Journal of Economic Policy and Management Issues
ISSN: 2958-6313 Volume 2, Issue 2, 2023, pp. 31-48

The gendered impacts of COVID-19 and business closure due to lockdown on wage employment in Kenya

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Keywords:
- Disease pandemic
- Covid-19 containment measures
- Covid19 incidence
- Covid19 vulnerability index
- Panel data
- Wage employment
- Kenya

Abstract

The COVID-19 crisis has had a huge shock on labor markets worldwide. However, systematic quantitative evidence documenting the impacts of the pandemic and of the associated government containment measures on employment in African countries, particularly Kenya, is lacking. Using high-frequency panel data survey data for 2020/2021 on COVID-19 in Kenya collected by the World Bank, in collaboration with the Kenyan National Bureau of Statistics (KNBS), the United Nations High Commissioner for Refugees (UNHCR) and the University of California, Berkeley, this study analyses the impacts of Covid-19 incidence, Covid-19 vulnerability, and business closure due to the government containment measures/lockdown on participation in wage employment. Regression results show that the COVID-19 incidence, the COVID-19 vulnerability, and the business lockdowns had large, negative impacts on paid work, with the males having a significantly increased the probability of wage employment compared to females. We argue that men with Covid-19 infection or symptoms engage in paid work at a higher rate relative to women – with the same condition. It is not clear whether the men's labor market behavior detected in this data set is due to a greater ability to bear risk or to risk preference.

1. Introduction

The 2019 novel coronavirus disease (COVID-19) was first reported in China as an infectious upper respiratory disease. Kenya reported the first case in East Africa on 12th March 2020 when the Ministry of Health confirmed the first case of Coronavirus disease (COVID-19) in Nairobi. Since then, Kenya has been severely affected by the pandemic, triggering stringent containment measures to slow the spread of the virus, which, while necessary to minimize the loss of life and lay the foundation for eventual recovery, resulted in widespread economic disruption and losses in earnings and employment. These containment measures were progressively eased from July 2020 onward, and mobility nearly returned to pre-pandemic levels by October 2020, only to be tightened again in November 2020 and in March 2021 as Kenya faced the second and third waves of the virus (World Bank, 2021). As of March 8, 2022, the number of officially recorded cases since the onset of the outbreak totaled 323,094, while total deaths were 5,641, and successful recoveries were 317,181 (Worldometer, 2022).

To limit the rapid spread of COVID-19, policymakers around the world enacted stringent containment and closure policies. Countries across the globe adopted varying public health policies intended to prevent the spread of the virus, including social distancing measures (Fang et al., 2020). As part of social distancing, businesses, schools, community centers, and non-governmental organisations (NGOs) were closed down, mass gatherings were prohibited, and lockdown and masking measures were imposed in many countries, allowing travel only for essential needs. The goal was that through social distancing and masking, countries would be able to “flatten the curve”, i.e., reduce the number of new cases related to COVID-19 to halt the exponential growth of the pandemic and reduce pressure on medical services (Johns Hopkins University, 2020). Although the health impacts are through the contagion channel, the economic impacts of the contagion were compounded by the preventive measures adopted by national governments (World Bank, 2020).

Muna et al. (2020:4) argue that the COVID-19 pandemic exposed and reinforced socioeconomic inequalities within and across countries. Across the world, interventions such as social distancing, hand hygiene and coughing etiquettes were recommended to break the virus transmission cycle. However, compliance with these guidelines depends on the appropriate home environment and personal behaviors (Brown & Ravallion, 2020; Brown et al., 2020). Moreover, there was uncertainty about when most workers would be able to return to their jobs. According to Kenya National Bureau of Statistics (KNBS) (2020b), about 91.2% of workers who were reported absent from work during the period of the survey were not sure when they would return to work, while 8.9% expected their return to work to be delayed by between one and six months.

In Kenya, the measures imposed by the government to mitigate the spread of COVID-19 resulted in job losses, both for casual workers in the informal sector and for daily-wage earners in the formal sector, both of which employ a high proportion of women (International Labor Organization (ILO), 2021). Due to curfews and limited movement of people, many work roles, such as daily maintenance of business premises, became redundant. According to the KNBS survey, the virus disrupted the workflow as a result of curfews. The average number of hours of work available per week for employees significantly went down in almost all sectors of the economy, particularly the education and hotel industry sectors (KNBS, 2020a). The strict containment measures in Kenya initially reduced mobility, but movement increased over time. The government adopted various measures to contain the outbreak, and people’s behavior also responded to the pandemic. This impacted on economic activity and, therefore, the labor market.

A precise response to the COVID-19 pandemic, therefore, calls for public health reflections on who is the most vulnerable to the virus and their geographical locations. Lancet Global Health (2020) redefined the vulnerable groups and pointed out that they are not only elderly people, those with ill health and comorbidities, or homeless or under-housed people, but also people from a gradient of socioeconomic groups that might struggle to cope financially, mentally, or physically with the crisis. Furthermore, Upshaw et al. (2021) identified socioeconomic status, deprivation, and housing insecurity as the main drivers of vulnerability. Gordon (2020) came up with nine indicators to measure vulnerability to COVID-19 infection, such as a large household, overcrowding in a room, over 60-year-olds, living with young people, obesity, not washing with soap or detergents, having no refrigerator or a personal toilet facility, not being able to cook food from home, and not having a water source within the household. Macharia et al. (2020) computed three vulnerability indices to identify areas and people who required greater support in Kenya during the height of the COVID-19 pandemic. They included the social vulnerability index (SVI), epidemiological vulnerability index (EVI), and a composite of the two, that is, the social-epidemiological vulnerability index (SEVI).

Moreover, Brown et al. (2020), Jones et al. (2020), and Gordon (2020) descriptively explored the readiness of countries to face the COVID-19 pandemic. Some preliminary cross-country and within-country-level analyses have been conducted in Africa (see, for example, Egger et al.,2020; Danquah & Schotte, 2020), but systematic quantitative evidence on the gendered impacts of COVID-19 and business closure due to lockdown on Wage Employment in Kenya is lacking to the best of our knowledge. In addition, as with most aggregated measures, the aggregate analyses conceal the heterogeneity of sub-national situations. The specific objectives of this paper are to examine the determinants of COVID-19 incidences and COVID-19 Vulnerability index in Kenya; evaluate the gendered impact of COVID-19 incidence and business closure on wage employment in Kenya; analyze the gendered impact of COVID-19 vulnerability index and business closure on wage employment in Kenya. This study draws on information from a set of Kenya COVID-19 rapid response phone surveys with households, collected and harmonized by the World Bank in collaboration with the Kenya National Bureau of Statistics and the University of California Berkeley in 2020 (World Bank, 2020).

Against this background, the main objective of this study is to examine the gendered impacts of COVID-19 and business closure due to the lockdown on wage employment in Kenya. The rest of the paper is structured as follows: Section 2 covers the methodology and data. Section 3 focuses on empirical results and discussion of findings, while section 4 gives the summary, conclusions and policy implications.

2. Methodology and data

2.1 Empirical model

We begin by specifying a model which provides a synthesis of *fixed (FE)* and *random (RE)* effects of the COVID-19 pandemic and business closure on wage employment levels in Kenya. Our specification of the model assumes that for a random draw of i individual over a time period t, there is an underlying latent variable that can be modeled. The models for the gendered impact of COVID-19 incidence and business lockdown on wage employment (1) and that of the impact of the COVID-19 vulnerability index and business lockdown on wage employment (2) were estimated separately.

$$Emp_{it}^{*} = \alpha + \lambda C19inc_{it} + \omega Bld_{it} + \beta Z_{it} + \delta W_i + \psi_t + r_i + u_{it} \quad \ldots 1$$

$$Emp_{it}^{*} = \alpha + \lambda C19vulind_{it} + \omega Bld_{it} + \beta Z_{it} + \delta W_i + \psi_t + r_i + u_{it} \quad \ldots 2$$

$$Emp_{it} = 1\left[Emp_{it}^{*} \geq 0\right], i = 1,2,3....N(individuals); t = 1,2,3....,T(years) \quad \ldots 3$$

Where:

Emp_{it}^{*} = Labor force participation in wage employment

$C19inc_{it}$ = is an endogenous binary COVID-19 Incidence variable

$C19vulind_{it}$ = is an endogenous continuous COVID-19 Vulnerability Index variable

Bld_{it} = Closure of the business enterprise due to containment measures particularly lockdown or curfew

Z_{it} is an $1\times\left[K-1\right]$ vector of other exogenous covariates

W_i =a variable that does not change over time (i.e., gender or scholastic ability score, determined in childhood

ψ_t = is the time effect

r_i = the time-constant unobservable/ an unobserved effect (varies with individuals but not with time);

u_{it} = the idiosyncratic shocks which are serially uncorrelated error such that $Var\left[u_{it}\right] = 1$

$1\left[Emp_{1it}^{*} \geq 0\right]$ = is an indicator function.

In the estimation of (1) and (2), the labor force participation in wage employment (Emp_{it}^{*}) and both COVID-19 Incidence variable($C19inc_{it}$) and Covid-19 Vulnerability Index ($C19vulind_{it}$) are likely to be jointly determined by the *innate ability, skills or intellectual ability* attributes in the error term (u_{it}) which is likely to correlate with $C19inc_{it}$ and $C19vulind_{it}$ and which also influences Emp_{it}^{*} causing endogeneity as a potential problem that needs examination and should be addressed if present. In addition, unobserved heterogeneity of household preferences due to the non-linear interaction of the Covid-19 incidence/vulnerability index with unobservable variables (such as inherited traits or behaviour) could bias the estimation of the employment-generating function. When panel data models contain unobserved heterogeneity and endogeneity (omitted time-varying variables), the Control Function Method is applied to address the two potential issues (Heckman, 1976; Wooldridge, 2002, 2015). A Two-Stage Residual Inclusion (2SRI) procedure that follows Papke and Wooldridge (2008) is therefore estimated.

The First Stage involved estimating the reduced form models for both Covid-19 incidence (4) and COVID-19 vulnerability index (5), which separately regresses the endogenous Covid-19 variables on the instruments (IV_{it}) and other exogenous variables. Models (4) and (5) give the determinants of both Covid-19 incidence and the COVID-19 vulnerability index, respectively. Since the Covid-19 incidence is binary, model (4) will be a linear probability model (LPM). The COVID-19 vulnerability index is a continuous variable and therefore model (5) will be an Ordinary Least Squares (OLS) model.

$$C19inc_{it} = \mu + \omega Bld_{it} + \beta Z_{it} + \sigma IVavctyinc_{it} + \varepsilon_{it} \quad \ldots 4$$

$$C19vulind_{it} = \mu + \omega Bld_{it} + \beta Z_{it} + \sigma IVavctyind_{it} + \gamma IVavtemp_{it} + \varepsilon_{it} \quad \ldots 5$$

Where:

$IVavctyinc_{it}$ =The average county level COVID-19 incidence instrumental variable that affects the overall Covid-19 incidence ($C19inc_{it}$) but has no direct effect on wage employment (Emp_{it}).

$IVavctyind_{it}$ = The average county level COVID-19 vulnerability index instrumental variable that affects the overall Covid-19 vulnerability index ($C19vulind_{it}$) but has no direct effect on wage employment (Emp_{it}).

$IVavtemp_{it}$ = The average temperature for the 47 counties' instrumental variable that affects the overall Covid-19 vulnerability index ($C19vulind_{it}$) but has no direct effect on wage employment (Emp_{it}).

$\varepsilon_{it} = r_i + u_{it}$ = a new composite error term, where r is fixed, and u is an idiosyncratic term.

Following Wooldridge (2015: 427-428), models (4) and (5) can be considered logit reduced form models of Covid-19 incidence and Covid-19 vulnerability index, respectively. To address the potential endogeneity of Covid-19 incidence/vulnerability index - resulting from their correlation with the respective error terms, we estimate the First Stage Logit models, predict their generalized residuals, and generate the interaction between their generalized residuals and the Covid-19 variables, then include them in the Second Stage regression. The Second Stage, which is the structural model, separately regresses wage employment on the potentially endogenous Covid-19 incidence (6) and the Covid-19 vulnerability index (7) plus their residuals, and the interaction terms between their residuals and the potentially endogenous variables themselves, respectively. The panel data models are thus specified as:

$$Emp^{*}_{it} = \alpha + \lambda C19inc_{it} + \omega Bld_{it} + \beta Z_{it} + \gamma C19incres_{it} + \theta C19incressq_{it} + \pi \operatorname{int}(C19incres * C19inc)_{it} + \varepsilon_{it} \quad \text{………………………..…6}$$

$$Emp^{*}_{it} = \alpha + \lambda C19vulind_{it} + \omega Bld_{it} + \beta Z_{it} + \gamma C19vulindres_{it} + \pi \operatorname{int}(C19vulindres * C19vulind)_{it} + \varepsilon_{it} \quad \text{…………………………………….…….7}$$

Where:

$C19incres_{it}$ = Predicted Covid-19 incidence residual

$C19incressq_{it}$ = Predicted Covid-19 incidence residual squared

$\operatorname{int}(C19incres * C19inc)_{it}$ = Interaction of the predicted COVID-19 incidence residual and the COVID-19 incidence itself

$C19vulindres_{it}$ = Predicted COVID-19 vulnerability index residual

$\operatorname{int}(C19vulindres * C19vulind)_{it}$ = Interaction of the predicted COVID-19 vulnerability index residual and the COVID-19 vulnerability index.

The residuals serve as a control function variable that renders COVID-19 incidence/COVID-19 vulnerability index exogenous (Wooldridge, 2015). The interaction terms address the unobserved heterogeneity of the coefficient on COVID-19 incidence/vulnerability index, keeping it constant across units of analysis; ε_{it} is a composite error term comprising the random and the nonrandom, fixed part of the of the error term; and $\alpha, \lambda, \beta, \delta, \gamma, \omega$ and π are vectors of parameters to be estimated. Under fairly weak assumptions, Equation (6) and (7) yields parameter estimates that are unbiased and consistent (Wooldridge, 2015). Equation (6) and (7) allows the use Durbin–Wu–Hausman (DWH) test to determine whether or not Covid-19 incidence/vulnerability index is endogenous. Covid-19 incidence/vulnerability index is endogenous if the null hypothesis that $\gamma = 0$ cannot be rejected (Wooldridge, 2015). Moreover, the augmented regression test/ Hausman specification test helps distinguish between RE and FE specifications in panel data analysis by setting $\gamma = 0$ when estimating the RE model, i.e., by assuming that Covid-19 incidence/vulnerability index is uncorrelated with the error term, while FE estimates γ in (6) and (7).

The Hausman test, in the choice between RE and FE the Hausman test is made robust to heteroskedasticity and serial correlation and allows the construction of $H_0 : RE \rightarrow \gamma = 0 \Rightarrow$ No Correlation between the Covid-19 incidence/vulnerability index and the error term (No endogeneity) against $H_1 : FE \rightarrow \gamma \neq 0 \Rightarrow$ There is a correlation between the Covid-19 incidence /vulnerability index (Endogeneity). Intuitively, the Hausman statistic tests whether the difference between FE and RE estimates is equal to zero. If the p-value is small (less than 0.05) reject the null hypothesis. If we reject H_0 at a sufficiently small significance level, we reject RE in favor of FE. Therefore, the FE estimates (obtained via the panel data procedures) are preferred because their calculation takes into account the endogeneity of Covid-19 incidence/vulnerability index (the correlation of Covid-19 incidence/vulnerability index with the disturbance term). However, if the p-value is large (greater than 0.05), the equality assumption cannot be rejected and the RE estimates (obtained via GLS) are preferred because they have smaller standard errors.

2.2 Variables

As indicated in Table 1, the dependent variable is the labour force participation in wage employment. The main explanatory variables are COVID-19 incidence, COVID-19 Vulnerability Index and business closure due to lockdown. Other control variables are also included in the table, as well as the instrumental variables including the county level COVID-19 incidence, which controls for the endogeneity of the COVID-19 incidence; and the county-level COVID-19 vulnerability index, as well as the Average temperature for the 47 counties which controls for the endogeneity of COVID-19 Vulnerability Index.

Table 1: Variables used in the wage employment generating function

Variables	Measurement
Dependent variable	
Labour force participation in wage employment	A dummy variable taking the value 1 if an individual participated in wage employment, 0 otherwise
Explanatory variables	
COVID-19 Incidence	A dummy variable taking the value 1 if an individual experienced any of the symptoms related to COVID-19 (fever; persistent cough; always feeling tired; muscle pain (myalgia); headache; diarrhoea/nausea/vomiting; difficulty breathing; runny nose; sore throat; pneumonia; loss of sense of smell or tested and found to have Covid-19), 0 otherwise
COVID-19 Vulnerability Index	A continuous variable which is the uncentered Principal Component Analysis (PCA) constructed by weighting the following variables: total household size greater than 6 members; age of a household member greater than 58 years; households with no fridge; doctor visits; household visits and household with no access to radio and TV
Lockdown or closure of the business enterprise due to containment measures, particularly lockdown or curfew	A dummy variable taking the value 1 if the business was closed due to COVID-19 and government containment measures of lockdown and curfew, 0 otherwise
Interaction of gender and the closure of the business enterprise due to containment measures, particularly lockdown or curfew	A dummy variable taking the value 1 if the male gender experienced the closure of the business enterprise due to containment measures particularly lockdown or curfew, 0 otherwise
Marital Status of an individual	A dummy variable that takes the value 1 if one is married, 0 otherwise
Urban residence	A dummy variable taking the value 1 if an individual resides in an urban area, 0 otherwise
Interaction of urban residence and covid-incidence	A dummy variable taking the value 1 for urban dwellers with COVID-19 incidence, 0 otherwise
Interaction of urban residence and the Covid-19 vulnerability index	A continuous variable interacting urban residence and COVID-19 vulnerability index
Gender	A dummy variable taking the value 1 if an individual is male, 0 otherwise
Interaction of gender and COVID-19 incidence	A dummy variable taking the value 1 for males with COVID-19 incidence, 0 otherwise
Interaction of gender and Covid-19 vulnerability index	A continuous variable interacting male gender and COVID-19 vulnerability index

Age of an individual	Age of an individual in years
Age of an individual squared	Age squared of an individual in years
No Education	A dummy variable taking the value 1 if an individual has no formal education, 0 otherwise
Pre-primary Education Level	A dummy variable taking the value 1 if an individual has pre-primary education, 0 otherwise
Primary Education Level	A dummy variable taking the value 1 if an individual has primary education, 0 otherwise
Vocational Education Level	A dummy variable taking the value 1 if an individual has post-primary vocational training, 0 otherwise
Secondary Education Level	A dummy variable taking the value 1 if an individual has secondary education, 0 otherwise
College Education Level	A dummy variable taking the value 1 if an individual has post- secondary college education, 0 otherwise
University Education Level	A dummy variable taking the value 1 if an individual has university education, 0 otherwise
The log of childcare hours	A continuous variable representing the natural logarithm of the number of hours taken in childcare
Instruments (IV)	
County-level COVID-19 incidence	A continuous variable representing the average county COVID-19 incidence is the average of total COVID-19 incidence excluding own County COVID incidence divided by 46 counties. For instance, the average for Nairobi excludes Nairobi County incidence
County-level COVID-19 vulnerability index	A continuous variable representing the average county COVID-19 vulnerability index is the average of total COVID-19 vulnerability excluding own County COVID vulnerability index divided by 46 counties. For instance, the average for Nairobi excludes Nairobi County vulnerability index
Average temperature for the 47 counties	A continuous variable representing the average 30 years temperature for each of the 47 counties

Appendix 1 shows the variables used to construct the COVID-19 vulnerability index which is the weighted uncentered Principal Component Analysis (PCA). This is a composite index of different risk factors signifying high exposure leading to fear of going to work because one can get sick. All the variables were generated in such a way that they increase the vulnerability. The vulnerability due to all the risk factors were aggregated. Different components of risk factors are acting and interacting together to contribute to the vulnerability. It is not necessary to separate them because they are interacting i.e., when one is changing, the other one is also changing. So, the solution is the composite index which is a proxy for Covid itself. In the aggregation of the Principal Component Analysis (PCA), the variables used were made to be positively correlated with vulnerability such that they are added together through PCA. The greater the number of factors pre-disposing people to Covid-19, the higher the risk of contracting the disease. Vulnerability is therefore an exposure to Covid-19 disease. High exposure means the presence of the disease which is a proxy based on the characteristics of the individuals and the environment in which they operate.

Appendix 2 indicates the variables used in constructing the COVID-19 incidence. The Covid incidence dummy was constructed from a list of variables exposing an individual to Covid-19 and therefore its unconditional risk and represents the proportion who faces risks irrespective of their characteristics. This is the disease itself.

2.3 Data

The paper uses the high-frequency phone survey data on the socio-economic impacts of COVID-19 in Kenya, which was implemented by the World Bank in collaboration with the Kenyan National Bureau of Statistics (KNBS) and the United Nations High Commissioner for Refugees (UNHCR) as well as by the University of California, Berkeley, collected in five waves. The duration of data collection for each wave was as follows: (i) Wave 1: May 14 to July 7, 2020; (ii) Wave 2: July 16 to September 18, 2020; (iii) Wave 3: September 18 to November 28, 2020; (iv) Wave 4: January 15 to March 25, 2021; and (v) Wave 5: March 29 to June 13, 2021.

3. Empirical results and discussion of findings

This paper analyses the gendered impacts of COVID-19 and business lockdowns on participation in wage employment in Kenya. COVID-19 incidence, COVID-19 vulnerability index, business closure and other control variables are separately regressed on Wage employment participation. To purge the problem of endogeneity and unobserved heterogeneity, a control function is estimated. Covid-19 Incidence and Vulnerability Index Logit Control Function models were estimated.

3.1 Descriptive statistics

Table 2 provides the descriptive statistics of the variables used to assess the impact of COVID-19 incidence and vulnerability on wage employment in Kenya. It is notable about 13% of the individuals participated in wage. Those who reported symptoms associated with Covid-19 incidence were about 7% of the entire sample. About 2% of business enterprises were closed due to containment measures in the face of the Covid-19 pandemic. About 12% of the sample were married individuals. The households residing in the urban areas were about 53%, while 48% of the samples were males. The average age of the sample is 34 years, with the youngest being 18 years and the oldest being 64 years. The percentage of people with preprimary education in the sample is 4%, 30% have primary education, 1% have vocational training, 45% have a secondary education, 11% have a college education, and about 4% have a university education. The individuals with no education were about 2% compared to those with different levels of education. The mean number of childcare hours was about 1hr, with the least hours taken in childcare being zero and 5 hrs maximum.

Table 2: Descriptive statistics of variables used in employment generating function

Variable	Mean	Std. Dev.	Min	Max
Labour force participation in wage employment	.1283688	.334503	0	1
COVID-19 incidence	.0724726	.2592712	0	1
COVID-19 Vulnerability Index	2.394855	2.039272	0	11.69287
Lockdown or closure of the business enterprise due to containment measures particularly lockdown or curfew	.0230848	.1501742	0	1
Marital Status of an individual	.1167185	.3210874	0	1
Urban residence	.5268514	.499283	0	1
Gender	.4776433	.4995044	0	1
Age of an individual	34.25111	12.24447	18	64
Age of an individual squared	1323.063	938.3628	324	4096
Pre-primary Education Level	.0403625	.1968096	0	1
Primary Education Level	.2950145	.4560534	0	1
Vocational Education Level	.0088636	.0937292	0	1
Secondary Education Level	.4534978	.4978373	0	1
College Education Level	.1057514	.307522	0	1
University Education Level	.0355441	.1851523	0	1
No Education	.0193272	.1376736	0	1
The log of childcare hours	.8645635	1.571983	0	5.129899
County level COVID-19 incidence	.0742135	.0002698	.0735674	.0746653
County-level COVID-19 vulnerability index	.9376543	.0117005	.9164517	.9624683
Average temperature for the 47 counties	21.62182	3.343888	15.90389	29.53153
COVID-19 incidence residual	-.000348	.2457485	-.2956178	1.016709
COVID-19 incidence residual squared	.0603913	.1798252	6.75e-11	1.033698
Interaction COVID-19 incidence and its residual	.0601525	.2158372	0	1.016709
COVID-19 vulnerability index residual	1.97e-10	1.955934	-5.832018	9.211856
The interaction of COVID-19 vulnerability index and its residual	3.825615	9.16901	-11.22406	107.713
Number of Observations	59838			

Appendix 3 indicates the descriptive statistics of variables used in constructing the weighted uncentered PCA Covid-19 Vulnerability Index, while Appendix 4 shows the descriptive statistics of variables used in constructing the Covid-19 Incidence.

3.2 Determinants of COVID-19 incidence and COVID-19 vulnerability

The reduced form first-stage regression was done to generate the determinants of COVID-19 Incidence and COVID-19 Vulnerability and to test the validity of the instruments used in the study. In Table 3, column (1) shows estimates of Covid-19 incidence using Linear Probability Model (LPM), while column (2) shows estimates of Covid-19 vulnerability using OLS model. The average county COVID-19 incidence was the only instrument for the COVID-19 incidence, while the average county COVID-19 vulnerability and the average temperature for the 47 counties were the instruments for the Covid-19 vulnerability index. The first-stage regression involves regressing the COVID-19 incidence and vulnerability on instrumental variables and other exogenous variables as shown in Table 3.

Table 3: COVID-19 incidence and COVID-19 vulnerability-generating functions

Variables	**Estimated model results**	
	LPM: Dependent variable is COVID-19 incidence (1)	**OLS regression: Dependent variable is COVID-19 vulnerability index (2)**
County level COVID-19 incidence (IV)	-34.46664*** (3.935012)	……
County-level COVID-19 vulnerability index (IV)	…..	-19.93258*** (.7236414)
Average temperature for the 47 counties (IV)	…..	.0158882*** (.0025797)
Closure of the business enterprise due to containment measures particularly lockdown or curfew	-.0036432 (.0070657)	-.0511705 (.0548178)
Marital Status of an individual	.0085679** (.0036515)	-.9638407*** (.0283258)
Residence	.0018496 (.002138)	-.1358489*** (.0168361)
Gender	.0050817** (.0021577)	.0098989 (.0167398)
Age of an individual	.0026402*** (.0005533)	-.1240255*** (.0042991)
Age of an individual squared	-.0000191*** (7.19e-06)	.001723*** (.0000558)
Preprimary Education	.0331182*** (.0068939)	.5715924*** (.0535084)
Primary Education	.0338505*** (.0047528)	.450965*** (.0368859)
Vocational Training	.0531195*** (.0120659)	.5167514*** (.0935995)
Secondary Education	.0190637*** (.004599)	.1965307*** (.0357232)
College Education	.0172333*** (.0054503)	-.0051972 (.0423392)
University Education	.0294652*** (.00713)	.1042436** (.0553816)
The log of childcare hours	.0384942*** (.0007569)	.0609957*** (.0058719)
Constant	2.504344*** (.2923347)	51.57437*** (1.747799)
Number of observations	55,621	55,621

R-squared	0.0703	0.0727
Adj R-squared	0.0700	0.0724
Root MSE	.25003	0.0724

*** Significant at the 1% level; ** significant at the 5 % level, * significant at the 10% level. Standard errors are in the parenthesis.

According to Mwabu (2009), a valid instrument must be relevant, strong and exogenous. The instrumental variables, which include average county COVID-19 incidences, the average county Covid-19 vulnerability index, and the average temperature for the 47 counties are all statistically significant, indicating that they are relevant and valid. The closure of the business enterprise due to containment measures, particularly lockdown/curfew, significantly reduced the probability of COVID-19 incidences by 0.36% and COVID-19 vulnerability by 5.11%. Business closures due to lockdown and other COVID-19 containment measures therefore significantly reduced the COVID-19 incidences and COVID-19 vulnerability. Marriage significantly increased the probability of COVID-19 incidences by 0.85% and COVID-19 vulnerability by 96.3%. This could be attributed to the fact that married people are very cautious to take the risk of contracting the disease because they care for their families. Childcare hours affected both COVID- 19 incidence and COVID-19 vulnerability positively. An increase in childcare hours by 1 hour significantly increased the probability of COVID-19 incidences by 0.038% and the vulnerability by 0.06%. This is an indication that longer hours taken in childcare increased the COVID-19 incidences and the COVID-19 vulnerability, but the impact was larger on the vulnerability index as compared to the incidences.

Living in an urban area increases the probability of COVID-19 incidences significantly by 0.18%. This could be attributed most likely to overcrowding in urban areas. However, living in urban areas reduces COVID-19 vulnerability significantly by 13%. This is similar to Macharia et al. (2020), who found that in Kenya, the COVID-19 vulnerability is higher in the North and North-Eastern rural areas and low in the Central region (which is mainly urban) and the Western region. The probability of COVID-19 incidences significantly increased by 0.51% for males compared to females. This means that the males had a higher infection rate of COVID-19 as compared to the females, ceteris paribus. The risk of contracting COVID-19 is significantly higher by 0.98% for males compared to females. There seems to have been a higher risk of new infections and the risk of exposure to COVID-19 for males compared to females. An increase in the proportion of the aged people by 1% significantly increased the probability of COVID-19 incidences by 0.27%. However, age reduced the COVID- 19 vulnerability by 12.01%, assuming other factors constant. This means that being old increases the COVID-19 incidences but reduces the COVID-19 vulnerability index or the risk of exposure to COVID-19.

Being with preprimary education significantly recorded a higher probability of COVID-19 incidences by 3.31% and COVID-19 vulnerability by 57.5% compared to those with no education at all. This indicates that holders of preprimary education levels have a high chance of contracting COVID-19 and are also vulnerable to the exposure to COVID-19 compared to those without any education. For primary school holders, the probability of COVID-19 incidences increased by 3.38% while the COVID-19 vulnerability significantly increased by 45.1% compared to those with no education. This means that primary education had a higher impact on the COVID-19 vulnerability index than on COVID-19 incidence. Individuals with vocational training had their probability of COVID-19 incidences significantly increasing by 5.31%, while the COVID-19 vulnerability index significantly increased by 51.6%, assuming all other factors are constant. Vocational training had, therefore, a higher impact on COVID-19 vulnerability than on COVID-19 incidence compared to those without education. The probability of COVID-19 incidences significantly increased by 0.90%, while the COVID-19 vulnerability increased by 19.6% for individuals with secondary education, ceteris paribus. Secondary education, therefore, had a higher impact on the COVID-19 vulnerability index than on COVID-19 incidence compared to no education. The individuals with a college education had their probability of COVID-19 incidences significantly higher by 1.72% compared to those with no education, while the risk of contracting COVID-19 significantly reduced by 0.52%, assuming all other factors are constant. This implies that those with a college education had a significantly reduced chance of vulnerability to COVID-19. A higher proportion of those with a university education had significantly higher COVID-19 incidences by 2.94% compared to those with no education. The COVID-19 vulnerability was higher for the same category by 10.4% compared to those without education. This is consistent with previous studies (Zhang et al., 2021; Upshaw et al., 2021). For instance, Zhang et al. (2021) found that COVID-19 incidence was 30% for individuals who had attained junior school education, 27.3% for those who had senior school education and 41.8% for college students.

3.3 Wage employment-participation estimates

The Durbin-Wu-Hausman (DWH) Test was used to test for endogeneity of COVID-19 incidences and COVID-19 vulnerability. With the coefficients of COVID-19 incidence residual and the residual of the COVID-19 vulnerability index being significant, we conclude that endogeneity is indeed a serious problem and the estimation of a control function is in order. Both the interaction of COVID-19 incidence and its residual and that of COVID-19 vulnerability index and its residual are significant, which indicates that unobserved heterogeneity is indeed present, justifying the use of the

Control Function Approach To control for it. The estimation in columns (1) and (2) of the random effects Logit control function accounts for both endogeneity and heterogeneity. The Hausman test specification preferred a random effects model (RE). Table 4 presents the estimated results.

Table 4: Wage employment generating logit control function

Variables	**Estimation methods (standard errors in parentheses)**	
	Structural form logit RE, marginal effects	
	COVID-19 incidence (1)	**COVID-19 vulnerability index (2)**
COVID-19 incidence	-.0475682*** (.0040734)	………
COVID-19 vulnerability index	………	-.0581228*** (.0064621)
Lockdown or closure of the business enterprise due to containment measures particularly lockdown or curfew	-.0320886** (.0169554)	-.0398818** (.0168118)
Marital Status of an individual	-.0535641*** (.0045652)	-.1149915*** (.0074053)
Urban residence	.0331224*** (.0037462)	.0244365*** (.0052849)
Interaction of urban residence and COVID-19 incidence	.006157 (.0090728)	……….
Interaction of gender and the closure of the business enterprise due to containment measures particularly lockdown or curfew	.0028914 (.021901)	.0077567 .0216849)
Interaction of gender and COVID-19 vulnerability index	……….	.0037058*** (.0013953)
Interaction of gender and COVID-19 vulnerability index	……….	-.0007059 (.0013805)
Gender	.0902726*** (.0038822)	.084948*** (.0051199)
Interaction of gender and Covid-19 incidence	-.001573 (.0090771)	………..
Age of an individual	.0242825*** (.0011416)	.0205546*** (.0013396)
Age of an individual squared	-.0003036*** (.0000141)	-.0002378*** (.0000179)
Pre-primary education level	-.0078004 (.0139767)	.0585746*** (.0127524)
Primary education level	.0251507** (.0107838)	.0806692*** (.0090031)
Vocational education level	.0758426*** (.0190898)	.135953*** (.0163475)
Secondary education level	.0860723*** (.0091011)	.117743*** (.0083565)
College education level	.1579764*** (.0094125)	.175311*** (.008798)
University education level	.1417111*** (.0115853)	.1701477*** (.0100829)
The log of childcare hours	.0101649 (.0076481)	.0082448*** (.0010981)
Covid-19 incidence residual	-1.342076***	……

	(.2041981)	
Covid-19 incidence residual squared	-5.915691*** (.431576)	……
Interaction Covid-19 incidence and its residual	12.08273*** (.8582061)	……
COVID-19 vulnerability index residual	…………..	.0850468*** (.0063893)
The interaction of COVID-19 vulnerability index and its residual	……………	-.0036195*** (.0002816)
Number of observations	55,621	55,621

$p \leq 0.01$(***); $p \leq 0.05$(**); $p \leq 0.1$(*)

Table 4 shows that a one-percent increase in the proportion of people with COVID-19 incidences significantly reduces the probability of participation in wage employment by 4.8%, while a one-percent increase in the COVID-19 vulnerability significantly reduces the probability of participating in wage employment by 5.8%. Since COVID-19 incidences represent the disease itself, having the disease makes one to be unwell and participate less in wage employment. The risk of exposure to COVID-19 reduces the probability of participating in the wage employment due to the fear of getting the disease. A broad number of studies record similar significantly negative effects of COVID-19 on hours of work and on participation in wage employment (see e.g., Ludvigson, et al., 2020; Elenev et al., 2020; Baldwin, 2020; Gourinchas, 2020; Bodenstein et al., 2020). These results are consistent with the studies indicating that there is labor shrinkage and lower working hours from the population susceptible to COVID-19 (Eichenbaum et al., 2020). These findings mostly fit under industries where there are high face-to-face interactions, which make them highly likely to lose their jobs (Adams-Prassl et al., 2020), unlike those that allow for home-based work less likely to be affected by the prevalence of COVID-19.

Business closure due to containment measures, particularly lockdowns or curfews, significantly reduced the probability of participation in wage employment by 3.2% when controlling for COVID-19 incidences and by 4% when controlling for COVID-19 vulnerability. These results are in line with evidence in the previous literature that finds that the closure of business enterprises due to containment measures led to the loss of jobs and firms' earnings (Mulligan, 2020; Bodenstein et al., 2020; Bartik et al., 2020; Bonadio et al., 2020; Gupta et al., 2020).

Being married significantly reduced the probability of participation in wage employment by 5.4% when controlling for COVID-19 incidences and by 11.5% when controlling for COVID-19 vulnerability. Overall, these results are consistent with other studies showing that married women have been more severely affected by the loss of wage employment than their married male counterparts (Heggeness, 2020; and Fabrizio et al., 2021). A one-percent increase in the proportion of people in urban areas significantly increased the probability of participation in wage employment by 3.3% when controlling for COVID-19 incidences and by 2.4% when controlling for COVID-19 vulnerability. This could be attributed to the proximity to industries providing jobs in the urban areas and more abundant opportunities in the urban areas. Furthermore, when the urban residence was interacted with Covid-19 incidences, the results indicate an increment in the probability of wage employment participation by 0.6%. These findings are, however, contrary to Kugler et al. (2021), where the widespread loss of household income was prevalent in urban areas due to employment disruptions.

The interaction of the closure of business enterprises with gender shows that a one-percent increase in the closure of male-run business enterprises due to containment measures, particularly lockdowns or curfews, increased the probability of wage employment participation by 0.3% when controlling for COVID-19 incidences and 0.8% when controlling for COVID-19 vulnerability compared to the female-run business enterprises. During the lockdown, business enterprises were closed hindering the chances of participating in the labor force and hence the reduced probability.

The interaction of gender and COVID-19 vulnerability showed that a one-percent increase in the proportion of males exposed to the risk of getting COVID-19 significantly increased the probability of participating in wage employment by 0.4% compared to the females facing the same risk. The males facing a higher risk of exposure to the disease still went out to work as a way of fending for their families. These findings can be supported by (Khamis et al., 2021; and Kugler et al., 2021), who found that the consequences of the pandemic in terms of loss of employment were borne largely by women rather than men. Several studies concur with the findings (Dang and Nguyen, 2021; Fukai, 2021; Kikuchi et al.,2021) as we find more women bore the negative loss of jobs as opposed to their male counterparts who had an increased probability of wage employment.

The interaction between urban residence and COVID-19 vulnerability showed that an increase in the proportion of urban dwellers with a higher COVID-19 vulnerability reduced the probability of participating in wage employment by 0.1% compared to their rural counterparts. These findings are similar to Kugler et al. (2021), who found that those in urban areas were more severely affected in terms of loss of employment than their rural counterparts.

Being a male significantly increased the probability of participation in wage employment by 9.0% when controlling for COVID-19 incidences and by 8.5% when controlling for COVID-19 vulnerability compared to being a female. This was very clear during the peak of COVID-19 as men were more willing to take risks and participate in the labor force rather than let their families go hungry. A number of men were of the idea that they would rather die from COVID-19 disease than from hunger. The female gender was, therefore, disadvantaged in both cases of COVID-19 vulnerability and the lockdown.

The interaction of gender with COVID-19 incidences results indicated that an increase in the proportion of males experiencing COVID-19 incidences reduced the probability of wage employment participation by 0.2% compared to females. Similar results to our findings were based on a study done in the US, where there was a fall in wage employment of immigrant men as opposed to native men (Borjas and Cassidy, 2020).

A one-year increase in the age of an individual significantly increases the probability of wage employment participation by 2.4% when controlling for COVID-19 incidences and by 2.1% when controlling for COVID-19 vulnerability. This means that older people with COVID-19 incidences or the risk of exposure are likely to participate more in wage employment compared to younger people. These findings have been documented by studies done by (Adams-Prassl et al.,2020; Yasenov,2020; Lee et al.,2021; Kikuchi et al., 2021; Kugler et al., 2021) where we see younger workers significantly more likely to experience more job losses.

Those having preprimary education reduce the probability of wage employment participation by 0.8% when controlling for COVID-19 incidences but increase the probability of participating in wage employment by 5.9% when controlling for COVID-19 vulnerability. Overall, these results are consistent with other studies showing workers with lower levels of education were significantly at risk of experiencing job loss (Yasenov, 2020; Adams-Prassl et al., 2020; Lee et al., 2021).

A one-percent increase in the proportion of people having primary education significantly increases the probability of wage employment participation by 2.5% when controlling for COVID-19 incidences and by 8.1% when controlling for COVID-19 vulnerability. In contrast, Kulger et al. (2021) defined low levels of education as those with primary education, and there were negative impacts on wage employment, contrasting our findings.

Having a vocational training education level significantly increases the probability of wage employment participation by 7.6% when controlling for COVID-19 incidences and by 13.6% when controlling for COVID-19 vulnerability. This is in line with Kulger et al. (2021), where the most negatively affected in terms of job loss are those with low levels of education, unlike those holding vocational training.

A one-percent increase in the proportion of people having secondary education significantly increases the probability of wage employment participation by 8.6% when controlling for COVID-19 incidences and by 11.8% when controlling for COVID-19 vulnerability. Similarly, Kulger et al. (2021) found that those with lower levels of education were substantially more likely to stop working due to the pandemic, unlike their counterparts with secondary education. Possession of a college education level significantly increases the probability of wage employment participation by 15.8% when controlling for COVID-19 incidences and by 17.5% when controlling for COVID-19 vulnerability. Our findings are similar to (Adams-Prassl et al., 2020; and Lee et al., 2021), which found that those with no college education, especially women, were at risk of job loss due to the pandemic.

A one-percent increase in the proportion of people having a university education significantly increases the probability of wage employment by 14.2% when controlling for COVID-19 incidences and by 17% when controlling for Covid-19 vulnerability cases. These findings are in line with evidence in literature asserting that those who lacked a university degree were likely to experience loss of wage employment, unlike their counterparts with higher education (Adams-Prassl et al., 2020; Lee et al., 2021). A percentage increase in childcare hours increases the probability of wage employment participation by 1% when controlling for COVID-19 incidences and by 0.8% when controlling for Covid-19 vulnerability. Contrary to our findings, several studies demonstrate a huge negative impact of increased childcare hours on the employment of women with children than that of men (Adams-Prassl et al., 2020; Forsythe, 2020; Yasenov, 2020; Ikeda and Yamaguchi, 2021).

4. Summary, conclusions and policy implications

4.1 Summary and conclusions

Regarding the determinants of COVID-19 incidences and vulnerability, the closure of the business enterprise due to containment measures, particularly lockdown or curfew, was found to have significantly reduced the probability of COVID-19 incidences and COVID-19 vulnerability. This might have been because of restrictions in movement, which reduced the new infections and the vulnerability of getting the disease. Being married significantly increased the probability of COVID-19 incidences but reduced the COVID-19 vulnerability. Those living in urban areas experienced an increase in the probability of COVID-19 incidences and vulnerability. This could be attributed to the obvious overcrowding in urban areas. The male gender had an increased probability of COVID-19 incidence and was equally more vulnerable compared to the female. This may be because the males are more risk-takers and are always ready to move outside their homesteads compared to the females. This increases their risk of exposure to the disease. An additional year of life increased the probability of COVID-19 incidences but reduced the vulnerability or the risk of exposure to COVID-19. This may be due to the old people being risk-averse, leading to their staying indoors most of the time and hence reducing their risk of exposure or contracting the disease. The COVID-19 pandemic did not spare the educated population either. Those with pre-primary, primary, secondary, vocational training, and university education had a higher probability of COVID-19 incidences and a higher vulnerability. Only a college education significantly reduced the vulnerability.

On the gendered impact of COVID-19 incidence, COVID-19 vulnerability, and the business closure on wage employment, the results indicated that a higher proportion of COVID-19 incidences significantly reduced the probability of wage employment. Since COVID-19 incidences represent the disease itself, having the disease makes one be unwell and hence participate less in wage employment. COVID-19 vulnerability was also found to reduce participation in wage employment due to the fear of getting the disease. Intuitively, an increase in COVID-19 vulnerability leads to an increase in the exposure risk, which reduces the wage employment. This makes people hesitate to go to work. Therefore, the COVID-19 vulnerability affects employment indirectly, while the COVID-19 incidence affects employment directly. The COVID-19 vulnerability index is a proxy for having the disease, while COVID-19 incidence is the disease measured directly. COVID-19 incidences represent those who are sick and unable to go to work. Individuals can still have COVID-19 even if the exposure is low and this affects employment. With high exposure, people will fear to go out and work. If the vulnerability index increases, exposure is high; therefore, people fear going to work. Even if it's low, people will still fear going to work.

The closure of business enterprises due to containment measures, particularly lockdowns or curfews, as well as being married, significantly reduced the probability of wage employment when controlling for COVID-19 incidences and COVID-19 vulnerability. However, an increase in the proportion of people living in urban areas significantly increased the probability of wage employment in both models. This could be attributed to the proximity to industries providing jobs in the urban areas and more abundant opportunities in the urban areas. Furthermore, when the urban residence was interacted with COVID-19 incidences, the results indicate an increment in the probability of wage employment participation. This means that those living in urban areas with COVID-19 incidences participated less in wage employment.

In terms of gender and wage participation, being a male significantly increased the probability of wage employment when controlling for both COVID-19 incidences and COVID-19 vulnerability models compared to being a female. This was very clear during the peak of COVID-19 as men were more willing to take risks and participate in the labor force rather than let their families go hungry. A number of men were of the idea that they would rather die from COVID-19 incidences than from hunger. The female gender was, therefore, disadvantaged when controlling for both COVID-19 incidences and vulnerability.

In addition, the interaction of gender and business closure revealed that the closure of male-run business enterprises due to containment measures, particularly lockdown or curfew, increased the probability of wage employment participation when controlling for both COVID-19 incidences and COVID-19 vulnerability compared to the female-run business enterprises. During the lockdown, business enterprises were closed hindering the chances of participating in the labor force and hence the reduced probability.

The interaction of gender and the COVID-19 vulnerability showed that an increase in the proportion of males exposed to the risk of getting Covid-19 significantly increased the probability of participating in wage employment. The males facing a higher risk of exposure to the disease still went out to work as a way of fending for their families.

The interaction of the urban residence and the COVID-19 vulnerability showed that an increase in the proportion of urban dwellers with a higher COVID-19 vulnerability reduced the probability of participating in wage employment compared to their rural counterparts. On the other hand, the interaction of gender with COVID-19 incidence results indicated that an increase in the proportion of males with COVID-19 incidences reduced the probability of wage employment participation.

Contrary to most findings, an additional year of life significantly increased the probability of wage employment participation. This means that older people with cOVID-19 incidences or the risk of exposure are likely to participate more in wage employment compared to younger people. However, when the age of the individual was squared, the results indicated that an additional year of life significantly reduced the probability of wage employment participation when controlling for both the COVID-19 incidences and vulnerability, which corroborates most of the findings that older people participate less in wage employment.

Those with pre-primary education levels had a reduced probability of participating in wage employment when controlling for COVID-19 incidences and an increased probability of wage employment participation when controlling for COVID-19 vulnerability. However, individuals with primary, secondary, vocational training, college, and university education had a significantly higher probability of wage employment participation when controlling for both COVID-19 incidences and vulnerability. This clearly shows that higher levels of education are paramount to wage employment participation.

4.2 Policy implications

The pandemic has highlighted, more than ever, that neglecting certain sectors such as health, social protection, housing, sanitation, and hygiene makes people living in poverty more vulnerable. There is a need for more scrutiny of budget plans, their execution, and the performance of these sectors, all of which should support those living in poverty and boost wage employment. To ensure socioeconomic recovery within a reasonable period, the government should put in place plans and resources that do not continue to weigh disproportionally on people living in poverty. Reduced earnings from sluggish economic activities and job losses as a result of confinement measures and business closures by the government have to be balanced in the future against consideration of the daily needs of those living in poverty, as well as now-looming food insecurity across the country. In addition, the COVID-19 vulnerability indices estimated present tools that can be used by the Kenyan government and stakeholders to create a better plan by prioritizing the counties and sub-counties that are moderate to highly vulnerable. There is a need to provide wage subsidies, particularly to those employers hiring casual labourers and daily income earners, to support the sustainability of employment. Furthermore, sustaining local industries (micro, small and medium businesses) that provide jobs to people living in poverty should be prioritised in the short and medium term. This could be through access to loans and waiver of license fees and taxes. The government should prioritise tender awards to industries that are able to produce or provide input for the production of protective equipment such as masks and hand sanitizers, and a bailout fund should be launched to keep these industries afloat.

Competing interests: The authors have declared that no competing interests exist.

Funding: This research was accomplished with generous funding from the African Research Universities Alliance (ARUA)-African Centre of Excellence for Inequality Research (ACEIR), University of Nairobi Node, Kenya.

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Appendices

Appendix 1: Variables that constructed Covid-19 vulnerability index

Total household size greater than 6 members	A dummy variable taking the value 1 for households with more than 6 members, 0 otherwise
Age of a household member greater than 58 years	A dummy variable taking the value 1 for households with members aged 58 years and above, 0 otherwise
Households with no fridge	A dummy variable taking the value 1 for households with no fridge, 0 otherwise
Households visiting the doctor	A dummy variable taking the value 1 for households who visited a doctor, 0 otherwise
Household visiting other households	A dummy variable taking the value 1 for households who visited other households, 0 otherwise
Households with no access to radio and Television (TV)	A dummy variable taking the value 1 for households with no access to radio and TV, 0 otherwise

Appendix 2: Variables that constructed Covid-19 incidence

Fever	A dummy variable taking the value 1 for presence of fever, 0 otherwise
Persistent cough	A dummy variable taking the value 1 for persistent cough, 0 otherwise
Always feeling tired	A dummy variable taking the value 1 for always feeling tired, 0 otherwise
Muscle pain	A dummy variable taking the value 1 for muscle pain, 0 otherwise
Headache	A dummy variable taking the value 1 for headache, 0 otherwise
Diarrhoea/Nausea/vomiting	A dummy variable taking the value 1 for diarrhoea/nausea/vomiting, 0 otherwise
Difficulty in breathing/chest tightness	A dummy variable taking the value 1 for difficulty in breathing/chest tightness, 0 otherwise
Runny nose	A dummy variable taking the value 1 for runny nose, 0 otherwise
Sore throat	A dummy variable taking the value 1 for sore throat, 0 otherwise
Pneumonia	A dummy variable taking the value 1 for Pneumonia, 0 otherwise
Loss of sense of smell	A dummy variable taking the value 1 for loss of sense of smell, 0 otherwise
Tested and found COVID-19 positive.	A dummy variable taking the value 1 for those tested and found COVID-19 positive., 0 otherwise

Appendix 3: Descriptive statistics of variables that constructed Covid-19 vulnerability index

Variables	**Mean**	**Std. Dev.**	**Min**	**Max**
Total household size greater than 6 members	.2251746	.4177008	0	1
Age of a household member greater than 58 years	.1886427	.3912278	0	1
Households with no fridge	.4100237	.4918418	0	1
Households visiting the doctor	.1615863	.3680739	0	1
Household visiting other households	.3895518	.4876527	0	1
Households with no access to radio and television (TV)	.260353	.4388308	0	1
Number of observations	59,838			

Appendix 4: Descriptive Statistics of Variables That Constructed Covid-19 Incidence

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Fever	.0056987	.0752751	0	1
Persistent cough	.0032254	.0567012	0	1
Always feeling tired	.0014873	.0385378	0	1
Muscle pain	.0035596	.0595567	0	1
Headache	.0397072	.1952721	0	1
Diarrhea/Nausea/vomiting	.0028744	.053537	0	1
Difficulty in breathing/chest tightness	.0013704	.0369934	0	1
Runny nose	.0103279	.1011009	0	1
Sore throat	.0027742	.0525976	0	1
Pneumonia	.0021224	.046021	0	1
Loss of sense of smell	.0010863	.0329409	0	1
Tested and found COVID-19 positive.				
Number of observations	59,838			