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Effects of COVID-19 on Catastrophic Health Expenditures and Inequality in Benin: A Microsimulation Approach

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Abstract

This study assesses the effects of the COVID-19 pandemic on catastrophic health expenditures and income inequality in Benin. A microsimulation was calibrated to estimate the impact of the pandemic under three different shock scenarios: low, moderate, and severe. The analysis relies on secondary data from household living condition surveys. The results indicate that the COVID-19 crisis would lead to a significant average income loss of up to 20% and income inequality, while the number of households with catastrophic health expenditures would increase by 4%. More importantly, the findings reveal heterogeneous impacts across households, with urban residents, younger individuals, more educated households, and male-headed households experiencing the greatest income decline. These findings underscore the need for targeted health coverage and employment policies to better protect vulnerable populations in Benin in the face of future shocks.

Keywords: health expenditures; inequalities; microsimulation; COVID-19

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1. Introduction

In 2019, the world experienced an unprecedented health shock, that of the COVID-19 pandemic. This deadly infectious disease caused by severe acute respiratory disorders of coronavirus syndrome was declared a global pandemic by the World Health Organisation (WHO) on 11 March 2020 (WHO, 2020). The magnitude of the pandemic was estimated to be nearly half a billion people infected by 11 March 2022, and more than 6.5 million deaths worldwide, and 12 million people infected and 254 thousand deaths in Africa (WHO, 2022a). Thus, the number of people infected by the COVID-19 pandemic alone represents more than 71 times the number of people infected by the five largest epidemics the world has experienced in the last two decades, namely Zika in 2016, Ebola virus in 2014, Middle East Respiratory Syndrome Coronavirus (MERS-CoV) in 2012, H1N1 virus in 2009, and Severe Acute Respiratory Syndrome (SARS) in 2003 (Loungani et al., 2021).

Benin recorded the first confirmed case of COVID-19 on 16 March 2020, and the second case on 17 March 2020. The first death was recorded on 6 April 2020. These first events marked the beginning of the COVID-19 crisis in Benin. Figures 1 and 2 highlight that the crisis was characterised by two waves. The first wave indicates that the pandemic grew rapidly during the period from May to September 2020 before slowing down. The second wave spanned the period from June to August 2021, where both the number of new cases and the number of deaths increased more than in the first wave.

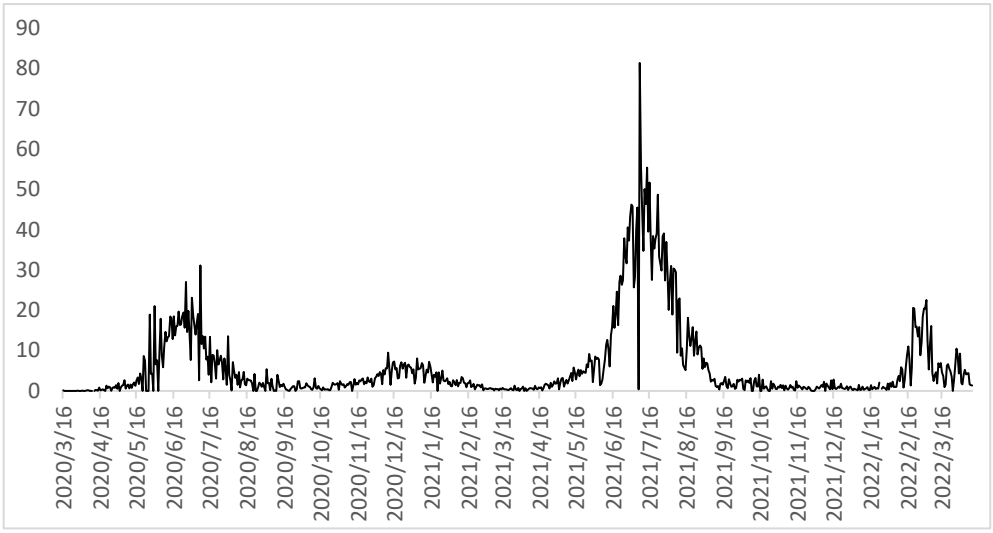


Figure 1. New confirmed COVID-19 cases per million in Benin. Source: Authors, using Johns Hopkins University CSSE COVID-19 data, 2022.

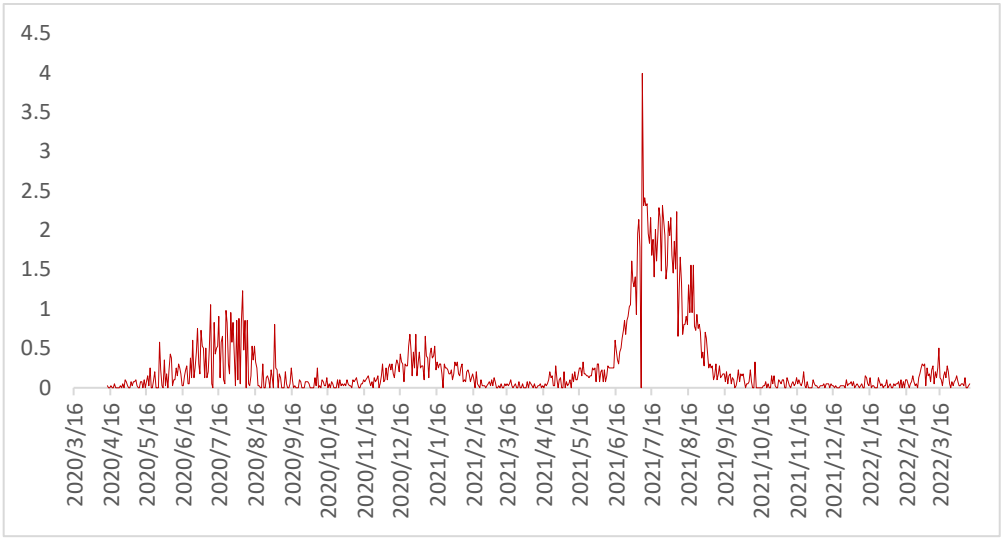


Figure 2. Deaths per million of the population in Benin. Source: Authors, using Johns Hopkins University CSSE COVID-19 data, 2022.

Following confirmation of the first cases of COVID-19, the Beninese authorities took measures including the closure of land borders, systematic quarantine of all travelers entering by air, school closures, prohibition of public gatherings, restrictions on public transportation, the closure of certain commercial centers such as restaurants and bars, and of course the systematic wearing of masks, hand disinfection and the strict respect of social distancing. On 13 September 2021, the Benin government made COVID-19 testing convenient for USD 45 and later decided that COVID-19 testing or vaccination would be mandatory for access to all public services, including decentralised services, in the country. On 1 April 2020, the government's first social measures for the population were adopted through the sale of masks at a government-subsidised price of USD 0.36, implying a subsidy rate of 60% in twelve high-risk districts in Benin (Gouvernement Benin, 2022). On 20 April 2020, social measures continued with the government-subsidised sale of 250 mg chloroquine tablets for the treatment and prevention of COVID-19 at a subsidised price of USD 0.9 and a subsidy rate of 64%.

All of these measures to contain the pandemic had many economic and social implications. At the macro-level, COVID-19 led to a decline in economic growth of 1.9% in 2020 in the Sub-Saharan Africa region (AfDB, 2022). In terms of fiscal policy, public spending on health care, private sector subsidy programmes, and tax cuts led to an increase in the budget deficit of 8.4 percent of GDP in 2020, double its 2019 level of 4.6 percent of GDP. Beyond these macroeconomic implications, existing studies have relied on multiple regression and simulation approaches to show that the pandemic increased the poverty rate by 22.7% to 38.5% in a sample of 13 Latin American countries (Bracco et al., 2024). In comparison, it was around 60% in Ghana (Abu & Issahaku, 2020), 22% in Ethiopia (Yimer & Alemayehu, 2021), 9% in Nigeria (Andam et al., 2020), and 4% in Burkina Faso (Ouoba & Sawadogo, 2022). Other studies have focused on health expenditure; for example, Rajalakshmi et al. (2023) showed that the pandemic led to a 26% increase in health expenditures in South India. Similarly, Ayanore et al. (2024) demonstrated that 52% of households in Ghana spent more than 5% of their total expenditures on COVID-19-related health costs. These findings demonstrate the drastic impact of COVID-19 across the globe. However, the magnitude of the impact also varies drastically, raising the issue of country-specific characteristics. Moreover, the underlying mechanisms through which the pandemic increased poverty, as well as the gender aspects of the impacts, are of crucial importance for formulating policy-relevant recommendations. Though the COVID-19 pandemic has passed, our findings remain relevant for better management of future pandemics.

The main question underlying this study is whether and to what extent the COVID-19 pandemic affected households' health expenditures and poverty in Benin. The objectives of the study are threefold: (i) to estimate the effect of COVID-19 on household income; (ii) to estimate the effect of COVID-19 on household health expenditures; and (iii) to evaluate the distributional effects of COVID-19. For the sake of having an in-depth understanding of the social implications of COVID-19 on household welfare, we analysed the effects of COVID-19 on the share of health expenditures in relation to households' income to determine whether the pandemic led to catastrophic health expenditures. Health expenditures are qualified as catastrophic when the out-of-pocket payments spent by households for health care negatively affect the households' capacity to satisfy their basic needs (WHO, 2001). Though there is no consensus on the threshold share of health expenditures for catastrophic characterisation, most of the definitions are based on threshold values ranging from 10% to 40% of a household's income or non-food expenditures (Kockaya et al., 2021; WHO, 2001; Xu, 2005).

The rest of the paper develops as follows. The literature review is presented in Section 2. The conceptual framework is presented in Section 3. In Section 4, we present the empirical strategy and data used. The main findings are presented and discussed in Section 5. Lastly, the concluding remarks are presented in Section 6.

2. Literature Review

Empirical studies widely agree on the detrimental effects of the COVID-19 pandemic on welfare and poverty, but they differ significantly in methodology, focus, and explanatory power. One dominant strand of the literature adopts quantitative approaches (regressions and microsimulations), revealing that the pandemic has worsened income inequality, increased household vulnerability, and intensified multidimensional poverty.

Bracco et al. (2024), using harmonised microdata from 13 Latin American countries, employed microsimulations to show that the COVID-19 crisis caused a poverty increase ranging from 22.7% to 38.5%, and they advocated for strong compensatory measures to mitigate long-term impacts. Similarly, Kang et al. (2023) analysed the impact of COVID-19 on household income using nationally representative surveys in Chad from 2020 and 2021.

Based on multivariate regression, they found that two-thirds of households, both rural and urban, reported income reductions, with urban areas hit harder in 2020 and rural areas in 2021.

In the health domain, multiple studies report rising catastrophic health expenditures during the pandemic. Haakenstad et al. (2023), using OLS regressions on microdata from Mexico and Peru, estimated 5.6% and 13.5% increases in such expenditures, respectively. Similarly, Rajalakshmi et al. (2023) showed that, in South India, 26% of households experienced catastrophic health spending. Ayanore et al. (2024) reported that, in Ghana, 52.2% of households spent more than 5% of their total expenditures on COVID-19-related health costs, and 4.2% exceeded the 40% threshold, highlighting inequality in the financial burden of the pandemic.

Beyond developing countries, many studies have also confirmed the detrimental impact of COVID-19 on households. Militaru et al. (2024) used the EUROMOD tax–benefit microsimulation model to study income changes during the COVID-19 period (2019–2021) and the subsequent inflation crisis (2021–2023) in Romania. They found that although disposable income rose initially, the poorest benefited the least, and later inflation disproportionately impacted lower-income groups. However, their findings revealed that overall income inequality declined, emphasising the need for targeted policy support to protect vulnerable households. Kalar et al. (2023) relied on the same methodology to investigate the impact of COVID-19 on income in the European Union. This study finds that COVID-19 containment and mitigation measures had a regressive impact on income distribution, benefiting lower-income groups more, while their effectiveness varied by country context, with old democracies generally achieving better outcomes than new democracies, highlighting the need for tailored policy mixes. Alfani et al. (2024) relied on Recentered Influence Function regression to show that COVID-19 increased income inequality in the US and Brazil. Moreover, they highlighted that the disparities were persistent over time. Furthermore, Shen and Zhong (2023) focused on both human and animals and showed that the COVID-19 pandemic negatively affected both household income as well as animal food consumption in China.

Despite the robustness of these quantitative findings, a key limitation is their limited attention to causal mechanisms. These studies document income loss, increased food insecurity, or reduced health access, but often do not explain their mechanisms. Moreover, the effects vary widely across and within countries, pointing to the importance of contextual and institutional factors that are not sufficiently unpacked in these analyses.

Complementing this research is a second strand of studies that rely primarily on qualitative methods, offering a more nuanced view of the pandemic's impact on lived experiences, though often at the expense of generalisability. Musoke et al. (2024) use focus group discussions, key informant interviews, and household narratives to analyse the social and economic effects of the COVID-19 lockdown in Uganda. Their findings reveal family breakdowns, increased gender-based violence, rising child labour, and food insecurity, along with deteriorated educational outcomes due to school closures. Similarly, Kerschbaumer et al. (2024) employed qualitative methods with 151 participants in Austria to document heightened poverty, social exclusion, and psychological distress during the pandemic. In Indonesia, Mafruhat et al. (2025) used a non-random sample of 100 households across 30 districts to explore both material and spiritual poverty, finding that the pandemic has deepened both. In Spain, Ortega-Martin and Alvarez-Galvez (2025) conducted semi-structured interviews with 23 participants to highlight how COVID-19's effects extended beyond physical health to include economic stress, legal uncertainty, and weakened social cohesion. Finally, Karunarathne et al. (2025), using 22 years of panel data from 20 low-income countries, estimated the long-running impact of the pandemic on life

expectancy, concluding that it has significantly reduced life expectancy, particularly in countries with fragile health systems.

Together, these qualitative and mixed-method studies offer crucial insight into the social, psychological, and gendered dimensions of COVID-19's impact on welfare. However, their methodological limitations, including their small, non-representative samples and the lack of causal inference, limit the external validity and policy applicability of their findings.

In sum, while the existing literature convincingly demonstrates the negative impact of COVID-19 on poverty and welfare, two major gaps persist. First, the importance of the impacts from quantitative studies widely varies, and these studies fail to identify the mechanisms through which these effects unfold, especially across different social groups or policy environments. Second, qualitative studies, while rich in context, suffer from limited quantification and generalisability, preventing broader policy conclusions.

3. Conceptual Framework

COVID-19 affected household income and health expenditures through labour markets (demand and supply), moderated by government measures (transfers and barrier measures), and preventive and curative health expenditures by households. Figure 3 describes the channels.

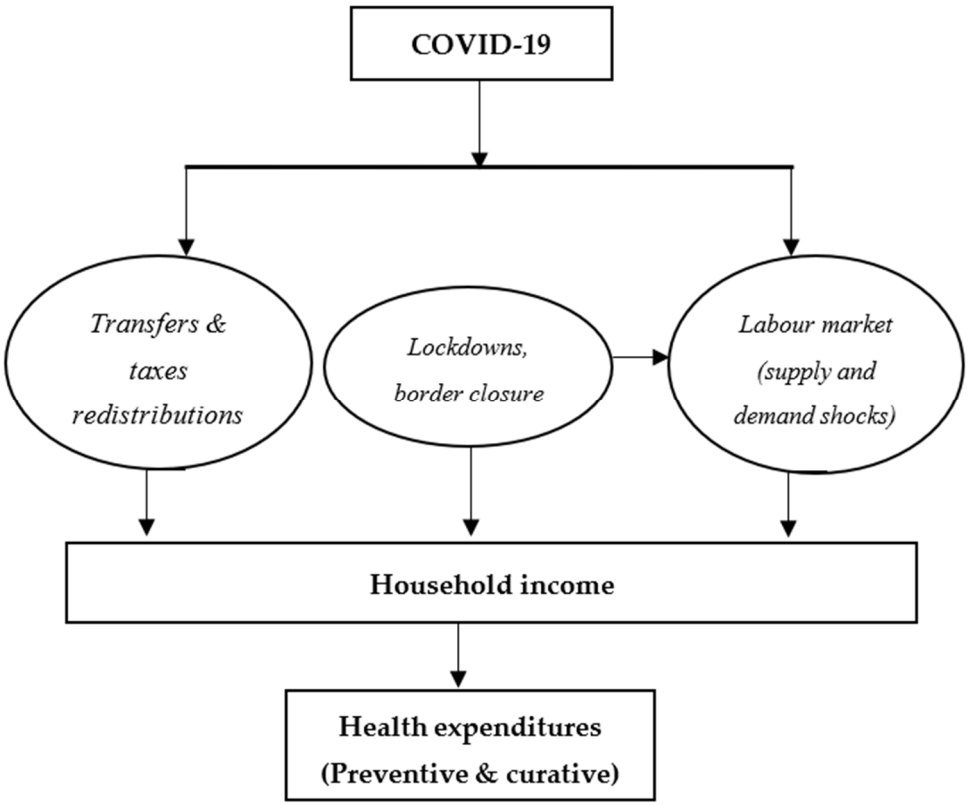


Figure 3. Effect of COVID-19 on household health expenditures. Source: authors.

The population affected by the COVID-19 outbreak can be classified into two groups, namely the infected and the susceptible, with the possibility of having both groups of people within the same household. On the one hand, those infected are drawn out of the labour market, increasing unemployment by reducing the labour supply and leading to a decrease in household income. The government intervenes to temper the decrease in income by cash transfers and tax redistribution. The treatment expenses increase directly with health expenditure (curative and preventive). However, since household income decreases, health expenditures may decrease as a consequence. On the other hand, the

susceptible population takes prevention measures that increase health expenses while simultaneously experiencing income losses. Moreover, to prevent contamination, the government takes barrier measures (e.g., lockdowns, internal and external border closures, and bans on public gatherings) that slow down economic activities and cause a recession that affects the labour markets through unemployment due to the decrease in labour demand. These governmental measures lead to a decrease in income and ultimately to a decrease in health expenditures at the household level. The channels through which COVID-19 affects income and health expenditures are instrumental to the evaluation of the effects of the pandemic.

4. Empirical Strategy

The best strategy for evaluating the effect of COVID-19 on household health expenditures is to use experimental—or by default quasi-experimental—impact assessment methods. These methods assume the existence of both control and treatment groups. The use of these methodologies is not feasible in the case of COVID-19 because no one could be excluded from exposure to the epidemic, resulting in the absence of an appropriate control group. Also, the lack of household and individual data before and after COVID-19 precludes the use of quasi-experimental impact assessment methods. In the face of these empirical constraints, we use a microsimulation approach to assess the effect of COVID-19. This approach is based on the behavioral function of individuals through which their reactions to a shock or policy are evaluated in terms of averages and distributional effects, considering the entire distribution (especially the tails) of the shock or policy effects. Unlike Computable General Equilibrium (CGE) models, which are criticised for aggregating economic phenomena (Hansen & Heckman, 1996), microsimulation models have the advantage of analysing in detail the effect of a shock or policy at the individual level.

Microsimulation models have been widely used in recent decades for the ex ante evaluation of poverty reduction policies and exogenous shocks, including the effects of COVID-19 (Andam et al., 2020; O'Donoghue et al., 2021; Ouoba & Sawadogo, 2022; Yimer & Alemayehu, 2021) and mostly for social programs and fiscal policies (Benczúr et al., 2018; Bover et al., 2017; Maskaeva et al., 2019, 2021). Our estimation strategy of the short-term effect of COVID-19 follows that of Aran et al. (2021). Our microsimulation strategy entails four steps as stated below.

4.1. Calculating the Effects of COVID-19

4.1.1. Calculating COVID-19 Household Income and Health Expenditure

We compute the monthly household health expenditures and monthly household income before the COVID-19 pandemic using the Harmonized Survey on Living Conditions of Households (EHCVM) dataset.

Concerning household income, our income generation process follows Sologon et al.'s (2021) approach. The total income is given by Equation (1):

$$y = y^L + y^K + y^O + y^B \tag{1}$$

where y is the household monthly income, y^L refers to the labour income, y^K measures the capital income, y^o is other household income, and y^B is public benefits (transfers). Contrary to Sologon et al. (2021), who used household disposable income, we used gross income. This choice is motivated by the fact that the tax information and public benefits are not available in our dataset. However, the consequences of this oversight of taxes are likely to be negligible, because, in developing countries like Benin, labour income is lightly taxed and the tax cost is probably balanced by public transfers.

The labour income y^L in a household equals the sum of individuals employed and self-employed within the household, aggregated as follows:

$$y^L = \sum_{i=1}^{n} \left(I_i^{employed} * y_i^{employed} + I_i^{self-employed} * y_i^{self-employed} \right) \quad (2)$$

where i refers to the individual member of the household and n the size of the household. Individual i is employed ($I_i^{employed} = 1$) and ($I_i^{employed} = 0$), with an income equal to $y_i^{employed}$. $I_i^{self.employed}$ and $y^{self.employed}$ are similarly defined. This aggregate formula also addresses the situation of individuals who combine salaried work and self-employment.

Household capital income comes from investment income and property income, most notably rental income. Capital income is then modelled as follows:

$$y^K = \sum_{i=1}^{n} \left(I_i^{investment} y_i^{investment} + I_i^{property} y_i^{property} \right) \quad (3)$$

Apart from labour and capital income, households may benefit from other incomes, such as private pensions and transfers received from relatives and nonrelatives. Such sources of income are computed as follows:

$$y^O = \sum_{i=1}^{n} \left(I_i^{private.pension} y_i^{private.pension} + I_i^{tranfers.relatives} y_i^{tranfers.relatives} + I_i^{tranfers.non-relatives} y_i^{tranfers.non-relatives} \right) \quad (4)$$

Finally, household income comes from public benefits (if available), both at the individual level (pensions, sickness or disability, unemployment insurance) and at the household level such as social security programs (food distribution, cash transfers, free healthcare for children and pregnant women). The aggregated income from public benefits at the household level is computed as follows:

$$y^B = y^{social.security} + \sum_{i}^{n} \left(I_i^{pensions} y_i^{pensions} \right) \quad (5)$$

The World Health Organisation defines health expenditures based on healthcare functions as out-of-pocket money spent by households in satisfying their core healthcare needs. Those healthcare functions included core items such as curative care, rehabilitative care, inpatient care, outpatient care, day care, long-term care, home-based care, ancillary services, pharmaceutical goods, therapeutic appliances, and preventive care (WHO, 2022b). Following this definition, we modelled the household health expenditure equation into three components, namely curative expenditures e^C, preventive expenditures e^P, and nonmedical expenditures e^O, as follows:

$$e = \sum_{i=1}^{n} \sum_{j} e_i^j, \text{ withi} = 1, 2, \ldots \text{n and j} = \text{C, P, O} \quad (6)$$

where e is the aggregated household monthly health expenditures for all the household members. All three components of health expenditures take into consideration both modern and traditional medicine. Curative health expenditures are composed of doctor consultation fees e^{cons}, medicines e^{med}, diagnostic testing e^{diagn}, and bed charges for hospitalisation e^{bed} as follows:

$$e^C = e^{cons} + e^{med} + e^{diagn1} + e^{bed} \quad (7)$$

Preventive health expenditures equal the sum of preventative diagnostic testing e^{diagn2}, vaccines e^{vac}, and other nonmedical goods e^{other} such as face masks.

$$e^P = e^{diagn2} + e^{vac} + e^{other} \quad (8)$$

Finally, household health expenditures encompass other nonmedical expenditures e^o, notably transport e^{trans} and communication fees e^{com} as follows:

$$e^O = e^{trans} + e^{com} \tag{9}$$

It is worth noting that the measure of health expenditures used in this study refers exclusively to out-of-pocket payments reported by households. It does not include health spending covered by government subsidies, public insurance schemes, or donor-funded programmes. Data on these variables were not available.

4.1.2. Calculating the COVID-19 Job Loss Index After the Outbreak

The COVID-19 job loss index is calculated by multiplying the risk of job loss conditional to the sector of activity, gender, and residence as follows[1]:

$$\text{Job loss index}_{t=1} = \text{Risk}(\text{job loss}|\text{sector}_k) * \text{Risk}(\text{job loss}|\text{gender}_i) * \text{Risk}(\text{job loss}|\text{residence}_j) \tag{10}$$

where t = 1 refers to the COVID-19 period. The risk of job loss conditional to sector of activities and residence is calculated using the results of the rapid evaluation conducted during the COVID-19 pandemic (March–July 2020) by the National Institute of Statistics and Economic Analysis (INSAE BENIN, 2020). This study reported that 80%, 77% and 74% of Cotonou city residents, other urban residents, and rural residents, respectively, did not work during the period considered. Equally, the risk of job loss in the wholesale and retail trade was the highest (37.29%), while it was 0% in the agriculture sector. The full job loss probabilities according to the sector of activities, are reported in Table A1 in Appendix A. Furthermore, this report indicated that 50% of households lost their job during the period, which accounts for 87.5% of men and 13% of women. Hence, we calculated the probabilities of job loss based on gender as follows[2]:

$$\Pr(\text{job loss}|\text{gender}_i) = \frac{\Pr(\text{job loss} \cap \text{gender}_i)}{\Pr(\text{gender}_i)} \tag{11}$$

The results from Equation (11) indicated probabilities of job loss of 0.55 and 0.30, respectively, for men and women. Then, we calculated the risk of job loss conditional to gender and residence using a multiplier as follows:

$$Risk(job\ loss|gender_i) = \frac{2Pr(job\ loss|gender_i)}{\sum_{i=1}^{2} 2Pr(job\ loss|gender_j)}, \tag{12}$$

and

$$Risk(job\ loss|residence_k) = \frac{3Pr(job\ loss|residence_k)}{\sum_{i=1}^{3} 2Pr(job\ loss|residence_l)}$$

The risk of job loss coefficients by gender and residence are reported in Table A2 in the Appendix A. This risk factors are not probabilities, but multipliers addressing the fact that certain individuals are more susceptible to job loss than some others depending on their characteristics (gender or place of residence).

We considered the job loss indices calculated in Equation (12) as the mean shocks, so they are set as the baseline assumptions (moderate shock). The low and severe assumptions are set by considering that low shock is 0.5 times the baseline and severe is twice the baseline assumption. The job loss indices in the low, moderate, and severe assumptions are reported in Table 1.

Table 1. Job loss indices by severity of shock.

Income Loss	Obs	Mean	Std. Dev.	Min	Max
Low shock	899	0.058	0.042	0.000	0.316
Moderate shock	899	0.116	0.083	0.000	0.631
Severe shock	899	0.201	0.101	0.035	0.947

Source: authors.

4.1.3. Calculating Incomes After COVID-19

We compute income loss during the COVID-19 pandemic by adjusting the pre-COVID-19 income for the after-COVID-19 job loss index. The post-COVID-19 income[3] loss is specified as follows:

$$Income\ loss_{t=1} = \text{Income}_{t=0} * \text{job loss index}_{t=1} \tag{13}$$

Finally, the after COVID-19 income is calculated as follows:

$$Income_{t=1} = Income_{t=0} \times (1 - job\ loss\ \text{index}_{t=1}) \tag{14}$$

4.1.4. Calculating After COVID-19 Health Expenditures

We estimate the effect of COVID-19 on health expenditures. COVID-19 affects household health expenditures through an increase in preventive (purchase of face masks, vaccination, and hand sanitisers) and curative health expenditures (drugs and hospitalisation), ceteris paribus. Following Olasehinde and Olaniyan (2017), household health expenditures in developing countries depend on income and household sociodemographic characteristics as follows:

$$\begin{aligned} ln(health\ Expenditures_{t=0}) \quad &= \varphi_0 + \varphi_1 ln(Income_{t=0}) + \varphi_2 household\ size + \varphi_3 Educ \\ &+ \varphi_4 illess + \varphi_5 Gender + \varphi_6 Insurance + \varphi_7 Residence\ + \psi_i \end{aligned} \tag{15}$$

φ_i are coefficients to be estimated. Specifically, φ_1 denotes the income elasticity of health expenditures. The hierarchical structure of the data indicates there is no independent individual-level observations. This absence of independence arises because individuals are nested within households. To address this concern, we use multilevel mixed-effects linear regression in estimating the health expenditure equation. This allows us to consider the variability in health expenditures as either fixed at the household level or random at the individual level (Gelman & Hill, 2006; Baayen et al., 2008). We then calculated the health expenditures after the COVID-19 pandemic as follows:

$$\text{Health expenditures}_{t=1} = (1 - \varphi_1 \times (\text{income loss coefficient})) \times \text{health expenditures}_{t=0}) \tag{16}$$

The catastrophic health expenditures (CHEs) indicator is computed by the ratio of health expenditures to household income.

4.2. Data

This study uses secondary data from the first edition of the Harmonized Survey on Living Conditions of Households (EHCVM) in Benin (INSAE BENIN, 2019). This survey was conducted in the eight countries of the West African Economic and Monetary Union (UEMOA) between 2018 and 2019 with joint funding from the World Bank and the UEMOA Commission and carried out by the Institut National de la Statistique et de l'Analyse Economique du Bénin (INSAE). The EHCVM was based on a nationally representative sample of 7956 households containing 21,922 individuals distributed in 670 clusters across the 12 departments of Benin. The sample was selected randomly using the household sampling frame from the 2013 General Census of Population and Housing of

Benin (RGPH 4). The EHCVM has two modules. The first is the household–individual module, which provides information on sociodemographic characteristics (age, gender, place of residence, household size, education, health) and economic characteristics (sector of activity, employment status, income, consumer spending, asset ownership). The second module, entitled community, provides information on the characteristics of the household environment. The second source of data used comes from Benin government official releases and the official statistics of Benin institutions, such as the National Institute of Statistics, the Ministry of Economics and Finance, the Ministry of Health, the Ministry of Agriculture, and the Ministry of Industry. These data sources provide information on government measures and the reaction of economic sectors to COVID-19. This information is important in setting out our simulation hypotheses.

The dataset contains many missing data. For example, most of the households did not report their income. Overall, 5967 households that declared having a job did not report their income or health expenditures. To limit the biases that can arise when imputing missing data, we simply dropped observations with missing data regarding income and health expenditures, leaving a sample of 899 households. Indeed, we further checked the missing data patterns using the covariate-dependent missingness (CDM) test (Little, 1988). The result strongly rejected the null hypothesis that income and health expenditures are jointly CDM given the households' sociodemographic covariates[4], meaning that the missing data are not completely random.

5. Empirical Results

This section presents the descriptive statistics of the study variables, the regression results, and the microsimulation outputs. Given the complex survey design of the EHCVM, which includes stratification, clustering, and unequal sampling probabilities, survey design features were incorporated into the analysis to ensure unbiased and efficient estimates, including the summary statistics. Specifically, sampling weights were applied to correct for unequal probabilities of selection, and standard errors were adjusted to account for clustering at the primary sampling unit (PSU) level. All analyses were performed using survey-adjusted regression techniques (the svy suite in Stata), which allow for correct inference under complex sampling designs.

5.1. Summary Statistics

This section presents some key statistics drawn from the dataset used. The Benin's Harmonised Households Living Conditions Survey dataset classified household activities into 18 branches, as presented in Table 2. The results presented are based on the main type of activity of the head of household. This table indicates that the agriculture, fishing and forestry sector was the most important type of household activity, accounting for 47.5% of households, followed by the trade sector (28.6%) and the manufacturing sector (14.6%). The rest of sectors represent less than 5% of household employment. These results reflect the economic structure of the majority of SSA countries, where the agricultural sector is the sector with the most employment, supplying an important share of government export revenue.

Table 3 outlines the summary statistics for household socioeconomic and demographic characteristics, such as income, health expenditures, age, gender, place of residence, and household size. All the statistics are calculated at the household level, meaning they are based on information from the head of household (gender, age, employment status, residence, and education) or information that does not vary across a household's members (access to clean water, electricity, health coverage). However, we considered that a household suffered from one of the diseases considered when at least one member of the

household was sick. For quantitative variables such as income and health expenditures, we aggregated the values at the individual level within the household and then calculated the mean at the household level.

Table 2. Type of activities.

Activity	Percent
1. Agriculture, fishing, and forestry	47.49
2. Mining	0.52
3. Manufacturing	14.57
4. Water, electricity, and gas	0.04
5. Construction	1.12
6. Wholesale and retail trade, repair of motor vehicles, and other motors.	28.58
7. Hotels and restaurants	0.52
8. Transport and communication	1.61
9. Financial activities	0.07
10. Real estate, leasing, and business services	0.30
11. Public administration services	0.52
12. Education	1.57
13. Health and social work activities	0.19
14. Associative activities	0.15
15. Arts, entertainment, and recreation	0.19
16. Personal service activities	2.36
17. Housework and other home services	0.19
Total	100.00

Source: authors.

Table 3. Households' characteristics.

(a) Household Characteristics		
Variable	**Number of Observations**	**Mean/Percent**
Access to clean water *(1 if access to clean; 0 otherwise)*	7956	0.095
Access to electricity *(1 if yes; 0 otherwise)*	7956	0.31
Health insurance (*1 if yes; 0 otherwise)*	7956	0.06
Job status *(1 if has a job; 0 otherwise)*	5967	0.97
Gender *(1 if male: 0 if female)*	7956	0.49
	Diseases	
Malaria	4533	56.97
Accident	920	11.56
Cough	1401	17.61
Blood pressure and diabetes	1103	13.86
Total	7956	100
	Residence	
Cotonou	570	7.16
Urban	3175	39.91
Rural	4211	52.93
Total	7956	100
	Category of employee	
Higher manager	345	4.34
Medium manager	1141	14.34
Unskilled worker	5134	64.53
Paid intern	420	5.28
House worker	128	1.61
Independent	787	9.89
Total	7956	100
	Education	
Primary	2274	28.58
Secondary	4044	50.83
Higher	1638	20.59
Total	7956	100

Table 3. *Cont.*

(b) Household characteristics (F CFA)					
Variable	**Number of Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Household Income (CFA)	899	91,882	205,002	0	3,000,000
Household Health Expenditures	899	2159	4655	0	50,250

Source: authors.

5.2. Effect of COVID-19 on Household Income

Table 4 presents the effect of COVID-19 on household income and per capita income, respectively. The results indicate that COVID-19 led to a decline in household income. The average income would move from 91,882 before the COVID-19 pandemic to 86,545 after a low COVID-19 shock and 70,565 after a severe shock. A similar pattern of income decline is observed in the per capita income, as outlined in Table 4b. More specifically, Table 5 shows that the magnitude of income loss is proportional to the degree of shock. Notably, the scenario of a low COVID-19 shock would lead to a shrinkage in income by 5.8%, while the scenarios of moderate and severe shock would shrink household income by 11.6% and 20.1%, respectively. Furthermore, households would lose up to 94.7% of their income after a severe shock. Our findings align with those found by existing studies in SSA countries. For instance, Andam et al. (2020) studied the effect of COVID-19 on food security and poverty in Nigeria. Using the SAM multiplier approach, they found that the COVID-19 pandemic reduced households' income by 22.6% on average. Similarly, Diao et al. (2020) investigated the effect of COVID-19 on households' income and poverty in Rwanda based on microsimulation modelling. They concluded that the COVID-19 crisis led to a household income loss of 33% on average.

Table 4. Before and after COVID-19 incomes.

(a) Before and after COVID-19 incomes (F CFA)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Before COVID-19	899	91,882	205,002	0	3,000,000
After low shock	899	86,545	193,570	0	2,835,360
After moderate shock	899	81,209	182,268	0	2,670,720
After severe shock	899	70,565	160,143	0	2,341,441
(b) Before and after COVID-19 per capita incomes (F CFA)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Before COVID-19	899	39,424	101,279	0	1,500,000
After low shock	899	37,038	95,488	0	1,417,680
After moderate shock	899	34,652	89,773	0	1,335,360
After severe shock	899	29,909	78,619	0	1,170,720

Table 5. Share of lost income after COVID-19 (%).

Income Loss Coefficient (%)	Obs	Mean	Std. Dev.	Min	Max
Low shock	899	5.79	4.15	0.00	31.56
Moderate shock	899	11.58	8.30	0.00	63.11
Severe shock	899	23.14	16.45	0.00	100.00

Source: authors.

More importantly, the distributional analysis of the effect of COVID-19 on income revealed that there was a heterogeneous shrinkage in household income. As depicted in

Figure 4, low- and middle-income households were the most vulnerable to COVID-19. Indeed, it can be seen that the gap between the before-COVID-19 curve and that of the after-COVID-19 decreases from lower-income to higher-income. Our results confirmed those of Diao et al. (2021) in Rwanda. These authors concluded from microsimulation modelling that COVID-19 had a heterogeneous effect on household income. Notably, middle- and high-income quintile households experienced the highest decline in income (35%), whereas income declined by 28% on average in low-income quintile households. Andam et al. (2020) also studied the effect of COVID-19 on poverty in Nigeria and found that the first two quintiles of income groups recorded a decline in their income by 15% on average, while the third, fourth, and fifth income quintiles experienced an income shrinkage of 24% on average during six weeks of lockdown in Nigeria. Furthermore, they concluded that urban household residents were the most affected by the COVID-19 pandemic, which lowered their income by 27% on average, whereas rural residents lost an average of 18%.

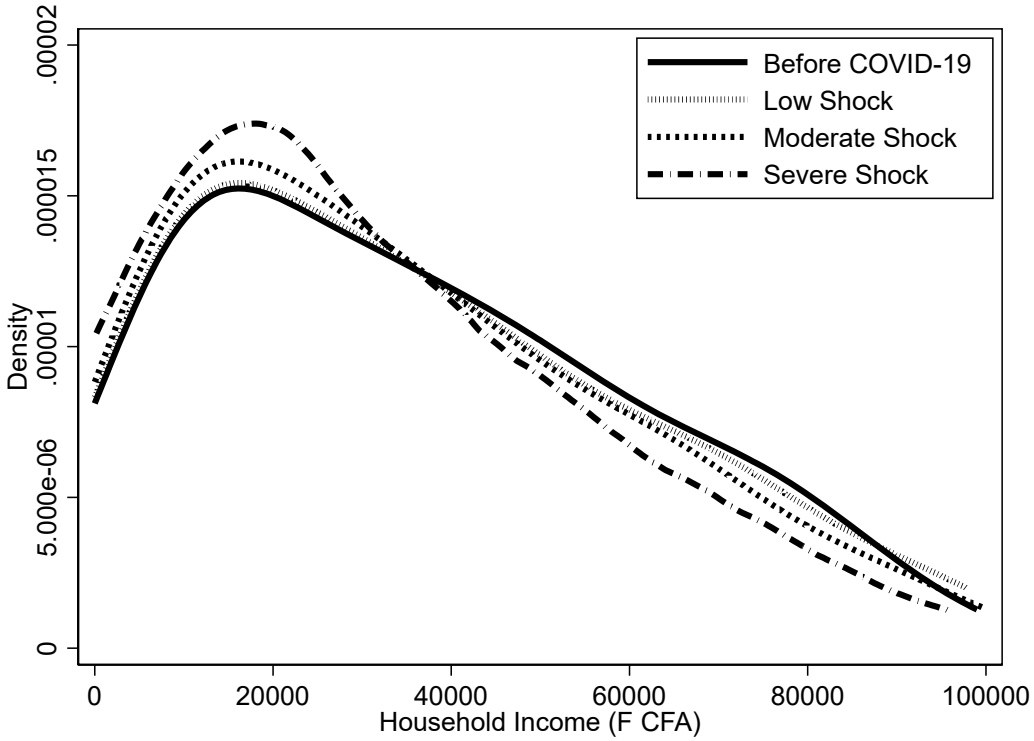


Figure 4. Before and after COVID-19 income[5]. Source: authors.

In addition to vulnerability based on economic status, our results reveal that the severity of the impact of COVID-19 varies according to the age, educational level, and gender of the household head, as well as the place of residence. Table 6 indicates that households headed by younger individuals are the most affected, followed by those headed by adults. Secondly, gender-based analysis shows that male-headed households experience the greatest income losses, regardless of the scenario considered. For instance, under a moderate COVID-19 shock, income fell by 14.74% for male-headed households, compared to an 8.23% decline for those headed by females. Thirdly, households headed by individuals with higher education are the most affected, followed by those with secondary education. Finally, the place of residence also matters: households residing in the capital city, Cotonou, are the most affected, followed by those in other urban areas. Under a moderate COVID-19 shock scenario, households in Cotonou and other urban areas would experience income declines of 15.6% and 11.8%, respectively, compared to 9.7% among rural households.

Table 6. Share of lost income by age, education, gender, and residence.

Age Group	Low Shock	Moderate Shock	Severe Shock
Young (0–17)			
Mean	7.52%	15.04%	29.90%
Standard error	5.31%	10.63%	20.55%
Minimum	0.00%	0.00%	0.00%
Maximum	31.56%	63.11%	100.00%
Adult (18–66)			
Mean	6.57%	13.13%	26.27%
Standard error	3.19%	6.39%	12.78%
Minimum	0.00%	0.00%	0.00%
Maximum	12.67%	25.34%	50.67%
Elderly (>66)			
Mean	5.28%	10.55%	21.10%
Standard error	3.85%	7.71%	15.42%
Minimum	0.00%	0.00%	0.00%
Maximum	24.11%	48.22%	96.43%
Head of household gender	Low shock	Moderate shock	Severe shock
Female			
Mean	4.12%	8.23%	16.46%
Standard error	2.73%	5.46%	10.92%
Minimum	0.00%	0.00%	0.00%
Maximum	17.26%	34.51%	69.02%
Male			
Mean	7.37%	14.74%	29.43%
Standard error	4.62%	9.24%	18.22%
Minimum	0.00%	0.00%	0.00%
Maximum	31.56%	63.11%	100.00%
Head of household education	Low shock	Moderate shock	Severe shock
Primary or below			
Mean	5.62%	11.24%	22.48%
Standard error	3.51%	7.02%	14.04%
Minimum	0.00%	0.00%	0.00%
Maximum	11.58%	23.16%	46.32%
Secondary			
Mean	7.27%	14.54%	29.08%
Standard error	4.18%	8.35%	16.71%
Minimum	0.00%	0.00%	0.00%
Maximum	24.11%	48.22%	96.43%
Higher			
Mean	9.29%	18.59%	36.46%
Standard error	5.84%	11.68%	20.84%
Minimum	0.00%	0.00%	0.00%
Maximum	31.56%	63.11%	100.00%
Place of residence	Low shock	Moderate shock	Severe shock
Cotonou			
Mean	7.80%	15.59%	31.01%
Standard error	3.59%	7.17%	13.25%
Minimum	0.00%	0.00%	0.00%
Maximum	31.56%	63.11%	100.00%
Urban			
Mean	5.89%	11.77%	23.55%
Standard error	4.33%	8.66%	17.32%
Minimum	0.00%	0.00%	0.00%
Maximum	24.11%	48.22%	96.43%
Rural			
Mean	4.87%	9.74%	19.49%
Standard error	3.86%	7.72%	15.44%
Minimum	0.00%	0.00%	0.00%
Maximum	23.17%	46.34%	92.67%

Source: authors.

5.3. Effect of COVID-19 on Income Inequality

To assess whether the effects of COVID-19 are significantly heterogeneous, we calculated the Gini index. The results reported in Table 7 indicate that COVID-19 would increase income inequality in Benin by 0.1 percentage point. Moreover, the increase in inequality is more pronounced among men, younger individuals, and those with higher levels of education, who appear to be the most affected groups, as outlined in Table 8. These findings are consistent with the magnitude of the income decline observed within these subgroups, as discussed in the previous section.

Table 7. Gini index by age and severity of shock.

GINI Index	BEFORE	LOW	MODERATE	SEVERE
Overall	0.622	0.623	0.624	0.628
Young	0.577	0.579	0.583	0.598
Adult	0.550	0.548	0.546	0.544
Elderly	0.640	0.640	0.641	0.647

Table 8. Gini index by gender and severity of shock.

(a) Gini index by gender and severity of shock.				
GINI index	**BEFORE**	**LOW**	**MODERATE**	**SEVERE**
Overall	0.622	0.623	0.624	0.628
Women	0.672	0.672	0.672	0.673
Men	0.562	0.562	0.563	0.571
(b) Gini index by education level and severity of shock.				
GINI index	**BEFORE**	**LOW**	**MODERATE**	**SEVERE**
Overall	0.622	0.623	0.624	0.628
Primary and below	0.490	0.488	0.487	0.485
Secondary	0.573	0.574	0.577	0.586
Higher	0.377	0.383	0.393	0.405
(c) Gini index by place of residence and severity of shock.				
GINI index	**BEFORE**	**LOW**	**MODERATE**	**SEVERE**
Overall	0.622	0.623	0.624	0.628
Cotonou	0.695	0.698	0.703	0.715
Urban	0.559	0.561	0.563	0.575
Rural	0.599	0.599	0.600	0.606

Source: authors.

5.4. Effect of COVID-19 on Household Health Expenditures

As depicted in our conceptual framework, it is argued that the COVID-19 crisis has affected (increased) household health expenditures through direct and indirect channels. Indeed, the health expenditures of households increase with exposure to COVID-19 contamination risk. Thus, the expenditures for averting measures (hand sanitiser, face masks, vaccine, COVID-19 tests, etc.) and money spent out-of-pocket on medical visits and medicine directly increase household health expenditures. The effects of COVID-19 on health expenditure were examined by estimating the health expenditure equation in (14).

The drivers of health expenditure were estimated using multilevel mixed-effects linear regression (Table 9). The validation parameters of the model show that the random intercept at the household level significantly varies, as indicated by a variance coefficient equal to

1.38 with a standard error coefficient equal to 0.40. This result indicates that ignoring the random effect by estimating only the fixed effect would lead to biased estimates. Moreover, the likelihood ratio (LR) test strongly supports that the mixed-effects model better fits our data than the ordinary least squares (OLS) model, as confirmed by the *p*-value of 0.000. Thus, the results of the fixed-effects components revealed in Table 9 indicate that income, age, and risk of diseases such as cough, high blood pressure, malaria, and road accidents have positive and significant effects on health expenditure. Notably, a 10% income improvement increases health expenditure by 3%, confirming previous findings in Africa. Indeed, Olasehinde and Olaniyan (2017) relied on the ordinary least squares technique to estimate the determinants of household health expenditure in Nigeria. They found that a 1% increase in household income increases health expenditures by 0.57%. Ampaw et al. (2019) used a nationally representative sample of 16,772 households to analyse the effect of income on health expenditure in Ghana. Their findings from ordinary least squares regression confirmed a positive and significant effect of household total income on health expenditure. Equally, Houeninvo and Assouto (2023) recently used a sample of 20 low-income African countries over 1995–2018 to calculate income elasticities. Based on panel-pooled mean group estimates, they concluded that a 1% improvement in per capita income increases private health expenditure by 0.54% in the long run. Furthermore, our findings revealed that households residing in rural and urban areas are less likely to have higher health expenditures than those in the capital city of Cotonou. Our results further confirmed the nonlinear relationship between age and health expenditure, as found in previous studies such as those of Ampaw et al. (2019) in Ghana and Olasehinde and Olaniyan (2017) in Nigeria.

Table 9. Multilevel mixed-effects linear regression model of household health expenditure.

Log (Health Expenditure)	Coef.	St. Err.	[95% Conf	Interval]
Log (income)	0.292 ***	0.089	0.117	0.466
Gender head household (ref = female)				
Male	−0.191	0.181	−0.546	0.165
Log (Age)	0.035 **	0.017	0.002	0.067
Log (Age square)	−0.001 **	0.000	−0.001	0.000
Education of head household (ref = primary)				
Secondary	−0.124	0.231	−0.576	0.328
Higher	−0.221	0.309	−0.825	0.384
Health coverage (ref = no)	−0.362	0.435	−1.215	0.490
Residence (ref = Cotonou)				
Urban	−0.523 **	0.252	−1.017	−0.029
Rural	−0.731 ***	0.274	−1.268	−0.194
Cough last 3 months (ref = no)	1.817 ***	0.414	1.004	2.629
High blood pressure (ref = no)	2.729 ***	0.679	1.397	4.060
Malaria last 3 months (ref =no)	0.637 ***	0.269	0.110	1.164
Road accident last 3 months (ref = no)	3.292 ***	0.958	1.414	5.170
Constant	3.579 ***	0.994	1.631	5.527
Random-effects parameters				
Intercept at household level	1.383	0.405	0.779	2.456
Residual variance	2.281	0.387	1.635	3.181
Mean dependent var		2.078		
Number of obs		78.188		
Prob > chi2		1761.402		

Note: Any statistically significant estimates are denoted with asterisks: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We now simulate the effects of COVID-19 on health expenditure. The results presented in Figure 5 indicate that households experienced an increase in health expenditures after the COVID-19 shock, with heterogeneous effects. Indeed, a decrease in household income, ceteris paribus, will lead to a decrease in household health expenditures. Before COVID-19, the pre-COVID-19 shock curve, as shown in Figure 5, was above the post-COVID-19 one. In addition, the results show that the effect of COVID-19 on health expenditures is heterogeneous, meaning that households with low health expenditures were the most affected by the COVID-19 pandemic. The gap between the before-COVID-19 curve and the after-COVID-19 curves decreases from low health expenditures to high health expenditures.

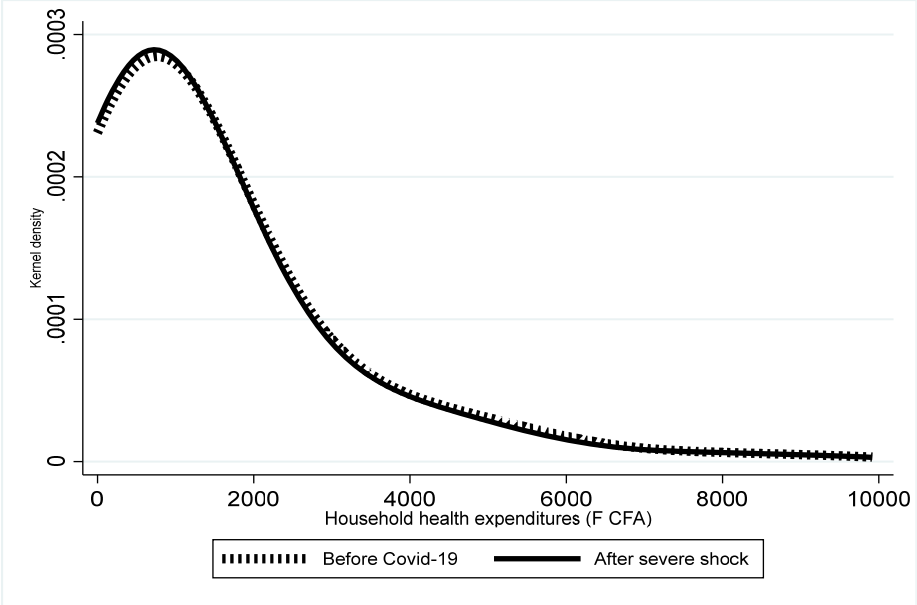


Figure 5. Household health expenditures[6]. Source: authors.

These results can be explained by the fact that households with low health expenditures are generally characterised by low income. This result confirms our early findings, indicating that the low-income groups of households were the most affected by COVID-19. More importantly, our summary statistics reported that less than 1% of Benin's households do not have health coverage. Indeed, though COVID-19 decreased both household income and health expenditure, the increase in health expenditures indicates that the decline in income was greater than that of health expenditures.

Figure 6 depicts the effects of the COVID-19 crisis on households' catastrophic health expenditures. Two main conclusions can be drawn from these results. First, the COVID-19 crisis pushed a significant share of households into catastrophic health expenditures, with a greater effect when the magnitude of the shock increased. Notably, the share of households with catastrophic health expenditures at the 10% threshold increased from 16% before the COVID-19 period to 20% after a severe shock. Second, these findings are robust when moving from a 10% to a 40% threshold of catastrophic health expenditures.

A gender analysis of the catastrophic health expenditures of the COVID-19 crisis revealed that men were the most affected (Figure 7). Although the share of women with catastrophic health expenditures was greater than that of men before the pandemic, it is worth noting that the share of men with catastrophic health expenditures after the COVID-19 pandemic increased more than that observed among women. Furthermore, the regional analysis also supports the evidence of heterogeneous effects of the COVID-19 pandemic on household health expenditures. More specifically, the results from simulations indicated that urban residents experienced the greatest burden in terms of an increase in

health expenditures, though Cotonou residents were the most vulnerable before COVID-19 (Figure 8).

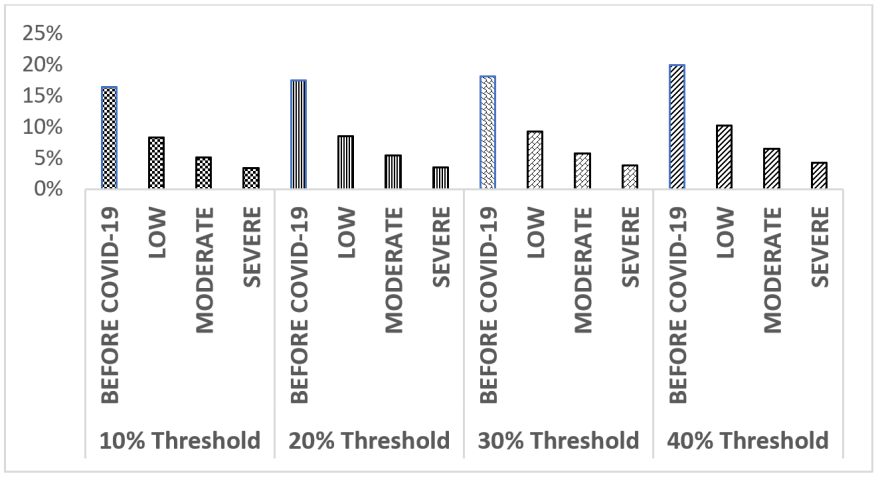


Figure 6. Share of households with CHE[7]. Source: authors.



Figure 7. Change in the share of households with CHE by gender (percentage points)[8]. Source: authors.

5.5. Discussion

Our findings revealed that, regardless of the considered scenario (low, moderate, and severe COVID-19 shock), households in urban areas saw their income decline faster than those in rural areas. Equally, low-income households and men were the most vulnerable to COVID-19. This can be explained by the fact that, in urban areas, the commercial sector, representative of the most employed section of urban residents, was strongly affected by COVID-19. Indeed, the public health measures undertaken by the government to contain the spread of the pandemic, such as limitations on public gatherings, border closures, and the restriction imposed on public transportation, drastically limited households' day-to-day activities. Equally, low-income households are generally those with low skills, meaning that they cannot work remotely as skilled workers. These findings align with those of Laborde et al. (2021) and Andam et al. (2020), who found that the incomes of urban households were the most affected by the COVID-19 pandemic compared to rural households, who lost an average of 18% of their income.

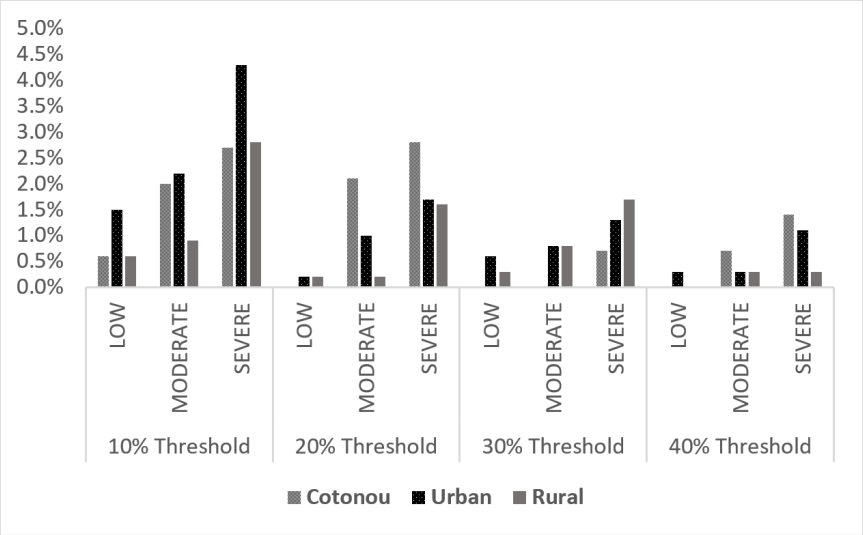


Figure 8. Change in CHE by place of residence (percentage points)[9]. Source: authors.

We found that the share of household health expenditures between the before COVID-19 and after COVID-19 periods is increasing with regard to the magnitude of the shock. This result can be explained by the decline in household income on the one hand and the increase in preventive and curative health expenditures on the other. Thus, based on 10% and 20% thresholds, the simulations showed that the share of households with catastrophic health expenditures increased with the magnitude of COVID-19 shock. More importantly, the heterogeneous effects on health expenditures revealed that households with a higher share of health expenditures before the pandemic experienced a greater increase in health expenditures. Before the COVID-19 pandemic, the proportion of households in rural areas with catastrophic health expenditures was higher than that of urban households, including Cotonou. Similarly, the proportion of households with catastrophic health expenditures considering different shock scenarios (low, moderate, and severe) was high in urban areas, especially in Cotonou, compared to households in rural areas. These results are in line with those of Rajalakshmi et al. (2023), who showed that during the COVID-19 pandemic, catastrophic household health expenditure increased. We explain this result by the fact that the established cordon sanitaire limited the movement of humans and goods between rural and urban areas as much as possible, which made it possible to reduce the risks of infection in rural areas and therefore limit medical expenses.

Our findings reveal that the negative impact of the COVID-19 pandemic on household income was more pronounced among male-headed households, more educated ones, young headed-households, and urban residents, with a simultaneous rise in catastrophic health expenditures. These results can be explained by the socioeconomic structure of Benin. Households headed by younger individuals appear more affected by COVID-19-related income shocks because they are more likely to be engaged in informal, unstable, or entry-level jobs, such as petty trade or apprenticeships, that were severely disrupted during lockdowns. In contrast, older household heads may benefit from more stable occupations or accumulated resources. Male-headed households experienced greater income losses, which reflects their higher concentration in sectors heavily impacted by the crisis, such as transportation, construction, and large-scale trade. Female-headed households, although often more economically vulnerable overall, are more likely to be involved in small-scale, community-based commerce, which proved relatively resilient. Interestingly, households with more educated heads suffered larger income declines. This may be due to their higher dependence on formal sector employment, which was more exposed to wage cuts, layoffs, and contract suspensions during the pandemic. Finally, urban households,

particularly those in Cotonou, were the most affected, due to their greater exposure to mobility restrictions, market disruptions, and the informal urban economy's vulnerability to shocks. In contrast, rural households, while generally poorer, tend to rely more on subsistence agriculture and informal mutual support systems, which offered a relative buffer against income losses. These findings highlight the differentiated impact of COVID-19 and suggest that recovery policies should be sensitive to age, gender, education level, and place of residence.

Furthermore, the increased catastrophic health expenditure suggests a heightened vulnerability to out-of-pocket health costs during the pandemic, possibly due to limited access to subsidised care or increased reliance on private health providers in emergency contexts. Furthermore, the disproportionate effect on urban households may reflect the concentration of COVID-19 cases, the stricter enforcement of containment measures, and the higher cost of living in urban areas compared to rural ones. Urban residents also tend to depend more on cash-based, non-agricultural livelihoods that were acutely sensitive to lockdowns and economic disruptions. While 39.5% of households already live in poverty (INSAE BENIN, 2019), these findings underscore the importance of tailoring social protection responses to account for gender dynamics and spatial inequalities, particularly in the design of post-crisis recovery and health financing policies.

It is worth noting that this study is subject to several limitations, and as such, the findings should be interpreted with caution. A key limitation concerns the use of self-reported data. The survey datasets rely on household-reported information related to health and income, which may be subject to reporting biases, notably recall bias or social desirability bias. In addition, due to the absence of tax-related information in the datasets, gross income was used as a proxy for household welfare instead of disposable income. This empirical choice may lead to an underestimation of the impact of COVID-19 on the ratio of health expenditures to income, suggesting that post-COVID-19 health-related spending may have been even more catastrophic than indicated by the findings of this study.

6. Conclusions and Policy Implications

In this study, we investigated the socioeconomic implications of the COVID-19 pandemic in Benin. To this end, a nationally representative dataset from the Benin household living conditions survey and a rapid survey after the COVID-19 outbreak were used for empirical estimations. We adopted static microsimulation modelling to estimate the short-term effect of COVID-19 on household income and health expenditures under different scenarios of COVID-19 shock. The results showed that the COVID-19 pandemic had a huge negative effect on household income, on the one hand, due to the closure of borders, which limited trade between Benin and its neighbouring countries, and on the other hand, because of the sanitary cordon that limited trade between urban towns and rural areas. Similarly, COVID-19 increased household health expenditures with heterogeneous effects across income levels, place of residence and gender. Due to the absence of tax information in our dataset, we used gross income instead of disposable income as a measure of welfare. This empirical strategy may lead to the undervaluation of the effects of COVID-19 on the health expenditures–income ratio, meaning that the post-COVID-19 health expenditures may be more catastrophic than the results of this study have shown. These findings have implications for health financing in Benin. Targeted health coverage policies, along with social policies aimed at reducing employment vulnerability and targeted cash transfers, are necessary to address the vulnerability of households to health crises in Benin.

The government needs to target the poorest households led by men and urban residents for health coverage programmes to address the vulnerability of households to health crises, as highlighted by the COVID-19 pandemic. Though Benin's government, with the

support of organisations like the WHO, has been working towards expanding health coverage and implementing measures to improve access to healthcare for the most vulnerable populations[10], it is crucial to focus on both the supply and demand sides when formulating health policies. According to the 2018 demographic and health surveys report, only 1.2% of the population in Benin had access to health coverage, while 38.5% lived below the monetary poverty line. These data emphasise that even in the absence of health pandemics, a significant portion of the population faces difficulties in accessing health due to financial constraints. United Nations organisations such as the World Health Organisation (WHO), civil society, and local and foreign private sectors could play a core role in supporting governments to design and mobilise sustainable financing.

The Benin government should design social policies aimed at reducing employment vulnerability among the population, notably for urban residents and the poorest households led by men. The private sector could be the core partner in improving the conditions of job vulnerability. The COVID-19 pandemic has led to income loss, disproportionately affecting lower-income quintiles. While the Benin National Institute of Statistics and Demography reported an unemployment rate of about 2% in 2018, with a high rate of vulnerable employment at 84.1%, it is worth noting that the government addresses the issue of under-employment, especially during periods of crises. In addition to targeted health coverage policies and reducing employment vulnerability, it is essential to design targeted cash transfer programs to reduce the vulnerability of the poorest households when pandemics occur.

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Appendix A

Table A1. Sectoral job vulnerability coefficients.

Type of Activity	Percent
1. Agriculture, fishing, and forestry	0.00
2. Manufacturing and mining	16.95
3. Construction	18.64
4. Wholesale and retail trade, repair of motor vehicles, and other motors.	37.29
5. Hotels and restaurants	3.39
6. Transport and communication	5.08
7. Education and public administration	0.00
8. Health and social work activities	6.78
9. Other services	11.86

Table A2. Risk of job loss coefficients by gender and residence.

	Gender		Residence		
	Male	**Female**	**Cotonou**	**Urban**	**Rural**
Risk coefficients	1.29	0.71	1.04	1.00	0.96

Table A3. Health expenditures before and after COVID-19.

Household Health Expenditures	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Before COVID-19	899	2158.64	4655.426	0	50,250
Low shock	899	86,545.321	193,570.45	0	2,835,360
Moderate shock	899	81,208.87	182,267.61	0	2,670,720.3
Severe shock	899	73,968.176	169,792.54	0	2,506,080.3

Table A4. Summary statistics for catastrophic health expenditures.

Threshold	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Catastrophic health expenditures (Before COVID-19)					
10%	899	0.165	0.371	0	1
20%	899	0.083	0.277	0	1
30%	899	0.051	0.22	0	1
40%	899	0.034	0.183	0	1
Catastrophic health expenditures (After COVID-19-low shock)					
10%	899	0.175	0.38	0	1
20%	899	0.086	0.28	0	1
30%	899	0.055	0.227	0	1
40%	899	0.036	0.185	0	1
Catastrophic health expenditures (After COVID-19-oderate shock)					
10%	899	0.181	0.385	0	1
20%	899	0.092	0.29	0	1
30%	899	0.058	0.234	0	1
40%	899	0.038	0.191	0	1
Catastrophic health expenditures (After COVID-19-severe shock)					
10%	899	0.199	0.4	0	1
20%	899	0.102	0.303	0	1
30%	899	0.065	0.246	0	1
40%	899	0.042	0.201	0	1

Table A5. Summary statistics for health expenditure by gender.

Threshold	**Scenario**	**Man**	**Woman**
10%	Before COVID-19	0.136	0.195
	Low	0.149	0.202
	Moderate	0.156	0.209
	Severe	0.181	0.218

Table A5. *Cont.*

Threshold	Scenario	Man	Woman
20%	Before COVID-19	0.073	0.094
	Low	0.076	0.096
	Moderate	0.084	0.101
	Severe	0.099	0.106
30%	Before COVID-19	0.043	0.06
	Low	0.045	0.064
	Moderate	0.052	0.064
	Severe	0.056	0.073
40%	Before COVID-19	0.03	0.039
	Low	0.032	0.039
	Moderate	0.037	0.039
	Severe	0.043	0.041

Table A6. Summary statistics for health expenditures by residence.

Threshold		Cotonou	Urbain	Rural
10%	Before COVID-19	0.188	0.155	0.166
	Low	0.194	0.17	0.172
	Moderate	0.208	0.177	0.175
	Severe	0.215	0.198	0.194
20%	Before COVID-19	0.076	0.085	0.085
	Low	0.076	0.087	0.087
	Moderate	0.097	0.095	0.087
	Severe	0.104	0.102	0.101
30%	Before COVID-19	0.056	0.052	0.048
	Low	0.056	0.058	0.051
	Moderate	0.056	0.06	0.056
	Severe	0.063	0.065	0.065
40%	Before COVID-19	0.035	0.037	0.031
	Low	0.035	0.04	0.031
	Moderate	0.042	0.04	0.034
	Severe	0.049	0.048	0.034

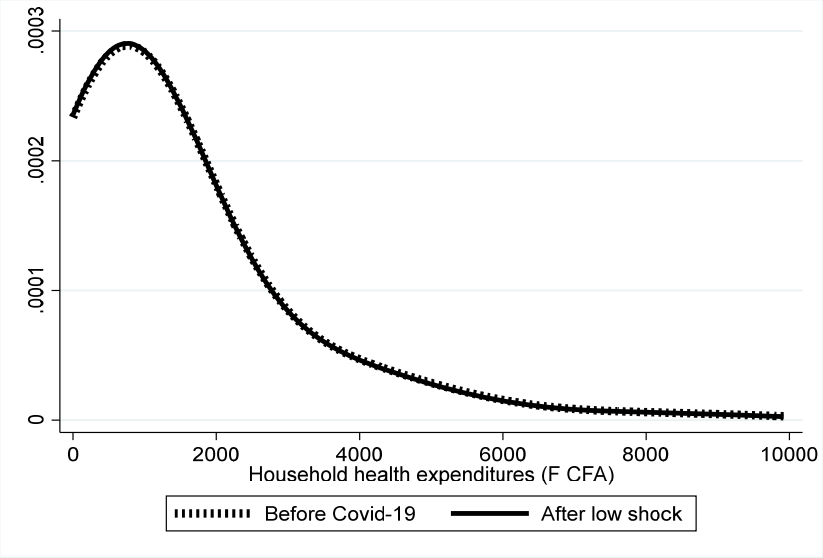


Figure A1. Health expenditures after a low shock.

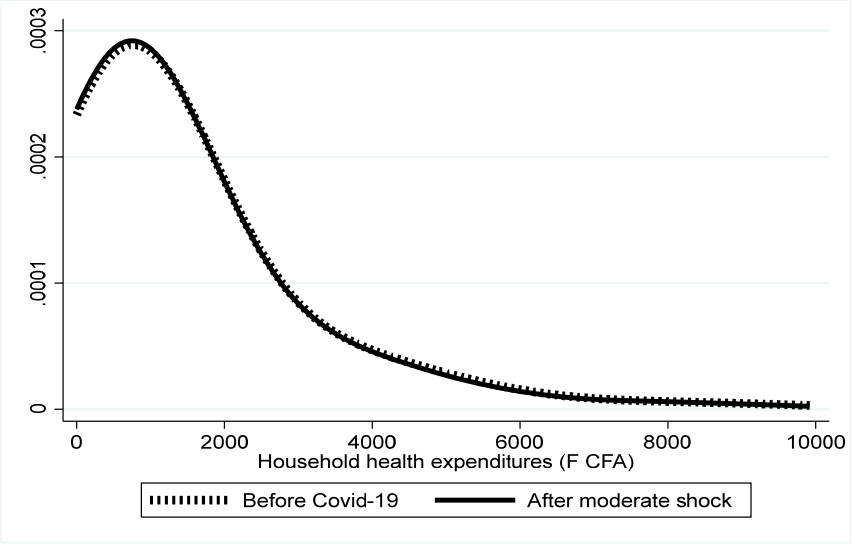


Figure A2. Health expenditures after a moderate shock.

Notes

1 Note that in the absence of information on job loss by gender and residence within the sector of activities, we assume independence between the sector of activity, gender, and residence. With the absence of job status of individuals who have lost their job, we assume a random selection of job loss within each sector, each gender, and each residence. Hence, we assume that the percentage of job loss equals the percentage of income loss.

2 In the absence of information on the gender composition of the INSAE BENIN (2020) study, we assume that this study is nationally representative, so we used the gender composition of the Harmonised Survey on Living Conditions of Households in Benin (INSAE BENIN, 2019). These data indicated that 78.55% and 21.45% of heads of households were men and women, respectively.

3 Recall that within the same household, members can have different branches of activity, places of residence, and genders. To take into consideration the composition of households, we calculated the income loss coefficient at the individual level and then aggregated it at the household level.

4 The Chi-2 distance of the CDM test was 27.63, and the *p*-value equaled 0.016.

5 For a better visualisation of the plot, we limited the upper value of the distribution of income to 100,000 F CFA. Full descriptive statistics are reported in Table 4.

6 For a better visualisation of the plot, we limited the upper value of the distribution of health expenditures to 10000 F CFA. Plots for low and moderate shocks are reported in Figures A1 and A2 in Appendix A. Full descriptive statistics are reported in Table A3 in Appendix A.

[7] The full descriptive statistics are reported in Table A4 in Appendix A.
[8] The full descriptive statistics are reported in Table A5 in Appendix A.
[9] The full descriptive statistics are reported in Table A6 in Appendix A.
[10] Benin's government has taken steps towards expanding health coverage and addressing the challenges faced by the poorest populations. The establishment of the Assurance pour le renforcement du capital humain (ARCH) in 2019 aimed to provide a holistic approach to social insurance, including health insurance. Through this programme, individuals from the poorest strata have been identified and enrolled, benefiting from free treatment in public health facilities.

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