SOCIOECONOMIC IMPACTS OF COVID-19: THE RURAL-URBAN DISPARITIES IN KENYA

BY

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Declaration

I, Muendo Festus Kavita do declare that this is my original work and has never been presented for the award of any degree in this or any other university.

STUDENT:

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The Approval:

This research work has been submitted for examination in the University of Nairobi with my approval as the University supervisor.

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Acknowledgement & Dedication

I acknowledge God for the gift of life and energy to put this work together; my able supervisor for the unwavering support, critique and invaluable guidance; my family for the encouragement and my fellow students and peers for the shoulder they provided.

I dedicate this work to my wife and son whom I love in the truth. God bless and prosper you.

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List of Acronyms

WHO	World Health Organisation
MOH	Ministry of Health
AEO	African Economic Outlook report
UNCTAD	United Nations Conference on Trade and Development
KNBS	Kenya National Bureau of Statistics
LMIC	Low- and Middle-Income Countries
IMF	International Monetary Fund
UN	United Nations
UNDP	United Nations Development Program
S-O-R	Stimulus Organism Response
SARS	Severe Acute Respiratory Syndrome
OLS	Ordinary Least Squares
ANOVA	Analysis of Variance
FE	Fixed Effects
RE	Random Effects

Abstract

The world has been severely hit by the COVID-19 pandemic that has led to the loss of lives and resulted in unquantifiable harm on livelihoods and wellbeing. Using quantitative research design, we analyzed high-frequency longitudinal phone survey data from the World Bank and her partners to investigate if the socioeconomic effects of the pandemic are different among rural and urban households in Kenya.

Generally, we find that location does not significantly influence the severity of COVID-19 effects in the short run. However, it is indeed vulnerable groups such as the poor, marginalized and those that do not possess any education and the unemployed that are severely affected no matter where these groups are located. This agrees with Lakner et al. (2020) who describe the heterogeneity of COVID-19 effects and provide evidence that the most affected people were those who have no education or possess low levels of education, those who own fewer assets or are less wealthy and those in the informal sector. Thus, the pandemic disproportionately affected vulnerable groups such the informal sector, women, youth, people with disabilities among others more than the less vulnerable groups and this is expected to increase the gap between the poor and the rich heightening inequalities (Bundervoet, Dávalos, & Garcia 2022). However, we find that COVID-19 effects were severe for large households, and for those who adopted any form of preventive measures i.e., stayed home, wore masks, practiced social distancing etc. On the contrary, those who practiced farming activities were less likely to lack food.

We recommend that government intervention and recovery policies should target vulnerable groups no matter where they are located. The government should also impose less or no restrictions but instead create awareness and create demand for vaccination as a way of prevention from contracting the pandemic. The government should also enhance and support growth of the agricultural sector and create awareness towards responsible birth control.

CHAPTER ONE

1.0 INTRODUCTION

In the last two and half years, the world has been hit by the COVID-19 pandemic that has led to the loss of lives, revolutionized the way people work and do business, disrupted global supply chains and altered the way people make decisions on their choices. As per the World Health Organization (WHO) (2022) COVID-19 dashboard, the total number of global infections and deaths stood at 494.5 million and 6.1 million respectively as of 8th April 2022. In Kenya, the Ministry of Health's (MOH) (2022) COVID-19 update of 25th April 2022 showed a total of 323,718 cases and 5,649 deaths since the first case was reported on 13th March 2020. This represents a fatality rate of 1.7% and a 92.8% recovery rate. Table 1 below represents details on the Kenya vaccination status as of 25th April 2022.

Table 1: Vaccination status for Kenya

Description (Status)	Administered Doses (Total)
Total Doses Administered	17,871,145
Doses Administered - (18+ years)	16,340,560
Fully vaccinated adult population	8,283,325
Partially Vaccinated adult population	2,626,018
Booster Doses	296,768
Doses Administered - (15-below 18yrs)	1,233,817
Partially Vaccinated- (15-below 18yrs)	801,986
Fully vaccinated- (15-below 18yrs)	216,094
Proportion of adults fully vaccinated	30.40%

Source: *MOH (2022) COVID-19 Vaccination Program- Daily Situation Report. The total vaccine doses administered represent all five vaccine types used in Kenya, i.e., Moderna, AstraZeneca, Pfizer, Johnson &Johnson and SinoPharm vaccines.*

The MOH (2022) COVID-19 Vaccination Program Report indicates that Kenya plans to vaccinate 70% of her adult population by June 2022, which is approximately 19 million adults. The plan is also to fully vaccinate the remaining 30% the end of 2022. Correspondingly, the government aims to vaccinate all 5.8 million teenagers (aged 15-17 years) by the end 2022 while aiming to achieve 50% of this (2.9 million teenagers) by June

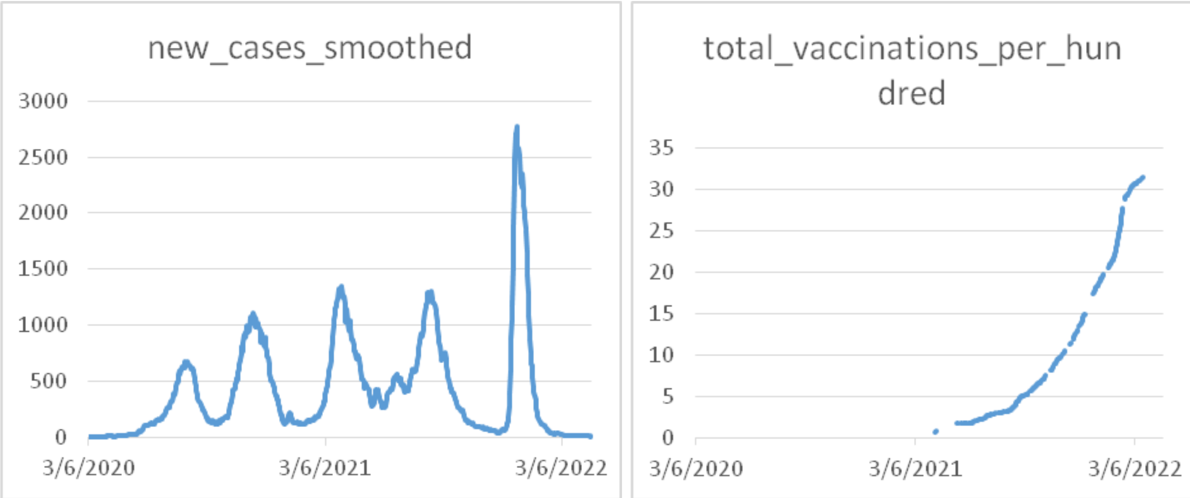
2022. To achieve this, the MOH has allocated targets to the 47 counties as per their population proportions. Figure 1 below is a graphic representation of the top and bottom 10 counties according to adult population vaccination statuses (As of 25th April 2022).

Figure 1: Adult- full vaccination status by county (Top and Bottom 10 counties).

Source: *Author's computation*

From the data, counties like Nyeri (52.6%), Nairobi (48.2%) and Kakamega (39.0%) seem to be on the right trajectory and may achieve close to 100% adult full vaccination status by end of 2022 if the trajectory continues. On the contracly, counties such as Marsabit (9.7%), Mandera (10.3%), Tana River (10.6%), Wajir (11.0%), Garissa (12.7%), Isiolo (12.9%), West Pokot (14.5%), and Kilifi (14.7%) are laggig far behind- below the 15% adult full vaccination. Frome these data, it is evident that Kenya as a whole may not achieve the targeted 100% adult full vaccination by the end of 2022. We also compare the number of new cases per day in Kenya between 6th March 2020 and 20th April 2022 and total vaccinations as shown in Figure 2 below.

Figure 2: New daily infections vis-à-vis total number of vaccinations



Source: *Author's computation*

Figure 2 above shows the four waves of infections that Kenya has experienced since the first case was confirmed in the country vis-à-vis the total number of vaccinations. As Brand et al. (2021) point out, the various waves were occasioned by the level of stringency or non-stringency the restrictions were at the time and how they were adhered to, emergency of new higher-transmissibility variants for example the delta variant and the spread of the disease to more susceptible populations. The increasing number of vaccinations didn't seem to have any effect on the new infection initially, but it is evident that since January 2022 to date the rate of new infections has gone down drastically.

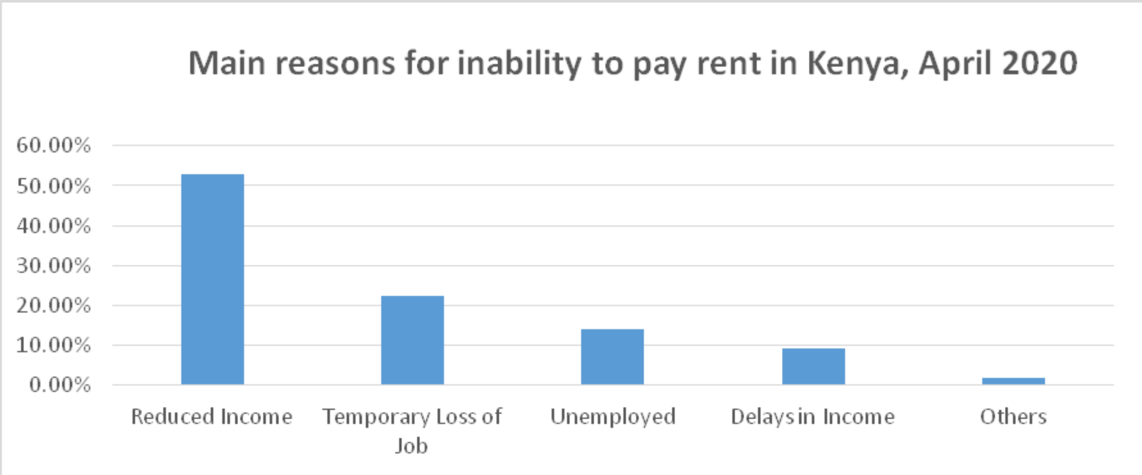
1.1 BACKGROUND OF THE STUDY

Generally, the pandemic has exerted a global negative shock on economies. It is estimated that in 2020 alone, between 119 million and 124 million additional people were pushed into extreme poverty. (World Bank, 2020a); using the $1.90 international poverty line estimate defined by the World Bank. To contain the spread of the virus, various governments responded through various means such as imposition of travel restrictions, closure of learning institutions and businesses, curfew impositions and social distancing requirements. These disruptions led to a worldwide contraction of global economies by an average of 3.5% (IMF, 2021) due to loss of household income. In the African scene, the African Economic Outlook report (AEO) (2021) estimated a 2.1% contraction of the African economy in 2020. The report projects that by the end of 2021, over 39 million people in the continent will fall below the poverty line. According to United Nations Conference on Trade and Development (UNCTAD) (2021), 490 million people lived in extreme poverty in Africa by the end of

2021, and this represents 12 million additional people from the 478 million in 2019. However, this is 37 million people more that the pre-pandemic projections.

These aggregated impacts emanate from household-level socio-economic effects on livelihoods brought about by among others, the disruptions of forces of supply and demand, job losses, business and school closures, work from home arrangements and their effects, restriction of movements etc. In Kenya for example, schools were closed only two days after the first case was detected on 13th March 2020, with employers urged to adopt a work-from-home strategy. Businesses such as hotels and bars were closed indefinitely and on 27th March 2020, a national curfew was imposed restricting movements and affecting businesses immensely (Were, 2020). Lakner et al. (2020) describe the heterogeneity of the effects and provide evidence that the most affected people were those who have no education or possess low levels of education, those who own fewer assets or are less wealthy and those in the informal sector. Thus, the pandemic disproportionately affected vulnerable groups such the informal sector, women, youth, people with disabilities among others more than the less vulnerable groups and this is expected to increase the gap between the poor and the rich heightening inequalities (Bundervoet, Dávalos, & Garcia 2022). In a country like Kenya where 36% of people are poor, the effects are likely to be disastrous (Awiti et al., 2018). Lakner et al. (2020) pointed out that the infections will reduce the active workforce as sickly or dead people won't be able to work. This is worse in the African setting which has a larger informal sector compared to the formal one. The pandemic has also dealt a blow to many households as many decision-makers have had to re-allocate meagre income to purchase items that were otherwise not necessary e.g., masks, sanitizers, gloves, etc. For example, according to the Kenya National Bureau of Statistics (KNBS) April 2020 survey, 30.5% of Kenyans were not able to pay rent on time. This was due to income losses because of pay cuts, job losses, and income reallocation. Figure 3 explores the reasons as per the mentioned survey.

Figure 3: Main reasons why 30.5% of Kenyans were unable to pay rent in April 2020



Source: *Author's computation drawn from KNBS (2020) data.*

Reallocation of household income has led to a reduction in the allocation for basic needs such as food and water purchase, clothing, education among others (Lakner et al. 2020). Additionally, the World Bank (2020b) projects that the disruptions on markets and reduced aggregate demand will exact inflationary pressures leading to price increases on basic commodities.

By combining high-frequency surveys data with those from stringency of containment measures for 31 developing countries, Bundervoet, Dávalos & Garcia (2022) explored the cross and within-country short-term effects of the pandemic on livelihoods using indicators such as learning, employment, food security and income. They found out that 30% of children discontinued learning due to school closures, 36% of the respondents stopped working because of the pandemic and 65% of households reported a decrease in household income. This was as a result of job and business loses that were proportional to how stringent the containment measures imposed were. Further, the study pointed out the heterogeneous nature of the impacts with the vulnerable members of the population such as youth and women and the less educated (mostly in rural areas) who formed the big chunk of the informal sector workers highly affected. These groups are likely to sell off their productive assets leading to a greater loss of livelihoods for the longer term. Evidence is available that lockdown measures though, mostly affected the urban poor in Ethiopia and Nigeria which is replicable in other Low- and Middle-Income Countries (LMICs) (Wieser et al, 2020; World Bank, 2020b).

1.2 STATEMENT OF THE PROBLEM

The pandemic poses a huge, short and long-term negative shock to the global economy due to its effect on the forces of supply and demand. The World Bank (2020a) estimates that the pandemic pushed up to 124 million additional people to extreme poverty globally. According to the IMF (2021), the global economy contracted by 3.5% and this is primarily associated with the loss of household income due to job losses, salary cuts, business closures, curfew impositions among others. There is evidence that these effects were deeper among vulnerable groups such as those without formal education, the informal sector, youth, women, and people with disabilities (Lakner et al. 2020). With 36% of Kenya's population being poor (Awiti et al., 2018), these effects are expected to be disastrous necessitating targeted government intervention.

The question we wish to examine however, is on how these socioeconomic effects are spread-out with the lens of rural-urban geographies in Kenya. Has the pandemic affected both rural and urban populations alike or there are significant differences? Again, are there disparities in the way rural and urban populations coped or are coping with these effects? The UN Habitat COVID-19 response plan report (2020) stressed on the urban nature of the disease pointing out that 95% of all infected cases were in urban centres. According to WHO (2020), internationally connected megacities were the initial major transmission centres of the pandemic. This study follows in spirit of previous studies such as; the United Nations Development Program (UNDP) (2020), Owino (2020), Oyando et al. (2021), Bundervoet, Dávalos, Garcia (2022) & Kiriti-Nganga (2021) among others, all of which have examined the impact of COVID-19 using socioeconomic indicators such as poverty and inequality, refugees, women and girls, education, food security, nutrition, governance among others. This paper will look at the rural-urban disparities in the effects that previous papers have not looked at. There is a need to develop evidence on how rural and urban populations are coping and this will facilitate the government and policymakers to enact targeted policies toward recovery and future resilience.

1.3 RESEARCH QUESTIONS

1.3.1 Overall Research Question

This study seeks to answer this overall question: How are COVID-19 socioeconomic effects distributed between rural and urban populations? Specifically, the study seeks to answer two main questions:

1.3.2 Specific Research Questions

1. Has the pandemic affected both rural and urban populations alike or there are significant differences?
2. Are there disparities in the way rural and urban populations coped or are coping with these effects?

1.4 RESEARCH OBJECTIVES

1.4 .1 General Research Objectives

This study's general objective is to investigate the disparities of COVID-19 impacts between rural and urban populations in Kenya.

1.4.2 Specific Research Objectives

i. To investigate whether COVID-19 affected rural and urban household-level populations differently.

ii. To investigate how the COVID-19 socioeconomic impact disparities are distributed between rural and urban populations in Kenya and how households coped or are coping.

1.5 SIGNIFICANCE OF THE STUDY

This study goes beyond the description of how the shocks occasioned by the pandemic have impacted livelihoods within households to a close examination of how these impacts have been distributed across rural and urban populations in Kenya. More specifically, this study adds a layer to the literature in developing countries by looking keenly at the geographic disparities that exist in Kenya. At a time when COVID-19 infections have begun to abate, this will be very crucial in informing policy formulation and resilience plans that are more targeted other than generalized.

1.6 ORGANIZATION OF THE STUDY

This paper has five chapters: Chapter 1 sets the stage of the study by outlining the introduction, background, statement of the problem and the questions that the study intents to answer. It also describes the objectives of the study. Chapter 2 explores the existing literature. It is categorized into theoretical and empirical literature. Chapter 3 describes the methodology that is used, the models to be estimated and the data availability and source. Chapter 4 represents data analysis and interpretation using Stata software and Chapter 5 presents the findings, conclusion and policy recommendations arising from the findings.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Introduction

This chapter summarizes the literature that exists on how COVID-19 has impacted livelihoods both in Kenya and in other LMICs. It starts by outlining the theoretical literature upon which this study is built and then proceeds to explore various empirical findings from other researchers in the field of study. At the end of the chapter, we provide an overview of the literature.

2.2 Theoretical Literature

2.2.1 The Rational Choice Theory

The concept of rationality in consumer theory was first advanced by Adam Smith in the mid-1770s. It builds on the idea that in a free market economy, rational economic agents (consumers, producers & the government) make choices on how to spend scarce resources subject to individual preferences and budget constraints (Zin & Roper 2013). Rationality describes the concept that economic agents always make decisions that maximize their interests or satisfaction, otherwise known as utility maximization. This is based on prospected costs and rewards (benefits) that may be either monetary or non-monetary i.e., emotional, among others. Rationality is a major cornerstone of neoclassical economics. The theory can be applied in this study as it informs how households are likely to make decisions in an effort to cope with the effects of the pandemic. For example, the importance that an individual places on personal health will inform whether he/she will be willing to stay home as opposed to going to the market to sell his/her wares. This is because going out will increase the cases of infection but also staying home means income forgone from the business.

2.2.2 Game Theory

The concept of Game theory in Economics is originally associated with John von Neumann, a mathematician, and Oskar Morgenstern a 1940s renown economist. The concept was later extended by John Nash who developed the concept of Nash equilibrium (Princeton University Press, 2022). Game theory can simply be defined as the science of strategy and it presents a framework through which different competing players (strategic decision-makers) make decisions that maximize their self-interest (payoff) while in anticipation of what other players' decisions are likely to be. In playing the game, the payoff of one player is dependent on the actions of the other competing player who is also after self-interest optimization. The game is very dependent on what information is available to the players through which they can anticipate the actions of their opponents. The game's optimal level is called the Nash Equilibrium (after John Nash) which is a point where none of the players can better their payoffs by changing their decisions unilaterally.

The COVID-19 pandemic and its effects present a social dilemma as individuals weigh the benefits (payoffs) and losses associated with behavioral change i.e., staying at home, wearing masks, closing businesses, etc. vis a vis the general outcome of slowing down infection rates (Karlsson and Rowlett 2020). This is a game of strategic interaction between players such as the government which seeks to minimize infections through various control measures, the disease seeks to maximize infections, and individuals that have to make decisions to maximize economic outcomes while minimizing the rate of infections. This informs human behavior based on individual preferences and the maximizing behavior of economic agents.

2.2.3 The Prospect Theory/ Loss- Aversion Theory

Developed by Kahneman and Tversky (1979), the Prospect theory describes how people make decisions under situations of risk. Ideally, the theory argues that economic agent's e.g., investors place more weight on perceived gains other than on perceived losses. This is because decisions are based on emotional impact that they bear with losses associated with greater emotional loss. The COVID-19 pandemic poses great uncertainties which will greatly influence the behaviour of consumers, producers and governments. However, how they act and make decisions on various socioeconomic factors will depend on the perceived gains and losses arising from their actions.

1.7.2 Empirical Literature

Using cross-sectional phone survey data, linear regression analysis and concentration curves to examine how the mitigation measures against the spread of COVID-19 impacted livelihoods Nairobi, Kisumu (urban counties) and Kilifi (rural county) in Kenya, Oyando et al. (2021) found a substantial negative impact on the poor and the elderly among other vulnerable groups. Income disruptions were highest (74%) while domestic violence disruptions were lowest (30%). Overall, disruptions in urban counties (Nairobi & Kisumu) were higher compared to those of Kilifi (rural) except for income and food security. Disruptions in learning were Kisumu (48%), Nairobi (50%) and Kilifi (27%).

In a study to determine COVID-19 effects on households in 31LMICs, Bundervoet, Dávalos & Garcia (2022) argue that 65% of households had to cope with reduced income, 36% of respondents stopped working and 30% of children discounted learning activities. They established a positive correlation between job and income losses and the stringency of measures employed by various governments in an effort to curb infections. Contrary to Oyando et al. (2021) findings, learning was more affected in rural areas as opposed to urban areas. However, women, youth, the informal sector and other vulnerable groups bore the brunt of the pandemic.

Heemann, Pape & Vollmer (2022) compared labor market outcomes between rural and urban populations in Kenya during the pandemic. They argue that people from rural areas were unlikely to join the labor force while income from hours worked significantly reduced in urban settings. While it was easy to re-enter employment in the rural areas, people left the workforce much quicker in urban settings than they entered. KNBS (2020) found that in April 2020, 30.5% of households were not able to pay rent on time while 21.5% were unable to pay rent at all in the month. This is due to reduced income.

Furbush et al. (2021) found that in Uganda, Malawi, Ethiopia, and Nigeria, 77% of the population experienced a loss in income and above 40% employed one or more coping strategies. This was either the use of prior savings, asset sale, reduction in food consumption, or help from family or government. They also argue that Malawi and Nigeria experienced above 60% prevalence of food insecurity and overall learning activities fell by 46% in the first few months after the detection of the first case in these countries. The study used longitudinal high-frequency survey data and regression analysis. Josephson, Kilic & Michler (2021) examined the heterogeneity of COVID-19 effects across rural and urban regions and how households coped Uganda, Malawi, Ethiopia, and Nigeria. They found that households in rural settings relied more on the sale of assets. Households in urban settings, however, coped by reducing food consumption and receiving aid from family and friends. Interestingly, income losses were borne similarly between rural and urban populations and the authors found no significant differences. Overall, 42% of the population suffered from job and income losses, increased input prices, disruptions in farming activities, death of income earners and increased food prices with 60% experiencing moderate food insecurity. They found that student-teacher contact had reduced from 96% (before COVID-19) to 17% (post-COVID-19).

Using granular financial data and household-level fixed-effects regressions, Janssens et al. (2021) found that low-income (rural) households in Kenya experienced up to one-third

reduction in income from work in the initial five months. Households reduced giving of remittances and gifts by two-thirds. However, rural households did not reduce food expenditure in order to cope but expenditures on transportation and schooling reduced significantly. Savings were reduced significantly as well as loan repayments. This agrees with Hrishipara Daily Diaries (2020) who found a 75% drop in income in Bangladesh in the first week of the pandemic. This study used a peri-urban sample as opposed to Janssens et al.'s rather rural sample. The Population Council (2020) found that 80% of respondents in Kenya's five largest informal settlements had experienced income loss and food price increases, with evidence of reduced food consumption. At least two in every three respondents had gone without a meal (at least once) two weeks before the survey.
Using qualitative phone interviews and household-level fixed effects regressions, Zollmann et al. (2020) estimate that 88% of their Kenyan respondents had had decreased income resulting from the pandemic effects. Further, the study shows the severity of the effects was experienced in urban regions. This is almost similar to Le Nestour, Mbaye, Sandefur, & Moscoviz (2020) study in Senegal that found 86% of respondents experienced below-average income in the early days of the infections. BRAC International, (2020) concluded that most respondents in Rwanda, Uganda, Liberia, and Philippines, reported less food consumption as compared to the pre- COVID-19 pandemic times in the urban regions. Middendorf et al. (2021) found that in Senegal 82.5% of the respondents feared that they would not get enough food because of closure of markets (79.5%) or due to disruption of markets (73.2%).

Hambira, Stone, & Pagiwa, (2022) argue that, in Botswana, the pandemic led to revenue losses, job losses, and business closures among other social-economic effects. In South Africa, Turok & Visagie (2021) estimate that 61% of rural dwellers had no money to buy food. This was the same for 48% of those dwelling in urban areas.

Kansiime et al. (2021) used probit regression analysis and found that 70% of their respondents in Uganda and Kenya had experienced reduced income because of the pandemic effects. The effect was 73% in Kenya. Poor food consumption was evident among income-poor respondents. Using multivariate regression, Mulugeta et al. (2021) argue that additional unexpected expenditures such as buying masks, sanitizers, detergents, etc. led to the diversion of income from purchase of basic commodities in Ethiopia. Kithiia et al. (2020) studied how the pandemic had affected Mombasa residents in Kenya and argue that 31% of the respondents experienced income losses while 7% felt that expenditures had gone up.

Kathula (2020) and Kiriti-Nganga (2021) studied COVID-19 effects on the Kenyan education sector using mixed-methods analysis. The studies reveal that the pandemic negatively impacted learning in Kenya with rural children unable to continue with learning due to lack of tools i.e., internet access, laptops, smartphones etc. In Ghana, Aduhene & Osei-Assibey (2021) found that the pandemic had negatively impacted learning in rural areas due to lack of technology.

Mekonnen & Amede (2022) found that in Uganda and Kenya, there was an increase in food insecurity by 44% and 38% respectively because of the pandemic. Hirvonen (2020) points out that the pandemic led to significant employment effects in urban sub-Saharan Africa (SSA) and lockdowns led to a 19% reduction of income in urban households in Ethiopia. Aragie et al., 2021 estimated this at 12.6% in rural households. Abay et al. (2020) argues that 50% of Ethiopians (out of the sample) could not meet their need for food and 11.7% of households in Ethiopia experienced food insecurity. In Uganda, rural households experienced a 44% decrease in food expenditure (Mahmud & Riley, 2021). In India Singh (2020) argues that farmers in the informal sector are at a significant risk to fall into extreme poverty.

On a global scale, Khetan et al. (2022) examined how the pandemic had affected livelihoods across five continents and found that 32.4% of participants reported financial loss, 8.4% lost their jobs, 14.6% could not meet their basic needs financial obligations and 16.3% had resulted to use of savings in order to survive. The study focused on both rural and urban settings.

Traoré, Combary & Zina (2022) used pooled multinomial logistic regressions to assess how COVID-19 had affected access of health and basic foods in Burkina Faso. They found that households in rural areas obtained basic foods with less difficult compared to urban residents.

1.7.3 Overview of Literature

COVID-19 is developing phenomenon and although literature about its socioeconomic impacts on people is building up, there is still a lot to be studied. Overall, using different methods and techniques such as qualitative and quantitative methods, systematic reviews, econometric regression models, mathematical modelling to predict future trends, etc. the literature suggests that the pandemic has led to significant widespread effects on people’s livelihoods both in Kenya and many other developing and low-income countries, as well as in the world. In general, vulnerable groups such as the poor, less educated, youth and women, and those in the formal sector have borne the brunt of the pandemic. It has greatly impacted socioeconomic factors such as; education/learning, food security, income, and health, among others. However, the heterogeneity of these effects as disaggregated by different factors such as; gender, region (rural/urban), status (poor/rich), age, household size, etc. is not very well defined in the long run. Most studies have documented the short-run effects using data that spanned only weeks or months into the pandemic. With the cases beginning to abate and the pathway to recovery taking center stage, there is a need to analyze data that spans the whole period of the pandemic in Kenya; 13th March 2020 to date in order to understand how deep the effects are. There is particularly no study that looks at the rural/urban heterogeneity of the effects using widespread data from across Kenya. This is what this study seeks to examine.

CHAPTER THREE: METHODOLOGY

3.0 Introduction

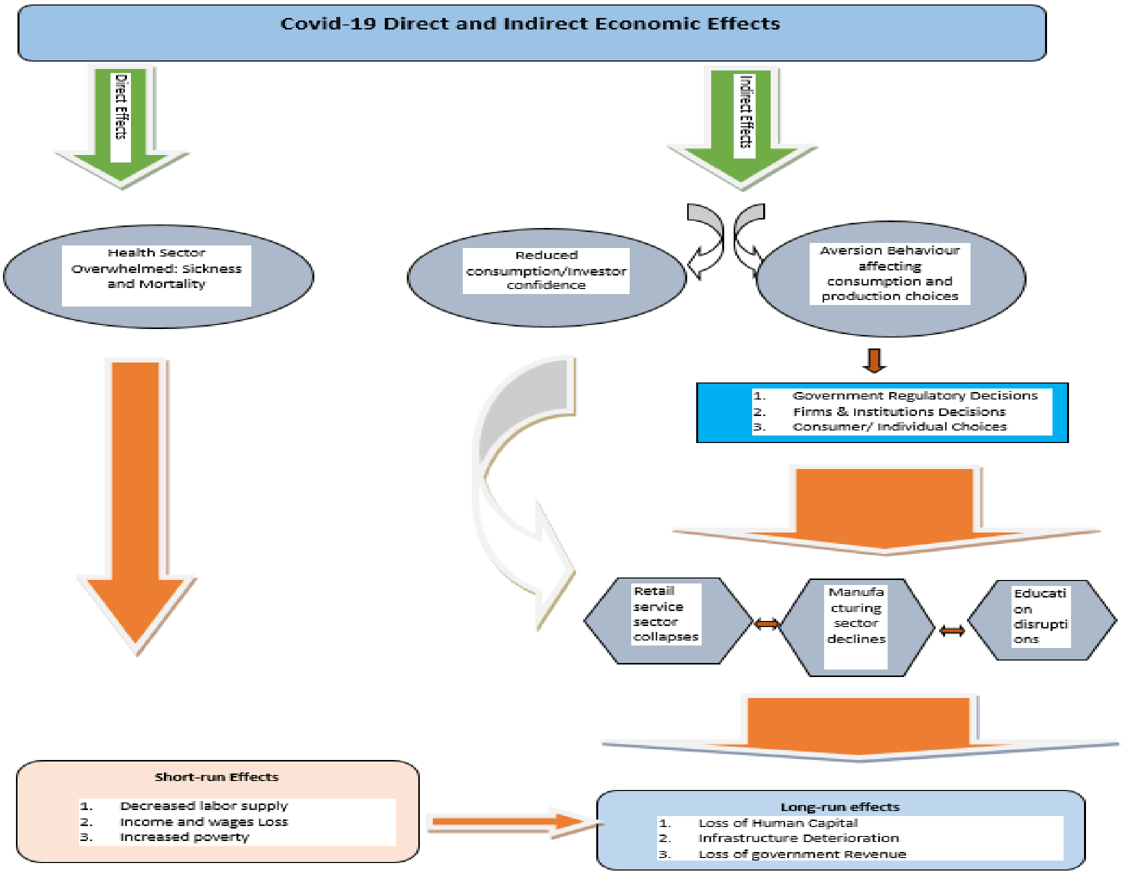
The chapter describes the conceptual framework upon which the study is built, the model specification, how the variables are defined and measured, data sources and management and the diagnostic tests.

3.1 Conceptual Framework

3.1.2 The Linkage between COVID-19 and the Economy

We build on the concept of rationality in consumer theory that was first advanced by Adam Smith in the mid-1770s. In a free market economy, rational economic agents (consumers, producers & the government) make choices on how to spend scarce resources subject to individual preferences and budget constraints (Zin & Roper, 2013). We present the theoretical economic linkage between the COVID-19 pandemic and the performance of the economy by exploring both direct and indirect pathways of impact as described in Figure 4 below, adopted from Evans & Over (2020).

Figure 4: Theoretical Linkages between COVID-19 and the Economy



Source: Authors compilation, adopted from Evans and Over (2020).

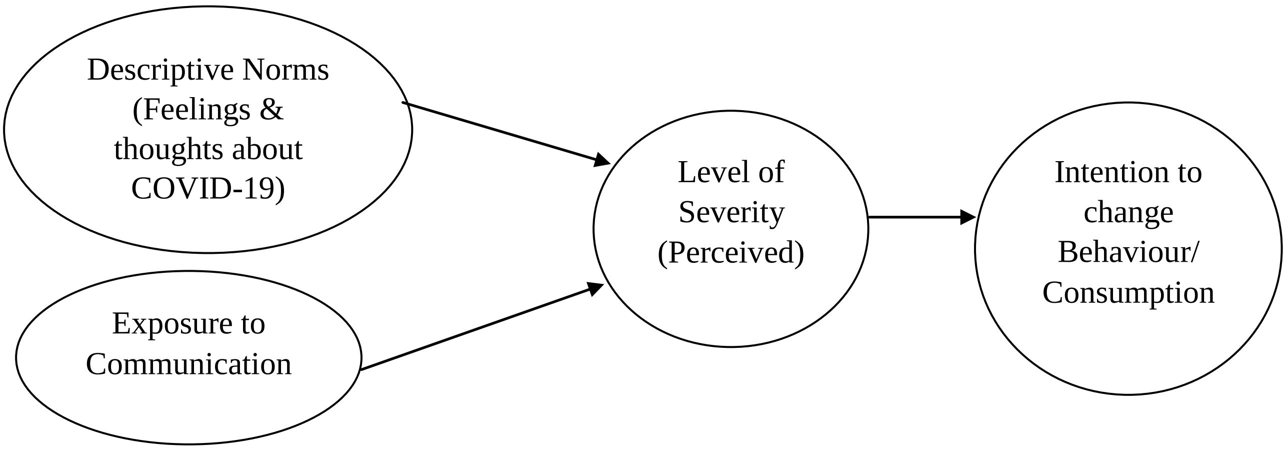
More directly, the pandemic led to sickness and deaths which reduced the number of active working hours leading to negative labor supply shocks. This led to the overburdening of the health sector as well as negligence of care of other disease burdens e.g., Malaria, Cancer, Children immunization, etc. (Singh 2020; Evans & Over 2020). The resultant short-run effects are reduced income & wages leading to increased poverty levels as households have to allocate reduced disposable income to meet their wants. In the long-run aggregate demand decrease leads to reduced production of goods and services.

The pandemic-induced uncertainties greatly influence consumer/investor confidence in making consumption/ investment decisions (Evans & Over 2020). This is due to the consumer/ producer aversion behaviour in making consumption and production choices arising from the measures that the government, individuals and firms took to curb infections e.g., closures of learning institutions, closure of bars and hotels, travel restrictions, curfew impositions, work-from-home arrangements etc. This impacted sectors such as manufacturing, education, retail services, trade and transport resulting to reduced income hence reducing aggregate demand and production. In the long run this would negatively impact human capital development (i.e., due to disruptions in learning activities), infrastructure deterioration and lead to loss of government revenue.

3.1.3 The Stimulus Organism Response (S-O-R) Model

The model was first developed by Mehrabian and Russell (1974) to explain consumer behaviour in the context of changing environment. The model presents the linear relationship between its three components i.e., stimulus, organism and response. The stimuli, defined as anything that can affect or influence an individual (organism), influences response through the cognitive and affective process that the individual (consumer) goes through as triggered by stimuli (Eroglu et al., 2001 & Xu et al., 2014). The S-O-R framework is a useful theoretical base to understand consumer behaviour during pandemics. The COVID-19 pandemic presents an exogenous shock or stimuli in the environment, influencing consumer choices through their consumption behaviour. Through a bidirectional response, consumers and businesses respond to the changes either directly or through avoidance behaviours as demonstrated in Figure 5, (Donovan and Rositer 1982).

Figure 5: Diagrammatic Representation of the S-O-R Model.



Source: Author's compilation: Adopted from (Renjini & George 2020).

Evidence from Ebola and SARS (Severe Acute Respiratory Syndrome), shows that pandemics affect human behaviour mainly through health mitigation efforts and consumer behaviour (Miri et al., 2020). The changes are accelerated by the resultant economic recession and unemployment (Laato et al. 2020). Communication and descriptive norms, that is, what most people think and feel about the pandemic affect the perceived severity of the pandemic leading to changes in consumption behaviour of the consumers. Due to income losses, consumers are will most likely consume less good and services, reduce or use savings to buy basic things, sell assets to cover for the income loss among others.

3.2 Model Specification & Estimation Techniques

Krouglov and Alexei 2020 found that the COVID-19 negatively impacted the economy through the supply-side shock. As a result of sickness and deaths, active working hours were reduced from the labor supply resulting to the short-run effects of reduced income and wages among others. This influenced consumer consumption behaviour negatively affecting aggregate demand in the long run. We build on the model used by Xiang, L., et al (2021) to demonstrate how the pandemic affected labor supply in the economy leading to detrimental socioeconomic impacts.

Assume that the total population at time t is given by P_t ;

We can show that:

$P_t = S_t + I_t$ ……………………………………………………………….………1

Where: S_t is the susceptible population and I_t is the already infected population.

Assume that: b = birth rate and d = death rate of the whole population.

$P_t = bP_t - dP_t$ …………………………………………………………………2

Assuming that one can become infected by coming into contact with an infected person and that once healed, one becomes susceptible to infection again, we can obtain the following differential equations:

$\dot{S}_t = bP_t + \gamma I_t - \alpha(I_t/P_t)\, S_t - dS_t$…………………………………………….…………..3

$\dot{I}_t = \alpha(I_t/P_t)\, St - dI_t - \gamma I_t$ ……………………………………………….….……..4

Where: γ is the rate of recovery and α is the rate of contact between the susceptible and the infected. Assuming random contact between the infected and the susceptible, the probability of contact is shown as the proportion of infected people out of the total population. This is given by:

$i_t = I_t/P_t$ ………………..………………………………………………………5

But the susceptible people's proportion out of the whole population is given by:

$s_t = S_t/P_t$ ……………………..………………………………………………………………6

This can further be shown as:

$s_t = S_t/P_t = 1 - i_t$ ……………..…………………………………………………………...7

Assuming that:

Death rate (infected population) = Death rate (total population); we can rework equations 2, 3 and 4 to obtain:

$\dot{s}_t = i_t (b + \gamma - \alpha s_t) = (1-st)(b + \gamma - \alpha s_t)$……………………………..……………………..8

During the pandemic, people in the active labor force are more vulnerable to contract the virus as compared to the whole population. This is because they are forced to go out for work and other business engagements rather than stay home. They are therefore more susceptible compared to the rest of the population. Thus, equation 8 above shows how labor supply changes dynamically during the pandemic.

Using the model advanced by Krouglov and Alexei 2020, we show how COVID-19 affected the demand-side in the long run. We begin by assuming that the pandemic permanently removed part of the labor supply from market. When the market is at equilibrium with no shocks, the forces of supply and demand act together to determine production and price levels of commodities.

Assuming a single commodity economy for example, assume that the market is at equilibrium until time $t = t_0$

We can show that:

$V_S (t) = V_D (t)$ ……………….…………………….…………………………….……………..9

Where: V_S (t) is the volume of product supply and V_D (t) is the volume of product demand.

If both V_S (t) and V_D (t) are developing with a constant rate, say r^0_D and that the commodity price, say P(t) at that time was fixed, we can show that:

$P(t) = P^0$ ………………………………………………………………………………10

$V_D\ (t) = r^0{}_D\,(t\text{-}t_0) + V^0{}_D$ …..……………………………………………………………11

Where: $V_D\ (t_0) = V_D{}^0$

COVID-19 is a supply shock in the economy breaking the equilibrium state that exists. However, market forces act to return the economy back to equilibrium. Assume the said supply shock, say $S_{SS}\,(t)$, develops with a constant acceleration since time

$t = t_0$ according to the formula :

$$S_{SS}\,(t) = \begin{cases} 0, & t < t_0 \\ \delta_{SS}\,(t\text{-}\ t_0) + \varepsilon_{SS}/2\ (t\text{-}t_0\,)^2\ , & t \geq t_0 \end{cases}$$

Where; $S_{SS}\,(t) = 0$ for all t that are greater than t_0

We obtain the following ordinary differential equations to show how market forces act to bring the market back to equilibrium state.

$dP\ (t)/dt\ \ = -\ \lambda_p\ \boldsymbol{(}\ V_S\,(t)\text{-}\ V_D\ (t)\ \text{-}\ S_{SS}\,(t))$……………………………………………………12

$d^2\ V_S\,(t)/\ dt^2 = \lambda_S\,(\ dP\ (t)/\ dt)$ ……………………………………………………….13

$d^2\ V_D\,(t)/\ dt^2 = -\lambda_D\ (\ d^2\ P(t)/\ dt^2)$ ……………………………………………………14

Where: λP, λS, $\lambda D \geq 0$ are constants. They represent the change in price, supply and demand in the economy respectively. It can be seen that the pandemic affected the economy through the supply-side shock which negatively affected the aggregate demand in the long-run.

3.2.1 Variable Definition and Measurement

To examine if one’s location (rural or urban) has any significant influence on the severity of the impacts of COVID-19 on Food Security, Income and various Coping mechanisms adopted by the respondents, we carry out panel data analysis using available longitudinal data collected by the World Bank across seven waves between March 2020 and February 2022. We define and estimate various panel data models to examine the random and fixed effects of location on the dependent variables. Given the available data for Kenya, the variables of interest are outlined as shown on Table 2. For scaling purposes and simplicity, we generate and use the natural log (ln) for various variables as indicated.

Table 2: Dependent Variables- Definition & Measurement

Category	**Dependent Variable (Y_{it}) Abbreviation**	**Type of Data Category**	**Measurement**
Food Security	Fs_Hungry Scaling: lnFs_Hungry= Natural log of Fs_Hungry	Discrete	It indicates the number of households that were hungry in the past 30 days before the data collection date but did not eat because they lacked enough money to buy food due to the adverse effects of the pandemic. The data is weighted by household weight and is available for all the six waves.
Food Security	Prev_AnyStaple. Scaling: lnPrev_AnyStaple=natural log of Prev_AnyStaple	Discrete	It indicates the number of households that had access to any staple food item within seven days before data collection date, when needed. The indicator is observed in all waves except wave 5
Income	Sold_Asse Scaling: lnSold_Asse= natural log of Sold_Asse	Discrete	It indicates the number of households which sold assets such as property to use the money for basic living expenses. This is as a result of reduced income earnings due to job losses, salary decrement among others. The indicator is observed in all waves except wave 4
Coping	Used_Sav Scaling: lnUsed_Sav= natural log of	Discrete	It indicates the number of households which used savings for basic living expenses. It is observed

	Used_Sav		in all waves except wave 5.
Coping	Red_Consu Scaling: lnRed_Consu=natural log of Red_Consu	Discrete	It indicates the number of households which reduced their consumption of essential or non-essential items. The indicator is observed in all waves except wave 5

The explanatory variables (X_{it}) are described as shown on Table 3.

Table 3: Explanatory Variables- Definition & Measurement

Category	Explanatory Variable (X_{it}) Abbreviation	Type of Data Category	Measurement	Expected Sign	References
Location	Loc	Dummy	It indicates whether the respondent is from urban or rural locality. The indicator is equal to 1 if urban or 0 if rural and is observed across the six waves.	+ve /-ve	Oyando et al. (2021); Bundervoet, Dávalos & Garcia (2022); Josephson, Kilic & Michler (2021); Mahmud & Riley, 2021; Traoré, Combary & Zina (2022)
Education	No_Educ Scaling: lnNo_Educ= natural log of	Discrete	It indicates the number of respondents who have no education at all. The indicator is observed in waves 1, 5 and 6	+ve	Kathula (2020); Aduhene & Osei-Assibey (2021)

	No_Educ				
Household Size	Hsize	Continuous	It indicates the average number of people in a household, weighted by the household size. Data is available across the six waves for this indicator	+ve	Gillies, C et al. (2022)
Labor Farm	Labor_farm Scaling: lnLabor_farm= natural log of Labor_farm	Discrete	It indicates the number of households that are engaged in any farming activities. The indicator is available for all waves.	-ve	Heemann, Pape & Vollmer (2022)
Preventive behaviors	Prev_AnyPrev Scaling: lnPrev_AnyPrev= natural log of Prev_AnyPrev	Discrete	It indicates the number of households that adopted any preventive behaviours (did not go to work, kept social distancing, etc. The indicator will help examine how restrictions affected people's livelihoods. The indicator is available in all six waves.	-ve	Aschwanden, D et al. (2021)

3.2.2 General Econometric Model for Estimation

The general econometric model for estimation is given by:

$Y_{it} = \beta_0 + \beta_1 X_{it1} + \beta_2 X_{it2} + \beta_3 X_{it3} + \beta_4 X_{it4} + \beta_5 X_{it5} + \mu_i$ 15

Where:

Y_{it} = *lnFs_hungry, lnSold_Asse, lnRed_Consum, lnPrev_AnyStaple and lnUsed_Sav*

β_0 = the constant term

β_{1}- β_{5} = the unknown population parameters to be estimated

X_{it} = Explanatory Variables (*Loc*, *lnNo_Educ*, *Hsize*, *lnLabor_Farm*, *lnPrev_AnyPrev*)

μ_{i} = the error term

3.2.3 Specific Models for Estimation-OLS

Specifically, we estimate the following regression equations to examine both random and fixed effects of location on the various socioeconomic variables (Y_{it})

i. $lnFs\_hungry = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$ ……………………………………………………………16

ii. $lnSold\_Asse = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$ ……………………………………………………………17

iii. $lnRed\_Consum = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$ …………………………………………….…………...18

iv. $lnPrev\_AnyStaple = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$ …………………………………………………………....19

v. $lnUsed\_Sav = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$ ………………..……………………………………….….......20

3.3 Fixed Effects and Random Effects Model

Since the study uses panel data analysis, we estimate both the FE and RE models. To remove biasedness from the estimated coefficients due to omitted time-invariant characteristics (unobserved heterogeneity for individuals/households) we estimate the Fixed Effects (FE) model. The model controls for time-invariant differences between the households that cannot be estimated in the random model.

The model is given by;

$Y_{it} = \beta_0 + \beta_1 X_{it1} + \beta_2 X_{it2} + \beta_3 X_{it3} + \beta_4 X_{it4} + \beta_5 X_{it5} + \mu_i + \varepsilon_{it}$ ……………………………………………………………………..…….….…………21

Where;

$I =$ household/ individual (i-n)

$t=$ time period

$\beta_0 =$ Intercept

X_{it1}- X_{it5} = Household characteristics

$\mu_i =$ fixed effects or unobserved effects (individual)

$\varepsilon_{it} =$ idiosyncratic error (unobserved factors that can influence Y_{it}.)

The Random Effects (RE) model represents random variations across households which are uncorrelated with both the dependent and independent variables. The model is given by:

$$Y_{it} = \beta_0 + \beta_1 X_{it1} + \beta_2 X_{it2} + \beta_3 X_{it3} + \beta_4 X_{it4} + \beta_5 X_{it5} + \delta_j + \gamma_t + \varepsilon_{it} \quad \ldots\ldots 22$$

We use the Hausman test to determine which model between FE and RE gives reliable results.

3.4 Source of Data

The study uses a quantitative research design in its analysis. It utilizes high-frequency longitudinal phone survey data that was and is being collected by the World Bank and her partners to track how COVID-19 has impacted households in 83 countries of the world. The data are aimed at providing real-time information on how COVID-19 has influenced household choices on topical issues that influence their wellbeing. It tracks 155 socioeconomic indicators in a series of seven waves. All data sets have been harmonized to standardize them since different questionnaires were used for different countries.

The indicators are categorized into: Demographic Characteristics (education, disability, dependency ratio, gender, household size and age); Geography (rural, urban and national); Housing Characteristics (homeowner, recent mover, rent payment ability, number of rooms per household); Food Security (food security, access to staple foods, access to water); Education (educational activities engagement, school enrolment); Health (access to medical services); Labour (working or not, job changes, work sector); Income (income shock, remittance decline); Safety nets (any assistance? type?); Coping mechanisms (sale of assets, reduced consumption, use of savings kept the future); Financial (access to financial institutions (ATM, Bank, Mobile Money); Preventative Behaviours (adopted handwashing and social distancing practices) and Subjective wellbeing (life satisfaction now and in one year, concern about coronavirus). This study specifically examines the Kenyan data to investigate the socioeconomic disparities between urban and rural populations. The samples are given as follows: Wave 1 = 5389; Wave 2= 6191; Wave 3= 6462; Wave 4= 4892; Wave 5 = 7410; Wave 6= 7172 and Wave 7 =6914.

3.5 Descriptive statistics

We carried out initial descriptive statistics to determine data frequencies, means, standard deviations, minimum and maximum values etc. We also analysed the Analysis of Variance section (ANOVA) section such as SS, R-Squared, Root MSE to determine the suitability of the model. The analysis is done at 95% confidence interval.

3.6 Data Limitations

In the time of COVID-19 pandemic most studies have made use of high-frequency surveys due to restrictions and difficulties around data collection activities. Although the data have been weighted to adjust to any differential differences, we point out some of the limitations that we envisage. Firstly, there is a likelihood of under coverage on those who do not own phones or have poor network coverage. The weights are carried out in a way that takes care of selection bias that would arise due to some respondents not having mobile phones or due to poor network coverage. Secondly, depending on the length of the phone-interview, this can limit the depth of the information given by the respondents.

3.7 Diagnostic Tests

3.7.1 Goodness of fit Test

This was determined using the R^2 value generated from the statistical analysis software STATA. The higher the value, the better our model is. R^2 shows the extent to which Y is influenced by the X variables.

3.7.2 Hausman Test: Fixed and Random Effects

To decide between FE and RE we run a Hausman test. The test helps determine if the unique errors (μ_i) in our model are correlated with the explanatory variables. It enables us to determine whether to use fixed or random effects model.

3.7.3 Autocorrelation Test

Using STATA, we perform the autocorrelation test to see if there is serial correlation in the data. In case there is serious autocorrelation, we use the Newey West standard errors, correct the misspecification of the model or make use of instrumental variable (IV) regression.

CHAPTER 4: DATA ANALYSIS, RESULTS AND DISCUSSION

4.0 Introduction

This chapter describes the findings obtained from the data analysis carried out to investigate the disparities in COVID-19 impacts on various socioeconomic factors between rural and urban populations in Kenya. Data analysis was done using Stata statical software version15.1. In this chapter, we present the descriptive statistics, econometric estimation results and discussion, and diagnostic tests to ascertain the validity of the model used.

4.1 Descriptive Statistics

Table 4 shows the descriptive statistics of the various variables with a specific focus on mean, median, standard deviation, frequency, and maximum and minimum values for each variable.

Table 4: Descriptive Statistics

Variable	Obs	Mean	Standard Dev.	Min	Max
Loc	45	.4888889	.505525	0	1
Demo_Hsize	44	2.495889	.892086	1.418151	4.502116
lnFs_hungry	42	7.820454	.277424	7.261527	8.542707
lnSold_Ass	32	5.360918	1.40019	.5438412	6.81468
lnRedu_Consu	32	7.889651	.2660195	7.444874	8.397142
lnUse_Sav	31	7.783802	.2951907	7.199846	8.397224
lnPrev_anystaple	30	8.422419	.1538737	8.080194	8.707286
lnPre_AnyPrev	44	8.802706	.1152334	8.489664	8.906096
lnLabor_farm	36	7.212427	.867255	5.140862	8.769145
lnNo_educ	37	4.434897	1.688879	.1147238	6.59843

Source: Authors Computation

From the results, location has a minimum value of 0 and a maximum value of 1. This is because it is a dummy variable, and it takes the value of 1 if urban and 0 if rural. The average household size for the sampled households is 2.49 people for both rural and urban population. It is important to note that 48.8% of the households interviewed were from urban settings while 52.2% were from rural areas. This presents quite a well-balanced sample between rural and urban households.

4.2 Correlation Analysis

To test if there is serious correlation between the variables, we present the correlation analysis matrix obtained on Table 5.

Table 5: Correlation Analysis Matrix

Corr. Matrix	lnFs_Hungry	lnSold_Asse	lnRedu_Consu	lnUse_Sav	lnPrev_anystap	lnPre_AnyPrev	lnLabor_farm	lnNo_educ
lnFs_Hungry	1.0000							
lnSold_Asse	0.0198	1.0000						
lnRedu_Consu	-0.0701	0.0384	1.0000					
lnUse_Sav	-0.1001	-0.1913	0.5822	1.0000				
lnPrev_anystap	-0.4063	0.6446	-0.2504	-0.4088	1.0000			
lnPre_AnyPrev	-0.2704	0.0473	-0.6508	-0.3581	0.4268	1.0000		
lnLabor_farm	-0.3843	-0.1687	-0.1646	-0.4976	0.3352	0.1072	1.0000	
lnNo_educ	-0.0305	0.6050	0.3278	0.1799	0.3294	-0.3774	0.1517	1.0000

Source: Author's computation

Based on the correlation matrix results, all the variables of the model are least or moderately correlated with each other. There are therefore no cases of perfect collinearity between them. This means that the model is reliable and won't give biased results due to serious collinearity.

4.3 Econometric Estimation

4.3.1 OLS Estimation Results

We first estimate the OLS regression model. Table 6 shows the results obtained from the OLS estimation for model 1. We also include the time parameters in the analysis (where they are significant), but as we shall see later, the joint time variables are not statistically important.

Table 6: OLS Estimation Results- Model 1

Model 1: $lnFs\_hungry = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$

Y= lnFS_hungry	**Coef.**	**P>t**	**[95% Conf. Interval]**

Loc	-.1456586 (.1187375) Wave (5,6,7) .6822054*** .5507826*** .4015963**	0.235 0.001 0.004 0.030	-.3941791	.1028618
lnNo_educ	-.0566163 (.0468527)	0.242	-.1546801	.0414476
Demo_hsizeHsize	.2884626** (.1077238)	0.015	.062994	.5139311
lnLabor_farm	-.1148228 (.0687337)	0.111	-.2586841	.0290385
lnPre_AnyPrev	1.857807** (.8035205)	0.032	-3.539595	-.1760193
_cons	24.69874** (7.185861)	0.003	9.658555	39.73892
R-squared = 0.3849 Prob > F = 0.0777*				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

The R-squared value shows that the independent variables explain 38.5% of variations in the dependent variable. We find that households in the urban areas had a 14.6% less chance of going hungry in the past one month before the data collection date but did not eat because they lacked enough money to buy food due to the adverse effects of the pandemic. This is as opposed to households in the rural settings. However, this is not statistically significant at 1%, 5% or 10%. Therefore, location did not influence lack of food by households. However, in the long run, the severity of lack of food shifts to urban households. In waves 5 6, and 7, 68.2%, 55.1% and 40.2% of urban households lacked food compared to their rural counterparts. This is important in understanding how the effects are shifting over time. Our findings agree with Oyando et al. (2021) who found that overall, the disruptions in food security and income losses caused by the pandemic in urban counties (Nairobi & Kisumu) were higher compared to those of Kilifi (rural). It is important to note that an increase in household size by one person increased the likelihood of the household going hungry by 28.8% notwithstanding where the households are located. This is expected as it will mean a higher food demand at the household level. Those households who adopted any preventive behaviour (did not go to work, kept social distancing, etc.) had a 18.7% chance of going hungry no matter where they are located. This agrees with Abay et al. (2020) who argued that 50% of their respondents could not meet their food needs and 11.7% of households in Ethiopia experienced food insecurity due to the restrictions adopted. In Uganda also, rural households experienced a 44% decrease in food expenditure (Mahmud & Riley, 2021) and Population Council (2020) found that 80% of respondents in Kenya's five largest informal settlements had experienced income loss and food price increases, with evidence of reduced food consumption. The study further found that at least two in every three respondents had gone without a meal (at least once) two weeks before the survey. On the other hand we find that engagement in farming activities and lack of education does not influence food security. Those engaged in labor farming activities were 11. 5% less likely to lack food as opposed to those who did not practice any farming.

Table 7 shows the OLS estimation results for Model 2.

Table 7: OLS Estimation Results- Model 2

Model 2: $lnSold\_Asse = \beta_0 + \beta_1 Loc + \beta 2lnNo\_Educ + \beta_3 Hsize + \beta 4lnLabo\_farm + \beta 5lnPrev\_AnyPrev + \mu_i$

Y= lnSold_Ass	Coef.	P>t	[95% Conf. Interval]	
Loc	-.392339 (.7361946)	0.605	-2.012692	1.228014
lnNo_educ	.5996394** (.2525861)	0.037	.0437012	1.155578
Demo_hsizeHsize	.4232319 (.697979)	0.557	-1.11301	1.959473
lnLabor_farm	-.4771279 (.4163225	0.276	-1.393447	.4391916
lnPre_AnyPrev	.7840044 (4.698884)	0.871	-9.558169	11.12618
_cons	-2.25809 (41.70018)	0.958	-94.03957	89.52339
R-squared = 0.5100 Prob > F = 0.1172				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

The R-squared value shows that the independent variables explain 51.0% of variations in the dependent variable. We find that location does not influence in a significant manner, the sale of assets by households in an effort to cope with the effects of the pandemic. Nonetheless, rural households' propensity to sell assets in order to cope is higher by 39.2% compared to urban households. This agrees with Josephson, Kilic & Michler (2021) who examined the heterogeneity of COVID-19 effects across rural and urban regions and how households coped in Uganda, Malawi, Ethiopia, and Nigeria. The authors found that households in rural settings relied more on the sale of assets. However, the variable is not statistically significant in our study. Furbush et al. (2021) also found that in Uganda, Malawi, Ethiopia, and Nigeria, 77% of the population experienced a loss in income and over 40% of households employed one or more coping strategies. This was the use of prior savings or asset sale. Interestingly, income losses were borne similarly between rural and urban populations and the authors found no significant differences.

Importantly, those without education had a 59.9% chance of selling assets in order to cope with COVID-19 impacts. This agrees with Lakner et al. (2020) who describe the heterogeneity of COVID-19 effects and provide evidence that the most affected people were those who have no education or possess low levels of education, those who own fewer assets or are less wealthy and those in the informal sector. Thus, the pandemic disproportionately affected vulnerable groups such those in the informal sector, women, youth, and people with disabilities more than the less vulnerable groups and this is expected to increase the gap between the poor and the rich heightening inequalities (Bundervoet, Dávalos, & Garcia, 2022).

However, household size, involvement in farming activities and the adoption of any preventable measures did not, significantly affect the sale of assets by the households at least in the short run. We expect that the results could be different in the long term.

Table 8 shows the OLS estimation results for Model 3.

Table 8: OLS Estimation Results- Model 3

Model 3: $lnRed\_Consum = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$

Y= lnRedu_Consu	**Coef.**	**P>t**	**[95% Conf. Interval]**	
Loc	-.0662036 (.0988264) Wave (2,3,6) .6450562*** .4974461*** .5078817***	0.517 0.001 0.006 0.000	-.2837192	.1513119

lnNo_educ	.0432251 (.033907)	0.229	-.0314038	.117854
Demo_hsizeHsize	-.167114 (.0936964)	0.102	-.3733383	.0391104
lnLabor_farm	-.0102014 (.0558869)	0.858	-.1332077	.1128049
lnPre_AnyPrev	1.261294* (.6307761)	0.071	-2.649623	.1270349
_cons	19.11499*** (5.597814)	0.006	6.794285	31.4357
R-squared = 0.4753 Prob > F = 0.1582				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

In the long run, we find that households in the urban areas reduced consumption of essential and non-essential items more than their rural counterparts. On average, 64.5%, 49.7% and 50.8% of households in urban centres reduced their consumption of essential and non-essential items compared to their rural counterparts in the last three waves. This could be associated with the re-allocation of meagre income by urban populations to purchase items that were otherwise not necessary e.g., masks, sanitizers, gloves, etc. The re-allocation of household income led to a reduction in the allocation for basic needs such as food and water purchase, clothing, education among others (Lakner et al. 2020). These findings agree in part with the findings of Population Council (2020) who found that 80% of respondents in Kenya's five largest informal settlements had experienced income loss and food price increases, with evidence of reduced food consumption. Janssens et al. (2021) also found that low-income (rural) households in Kenya experienced up to one-third reduction in income from work in the initial five months of the pandemic.

Lack of education, household size and the practice of farming activities did not influence the propensity to reduce consumption of essential and non-essential items as this is not significant in our data. However, those who adopted any preventive measures had a 12.6% more chance of reducing consumption of essential and non-essential items. This is expected because money that was meant for food and other items may have been used to buy masks, sanitizers, etc. Again, as Abay et al. (2020) points out, restrictions affected livelihoods negatively because households that adopted any preventive behaviours (did not go to work, kept social distancing, etc.) experienced a loss in income because they did not open their businesses, go to work etc. They found that 50% of households in Ethiopia could not meet their need for food and 11.7% experienced food insecurity due to the restrictions adopted.

Table 9 shows the OLS estimation results for Model 4.

Table 9: OLS Estimation Results- Model 4

Model 4: $lnPrev\_AnyStaple = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$

Y= lnPrev_anysta~e	**Coef.**	**P>t**	**[95% Conf. Interval] Coef.**	
Loc	-.078689 (.0563212) -.1705307***	0.179 0.002	-.1970154	.0396373
lnNo_educ	.0326625 (.0222968)	0.160	-.0141813	.0795063
Demo_hsizeHsize	.0301784 (.0473958)	0.532	-.0693966	.1297533
lnLabor_farm	-.0274299 (.0322458)	0.406	-.0951757	.0403159
lnPre_AnyPrev	-1.488402** (.6302396)	0.030	.164318	2.812487
_cons	-4.702023 (5.620767)	0.414	-16.51082	7.10677
R-squared = 0.4381 Prob > F = 0.0480**				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

In the short run, location had no significant influence on the number of households that reported the availability of staple food at home when needed. However, in the long run and specifically in wave 7, we find that households in the urban centres had a 17.5% less chance of having any staple food at home compared to their rural counterparts agreeing with Oyando et al. (2021) who argued that overall, the pandemic affected urban populations above their rural counterparts. This could be associated with travel restrictions in urban centres, closure of businesses like supermarkets and grocery shops. This affected the distribution and access to food products in the urban centres more than rural areas where restriction of movement was not as strict. Evidence is available that lockdown measures mostly affected the urban poor in Ethiopia and Nigeria which is replicable in other Low- and Middle-Income Countries (LMICs) (Wieser et al, 2020; World Bank, 2020b).

Again, those who adopted any preventive measures behaviours i.e., did not go to work, kept social distancing, etc. had a 14.9% less chance of having any staple food item at home. As explained, this could be because of income-reallocation to purchase masks, sanitizers, etc. but also because, as Abay et al. (2020) points out, restrictions affected livelihoods negatively since households that adopted any preventive behaviours (did not go to work, kept social distancing, etc.) experienced a loss in income since they did not open their businesses, go to work etc. Lack of education, household size and the presence of farm activities did not affect the availability of staple food in any significant manner in the short -run. We expect that this will be different in the long run based on evidence that the pandemic affected vulnerable groups (the poor, the uneducated the unemployed etc.) more adversely.

Table 10 shows the OLS estimation results for Model 5.

Table 10: OLS Estimation Results- Model 5

Model 5: $lnUsed\_Sav = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$

Y= lnUse_Sav	**Coef.**	**P>t**	**[95% Conf. Interval]** **Coef.**	
Loc	.0867323 (.1274652) .217499**	0.512 0.015	-.1972779	.3707425
lnNo_educ	.0508108 (.0455638)	0.291	-.0507116	.1523333
Demo_hsizeHsize	-.1408067 (.1531344)	0.379	-.4820115	.2003981
lnLabor_farm	-.0855128 (.0726172)	0.266	-.2473139	.0762883
lnPre_AnyPrev	-.3836866 (.8163291)	0.648	-2.202581	1.435208
_cons	11.80493 (7.258411)	0.135	-4.367822	27.97767
R-squared = 0.4002 Prob > F = 0.3254				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

We find that households in urban areas used past savings to buy food and other basic needs 21.7% more compared to those in the rural areas in the long run. We expect this to be so because urban populations have a higher propensity to save compared to the rural households. This is because most rural populations are informally employed or are subsistence farmers or /and are not included in financial institutions. This may mean that they had no prior savings to use as compared to urban populations. Janssens et al. (2021) points out that urban households in Kenya reduced and used savings significantly during the pandemic and reduced loan repayments. Accordingly, Furbush et al. (2021) found that in Uganda, Malawi, Ethiopia, and Nigeria, 77% of the population experienced a loss in income and above 40% employed one or more coping strategies. This was the use of prior savings, asset sale, or reduction in food consumption. However, lack of education, household size, the presence of farming activities and the adoption of any preventive measure did not affect the use of past savings in a significant manner in the short run. This could be because the uneducated have less or no savings due to their low or no income at all. Again, those who practiced farming activities were likely to be in the rural areas where farming is mainly for subsistence reasons. These have a low propensity to save as compared to urban populations. We expect that household size may affect the use of past saving in urban areas in the long run which could be an area for further investigation.

4.3.3 Random Effects Estimation Results

Because our data is longitudinal, we estimated the random and fixed effects models and present the results are as shown below.

Table 11 shows the RE estimation results for Model 1.

Table 11: Random Effects Estimation Results- Model 1

Model 1: $lnFs\_hungry = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$

Y= lnFs_hungry	Coef.	p>z ; p>t (FE)	[95% Conf. Interval]	
Loc	-.1456586 (.1187375)	0.220	-.3783799	.0870626
lnNo_educ	-.0566163 (.0468527)	0.227	-.1484459	.0352134

Demo_hsizeHsize	.2884626*** (.1077238)	0.007	.0773278	.4995974
lnLabor_farm	-.1148228* (.0687337)	0.095	-.2495384	.0198927
lnPre_AnyPrev	1.857807** (.8035205)	0.021	-3.432678	-.2829358
_cons	24.69874*** (7.185861)	0.001	10.61471	38.78277
Wald chi2(5) = 11.89 Prob > chi2 = 0.0363				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Similar to the OLS model, the random effects model reveal that location does not significantly influence the number of households that went hungry due to lack of food as a result of the pandemic. The results indicate that urban households were 14.6% less likely to lack food due to the pandemic as compared to rural populations. However, this is not statistically significant with our data. It means that in the short run, location did not influence the likelihood of lacking food but as we have seen in the OLS model results, the severity of the lack of food shifted to urban populations in the long run Oyando et al. (2021). This agrees with Josephson, Kilic & Michler (2021) who examined the heterogeneity of COVID-19 effects across rural and urban regions found no significant differences in food security and income losses in the short run. However, households who adopted any prevention mechanism (did not go to work, kept social distancing, etc.) had a 18.7% higher chance of going hungry. no matter where they are located. This could be associated with re-allocation of income to buy masks, sanitizers, gloves etc. but also because this group stayed home and did not go to work or open their businesses leading to reduced income and consumption.

An increase of household size by one person has a 28.8% increase in the probability of lacking food no matter where the households are located. This is expected as it will mean a higher food demand at the household level. We also find that households that are engaged in farming activities had a 11.5% less chance of going hungry. This is because of the availability of food from their farm produce, or income from the sale of the same.

Table 12 shows the RE estimation results for Model 2.

Table 12: Random Effects Estimation Results- Model 2

Model 2: $lnSold\_Asse = \beta_0 + \beta_1 Loc + \beta 2lnNo\_Educ + \beta_3 Hsize + \beta 4lnLabo\_farm + \beta 5lnPrev\_AnyPrev + \mu_i$

Y= lnSold_Asse	Coef.	P>z	[95% Conf. Interval]	
Loc	-.392339 (.7361946)	0.594	-1.835254	1.050576
lnNo_educ	.5996394** (.2525861)	0.018	.1045798	1.094699
Demo_hsizeHsize	.4232319 (.697979)	0.544	-.9447818	1.791246
lnLabor_farm	-.4771279 (.4163225)	0.252	-1.293105	.3388491
lnPre_AnyPrev	.7840044 (4.698884)	0.867	-8.425638	9.993647
_cons	-2.25809y (41.70018)	0.957	-83.98894	79.47276
Wald chi2(5) = 11.45 Prob > chi2 = 0.0432				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Location does not significantly influence the sale of assets by the households in an effort to survive. However, there is a 59.9% increase in the chances of selling assets for those with no education confirming that the pandemic affected vulnerable groups more adversely and agreeing with the findings of Oyando et al. (2021) and Population Council (2020) that the poor, the marginalized and those without education were adversely affected by the pandemic. This could be so because they did not have assets to sell in the first place. However, household size, the presence of farming activities and the adoption of any preventive measures did not affect the sale of assets at least in the short term. However, this could be different in the long run, something that could be an area for further investigation.

Table 13 shows the RE estimation results for Model 3.

Table 13: Random Effects Estimation Results- Model 3

Model 3: $lnRed\_Consum = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$

Y= lnRedu_Consu	**Coef.**	**P>z**	**[95% Conf. Interval]**	
Loc	-.0662036 (.0988264) Wave (2,3) .5306992*** .383089***	0.503 0.00 0.02	-.2598999	.1274926
lnNo_educ	.0432251 (.033907)	0.202	-.0232315	.1096817
Demo_hsizeHsize	.167114** (.0936964)	0.074	-.3507555	.0165276
lnLabor_farm	-.0102014 (.0558869)	0.855	-.1197378	.099335
lnPre_AnyPrev	1.261294** (.6307761)	0.046	-2.497592	-.0249955
_cons	19.11499*** (5.597814)	0.001	8.143477	30.0865
Wald chi2(5) = 9.97 Prob > chi2 = 0.0762				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Similar to OLS model, households in urban areas reduced consumption of essential and non-essential items in the long run by 53.1% and 38.3% in the last waves of data collection compared to their rural counterparts. This is associated to the effects of COVID-19 arising from less disposable income due to job losses and income reductions. As Bundervoet, Dávalos & Garcia (2022) pointed out, 65% of households in 31 countries had to cope with reduced income and subsequent reduced food consumption as a result of COVID-19 effects. An increase by one person into the household led to a 16.7% higher chance of reducing consumption of essential and non-essential items. This is due to higher consumption demand brought about by the extra person added into the household. We also find that, lack of education and the presence of farm activities did not significantly influence consumption of essential and non-essential items. However, there is a 12.6% higher chance of reducing consumption for those households who practiced any form of prevention measures associated with less disposable income due to business and job losses. This is consistent with Abay et al. (2020) who found that 50% of households in Ethiopia could not meet their need for food and 11.7% experienced food insecurity due to the restrictions adopted.

Table 14 shows the RE estimation results for Model 4.

Table 14: Random Effects Estimation Results- Model 4

Model 4: $lnPrev\_AnyStaple = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$

Y= lnPrev_anysta~e	**Coef.**	**P>z**	**[95% Conf. Interval]**	
Loc	-.078689 (.0563212) -.1705307***	0.162 0.001	-.1890765	.0316984
lnNo_educ	.0326625 (.0222968)	0.143	-.0110384	.0763634
Demo_hsizeHsize	.0301784 (.0473958)	0.524	-.0627157	.1230725
lnLabor_farm	-.0274299 (.0322458)	0.395	-.0906304	.0357706
lnPre_AnyPrev	-1.488402** (.6302396)	0.018	.2531554	2.723649
_cons	-4.702023 (5.620767)	0.403	-15.71852	6.314478
Wald chi2(5) = 14.03 Prob > chi2 = 0.0154				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Location does not influence the possession of any staple food, but in the long-run urban households had a 17.1% less chance of having any staple food at home as compared to their rural counterparts agreeing with Oyando et al. (2021) findings. This could be associated with food products distribution issues in urban areas. Those who practiced any form of prevention measures had a 14.8% less chance of having staple food at home. Again, those who adopted any preventive measures i.e., did not go to work, kept social distancing, etc. had a 14.9% less chance of having any staple food item at home. As explained earlier, this could be because of income-reallocation to purchase masks, sanitizers, etc. but also because, as Abay et al. (2020) point out, restrictions affected livelihoods negatively since households that adopted any preventive behaviours (did not go to work, kept social distancing, etc.) experienced a loss in income since they did not open their businesses, go to work etc. However, lack of education, household size and the presence of farming activities did not influence the presence of staple food available to the households in the short run.

Table 15 shows the RE estimation results for Model 5.

Table 15: Random Effects Estimation Results- Model 5

Model 5: $lnUsed\_Sav = \beta_0 + \beta_1 Loc + \beta 2lnNo\_Educ + \beta_3 Hsize + \beta 4lnLabo\_farm + \beta 5lnPrev\_AnyPrev + \mu_i$

Y=lnUse_Sav	**Coef.**	**P>z**	**[95% Conf. Interval]**	
Loc	.0867323 (.1274652) .217499***	0.496 0.009	-.1630949	.3365596
lnNo_educ	.0508108 (.0455638)	0.265	-.0384926	.1401142
Demo_hsizeHsize	-.1408067 (.1531344)	0.358	-.4409447	.1593313
lnLabor_farm	-.0855128 (.0726172)	0.239	-.2278398	.0568142
lnPre_AnyPrev	-.3836866 (.8163291)	0.638	-1.983662	1.216289
_cons	11.80493 (7.258411)	0.104	-2.421299	26.03115
Wald chi2(5) = 6.67 Prob > chi2 = 0.2461				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

In the long run, households in urban areas had a 21.7% higher propensity to use savings saved for other use to buy necessities. This is expected because rural households probably did not have any past savings to use, given that most of them are subsistence farmers. Again, households in rural areas could also be unaware or excluded from savings plans due to lack of education and awareness. Lack of education, household size, the presence of farming activities and the adoption of any preventive measures did not significantly influence the use of savings by households. We expect that household size may affect the use of past saving in urban areas in the long run which could be an area for further investigation.

4.3.4 Fixed Effects Estimation Results

Table 16 shows the FE estimation results for Model 1.

Table 16: Fixed Effects Estimation Results- Model 1

Model 1: $lnFs\_hungry = \beta_0 + \beta_1 Loc + \beta 2lnNo\_Educ + \beta_3 Hsize + \beta 4lnLabo\_farm + \beta 5lnPrev\_AnyPrev + \mu_i$

Y= lnFs_hungry	Coef.	p>z ; p>t (FE)	[95% Conf. Interval]	
Loc	-.1993409 (.1587805)	0.227	-.5359406	.1372587
lnNo_educ	-.0123947 (.0499587)	0.807	-.1183024	.093513
Demo_hsizeHsize	.1855227 (.1462962)	0.223	-.1246113	.4956568
lnLabor_farm	-.0870302 (.0790674)	0.287	-.2546456	.0805852
lnPre_AnyPrev	-2.249781* (1.139258)	0.066	-4.664899	.1653378
_cons	28.02151** (10.12415)	0.014	6.559273	49.48375
FE: Prob > F = 0.2867 F test that all u_i=0: F(3, 16) = 1.71 Prob > F = 0.2043				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Using the fixed effects model, location does not significantly influence the number of households that went hungry due to lack of food as a result of the pandemic effects. Contrary to the OLS and the RE model, the household size and presence of farming activities do not also influence the propensity to go hungry. However, those who adopted any prevention mechanism had a 22.5% lesser chance of going hungry which contradicts the OLS and RE models. This is because, as we shall see from the Hausam test, FE model is not reliable for our data and therefore the preferred model is OLS or RE. This may be due biases associated with unobserved time varying heterogeneity that is unlikely in OLS model.

Table 17 shows the FE estimation results for Model 2.

Table 17: Fixed Effects Estimation Results- Model 2

Model 2: $lnSold\_Asse = \beta_0 + \beta_1 Loc + \beta 2 lnNo\_Educ + \beta_3 Hsize + \beta 4 lnLabo\_farm + \beta 5 lnPrev\_AnyPrev + \mu_i$

Y=lnSold_Asse	**Coef.**	**P>z**	**[95% Conf. Interval]**	
Loc	-1.30772 (-1.30772)	0.256	-3.774824	1.159384
lnNo_educ	.773245** (.3090156)	0.037	.0606537	1.485836
Demo_hsizeHsize	-1.405523 (1.62621)	0.413	-5.155569	2.344523
lnLabor_farm	-.5031898 (.5128714)	0.355	-1.685873	.6794937
lnPre_AnyPrev	-6.981197 (9.11103)	0.466	-27.99127	14.02888
_cons	70.00188 (79.88456)	0.406	-114.2123	254.216
Prob > F = 0.1751 F test that all u_i=0: F(3, 8) = 0.82 Prob > F = 0.5163				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Location does not significantly influence the sale of assets by the households in an effort to survive. However, there is a 77.3% increase in the chances of selling assets for those with no education confirming Oyando et al. (2021) and Lakner et al. (2020) findings that the pandemic effects were severe on vulnerable groups. However, household size, involvement in farming activities and the adoption of any preventable measures did not significantly affect the sale of assets by the households at least in the short run. We expect that the results could be different in the long term. As Lakner et al. (2020) points out, this could be because the sale of assets as a coping mechanism was adopted by vulnerable groups explaining why those who had some form of farming activities did not need to sell assets. Again, household size and the adoption of any preventable measures may not have been a factor to selling assets but rather vulnerability.

Table 18 shows the FE estimation results for Model 3.

Table 18: Fixed Effects Estimation Results- Model 3

Model 3: $lnRed\_Consum = \beta_0 + \beta_1 Loc + \beta 2lnNo\_Educ + \beta_3 Hsize + \beta 4lnLabo\_farm + \beta 5lnPrev\_AnyPrev + \mu_i$

Y=lnRedu_Consu	**Coef.**	**P>z**	**[95% Conf. Interval]**	
Loc	-.0728128 (.1369259)	0.609	-.3885645	.2429388
lnNo_educ	.0108145 (.0395493)	0.791	-.0803864	.1020153
Demo_hsizeHsize	-.1857294 (.20813)	0.398	-.6656781	.2942193
lnLabor_farm	-.0498532 (.0656397)	0.469	-.2012186	.1015123
lnPre_AnyPrev	.4788212 (1.166073)	0.692	-2.210148	3.16779
_cons	4.273443 (10.224)	0.687	-19.30315	27.85004
FE: Prob > F = 0.8741 F test that all u_i=0: F(3, 8) = 1.17 Prob > F = 0.3785				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Location, lack of education, household size, presence of labor farm activities and adoption of preventive measures by the households do not influence the reduction of consumption by the households. This is contrary to the OLS and RE model. This is because, as we shall see from the Hausman test, FE model is not reliable for our data and therefore the preferred model is

OLS or RE. This may be due biases associated with unobserved time varying heterogeneity that is unlikely in OLS model.

Table 19 shows the FE estimation results for Model 4.

Table 19: Fixed Effects Estimation Results- Model 4

Model 4: *lnPrev_AnyStaple* = β_0 +β_1*Loc*+ β*2lnNo_Educ* + β_3*Hsize* + β*4lnLabo_farm* + β*5lnPrev_AnyPrev* + μ_i

Y=lnPrev_anysta~e	**Coef.**	**P>z**	**[95% Conf. Interval]**	
Loc	.0576378 (.141949)	0.691	-.2468125	.3620881
lnNo_educ	.0360256 (.025648)	0.182	-.0189838	.091035
Demo_hsizeHsize	-.0209376 (.0733579)	0.780	-.1782746	.1363994
lnLabor_farm	-.0455237 (.0382491)	0.254	-.1275599	.0365124
lnPre_AnyPrev	7.283253* (3.513993)	0.057	-.2535137	14.82002
_cons	-55.77072* (31.16002)	0.095	-122.6023	11.06089
FE: Prob > F = 0.0264 F test that all u_i=0: F(4, 14) = 1.21 Prob > F = 0.3491				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Location, lack of education, household size and the presence of farming activities do not influence the possession of any staple food of the households. However, those who adopted any preventive measures had a 72.8% higher chance of having any staple food at home. This is contrary to the OLS and RE models. This is because, as we shall see from the Hausman test, FE model is not reliable for our data and therefore the preferred model is OLS or RE. This may be due biases associated with unobserved time varying heterogeneity that is unlikely in OLS model.

Table 20 shows the FE estimation results for Model 5.

Table 20: Fixed Effects Estimation Results- Model 5

Model 5: $lnUsed\_Sav = \beta_0 + \beta_1 Loc + \beta 2lnNo\_Educ + \beta_3 Hsize + \beta 4lnLabo\_farm + \beta 5lnPrev\_AnyPrev + \mu_i$

Y=lnUse_Sav	**Coef.**	**P>z**	**[95% Conf. Interval]**	
Loc	.1356331 (.2282292)	0.571	-.4040432	.6753094
lnNo_educ	.0368932 (.0580567)	0.545	-.1003889	.1741754
Demo_hsizeHsize	-.1396709 (.3108005)	0.667	-.8745973	.5952555
lnLabor_farm	-.0953285 (.0984714)	0.365	-.3281763	.1375194
lnPre_AnyPrev	.8864557 (2.334769)	0.715	-4.634396	6.407307
_cons	.7117043 (20.60842)	0.973	-48.01946	49.44287
FE: Prob > F = 0.5652 F test that all u_i=0: F(3, 7) = 0.15 Prob > F = 0.9241				

Standard errors in parenthesis

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation using Stata software.***

Location, lack of education, household size, the presence of labor farm activities and the adoption of any preventive measures by the households did not significantly affect the use of savings. This contrasts with the findings of the RE and OLS models.

As we shall see, the appropriate model to use is the OLS or RE as opposed to FE model.

4.4 Diagnostic Test

4.4.1 Hausman Test

To determine which model between RE and FE is preferred, we ran a Hausman test. This basically tests whether the unique errors are correlated with the regressors in the model or not. The null hypothesis states that:

H_0: FE= RE

H_1: FE≠ RE

We present the Hausman test Chi-square results on Table 21 for the five models estimated.

Table 21: Hausman Test Results

Variable	Prob>chi2
Model 1: Y= lnFs_hungry (Loc)	0.1790
Model 2: Y= lnSold_Asse (Loc)	0.7859
Model 3: Y= lnRed_Cons (Loc)	0.6116
Model 4: Y= lnPrev_anyStaple(Loc)	0.3556
Model 5: Y= lnUse_Sav(Loc)	0.9951

***** p<0.01; **p<0.05; *p<0.1** ***Source: Authors computation***

Since, all our Chi-square results are not significant either at 1%, 5% or 10% for the model estimated, we therefore reject the null hypothesis that FE=RE. The preferred model is therefore the Random Effects.

4.4.2 Time Fixed effects

To test whether the joint time variables are important, we carry out the time fixed effects for the model. We obtained the following results as shown on Table 22:

Table22: Time Fixed Effects Results

Prob > F = 0.2043
Prob > F = 0.5163
Prob > F = 0.3785
Prob > F = 0.9241
Prob > F = 0.3491

Source: Author's compilation

Since all Prob > F are not significant at 1%, 5% or 10%, we conclude that it is not important to include the time parameters in our analysis.

4.4.2 OLS or Random Effects Model Test

We use Breusch and Pagan Lagrangian multiplier test for random effects to determine which model between OLS and RE best fits our model.

The results obtained for all the models indicate nonsignificant Prob > chibar2 =

.938; Prob > chibar2= 1; at 1% 5% and 10%. This means that the OLS and RE give similar results. This is evident from the results obtained in Tables 6 to Table 15. We therefore interpret our results based on OLS results.

CHAPTER 5: SUMMARY, CONCLUSIONS AND POLICY RECOMMENDATIONS

5.0 Introduction

In this chapter, we provide a summary of the results, conclusions, policy recommendations and areas of further research.

5.1 Summary of the Study findings

The study sought to examine the disparities of COVID-19 socioeconomic effects between rural and urban populations in Kenya. It also sought to investigate how rural and urban populations are coping with these effects. Using a quantitative research design in our approach, we analyzed high-frequency longitudinal phone survey data from the World Bank that tracks a total of 155 socioeconomic indicators in a series of seven waves.

We carried out panel data analysis using OLS, Random Effects and Fixed Effects models. We found that location of the households did not significantly influence the propensity of the households going hungry because they lacked enough money to buy food due to the adverse effects of the pandemic. However, our findings show that in the long term, urban households were likely to go hungry as opposed to rural ones agreeing with Oyando et al. (2021) findings that disruptions in food security and income losses caused by the pandemic were more in (Nairobi & Kisumu) than those of Kilifi (rural).

We also find that household size affected the ability of the households to cope. Huge households had greater food consumption demands and that of other items. One additional person into the household meant a 28.8% higher chance of going hungry notwithstanding the location of the households. Again, adoption of preventive measures led to more severity in the effects of lack of food. We also find that location is not important in influencing the sale of assets, and as Furbush et al. (2021) found out, that income losses were borne similarly between rural and urban populations and there were no significant differences.

Lack of education on the other hand led to 59.9% chance of selling assets in order to cope with COVID-19 impact confirming that the disease affected vulnerable groups more. These are people who have no education or possess low levels of education, those who own fewer assets or are less wealthy and those in the informal sector. Again, we find that location had no significant influence on the number of households that reported the availability of staple food at home.

Urban households however, used savings saved for other use to buy food and other basic needs 21.7% more than those in the rural areas. This could be associated with the fact that the propensity to save is higher in urban areas than in rural areas. We also find that engagement in labor farming activities led to less likelihood (11. 5%) of lacking food.

5.3 Conclusion

It is evident that COVID-19 has adversely affected vulnerable groups such as those without education, the unemployed, non-farmers etc. no matter where these groups are located. This agrees with Lakner et al. (2020) who describe the heterogeneity of COVID-19 effects and provides evidence that the most affected people were those who have no education or possess low levels of education, those who own fewer assets or are less wealthy and those in the informal sector. Thus, the pandemic disproportionately affected vulnerable groups such the informal sector, women, youth, people with disabilities among others more than the less vulnerable groups and this is expected to increase the gap between the poor and the rich heightening inequalities (Bundervoet, Dávalos, & Garcia 2022).

5.3 Policy recommendations

Based on the results and findings of this study therefore, we recommend the following;

i. that the government should create an enabling environment for agriculture both in urban and rural areas. This is a great factor to food security.

ii. That the government through the MOH should adopt and enforce other ways to curb the spread of the pandemic other than curfew and business closures and other restrictions since these were found to affect livelihoods and wellbeing adversely. This could be through further awareness on the need for vaccination.

iii. that government intervention and recovery policies should be targeted to vulnerable groups of the population notwithstanding where these groups are located.

iv. that the government should create awareness on responsible birth control to curb exponential population growth as these places a burden on the wellbeing of households in general.

5.3 Area of Further Research

We propose further research on the long-run effects of the pandemic on vulnerable groups in Kenya**.** We also recommend further research on the socioeconomic effects of COVID-19 utilizing both RE and FE models.

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