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# The impact of COVID-19 incidence, vulnerability and business closure on wages in Kenya

D.K. Manda[1]
University of Nairobi, Kenya
Email: dkmanda@gmail.com

M.O. Oleche
University of Nairobi, Kenya

S.Kipruto
Kenya National Bureau of Statistics, Kenya

G. Mwabu
University of Nairobi, Kenya

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## Abstract

*This study analyses the impact of COVID-19 incidence, vulnerability and business closures due to COVID-19 on wages. Further, it assesses the effectiveness of the government tax relief measures implemented to cushion workers from the negative impact of the pandemic. Analysis based on a high-frequency panel data collected in 2020 and 2021 is carried out using a Control Function Approach. The results show that COVID-19 incidence significantly reduces wages, while COVID-19 vulnerability and business closure have an insignificant effect on wages. Further, the government tax relief measures put in place to cushion workers from the negative impact of COVID-19 helped alleviate the negative effect of COVID-19 on wages. Urban dwellers benefitted more from government tax relief measures and were worse off in the period following the end of the government tax relief measures. This study provides evidence to validate tax relief measures undertaken by the government to cushion workers' wages from the adverse effects of the COVID-19 pandemic and accounts for endogeneity and heterogeneity.*

## 1. Introduction

The COVID-19 pandemic and the government containment measures put in place to help curtail its spread have had unprecedented effects on both the global and national economies and on labour markets, hurting millions of workers and enterprises. The economic impact is largely a consequence of the preventive/containment measures adopted by the respective governments to curtail the spread of COVID-19. Some of the key measures adopted by most countries to curtail the spread of the pandemic include border closures, partial or complete lockdowns of economies, and imposing curfews, which, among other things, resulted in the temporary or permanent closure of businesses, schools, and social services. In the labour market, millions of workers lost their jobs due to the pandemic and business closures due to measures put in place by governments to curtail its spread. In addition, workers' wages were affected in various ways, with some workers losing their earnings, while others took pay cuts to keep enterprises afloat.

Realising the enormous effect of the COVID-19 pandemic on their economies, many countries adopted several measures in an attempt to cushion their economies from the impending global recession (see e.g., Gondwe, 2020). Some of the measures adopted by countries at varying levels included cutting interest rates and the provision of liquidity assistance to cushion households and firms, increasing social protection expenditure to effectively cushion the poorest households during the lockdowns, tax subsidies for enterprises and workers, and other relevant fiscal and monetary policies. In Kenya, some of the measures adopted by the government included reducing the Central Bank rate from 8.25% to 7.25%, removing charges for mobile money transactions of up to Kshs. 1000, and increasing transaction limits of mobile money transfers. Furthermore, the



[1] Corresponding Author

Kenyan government implemented a tax relief measure in an effort to increase disposable income for workers and other Kenyans. In particular, from March to December 2020, the government put in place measures such as 100% tax relief for persons earning a gross monthly income of up to Kshs. 24,000 and a reduction in the income tax rate (PAYE) from 30% to 25% to cushion workers from the negative effects of the COVID-19 pandemic.

The COVID-19 pandemic had a negative impact on Kenya's economy, with economic growth declining in 2020 by 0.3 %. In addition, sectors such as tourism, which is a leading foreign exchange earner for Kenya, were adversely affected as international travellers/holiday makers avoided travel, with international airlines discontinuing operations, significantly hurting the economy. According to a report released by the Kenyan National Bureau of Statistics in September 2020, the unemployment rate doubled to 10.4% as compared to 5.2% in March 2020 and as many as 1.7 million Kenyans lost their jobs in the first few months of the COVID-19 pandemic. While the impact of the pandemic on the economy, sectors, employment, and jobs in the Kenyan labour market has been widely documented (see, e.g., Chacha et al., 2021), its effects on wages are largely unknown. Worldwide, literature on the impact of the pandemic on earnings is scarce. This leads us to raise the following questions. What is the impact of the COVID-19 pandemic (incidence and vulnerability) and business closure due to the pandemic and the curtailment measures put in place by the government on wages in Kenya? How well did the government relief measures put in place in 2020 help cushion workers to avoid the negative impact of COVID-19 pandemic?

This study analyses the effect of COVID-19 incidence, vulnerability and business closure due to government containment measures to curtail COVID-19 on wages in Kenya. This study also assesses the effectiveness of government tax relief measures in cushioning workers' wages from the adverse effects of COVID-19. The analysis makes use of the high-frequency panel data collected by the World Bank and Kenya National Bureau of Statistics in 2020 and 2021 to carry out the analysis. The data were collected from May 2020 to June 2021, with three waves of the panel collected in 2020 and the remaining two waves collected from January to June 2021, which enables the comparison of the effect of COVID-19 on wages over the period when government tax relief measures were in place (May-December 2020) and the period after the end of the measures (January –June 2021). This study adds to the existing literature by going beyond what has been done in previous studies on wage determination in Kenya (see, e.g., Kimenyi et al., 2006; Kabubo-Mariara, 2003; Manda 2002) by controlling for COVID-19 incidence, vulnerability, and business closure due to the pandemic and government containment measure of the pandemic, in addition to the usual determinants of earnings. It also controls for endogeneity and heterogeneity using a Control Function Approach. In addition, owing to the scarcity of literature on the effect of COVID-19 on wages in Kenya and other developing countries, this study provides crucial evidence that can inform policymaking. It also provides evidence to validate some of the measures taken by the government to cushion workers from the effects of the COVID-19 pandemic.

The remainder of the paper is organised as follows: Section 2 examines the literature on COVID-19 pandemic and earnings/wages in Kenya and other countries. Section 3 outlines the methodology used in the study, while Section 4 presents the empirical results. Finally, Section 5 concludes the study.

## 2. COVID-19 and Earnings

Studies on the effect of COVID-19 on earnings/wages are scarce in developing countries, with few studies available in developed countries. Worldwide, the ILO (2020a) shows how the pandemic has put pressure on wages, widening the gap between top-earners and low-wage workers, with women and the low-paid bearing the brunt. The effect of the pandemic on wages could have been worse if governments and central banks had not stepped in to dissuade companies from laying off workers during the lockdowns (ILO, 2020b). The measures undertaken by governments have allowed millions of wage earners to retain all or part of their income, in contrast to the impact of the global financial crisis a decade ago. The report shows that wage growth slowed or reversed in two-thirds of the countries for which the data were available.

Studies in the US show varying empirical evidence of the impact of COVID-19 on earnings. For instance, in April 2020, a few months after the onset of the pandemic, the Bureau of Labor Statistics (BLS) report shows that occupations with lower wages were more common in the shutdown sectors than elsewhere in the economy and that higher-paying jobs were less common in those sectors. Therefore, shutdown policies disproportionately affected workers in lower-paying jobs (Dey and Loewenstein, 2020). In another study, Tamara (2021) shows that the year 2020 began with a tight labour market and rising wages, followed suddenly by stay-at-home orders and massive job losses that affected the labour market as companies adjusted to survive. For instance, in spring 2020, one-fourth of the companies reduced pay (most of them temporarily) when, due to COVID-19, a large swath of the economy was shut down. Further, empirical evidence from the US shows that in 2021, the impact of the COVID-19 pandemic on pay varied by industry, region, and even by job within companies (Tamara, 2021).

Across European Union countries, the 2020 COVID-19 crisis had a significant impact on wages and wage setting. The uncertain economic scenario due to COVID-19, together with the difficulties inherent in online bargaining, led to a general postponement of collective agreements to 2021, especially at the company level (see Molina, 2021). Real wages maintained a positive trend in 2020 in most EU countries, with only modest to higher increases in the public sector (Molina 2021). Wage support mechanisms introduced by governments also contributed to supporting wages in the private sector for workers whose hours of work had been reduced or who had been temporarily laid off. The pandemic seems to have particularly affected low-wage workers, occupations, and sectors (see Molina, 2021; Baena-Diez et al., 2020). Wage support mechanisms and minimum wages played a key role in reducing the impact of the COVID-19 crisis on growing earning inequalities. In the EU and UK, analysis of wage-setting practices and wage development revealed that there were no signs of downward wage adjustment taking place in most European countries with real wage increases during 2020, despite a fall in GDP. Finally, the government increased minimum wages, as happened in most EU countries and the UK for 2021, to partly reduce the growing earnings inequality caused by a stronger impact on labour-intensive, low-wage sectors, where there was a predominance of young people, immigrant workers, and women (see, e.g., Almeida et al., 2022 and Baena-Diaz et al., 2020).

Studies in developing countries predicted a decline in earnings due to COVID-19. For instance, according to Fox and Signe (2020), the scale and reach of the impact of COVID-19 on employment differ among countries and sectors, but the main effects are a drop in earnings (income) and increased under-employment (reduced hours) rather than unemployment. In Kenya, while there are several studies examining the effect of the pandemic on the economy, sectors, and employment, there are very few studies analysing the effect of COVID-19 and the curtailment measures put in place by the government on wages. One such study is that by Chacha et al. (2021), which shows that the reduction in the firm-level workforce is also reflected in the reduction in firm-level aggregate payrolls, but the distribution of average firm-level salaries remains largely unchanged. The other study, Mwabu (2023), analyses the impact of COVID-19 vulnerability on wages in Kenya and finds that it has a negative effect on wages. However, whereas the study by Mwabu (2023) controls for COVID-19 vulnerability, it does not control for COVID-19 incidence, which may have an even bigger impact on earnings. In contrast, this study analyses the impact of COVID-19 (incidence and vulnerability) and business closures due to COVID-19 curtailment measures on wages in Kenya using high-frequency panel data collected by the World Bank and Kenya National Bureau of Statistics in 2020 and 2021. Furthermore, this study provides an assessment of some of the measures taken by the government to cushion workers' earnings from the effects of the COVID-19 pandemic.

## 3. Methodology

This section begins by outlining the model used in this analysis. This is followed by a description of the variables and data used in the analysis.

### *3.1 The Model*

A modified Mincer [1974] semi-logarithmic wage equation that controls for COVID-19 incidence, vulnerability, and business closure due to COVID-19 curtailment measures put in place by the government is estimated. The semi-logarithmic wage equation is as follows:

$$\mathbf{ln(}\boldsymbol{W}_{\mathbf{it}}\mathbf{)} = \boldsymbol{\alpha} + \boldsymbol{\phi}\mathbf{C19inc}_{\mathbf{it}} + \boldsymbol{\mu}\mathbf{C19vul}_{\mathbf{it}} + \boldsymbol{\gamma}\mathbf{BC}_{\mathbf{it}} + \boldsymbol{\Sigma\beta}_{\mathbf{k}}\boldsymbol{S}_{\mathbf{kt}} + \boldsymbol{\lambda}\boldsymbol{A}_{\mathbf{it}} + \boldsymbol{\delta}\boldsymbol{Z}_{\mathbf{it}} + \mathbf{u}_{\mathbf{it}} \qquad (1)$$

where $\mathbf{ln(W_{it})}$ is the logarithm of hourly wages for worker i at time t; $\mathbf{C19inc_{it}}$ is a dummy variable capturing the COVID-19 incidence; $\mathbf{C19vul_{it}}$ is an index measuring COVID-19 vulnerability; $\mathbf{BC_{it}}$ is a dummy variable capturing business closure due to COVID-19 and its curtailment measures such as curfew and lockdown put in place by the government; $\mathbf{S_{kt}}$ are dummy variables representing the highest level of schooling attained by a worker with k representing the levels of education; $\mathbf{A_{it}}$ is the potential experience represented by the age of the individual in years and age in years squared ; $\mathbf{Z_{it}}$ is a vector of other control variables such as sex, education and regional dummy variables; and $\mathbf{u_{it}}$ is an error term.

In estimating equation 1, three estimation problems are likely to be encountered: endogeneity, heterogeneity, and sample selection. We tested for the presence of these problems, and if found to be severe, we controlled for them as described below. First, wages (**ln (*W*it)**), COVID-19 incidence (**C19inc**$_{\mathbf{it}}$), and COVID-19 vulnerability (**C19vul**$_{\mathbf{it}}$) are likely to be jointly determined by *innate ability, skills or intellectual ability* attributes in the error term ($u_{it}$). COVID-19 incidence (**C19inc**$_{\mathbf{it}}$) and COVID-19 vulnerability (**C19vul**$_{\mathbf{it}}$**)** are likely to be correlated with the error term, leading to biased estimates. In addition, unobserved heterogeneity of household preferences due to the nonlinear interaction of COVID-19 incidence (**C19inc**$_{\mathbf{it}}$) and COVID-19 vulnerability (**C19vul**$_{\mathbf{it}}$) with unobservable variables (such as inherited traits or behaviour) could bias the estimation of the wage function. To control for these problems, the Control Function Approach is used to test and address the two potential issues (see, Wooldridge, 2002; 2015). To address these problems, a Two-Stage Residual Inclusion (2SRI) procedure that follows Papke and Wooldridge (2008) is used. The first stage involves estimating the reduced form equation (equations 2 and 3), which are the COVID-19 incidence and COVID-19 vulnerability-generating functions. This involves regressing the endogenous COVID-19 incidence and COVID-19 vulnerability to instruments and other exogenous variables.

$$\mathbf{C19inc_{it} = \alpha + \sigma\, ACC19inc_{it} + \gamma BC_{it} + \Sigma\beta_k \mathit{S}_{kt} + \lambda \mathit{A}_{it} + \delta \mathit{Z}_{it} + u_{it}} \qquad (2)$$

$$\mathbf{C19vul_{it} = \alpha + \sigma\, ACC19vul_{it} + \gamma BC_{it} + \Sigma\beta_k \mathit{S}_{kt} + \lambda \mathit{A}_{it} + \delta \mathit{Z}_{it} + u_{it}} \qquad (3)$$

where **ACC19inc**$_{\mathbf{it}}$ is the county-level average COVID-19 incidence, and **ACC19vul**$_{\mathbf{it}}$ is the average county-level COVID-19 vulnerability index.

Following Wooldridge (2015), equation 2 can be considered as a linear probability reduced-form equation of Covid-19 incidence and equation 3 can be estimated as an OLS regression of the COVID-19 vulnerability index. From this first step, the residuals are obtained for use in the second step.

The second stage estimation aims to purge the potential endogeneity of COVID-19 incidence and COVID-19 vulnerability and heterogeneity resulting from its correlation with the error term of the structural equation (see equation 4). The residuals obtained from equations 2 and 3 and the interaction between the respective residuals, COVID-19 incidence, and COVID-19 vulnerability are included as variables in the structural model, as shown in equation (equation 4).

$$\begin{aligned}\mathbf{ln(\mathit{W}_{it})} &= \mathbf{\alpha + \phi C19inc_{it} + \mu C19vul_{it} + \gamma BC_{it} + \Sigma\beta_k \mathit{S}_{kt} + \lambda \mathit{A}_{it} + \delta \mathit{Z}_{it} + \theta_1 C19inc\_res_{it} +} \\ &\quad \mathbf{\theta_2 C19vul\_res_{it} + \tau_1 (C19inc_{it}{*}C19inc\_res_{it}) + \tau_2 (C19vul_{it}{*}C19vul\_res_{it})} \\ &\quad \mathbf{\tau_3\, C19inc\_res\_squared_{it} + \tau_4\, C19vul\_res\_squared_{it} + \varepsilon_{it}} \qquad (4)\end{aligned}$$

where C19inc_res$_{it}$ and C19vul_res$_{it}$ are the residuals from equations 2 and 3, respectively. Inclusion of the residuals in equation 4 serves as the control for unobservable variables that correlate with COVID-19 incidence and COVID-19 vulnerability, thereby allowing the potentially endogenous variables to be treated as exogenous covariates during estimation.

When the coefficients of the residual residuals ($\theta_1$ and $\theta_2$) are statistically significant, endogeneity is an issue, and including the residuals in the equation helps to control for it. The interaction terms (C19inc$_{it}$*C19inc_res$_{it}$) and (C19vul_res$_{it}$*C19vul$_{it}$) of the residuals with the actual values of each of the potential endogenous explanatory COVID-19 variables controls for the unobserved heterogeneity when their estimated coefficients (**$\tau_1$** and **$\tau_2$**) are statistically significant.

Finally, the respective residual squares ($C19inc\_res\_squared_{it}$ and $C19vul\_res\_squared_{it}$) can be included to control for any nonlinearity in the estimation. When their estimated coefficients (**$\tau_3$** and **$\tau_4$**) are statically significant, this means that a nonlinear relation is a better linear formulation while if the coefficients are not statistically significant, then non-linearity is not an issue and hence no need to include them in the regression. $\varepsilon_{it}$ is a composite error term comprising the random and the unpredicted parts of the previous error terms; and α, **ϕ, μ, β, λ, δ, θ**, and **τ** are vectors of parameters to be estimated. Under fairly weak assumptions, one can obtain consistent, asymptotically normal estimators of the average structural functions provided suitable instruments are available. Therefore, equation 4 is expected to produce unbiased and consistent results (see Wooldridge, 2015).

Second, sample selectivity bias may be a problem when estimating the wage equation and may also lead to biased estimates of the wage equation. To correct this, an estimated wage employment participation equation was used, and an inverse Mills ratio was generated, which is included in the earnings equation to estimate the Heckman two-stage model (Heckman, 1976). In the Heckman two-stage model, the first step is to estimate a probit wage employment participation equation and generate inverse Mill's ratio. The second step is to include the generated inverse Mill's ratio in the wage equation and estimate it using OLS. If the coefficient of the inverse Mills ratio is statistically significant in the wage equation estimation, then it means that sample selection is a serious problem; therefore, estimating the Heckman two-stage model is the correct specification that provides unbiased results. If the coefficient is not statistically significant, then sample selection is not a serious problem; therefore, there is no need to estimate the Heckman two-stage method. Our estimation shows that the sample selection is not a serious problem (see Table 1 in the Appendix).

### *3.2 Variables*

Table 1 presents the variables used in the analysis and their definitions. The dependent variable in the wage equation is hourly wages obtained by dividing monthly wages by the hours of work in a month. COVID-19 incidence is a dummy variable that takes the value of 1 if an individual is affected by any of the disease symptoms associated with COVID-19 or is tested and found to have COVID-19. COVID-19 vulnerability is an index developed using household-level variables that can lead to exposure and/or risk of being infected by COVID-19. The indicators used to derive the COVID-19 vulnerability index include the following: large households with six or more members, any household that has a member aged 60 years and above, a household that does not own a fridge, a household that does not own a radio/television, and a household that has members making visits to other households or were visited by members of other households. The definitions for age of the individual, gender, region, marital status and education are self-explanatory, as shown in the table. Of course, there are other relevant variables that should be included in the analysis, such as industry, employment sector, and firm characteristics, but they are not included because the information is not available in the dataset. This may bias the estimated results to some extent. The last two variables are used as instrumental variables in the reduced-form equations 2 and 3. The exclusion of own county incidence measure and own county COVID-19 vulnerability from the average ensures that own county measure does not influence the average; hence, the average can be used as an instrument in the reduced-form equation.

Table 1: Variables and Variable Definition

| Variables | Variable Definition |
|---|---|
| Natural Logarithm of Hourly Wages | The natural logarithm of the hourly wages |
| COVID-19 Incidence | A dummy variable taking the value 1 if an individual an individual experienced any of the symptoms related to COVID-19 or tested and found to have COVID-19, 0 otherwise |
| COVID-19 vulnerability | A COVID-19 vulnerability index (the higher the index, the higher the vulnerability) |
| Business closure due to COVID-19 and containment measures by Government | A dummy variable taking the value 1 if business was closed due to COVID-19 and government containment measures of lockdown and curfew |
| Male | A dummy variable taking the value 1 if the individual is male, 0 otherwise |
| Urban Residence | A dummy variable taking the value 1 if the individual resides in an urban area, 0 otherwise |
| Marital status | A dummy variable that takes the value 1 if one is married, 0 otherwise |
| Age of individual in Years | Age of the individual in years |
| No education | A dummy variable taking the value 1 if the individual has no formal education, 0 otherwise |
| Primary | A dummy variable taking the value 1 if the individual has primary education, 0 otherwise |
| Vocational | A dummy variable taking the value 1 if the individual has post-primary vocational training, 0 otherwise |
| Secondary | A dummy variable taking the value 1 if the individual has secondary education, 0 otherwise |
| College | A dummy variable taking the value 1 if the individual has post- secondary college education, 0 otherwise |
| University | A dummy variable taking the value 1 if the individual has university education, 0 otherwise |
| County level COVID-19 incidence | 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. This variable is used as an instrumental variable in the control function |
| County level COVID-19 vulnerability index | 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. This variable is used as an instrumental variable in the control function |

*3.3 Data*

The COVID-19 Rapid Response Phone Survey Households 2020-2021 panel data was collected by the World Bank in collaboration with the Kenya National Bureau of Statistics (KNBS) and the University of California, Berkeley (see Sinha, 2020). The survey was conducted to track the socioeconomic impact of the COVID-19 pandemic and provide timely data to inform targeted responses. This dataset contains information from five waves of the COVID-19 RRPS, which was part of a bi-monthly panel survey targeting Kenyan nationals. The duration of each of the five waves and the sample size are outlined below.

Wave 1: May 14 to July 7, 2020; 4,063 Kenyan households
Wave 2: July 16 to September 18, 2020; 4,504 Kenyan households
Wave 3: September 18 to November 28, 2020; 4,993 Kenyan households
Wave 4: January 15 to March 25, 2021; 4,860 Kenyan households
Wave 5: March 29 to June 13, 2021; 5,854 Kenyan households

The initial sampling frame consisted of 92,999,970 randomly ordered phone numbers assigned to three networks: Safaricom, Airtel and Telkom. An introductory text message was sent to 5,000 randomly selected numbers to determine whether the numbers were in operation. Of these, 4,075 were active and formed the final sampling frame. There was no stratification and individuals who were called were asked to provide information about the households in which they lived. The survey was conducted in May 2020 and ended in June 2021. The same households were interviewed every two months using computer-assisted telephone interviewing (CATI) techniques. The dataset contains information from two Kenyan household samples. The first sample was a randomly drawn subset of all households that were part of the 2015/16 Kenya Integrated Household Budget Survey (KIHBS) Computer-Assisted Personal Interviewing (CAPI) pilot and provided a phone number. The second was obtained through the Random Digit Dialling method, by which active phone numbers created from the 2020 Numbering Frame produced by the Kenya Communications Authority were randomly selected.

The samples cover urban and rural areas and are designed to be representative of the Kenyan population using cell phones. All waves of this survey included information on household background, service access, employment, food security, income loss, transfers, health, and COVID-19 knowledge. The data are presented as three files. The first is an hh file, which contains household-level information. The 'hhid' uniquely identifies all households. The second is the adult-level file, which contains data on adult household members. Each adult in a household is uniquely identified by the 'adult_id'. The third file is a child-level file containing information for every child in the household. Each child in a household is uniquely identified by the 'child_id'. Our analysis was based on a sample of adults aged 18–64 years. Data on adults provides information on age, gender, marital status, region, and county of residence. We combined this information with the information provided at the household level on COVID-19 and COVID diseases symptoms and business closures. This provided an unbalanced panel with 55,621 observations of individuals, with only 6,020 reporting to receive wages.

There was no stratification, and individuals who were called were asked about the households they lived in until wave 5. Samples of households that were not reached in earlier waves were also contacted along with households that were interviewed before. From the data, descriptive statistics (see Table 2) show that the average hourly wages are Ksh 132.46 and are highly varied across individuals, as shown by the high standard deviation. The average COVID-19 incidence over the entire period was 7.2%, whereas the average COVID-19 vulnerability index was 2.3099, ranging from 0 to 11.66. On average, 2.3% of businesses closed due to COVID-19 and its curtailment measures, such as lockdowns and curfews put in place by the government. On average, the sample consisted of 47.7% males, 52.7% urban dwellers, and 11.7% married individuals. The fact that 52.7% of the sample consists of urban dwellers shows that the data could be biased and not representative of the population. However, this is expected given that this was a phone survey, with phone ownership being higher in urban households than in rural households. Therefore, there is a need for caution in generalising the results.

Table 2: Descriptive Statistics

| Variables | Obs | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| Hourly Wages | 6,020 | 132.71 | 190.74 | 0.0089 | 6750 |
| COVID-19 Incidence | 55,621 | 0.0725 | - | 0 | 1 |
| COVID-19 vulnerability index | 55,621 | 2.3099 | 2.012 | 0 | 11.66 |
| Business closure due to COVID-19 and containment measures by the government | 55,621 | 0.0231 | - | 0 | 1 |
| Male | 55,621 | 0.4776 | - | 0 | 1 |
| Urban Residence | 55,621 | 0.5269 | - | 0 | 1 |
| Married individuals | 55,621 | 0.1167 | - | 0 | 1 |
| Age of individual in years | 55,621 | 34.25 | 12.24 | 18 | 64 |
| No education | 55,621 | 0.0193 | - | 0 | 1 |
| Primary | 55,621 | 0.2950 | - | 0 | 1 |
| Vocational | 55,621 | 0.0089 | - | 0 | 1 |
| Secondary | 55,621 | 0.4535 | - | 0 | 1 |
| College | 55,621 | 0.1058 | - | 0 | 1 |
| University | 55,621 | 0.0355 | - | 0 | 1 |
| County level COVID-19 incidence | 55,621 | 0.0742 | 0.0003 | 0.0736 | 0.0747 |
| County level COVID-19 vulnerability index | 55,621 | 2.4122 | 0.012 | 2.3985 | 2.4557 |

The average age of the participants in the sample was 34.5 years. Approximately 2.0% of the individuals had no formal education, 4.1% had pre-primary education, 29.1% had primary education, and 1% had vocational training. The majority (45.2%) of the individuals had a secondary education, and those with college and university education constituted 10.5% and 3.5% of the sample, respectively.

## 4. The Results

First, as indicated in the previous section, sample selection is not a serious problem and therefore, there is no need to control for it. Second, a test for endogeneity and heterogeneity of COVID-19 incidence and COVID-19 vulnerability on wages was conducted using the control function approach. First, county-level COVID-19 incidence and county level COVID-19 vulnerability are statistically significant in the first stage regression. (see Appendix Table 2) This shows that they are valid instrumental variables to be used in the first stage of regression.

Table 3: Random Effects Regression Results - Dependent Variable is Natural Logarithm of Hourly Wage

| Variables | All waves (1-5) | Period of Gov't tax relief (wave 1-3) | Period after Gov't tax relief (wave 4& 5) |
|---|---|---|---|
| COVID-19 Incidence | -2.4484***<br>(1.088) | 1.1431<br>(3.130) | -3.3566***<br>(1.076) |
| COVID-19 Vulnerability | -0.0218<br>(0.049) | 0.0452<br>(0.138) | -0.0591<br>(0.048) |
| Business closure due to COVID-19 and containment measures by Government | -0.1630<br>(0.107) | -0.2947<br>(0.274) | -0.0841<br>(0.107) |
| Male | 0.0460<br>(0.042) | 0.1416*<br>(0.087) | 0.0120<br>(0.028) |
| Married | 0.0048<br>(0.064) | -0.0228<br>(0.159) | 0.0857<br>(0.073) |
| Urban Residence | 0.0379<br>(0.029) | -0.0575<br>(0.098) | 0.0848*<br>(0.045) |
| COVID-19 incidence & urban interaction term | 0.1067<br>(0.071) | 0.2402<br>(0.242) | 0.1086*<br>(0.066) |
| COVID-19 vulnerability & urban interaction term | -0.0029<br>(0.013) | 0.0779*<br>(0.042) | -0.0207*<br>(0.013) |
| Age of individual in Years | 0.0288**<br>(0.013) | 0.0397<br>(0.038) | 0.0236*<br>(0.010) |
| Age of individual squared | -0.0003*<br>(0.0002) | -0.0004<br>(0.0005) | -0.0002<br>(0.0002) |
| Primary | 0.0388<br>(0.075) | -0.0817<br>(0.147) | 0.1067<br>(0.099) |
| Vocational Training | 0.3663***<br>(0.140) | 0.0096<br>(0.375) | 0.4913***<br>(0.151) |
| Secondary | 0.2672***<br>(0.080) | 0.2931*<br>(0.174) | 0.2764***<br>(0.103) |
| College | 0.6713***<br>(0.085) | 0.9483***<br>(0.194) | 0.6051***<br>(0.106) |
| University | 1.0149***<br>(0.089) | 1.2880***<br>(0.193) | 0.8998***<br>(0.111) |
| Tax relief by Government | 0.1739***<br>(0.032) | | |
| COVID-19 incidence residual | 0.7215<br>(0.795) | -0.4923<br>(2.337) | 1.1309<br>(0.769) |
| COVID-19 vulnerability residual | -0.0281<br>(0.049) | -0.1914<br>(0.137) | 0.0282<br>(0.048) |
| COVID-19 Incidence and residual interaction term | 1.9212**<br>(0.989) | -0.9867<br>(2.737) | 2.5190***<br>(1.025) |
| COVID-19 vulnerability and residual interaction term | 0.0090***<br>(0.003) | 0.0225**<br>(0.011) | 0.0072***<br>(0.003) |
| Constant | 3.4667***<br>(0.304) | 2.7503***<br>(0.848) | 3.8801***<br>(0.306) |
| Number of observations | 6020 | 1435 | 4585 |

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

As shown in Table 3, the residuals from reduced-form equations 2 and 3 are not statistically significant, indicating that endogeneity is not a serious problem. However, the interaction term between COVID-19 incidence and COVID-19 vulnerability and their respective residuals are statistically significant, indicating that heterogeneity is an important issue in wage estimation and that including the interaction terms in the equation helps control for it. Finally, we tested whether we could estimate a pooled regression, fixed effects, or random effects model. The test results of the Hausman specification test show that random effects are the best specification for estimating this panel data. Given these test results, we estimated and interpreted the results of a random-effects control function wage equation (see Table 3).

Table 3 shows the random effects control-function wage estimates. The estimates in the first column are based on all five waves of the panel data, and those in the second and third columns are estimated separately for the waves that coincide with the period when the government provided tax relief to workers to cushion them from the effects of COVID-19 (May to December 2020) and the period after the end of government tax relief to the workers (January to June 2021). For each equation, we control for the effect of COVID-19 incidence, COVID-19 vulnerability, and business closure due to COVID-19 and government containment measures of the pandemic in addition to the usual controls included in the wage equation.

As shown in Table 3, the COVID-19 incidence has a negative and significant effect on wages in Kenya over the period (May 2020 to June 2021), a positive but insignificant effect over the period when the government provided tax relief to workers, and a statistically significant negative effect over the period after the end of government tax relief measures. Thus, the incidence of the pandemic significantly reduced employee wages, as the estimations in the first column show. Further, the results show that the government tax relief measures implemented from March to December 2020 were useful in cushioning workers' wages from the negative effects of COVID-19, as shown by the positive but insignificant effect of the COVID-19 incidence over that period. Ending the tax relief measure led to a reduction in workers' wages, as shown by the negative and significant effect of the COVID-19 incidence. COVID-19 vulnerability generally had an insignificant effect on employee wages. This is because the coefficient of COVID-19 vulnerability had a negative but insignificant effect on wages in Kenya over the period 2020/2021 and during the period after government tax relief measures ended, but a positive and insignificant effect over the period when the government provided tax relief to workers. Consistently, business closures due to COVID-19 and government COVID-19 curtailment measures have a negative but insignificant effect on wages.

In terms of gender, it is clear from the results that there is no significant difference in wages by gender, except during the period when government tax relief was in place when men received higher earnings than those of women. There was no significant difference in earnings between married and single individuals, as shown by the insignificant coefficient of the marriage dummy variable. There are differences in wages across rural and urban areas only for the period after the end of government tax relief, but not during the period when government tax relief measures were in place. This could be an indication that the government tax relief measure probably helped close the wage gap between rural and urban areas. Further, the coefficient of the interaction term for COVID-19 incidence and urban residence is positive but only significant in the period after the end of government tax relief measures. This shows that urban dwellers experiencing COVID-19 received higher wages than rural dwellers experiencing COVID-19. On the other hand, the coefficient of the interaction term for COVID-19 vulnerability and urban residence is positive and significant in the period in which the government implemented tax relief measures, and negative and significant in the period after the end of government tax relief measures. This shows that urban dwellers who were vulnerable to COVID-19 benefitted more from the government tax relief measures than their rural counterparts during the implementation of the government tax relief measures, while in the period after the end of the government tax relief measures, they were worse off than their rural counterparts.

Generally, wages significantly increase as age increases, but only up to some point beyond which they start declining, but this is only significant for the entire period of panel data and the period after the end of government tax relief measures. Moreover, wages increase with an increase in the level of education. The wages for those with vocational training are significantly higher than for those with no education, except for the period during the implementation of government tax relief measures, which could probably be an indication that government tax relief measures implemented in 2020 to cushion workers from the pandemic helped close the wage gap between those with no education and those with vocational training. On the other hand, the wages of those with secondary, college, and university education remained statistically significant for the entire period and for the period during and after the implementation of government tax relief measures.

In summary, the results show that COVID-19 incidence had a negative effect on wages, while COVID-19 vulnerability and business closure due to COVID-19 and government COVID-19 curtailment measures had insignificant effects on wages. The results also show that government tax relief measures put in place may help alleviate the effect of COVID-19 on wages or the period in which they were implemented.

Urban dwellers who were more vulnerable to COVID-19 benefited more from government tax relief measures and were worse off in the period after the end of the government tax relief measures.

## 5. Summary and Conclusion

This study has two main objectives. The first is to analyse the impact of COVID-19 incidence and vulnerability and business closure due to COVID-19 and COVID-19 government curtailment measures on wages. The second is to assess the effectiveness of government tax relief measures put in place to cushion workers from the negative impact of the COVID-19 pandemic. We use high-frequency panel data collected by the World Bank and Kenya National Bureau of Statistics in 2020 and 2021 for the analysis. To achieve the objectives, a random effects control function model is estimated using the entire five waves of panel data and also separately by dividing the panel data into two periods: the period when government tax relief measures were implemented (May-December 2020 comprising of the first three waves) and the period after the end of government tax relief measures (January to June 2021, comprising the last two waves of the panel data). The estimated random effects results show that COVID-19 incidence and vulnerability are not potentially endogenous, but heterogeneity is a severe problem. Therefore, estimating the control function helps solve the problem. The results show that the COVID-19 incidence reduced wages, while COVID-19 vulnerability and business closure due to COVID-19 and government curtailment measures had insignificant negative effects on wages. Government tax relief measures implemented during the pandemic helped alleviate the negative impact of COVID-19 on wages. Urban dwellers who are more vulnerable to COVID-19 benefited more from government tax relief measures and are worse off in the period after the end of the government tax relief measures. The results provide evidence to validate the tax relief measures undertaken by the government to cushion workers' wages from the adverse effects of the COVID-19 pandemic. Finally, this study is not without some limitations. The main limitation of this study is related to the data, as it may not fully represent the broader population. Being a phone survey, it may have captured relatively more urban than rural population. The data also does not have information on all the variables to be controlled for in a wage regression. Therefore, the estimated results may be biased and need to be handled with some caution.

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**Appendix**

Table1: Random Effects Regression Results - Dependent Variable is Natural Logarithm of Hourly Wage

| **Variables** | **All Waves (1-5)** |
|---|---|
| COVID-19 Incidence | -2.4409**<br>(1.089) |
| COVID-19 Vulnerability | -0.0216<br>(0.049) |
| Business closure | -0.1627<br>(0.107) |
| Male | 0.0471<br>(0.042) |
| Married status | 0.0025<br>(0.064) |
| Urban residence | 0.0395<br>(0.029) |
| COVID-19 incidence & urban interaction term | 0.1052<br>(0.071) |
| COVID-19 vulnerability & urban interaction term | -0.0029<br>(0.013) |
| Age | 0.0298**<br>(0.013) |
| Age-squared | -0.0003*<br>(0.0002) |
| Primary | 0.0526<br>(0.077) |
| Vocational training | 0.3803***<br>(0.141) |
| Secondary | 0.2841***<br>(0.084) |
| College | 0.6889***<br>(0.085) |
| University | 1.0322***<br>(0.092) |
| Tax relief by Government | 0.1744***<br>(0.032) |
| COVID-19 incidence residual | 0.6902<br>(0.797) |
| COVID-19 vulnerability index residual | -0.0283<br>(0.028) |
| COVID-19 Incidence & COVID-19 Incidence residual interaction term | 1.9242**<br>(0.989) |
| COVID-19 vulnerability & COVID-19 vulnerability residual interaction term | 0.0090***<br>(0.003) |
| Inverse Mill's Ratio | 0.0001<br>(0.0002) |
| Constant | 3.4240***<br>(0.311) |
| Number of observations | 6020 |

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

Table 2: Reduced Form Regressions for COVID-19 Incidence and COVID_19 Vulnerability

| Dependent variables | COVID-19 Incidence | COVID-19 Vulnerability |
|---|---|---|
| Variables | | |
| County level COVID-19 incidence | -53.7048*** (15.670) | |
| County level COVID-19 vulnerability index | | -5.8229*** (0.907) |
| Business closure | -0.0244 (0.039) | 0.0253 (0.128) |
| Male | -0.0212 (0.009) | -2.2847*** (0.037) |
| Married status | 0.0487*** (0.014) | -0.1705*** (0.045) |
| Urban residence | 0.0044 (0.009) | -0.0980*** (0.029) |
| COVID-19 incidence & urban interaction term | 0.9946*** (0.010) | |
| COVID-19 vulnerability & urban interaction term | | 0.1508** (0.054) |
| Age | 0.0099*** (0.003) | -0.0658*** (0.009) |
| Age-squared | -0.0001*** (0.00003) | -0.0008*** (0.0001) |
| Primary | -0.0137 (0.027) | -0.0353 (0.087) |
| Vocational training | 0.0339 (0.051) | -0.0181 (0.167) |
| Secondary | 0.0487* (0.026) | -0.1546* (0.084) |
| College | 0.0526** (0.026) | -0.2610*** (0.087) |
| University | 0.0447 (0.030) | -0.2073** (0.098) |
| Constant | 3.9600*** (1.166) | 15.3842*** (2.195) |
| R-squared | 62.1% | 66.3% |
| Number of observations | 6020 | 6020 |

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