just over 50% during the severe restrictions (table 2), an increase of around four percentage points. Furthermore, when the employment status of the head of household is taken into account, income inequality in households where the head of household is unemployed rose sharply by almost six percentage points, as a result of both the increase in the unemployment rate among heads of household and the reduction in sources of income.

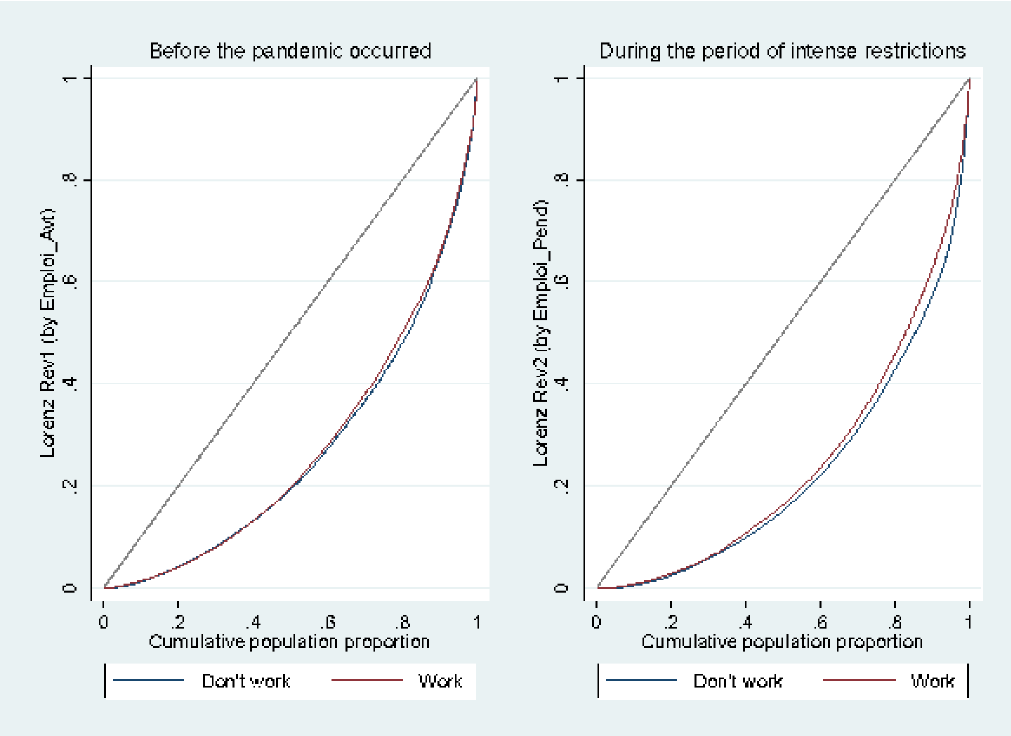
Table 2: Trends in household income inequality

	GINI index		Theil index	
	Before the pandemic	**During the severe restrictions**	**Before the pandemic**	**During the severe restrictions**
Don't work	0.463	0.520	0.402	0.539
Work	0.452	0.493	0.382	0.447
Package	0.458	0.506	0.390	0.482

Source: Based on data on the impact of COVID-19

However, despite continuing to work, households in which the heads kept their jobs also experienced an increase in inequality of four percentage points, which is due to the reduction in income following the pandemic. This reduction may be due to transfers or even to income from work, which may have fallen. Similarly, this increase in inequality is confirmed by the value of the Theil index. Several factors identified in the literature but awaiting validation in our situation could explain this result, as seen through the Lorenz curves (graph 3).

Graph 3: Lorenz curve by employment status of head of household



Source: compiled by the authors from data on the impact of COVID-19

The effect of employment status on household income inequality

Income inequalities within households are due to a number of factors, the importance of which is assessed through conditional and unconditional quantile regressions. The results of these analyses are summarised in Table 3. Panel (a) shows the differences in income between the two groups of households before the onset of the pandemic, while panel b shows these differences during the severe restrictions. Firstly, we find statistically significant gross differences in household income both before the pandemic and during the severe restrictions in some quantiles of the first-row distribution in panels a and b. With the exception of the third quantile and the ninth decile, the gross employment gap in household income before the pandemic, as reported in panel a, is always smaller than the respective gap in their income during the period of severe restrictions (panel b). While at the median the gross income gap between the two groups of households before the pandemic is around 4%, the corresponding gap during the severe restrictions is 10%, i.e., an increase of more than twice as much, whereas this increase is barely 20% at the first decile. In terms of the structure of the gross gap along the distribution, there are differences in household income between the two periods. In addition, the gross gap in household income according to the employment status of the head of household varies along the income distribution. This clearly shows that during the severe restrictions, the sources of household income changed to the disadvantage of the poor, who are highly dependent on the employment of the head of household, as noted by Dandonougbo et al. (2021).

Compared with the gross differences, the adjusted differences differ for both the CQR and the UQR. Before the occurrence of the pandemic, the use of the conditional distribution shows that a typical household would experience an improvement in income varying between 26% if it is ranked at the 10th percentile and 27% if it is ranked at the 90th percentile due to the employment of the head of household, assuming that his or her rank remained constant. Moreover, this effect is much higher than the crude difference. However, the impact is different between the two periods of analysis, and the trend is not the same between the quantiles. In the first quantile, the violence of the shocks generated by COVID-19 has meant that this segment of the population no longer depends on the employment of the head of household, since there is no longer any significant difference according to the employment status of the head of household. On the other hand, at the centre of the distribution (median), the impact of employment was higher, more than 14 percentage points higher during the severe restrictions than before the crisis. This trend is the same for the 75th and 90th percentiles and implies a reduction in household income sources. This population is generally made up of workers in the formal sector who have stable employment income and more variable transitory income in terms of the activity premium. The COVID-19 shock would have affected activity-related premiums, making households more dependent on employment income. These results are consistent with previous studies showing that employment is one of the main ways in which COVID-19 has affected the economy (Baldwin & Tomiura, 2020; Kansiime et al., 2021).

Furthermore, the UQR results recorded in the third row of Table 3 for both panels suggest that a change in employment status will have a heterogeneous impact on the overall inequality distribution. Indeed, in panel (b), if the proportion of unemployed heads of household were to increase by 1%, we would expect the inequality distribution to increase less rapidly at the extremes of the income distribution than at the centre. For example, at the 10th percentile, the inequality distribution increases by 18.4% and by 19.1% at the 90th percentile, although this coefficient is not significant. At this level, household incomes are not strongly linked to stable employment for the head of household. The poorest households generally have income from transfers or from the employment of the majority of their members who are at work. As for the richest households, most of their income comes from extra-wage activities that they carry out at the same time as their main job, and so the accumulated wealth can enable them to withstand shocks.

However, in the intermediate percentiles (25th, 50th, and 75th), the change in the employment status of heads of household should increase household income inequalities more rapidly. The rate of increase in inequality is higher than in the period before the pandemic. These quantiles generally represent the middle-income population who are wage earners or entrepreneurs whose incomes have fallen as a result of shocks to productivity and employment (Alstadsæter et al., 2020). This divergence in the adjusted gaps between the two groups of households could be analysed by decomposition.

Table 3: Difference according to employment status in the Conditional and Unconditional Quantile Regressions

	(1)	(2)	(3)	(4)	(5)
	10%	**25%**	**50%**	**75%**	**90%**
a) Before the pandemic occurred					
REG	-0.169*	-0.038	-0.044*	-0.087***	0.051**
	(0.125)	(0.092)	(0.032)	(0.025)	(0.030)
CQR	0.261**	0.158**	0.164**	0.308***	0.270***
	(0.108)	(0.073)	(0.078)	(0.077)	(0.091)
UQR	0.064	0.222*	0.171	0.196**	0.160
	(0.137)	(0.125)	(0.107)	(0.094)	(0.144)
b) During the period of intense restrictions					
REG	-0.206***	-0.086	-0.102***	0.038	-0.028
	(0.076)	(0.078)	(0.035)	(0.035)	(0.035)
CQR	0.115	0.163*	0.300***	0.413***	0.417***
	(0.108)	(0.087)	(0.073)	(0.081)	(0.082)
UQR	0.184	0.240*	0.246**	0.378***	0.191
	(0.139)	(0.124)	(0.108)	(0.113)	(0.130)
Comments	**570**	**570**	**570**	**570**	**570**

Source: Based on data on the impact of COVID-19. Values in brackets are standard deviations. *, (**) and [***] represent degrees of significance at 10%, (5%) and [1%]. REG stands for gross employment gap, CQR is conditional quantile regression, UQR is unconditional quantile regression.

Decomposition of household income inequality

A summary of the different sources of income inequality between employed and non-employed households obtained from the RIF decomposition is presented in Table 4. The specification errors are generally insignificant, thus validating the hypothesis of the linearity of the RIF specification. Depending on the counterfactual distribution of household incomes, variations in the distribution of observed household characteristics explain between 1 and 30% of the variations in income inequality along the distribution during the period of severe restrictions. During this period, the structural effect is significant in the middle of the distribution and very important in the total difference in inequality between the two groups, showing that the increase in inequality is a consequence of individuals changing their behaviour to cope with the pandemic.

Before the onset of the pandemic, the difference in income inequality between the two groups of households was evident for the first, second and third income quartiles, showing that employment plays an important role in income formation in this segment. Furthermore, 69% of the difference in income inequality in the first quartile is due to structural effects. Households in the first quartile are close to middle-income households that live just above the poverty line in Cameroon and generally carry out small jobs that give them the opportunity to move beyond their intrinsic endowments. However, in the 10th and 90th percentiles, the employment status of the head of household does not differentiate the income level of the two groups since the difference in income is not significant. However, the realities cannot be compared between these two extremes. For households in the 10th percentile, the employment of the head of household does not really lift the household out of precariousness, whereas those in the 90th percentile do not subsist on the employment income of the head of household.

Table 4: Summary of the results of the Rif Decomposition of household income inequalities

Variables		**Q(10)**	**Q(25)**	**Q(50)**	**Q(75)**	**Q(90)**
			Before the pandemic			
Overall	group_1	10.770	11.122	11.748	12.214	12.935
		(0.100) ***	(0.100) ***	(0.092) ***	(0.092) ***	(0.146)***
	group_c	10.773	11.228	11.852	12.427	13.211
		(0.104) ***	(0.099) ***	(0.091) ***	(0.125) ***	(0.128)***
	group_2	10.876	11.473	12.019	12.530	13.022
		(0.068) ***	(0.062) ***	(0.054) ***	(0.053) ***	(0.082)***
	tdifference	-0.106	-0.352	-0.272	-0.316	-0.087
		(0.121)	(0.117)***	(0.107)**	(0.106)***	(0.167)
	t_explained	-0.003	-0.107	-0.104	-0.212	-0.276
		(0.144)	(0.140)	(0.129)	(0.155)	(0.194)
	t_unexplained	-0.103	-0.245	-0.167	-0.104	0.188
		(0.124)	(0.116)**	(0.106)	(0.136)	(0.152)
	% unexplained	97.169	69.602	61.397	32.911	216.092
Observation		**566**	**566**	**566**	**566**	**566**
			During the severe restrictions			
Overall	group_1	10.219	10.866	11.398	11.935	12.424
		(0.114)***	(0.082)***	(0.089)***	(0.085)***	(0.102)***
	group_c	10.441	10.873	11.470	11.938	12.698
		(0.122)***	(0.080)***	(0.084)***	(0.082)***	(0.170)***
	group_2	10.485	11.063	11.655	12.339	12.773
		(0.077)***	(0.074)***	(0.067)***	(0.072)***	(0.080)***
	tdifference	-0.266	-0.198	-0.258	-0.404	-0.349
		(0.137)*	(0.110)*	(0.112)**	(0.111)***	(0.130)***
	t_explained	-0.223	-0.008	-0.073	-0.003	-0.274
		(0.167)	(0.115)	(0.123)	(0.118)	(0.198)
	t_unexplained	-0.043	-0.190	-0.185	-0.401	-0.074
		(0.144)	(0.109)*	(0.108)*	(0.109)***	(0.188)
	% unexplained	16.165	95.959	71.705	99.257	21.203
Observation		**548**	**548**	**548**	**548**	**548**

Source: compiled by the authors from data on the impact of COVID-19. Values in brackets are standard deviations. *, (**) and [***] represent degrees of significance at 10%, (5%) and [1%].

During the period of severe restrictions, the income differential between the two household groups varied from its pre-pandemic level. At the 10th percentile level, there was a significant increase in income inequality, reflecting the fact that the loss of the head of household's job plunged households in this segment further into precariousness. Similarly, households in the 90th percentile saw the employment of the head of household serve to maintain their standard of living, even though COVID-19 affected all sectors of the economy. Furthermore, the total difference in the first three quartiles is explained by the structural effect at 96% for the first quartile, 71.7% for the second, and 99% for the third, thus assuming a change in behaviour in terms of a change in activity or the use of assets.

Table 5: Sources of contribution to income inequality

Variables		**Q(10)**	**Q(25)**	**Q(50)**	**Q(75)**	**Q(90)**
Before the pandemic						
p_explained	Environment	0.144	0.012	0.010	0.102	0.144
		(0.092)	(0.087)	(0.078)	(0.082)	(0.131)
	Household	-0.074	-0.059	-0.091	-0.105	-0.133
		(0.061)	(0.059)	(0.057)	(0.059)*	(0.088)
	Personal	-0.094	0.018	-0.040	-0.020	-0.191
		(0.078)	(0.079)	(0.072)	(0.071)	(0.121)
p_unexplained	Environment	-0.238	-0.128	-0.344	-0.312	-0.062
		(0.179)	(0.161)	(0.139)**	(0.173)*	(0.183)
	Household	0.438	0.261	0.205	0.557	0.425
		(0.281)	(0.253)	(0.219)	(0.269)**	(0.292)
	Personal	-0.354	0.044	0.674	0.159	-1.052
		(0.607)	(0.546)	(0.472)	(0.569)	(0.638)*
	Constant	0.027	-0.456	-0.711	-0.580	0.747
		(0.605)	(0.544)	(0.470)	(0.565)	(0.637)
Observation		**566**	**566**	**566**	**566**	**566**
During the severe restrictions						
p_explained	Environment	-0.069	0.007	-0.021	-0.028	-0.027
		(0.107)	(0.075)	(0.077)	(0.075)	(0.100)
	Household	-0.053	-0.115	-0.126	-0.121	-0.137
		(0.088)	(0.065) *	(0.066) *	(0.065) *	(0.079) *
	Personal	-0.105	-0.047	-0.010	0.044	0.015
		(0.071)	(0.054)	(0.067)	(0.060)	(0.065)

continued next page

Table 5 Continued

Variables		Q(10)	Q(25)	Q(50)	Q(75)	Q(90)
During the severe restrictions						
p_unexplained	Environment	0.214	0.067	-0.055	-0.165	-0.349
		(0.213)	(0.143)	(0.152)	(0.154)	(0.276)
	Household	-0.336	0.022	0.308	-0.004	0.290
		(0.300)	(0.209)	(0.218)	(0.222)	(0.382)
	Personal	0.814	0.849	0.818	-0.539	-0.528
		(0.734)	(0.518)	(0.537)	(0.547)	(0.929)
	Constant	-0.770	-1.229	-1.319	0.273	0.346
		(0.730)	(0.517) **	(0.535) **	(0.545)	(0.923)
Observation		**548**	**548**	**548**	**548**	**548**

Source: Compiled by the authors from data on the impact of COVID-19. Values in brackets are standard deviations. *, (**) and [***] represent degrees of significance at 10%, (5%) and [1%]. "Environment" refers to the factor's region of residence and area of residence; "Household" refers to the factor's household size and land ownership; "Personal" refers to the factors age of head of household, sex of head of household, level of education, vocational training and marital status.

Table 5 presents a detailed breakdown of the contribution of the different variables to the income inequality differential between the two groups of households. The results show that the nature of the contribution changes according to the level of the distribution. Before the pandemic, the variables that had a net attenuating effect on income inequality differentials were the household environment, household characteristics, and the personal characteristics of the head of household. However, during the severe restrictions, only the household characteristics of household size and wealth attenuated the inequality gaps.

Contribution of the employment status of the head of household to income inequality

Employment, which is the most formal and tangible source of income, is affected by a series of considerations that contribute to creating differences between workers. Firstly, among the working population, the pay scale is not the same for workers in the formal and informal sectors. What's more, even in the formal sector, there is a difference between the formal private sector and the public sector, each of which is governed by a separate code. Beyond this factual construction, the literature has identified several factors that explain wage inequalities, including gender, education and human capital (Baye et al, 2023). The upheavals in employment caused by the pandemic would therefore have led to a modification of the contribution of employment to inequalities that which already existed before the pandemic.

The breakdown of inequality by employment status, marital status, level of education, gender of the head of household and age in the sample reveals a general bias against people who are not working in the income distribution. The contribution of employment status to income inequality has fallen by almost one percentage point in the sample, since job losses mean that employment no longer plays a sufficient part in the constitution of household income.

Table 6: Contribution of some characteristics to GINI inequality (Shapley method)

Sources	Before the pandemic (GINI)		During the period of severe restrictions (GINI)		Difference in contribution
	Absolute Contribution	Relative Contribution	Absolute Contribution	Relative Contribution	
Employment	0.035486	0.084126	0.036504	0.076655	-0.007471
Marital status	0.030476	0.072249	0.027722	0.058214	-0.014035
Degree (Licence)	0.028257	0.066989	0.040904	0.085893	0.018904
Gender HH (Female)	0.013388	0.03174	0.020164	0.042343	0.010603
Age HH	0.05396	0.127923	0.051119	0.107344	-0.020579
Residual	0.260252	0.616974	0.299802	0.629551	0.012577
Total	**0.42182**	**1**	**0.476215**	**1**	

Source: compiled by the authors from data on the impact of COVID-19.

6. Conclusion

The desire to limit the spread of COVID-19 led governments to introduce restrictive measures that affected the economy mainly through three shocks: the epidemiological shock, the supply shock and the demand shock. What these three shocks have in common is that they affect an individual's employment situation. The aim of this study is to analyse the effect of the employment situation of heads of household as a result of the COVID-19 pandemic on household income inequalities. This involves assessing inequalities before the onset of the pandemic and during the period of severe restrictions; determining the effect of employment on household income inequalities; determining the difference in inequalities according to employment status; and determining the contribution of employment to the level of inequalities. The data used for this study come from the survey carried out as part of the project on "the impact of public policies linked to the COVID-19 pandemic on businesses, women, and young people in Burkina Faso, Cameroon, Côte D'Ivoire and Senegal" in September 2021 by CEREG with NIS and financial support from IDRC. The analysis is based on a sample of 574 households in the Centre and Littoral regions that actually responded to the questionnaire. Conditional and unconditional quantile regression and decomposition were used to identify the determinants of household income inequality in Cameroon. The decomposition of inequality using the Shapley value allows us to assess the contribution of employment status to overall income inequality.

The results show that the introduction of restrictive measures to halt the spread of the pandemic increased income inequalities by at least four percentage points, and even more when the analysis is made taking into account heterogeneity in terms of the employment status of the head of household. Among households in which the head was not employed, the level of inequality rose from 0.463 before the onset of the pandemic to 0.520 during the severe restrictions, an increase of around 6 percentage points. The CQR shows that employment status had a significant and higher effect during the severe restrictions on the incomes of typical households in the 25th, 50th, 75th, and 90th percentiles. In addition, this resulted in an increase in the distribution of income inequalities within households in the first three quartiles. Furthermore, the significance of the structural effect in the decomposition reflects the fact that the difference in inequality between households whose heads are at work and those who are not is due to a difference in observable characteristics but rather in the returns to these characteristics. The COVID-19 pandemic created an environment in which individuals had to adapt their behaviour to the new circumstances. This was done in several ways, either by reducing the household standard of living, by turning to entrepreneurship to find a new job or by resorting to wealth. In addition, the contribution of employment status to income inequality fell by almost one percentage point across the whole sample.

Notes

1. Closing borders, closing places of entertainment at 6pm, banning gatherings of more than 50 people.

2. Economic and financial survey of businesses in 2017.

3. Second survey on employment and the informal sector in Cameroon (EESI 2) 2010.

4. based on ILO LABORSTA database and ILO Global Employment Trends, 2009.

5. The level of income inequality in Cameroon rose between 2001 and 2014 from 40.4% to 44%.

6. The three periods considered for the survey are: (P1) before the outbreak of the pandemic; (P2) during the severe restrictions; and (P3) after the lifting of the main measures.

7. The interpretation of parameter estimates is similar to that of OLS models, but is slightly different (Buhai, 2005; Koenker and Hallock, 2001). In OLS models, the coefficient of a specific predictor represents the expected change in the dependent variable that is associated with a unit change in . In contrast, the coefficient of in the quantile can be interpreted as the marginal variation (relative to the quantile value of the dependent variable) which is due to a unit variation of . Since can be specified as representing several values between 0 and 1, the estimations could yield a large number of coefficients, but in this study, we only report quantiles that are commonly used, that is, 0.10, 0.25, 0.5, 0.75 and 0.90.

8. The (ν) indicator can be the average, a quantile, the Gini coefficient, etc.

9. $\sigma_i = I\left(f(c_i^{t=1},...\right) - I\left(f(c_i^{t=0},...\right)$

10. Detailed tables of results can be obtained from the authors.

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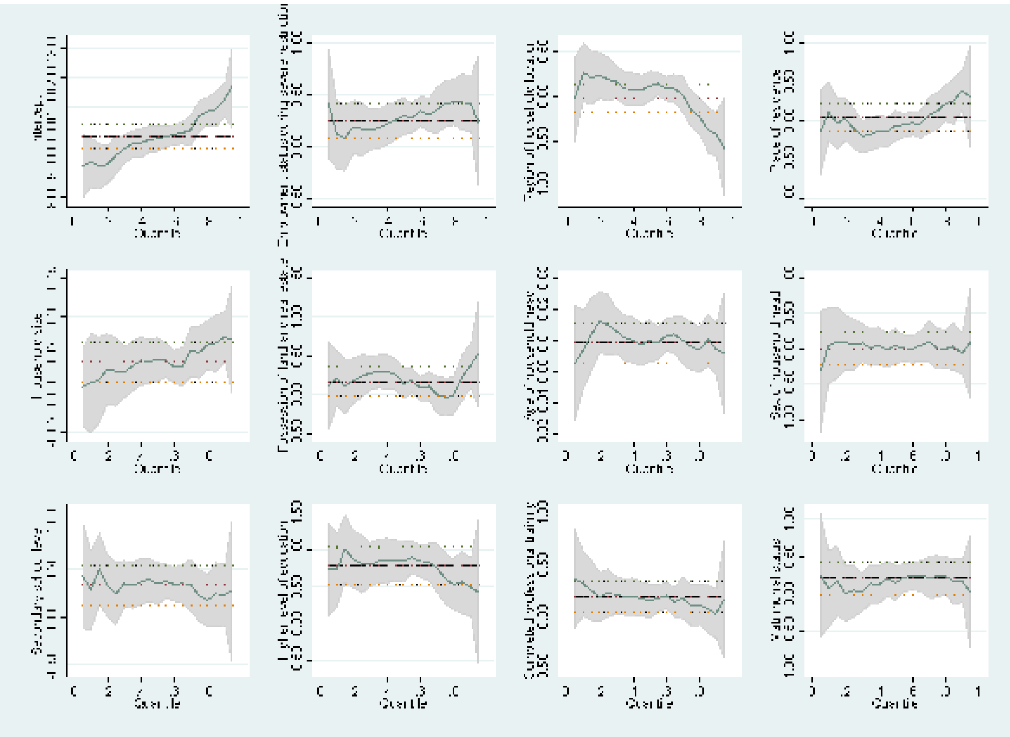
Appendix

Graph A1: Variable coefficients in the conditional quantile regression



Source: From data on the impact of COVID-19. Derived from conditional quantile regression.

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