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Essays on Digital Technologies, Entrepreneurship, and Economic Outcomes in Sub-Saharan Africa

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Declaration

I, Kebede Bekele Geleto, hereby declare that this dissertation titled **"Essays on Digital Technologies, Entrepreneurship, and Economic Outcomes in Sub-Saharan Africa"** is my original work and has not been presented for a degree in any other university or institution. All sources of information, ideas, and views used in this dissertation are fully acknowledged. Wherever this dissertation includes collaborative work, I have clearly indicated my contributions and those of my co-authors.

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This is to certify that the dissertation prepared by **Kebede Bekele Geleto "Essays on Digital Technologies, Entrepreneurship, and Economic Outcomes in Sub-Saharan Africa"** and submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Economics complies with the regulations of the university and meets the accepted standards with respect to originality and quality.

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Acronyms

2SLS-IV	Two-Stage Least Squares Instrumental Variable
AI	Artificial Intelligence
ATT	Average Treatment Effect on the Treated
COVID	Coronavirus Disease
CPI	Consumer Price Index
CSA	Central Statistical Agency
CSDID	Callaway and Sant'Anna Difference-in-Differences
DID	Difference-in-Differences
ES	Enterprise Survey
ESS	Ethiopian Socioeconomic Survey
FE	Fixed Effects
GDP	Gross Domestic Product
GHS	General Household Survey
GPS	Global Positioning System
GSM	Global System for Mobile Communications
GSMA	Global System for Mobile Communications Association
ICT	Information and Communication Technologies
IRT	Item Response Theory
ISIC	International Standard Industrial Classification
ITU	International Telecommunication Union
LSMS-ISA	Living Standards Measurement Study - Integrated Surveys on Agriculture
LTE	Long Term Evolution
MEP	Multidimensional Energy Poverty
NFE	Non-farm Entrepreneurship
OECD	Organization for Economic Co-operation and Development
PSM	Propensity Score Matching
SME	Small and Medium Enterprises
SSA	Sub-Saharan Africa
TWFE	Two-way Fixed Effects
UMTS	Universal Mobile Telecommunications System
UN	United Nations
UNCTAD	United Nations Conference on Trade and Development
UNDP	United Nations Development Programme
UNICEF	United Nations Children's Fund

1. Introduction

1.1. Background

Nearly three-quarters of the world's population had access to the internet in 2025. However, internet use directly correlates with a country's level of development. While about 94 percent of the population in high-income countries were online during the same period, the corresponding figure in low-income countries was just about 23 percent. Mobile broadband coverage likewise surpassed 96 percent of the global population, though it was only about 36 percent in Africa. Despite its relatively low internet penetration, the continent is experiencing one of the fastest growth rates in internet access (ITU, 2025).

Africa has yet to fully leverage emerging technologies. The digital divide remains profound, leaving remote areas highly disconnected. Low-Earth-orbit satellite technologies, such as Starlink, offer an alternative for expanding connectivity in underserved and remote areas, but their effectiveness is constrained by challenges related to affordability, infrastructure, regulatory, and digital skills (Falowo & Falowo, 2026). To start with, coverage does not mean access. For instance, while about 99 percent of the population was covered by a 3G network in Ethiopia,[1] only about 22 percent used the internet in 2024.[2] Even if households are covered by a mobile or satellite network, they may be unable to afford the costs of devices, subscriptions, or data usage. Moreover, the technologies require complementary infrastructure, including reliable electricity and local distribution networks. Regulatory and sovereignty issues are also other concerns (Del Portillo et al., 2021).

Internet connectivity by itself is not sufficient. The productive use of digital technologies requires complementary capabilities, including digital literacy, educational resources, and accessible online services. Consequently, the challenge in Africa is not merely expanding network coverage, but also ensuring that connectivity is affordable, reliable, productive, and leveraged to unlock broader economic potential (Begazo et al., 2023; Mwansa et al., 2025).

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[1] https://datahub.itu.int/data/?i=100095&s=430&e=1&v=chart

[2] https://datahub.itu.int/data/?e=ETH&i=11624&v=chart

Over the last two decades, digitalization has greatly transformed firms' production processes, service delivery, and communication. In particular, the proliferation of internet and mobile phone technologies facilitated the creation of new products and processes, new market channels, and organizational complexities (Myovella et al., 2020; Elfaki & Ahmed, 2024; Sithole et al., 2024). Firms' digitalization processes are thus associated with increased innovation and higher productivity growth (Cette et al., 2022; Cheng et al., 2023; Nucci et al., 2023).

The COVID-19 pandemic led to a swift increase in the deployment of digital technologies across sectors. Digitalization reduced the need for in-person interactions, allowing firms to lower coordination costs and information asymmetries, thereby improving their profits (Constantinescu et al., 2025). Most importantly, online sales and remote work arrangements were crucial in maintaining firms' connections to distant customers and employees (Avalos et al., 2024; Bilal et al., 2024). A natural empirical question, therefore, is the extent to which digitalization shielded firms against the economic losses induced by the pandemic.

The impact of digitalization extends beyond firm performance and resilience to shocks. Access to digital technologies also has important implications for human capital development. The rapid advancement in Information and Communication Technologies (ICT), particularly the internet, substantially transforms the diffusion of knowledge. Internet expansion offers broader learning opportunities, especially in sub-Saharan African countries with limited educational resources (Akpan & Akpan, 2017). However, widespread use of digital technologies presents its own challenges, including increased exposure to misinformation and distractions (Bala, 2025).

In pursuit of the United Nations goal of ensuring inclusive and equitable education, various initiatives have been launched by governments and relevant stakeholders to expand children's access to computers and the internet. A typical example of such initiatives was a nationwide One Laptop per Child (OLPC) program, first implemented in Uruguay in 2007, which aimed to provide a personal laptop to each student in primary and middle public schools and equip these schools with wireless internet (Yanguas, 2020). However, globally, about two-thirds of school-aged children (3 to 17 years) didn't have internet access at home by the end of 2020 (UNICEF & ITU, 2020).

Reflecting the competing effects in terms of both opportunities and potential challenges, evidence on the impacts of the internet on educational outcomes is fraught with disagreements. While most studies document a positive association between internet access and children's computer skills, they largely report its negative or insignificant impact on educational outcomes (e.g., Malamud et al., 2019; Henriksen et al., 2022; Okyere, 2022). Still other findings suggest a beneficial effect of the internet on educational attainments, particularly in developing countries (e.g., Derksen et al., 2022; Lakdawala et al., 2023; Elom et al., 2024; Tinjić & Nordén, 2024). One potential explanation for these discrepancies in empirical findings is the purpose for which the internet is used. For instance, Posso (2016) finds that the impact of the internet on academic achievement is negative when it is used for non-academic purposes, such as social networking.

Building on the preceding insights, the next two chapters of this dissertation examine the impacts of digital technologies on two distinct indicators for two different sub-Saharan African countries. Chapter two is devoted to the impact of digitalization on firms' resilience to the disruptions caused by the COVID-19 pandemic in Zambia. Put differently, it investigates the differential impact of the pandemic on the rate of change in sales revenue of firms with pre-pandemic websites and those without. Chapter three analyzes the effect of mobile broadband coverage on children's literacy in Nigeria.

In many developing countries, a large share of the workforce is self-employed. An improvement in returns to self-employment is attracting skilled workers, turning it into an attractive livelihood option rather than an occupation of last resort (Falco & Haywood, 2016). In particular, diversification into non-farm businesses has become an effective path out of poverty for rural households (Hoang et al., 2014; Kolawole, 2021; Asiimwe et al., 2025), offering a viable alternative to agriculture for fostering rural income growth (Nagler & Naudé, 2017; Tegebu, 2024). The income from these activities is often pro-poor, providing disproportionate benefits to economically disadvantaged households (Oostendorp et al., 2009; Kolawole, 2021).

Despite the broader welfare implications of rural income diversification (Alemu & Adesina, 2017; Asiimwe et al., 2025), its impact on energy poverty in developing countries has received little empirical attention. The fourth chapter of this dissertation specifically deals with the impact of

operating household owned non-farm enterprises on multidimensional energy poverty among households in rural and small towns in Ethiopia.

This dissertation thus aims to answer the following questions:

- Does pre-pandemic digitalization improve firm resilience during a major shock?
- Does 3G mobile broadband coverage improve literacy among primary-school-aged children?
- Does household engagement in non-farm entrepreneurship reduce multidimensional energy poverty?

Although the three essays focus on distinct units of analysis—firms, children, and households—they are closely integrated within a unified framework that examines whether access to productive resources, particularly digital infrastructure, and entrepreneurial capacity to organize and utilize those resources help alleviate development constraints in Sub-Saharan Africa. Specifically, the dissertation aims to shed light on how digital technologies and entrepreneurship enhance resilience to shocks, human capital accumulation, and household welfare in a developing country context.

The choice of countries is mainly guided by the availability of data and their contextual relevance to the research questions. The focus on Zambia in the first essay largely stems from the availability of relevant firm-level data immediately before and over a longer period of the pandemic. Zambia was also among the top four Sub-Saharan African countries in terms of confirmed COVID-19 cases, trailing only South Africa, Ethiopia, and Kenya (Worldometers, 2024). Nigeria experienced massive mobile broadband expansion between 2010 and 2016, providing an interesting setting for investigating its effects on literacy in a country where children's literacy remains a major concern. Ethiopia offers an ideal context owing to its persistent energy poverty and the availability of rich panel data on rural households.

1.2. Objective of the Dissertation

The overall objective of this dissertation is to investigate the effects of digital technologies on economic resilience and educational outcomes, and the link between non-farm entrepreneurship and household welfare in selected sub-Saharan African countries.

The dissertation has the following specific objectives:

- To analyze the impact of digitalization on firm resilience to the COVID-19 pandemic in Zambia
- To evaluate the impact of mobile broadband coverage on children's literacy in Nigeria
- To examine the effect of non-farm entrepreneurship on households' multidimensional energy poverty level in Ethiopia.

1.3.Data

This dissertation uses panel data from three sub-Saharan African countries. The second chapter relies on the World Bank Enterprise Survey conducted before COVID-19 and the Enterprise Survey Follow-up on COVID-19 for Zambia. The third chapter draws on two datasets for Nigeria: The General Household Survey (GHS) and the mobile broadband coverage map. The fourth chapter utilizes three waves of panel data from the Ethiopian Socioeconomic Survey (ESS).

The World Bank Enterprise Survey typically covers firms in the manufacturing and service sectors. This dissertation uses the data from the 2019 Enterprise Survey and the 2021 Enterprise Survey Follow-up on COVID-19 conducted in Zambia. The latter aims to assess how firms performed following the outbreak of the pandemic by reinterviewing the same firms surveyed before the pandemic.

The mobile broadband coverage map is primarily drawn from Collins Bartholomew Mobile Network Coverage Explorer and complemented with the data from OpenCelliD, a community project that provides the geographic locations of cell towers. This study exclusively focuses on the 3G technology, which enables users to browse the internet using mobile phones. The GHS panel is collected under the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) project. This dissertation employs three waves of the GHS panel collected in 2010/11, 2012/13, and 2015/16. For our analysis, we geographically match the GHS panel with the 3G mobile broadband coverage map.

The Ethiopian Socioeconomic Survey (ESS), like the Nigerian GHS, is part of the LSMS-ISA and is collected jointly by the Central Statistical Agency (CSA) of Ethiopia and the World Bank. This dissertation relies on three waves of ESS: 2011-12, 2013-14, and 2015-16. While the first wave of

ESS was limited to rural and small towns, the last two waves included medium and large cities. However, this study excludes medium and large towns as the concept of non-farm entrepreneurship fundamentally applies to rural and small towns.

1.4.Method of data analysis

This dissertation employs different analytical methods depending on the research question. Chapters two and three apply distinct versions of a difference-in-differences (DID) model. To examine whether pre-pandemic digitalization enhanced the resilience of firms to the disruptions induced by the COVID-19 pandemic, we use the canonical DID model with two periods and two groups. The outcome variable is the rate of change in sales revenue adjusted for inflation. The treated group comprises firms with pre-pandemic websites, while the control group includes firms that had no websites before the pandemic. To account for the potential endogeneity in website adoption, we evaluate the assumptions of parallel trends. In addition, we adopt the entropy balancing approach to achieve covariate balance between the treated and control groups at baseline (see, for example, Hainmueller, 2012; Neuenkirch & Neumeier, 2016; Apeti, 2023).

To estimate the effect of 3G mobile broadband coverage on literacy, we use the staggered DID model developed by Callaway and Sant'Anna (2021). One of the main advantages of this approach is that it accounts for staggered treatment adoption and heterogeneous treatment effects over time and across cohorts (Callaway & Sant'Anna, 2021; Roth et al., 2023; Bahia et al., 2024; Callaway et al., 2024). For the purpose this study, literacy is defined as a binary variable representing whether children (5-12 years) can read and write in any language.

To analyze the impact of non-farm entrepreneurship on energy poverty, this study employs the two-stage least squares instrumental variable approach. Specifically, it uses the share of households engaged in non-farm enterprises at a village (enumeration area) level as an instrument for a household's ownership of non-farm enterprises. This is based on the assumption that non-farm networks enhance information sharing that facilitates entry into non-farm businesses. It may also represent the peer effect within a village. However, a non-farm network is unlikely to impact household energy poverty directly (Hoang et al., 2014; Mathenge & Tschirley, 2015; Bui & Hoang, 2021; Koomson et al., 2023). In this study, non-farm entrepreneurship is a dummy variable equal to one if a household operates at least one non-farm enterprise, and zero otherwise. Energy poverty

is a weighted index of six indicators. These include modern cooking fuel, indoor pollution, access to electricity, household appliances, entertainment appliances, and means of communication.

1.5.Key findings

The findings suggest that the COVID-19 pandemic adversely affected firms' sales revenue in Zambia. The annual rates of change in sales declined from 3 percent in 2019 to about 34 percent in 2021. However, the loss in revenue was about 15 percentage points lower for digitalized firms than for other firms. The impact is more concentrated among firms in low-contact industries, such as manufacturing, construction, and wholesale trade. However, the effects are insignificant among high-contact firms, including hotels, restaurants, and retail trade. We find greater resilience of digitalized firms than their non-digitalized counterparts among non-trading firms (neither exporting nor importing). The results for trading firms (either exporting or importing) seem to vary across regions.

Furthermore, the results reveal that 3G mobile broadband coverage improves children's likelihood of writing and reading by about 10 percentage points in Nigeria. The findings show a statistically significant impact at the third wave, and insignificant impact at the second wave. While the impact across the early-treated and late-treated groups is statistically insignificant at the 5 percent level, the group-average impact is significant. The event study (dynamic treatment) estimation reveals that the effect of broadband expansion is statistically significant at the time of treatment, which turns insignificant one wave after the initial treatment.

This dissertation documents that non-farm entrepreneurship reduces multidimensional energy poverty levels among households in Ethiopia. The effect is particularly pronounced in rural areas and among male-headed households. However, it is statistically insignificant for households in small towns and those headed by females.

Finally, the findings from the dissertation are not necessarily generalizable to the whole of sub-Saharan Africa. The empirical evidence comes from specific sectors, age groups, households, and periods in three countries. Our conclusions from these papers are therefore interpreted as country- and context-specific evidence with broader implications, rather than as definitive evidence for the entire region.

1.6. Organization of the Dissertation

The remaining parts of this dissertation are structured as follows. Chapter two deals with the impacts of pre-pandemic digitalization on firms' resilience to the COVID-19 pandemic. This chapter is published in *Telecommunications Policy*, a reputable peer-reviewed journal. Chapter three presents the impact of mobile broadband coverage on children's literacy. Chapter four is devoted to the analysis of the effect of non-farm entrepreneurship on household energy poverty. Chapter five presents the overall conclusions and policy implications of this dissertation.

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2. Digitalization and firm resilience: Evidence from the COVID-19 pandemic in Zambia

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Abstract

Over the past few decades, internet access and the adoption of 3G/4G wireless networks have expanded across Africa. This digital transformation brings both opportunities and challenges. In this study, we use panel data from two rounds of the World Bank Enterprise Survey conducted in Zambia—before and after the COVID-19 outbreak—to examine the impact of digitalization on firm resilience in a developing-country context. Our analysis employs entropy balancing and difference-in-differences models and remains robust across various estimation techniques. A key finding is that firms that had adopted digital technologies before the pandemic experienced less revenue loss than other firms. The average effects are large but vary significantly across industries. These findings underscore the potential of digital strategies in mitigating economic disruptions.

Keywords: digitalization, firm resilience, COVID-19, Zambia

2.1. Introduction

The internet landscape in Africa has undergone significant changes, as improved telecommunications systems and the increasing use of mobile devices have made internet access more widespread across the continent. This growth in internet access has led to increased use of digital services, including social media, online shopping, and mobile payments. However, Africa has yet to reach its full potential with digital technology. For instance, only about 40 percent of the population had internet access in 2021, which was lower than the global average of 66 percent (Statista, 2024).

The COVID-19 pandemic led to a global surge in the use of digital technologies (UNCTAD, 2020), and evidence indicates that this enhanced firms' resilience to the pandemic.[3] However, because internet penetration rates are low in many African countries, it is unclear whether previous findings apply to the African context. A handful of studies include some African countries in their panel data, but they do not distinguish between them and other countries (see, for example, Cariolle & Léon, 2022; Comin et al., 2022; Calza et al., 2023; Copestake et al., 2024; Constantinescu et al., 2025).

This paper aims to shed light on and quantify the importance of digitalization at the firm level during the COVID-19 pandemic in Zambia. The pandemic represents a negative external shock that provides an opportunity to evaluate the role of digitalization amid severe cuts in demand for and supply of goods and services. Like most other countries, the Zambian government implemented lockdown measures and other restrictions following the outbreak of the COVID-19 pandemic in March 2020, despite the relatively modest number of confirmed cases, approximately 350,000 (Worldometers, 2024). The degree of government restrictions, as measured by the 0-100 Oxford Stringency Index, rose to 70 after a couple of months, due to an increase in COVID-19 cases and deaths. It then declined slightly below 50, where it hovered until early 2022.[4] Mobility was thus substantially restricted, even though the lockdown was less stringent than in most other countries (Goel & Nelson, 2023).[5] The pandemic exacerbated the challenges facing the Zambian economy, which was already struggling due to low global copper prices (Geda, 2021). The country's real per capita GDP declined by 1.6 percent in 2019, the year preceding the pandemic, and by 5.6 percent in 2020 (World Bank, 2024). By the end of 2020, approximately 5 percent of Zambia's enterprises had permanently closed (Finn et al., 2021). Thus, the country was severely affected by COVID-19, making it an interesting case for studying digitalization and resilience.

[3]See for example, Bartik et al. (2020); Dadoukis et al. (2021); Doerr et al. (2021); Li et al. (2022); Deole et al. (2023); Jaumotte et al. (2023); Oikonomou et al. (2023); Khan (2025).

[4]The data can be accessed at https://knoema.com/OXCOVIDGTR2020/oxford-covid-19-government-response-tracker.

[5]The trend in the changes of mobility relative to February 2020 is available at https://ourworldindata.org/covid-google-mobility-trends.

The question of how firms become more resilient to recessions or economic shocks through digitalization can be divided into two parts: their preparedness and their response. First, digitalization can be a key driver of innovation and sustainable productivity growth, as models based on endogenous growth theory show. To be more specific, the use of information and communication technologies (ICT) facilitates the adoption of more efficient business processes, such as optimizing inventory management, enhancing marketing strategies, and streamlining supply chains. It also accelerates technological advancements and the introduction of new applications. Moreover, ICT facilitates firms' access to workers, sources of raw materials, and potential consumers (Papaioannou, 2023; Bilal et al., 2024). Thus, firms that have been digitalized for an extended period are likely to be better prepared for recessions and adverse shocks than other firms.

Second, in addition to being better prepared, firms can benefit from digitalization during shocks, such as the COVID-19 pandemic, in various ways. It enhances resilience by enabling remote work, although this is not an option for firms that require workers to be physically present. Furthermore, digitalization makes it possible to increase online sales when face-to-face contact is restricted and helps maintain supply chains and distribution channels when interactions with suppliers are limited (Avalos et al., 2024; Khan, 2025). Hence, digitalization can increase sales through both price and quantity channels by improving efficiency, thereby undercutting competitors and sustaining operations through remote work and contactless payments (Copestake et al., 2024; Constantinescu et al., 2025).

Moreover, the literature shows that digitalization enhances firms' access to credit by reducing information asymmetry and signaling their innovation orientation (Pellegrina et al., 2017; Mushtaq et al., 2022; Liu et al., 2025). This, in turn, improves their liquidity and financial condition during recessions or shocks. Since firms often need cash before they receive revenue to cover essential transactions and operational outlays, limited access to finance can lead to reduced production and revenue, thereby amplifying the decline in demand induced by the shocks (Amin & Viganola, 2023).

This study addresses three related questions: First, how large was the effect of the COVID-19 pandemic on firms' sales revenue? Second, did a firm's pre-COVID-19 level of digitalization better

equip it to withstand the pandemic's impact on sales revenue? Third, how did the effects of digitalization vary across industries? In addition, since we find a positive effect of digitalization, we explore the role of potential mechanisms. Our study thus aims to provide new evidence on the role of digitalization in a Sub-Saharan African economy experiencing a severe recession. We use the World Bank Enterprise Survey (ES) and the Enterprise Survey Follow-up on COVID-19 (ES COVID-19), which were collected in 2019 and 2021, respectively. The former is a comprehensive survey that covers several aspects of enterprises in the private sector, including sales, infrastructure, employment, training, innovation, and business-government relations. The ES COVID-19 was primarily designed to provide information on the pandemic's impact. The collection of ES in 2019 makes Zambia the only SSA country with panel data from immediately before the COVID-19 outbreak and at a late stage of the pandemic, providing an opportunity to investigate the impact of the pandemic and whether digitalization mitigated it.[6]

In a broad sense, digitalization refers to the use of digital technologies, data, and interconnections that result in new activities or changes to existing ones (OECD, 2019); consequently, the measures used in empirical studies vary significantly. Our measure is the presence of websites before the pandemic, which is narrow but likely to be correlated with other forms of connectivity, such as email use and online payments. Avalos et al. (2024) show that having a website is strongly associated with having remote workers, utilizing digital technologies, and engaging in online sales.

The outcome variable is the sales growth, but firm resilience is a broader concept. Resilience may include survival, employment retention, profitability, recovery speed, supply-chain continuity, and access to finance. The chapter would be stronger if it acknowledged that the analysis measures revenue resilience rather than firm resilience in its full sense.

To evaluate whether digitalization affected firms' resilience to COVID-19-induced disruptions, we employ a difference-in-differences (DID) approach. Resilience is a broader concept that may include firm survival, employment retention, profitability, recovery speed, and supply-chain

[6]There exist ES COVID-19 surveys in a few sub-Saharan African countries, but they lack either nationally representative or temporally proximate pre-pandemic data. Guinea, Zimbabwe, and Togo conducted the latest pre-pandemic surveys in 2016; Niger in 2017; and Chad and Mozambique in 2018, offering limited temporal relevance. Somalia's 2019 survey was geographically limited, covering only two urban areas—Bosaso and Mogadishu.

continuity. In this study, it strictly refers to resilience in terms of sales revenue rather than broader aspects of firm resilience. The study's outcome variable is the change in revenue, measured as the annual rate of change in sales for 2019 and 2021. An identifying assumption is that the adoption of digital technology can be assumed to be predetermined because of the unanticipated nature of the pandemic (Bai et al., 2021; Kawaguchi et al., 2022). Although firms that became digitalized before the pandemic might, for example, be more efficient, we indirectly assess this by evaluating the parallel trends assumption and by employing the entropy balancing method to achieve covariate balance between our two groups of firms at the baseline. Entropy balancing should remove, or at least reduce, an eventual bias in our DID estimation (Hainmueller, 2012; Tübbicke, 2022; Källberg & Waernbaum, 2023). In addition, we estimate models with firm fixed effects to control for time-invariant differences across firms.

As expected, we find an adverse effect of COVID-19 on firms' sales revenue: the annual decline in revenue worsened from 3 percent to 34 percent. However, digitalized firms experienced approximately 15 percentage points lower declines than other firms, indicating a substantially larger difference than reported in previous studies across contexts (see, for example, Bai et al., 2021; Abidi et al., 2023; Copestake et al., 2024). Our results show heterogeneous impacts of digitalization. The loss in revenue was significantly lower for digitalized firms than for non-digitalized firms in low-contact industries (e.g., manufacturing, construction, and wholesale trade). In contrast, there was no difference between high-contact firms (e.g., hotels, restaurants, and retail trade). One reason is that online retail sales and home delivery of restaurant food were not well developed in Zambia. Among non-trading firms (neither exporters nor importers), the decline in revenue was significantly smaller for digitally enabled firms than for non-digital firms, whereas the results for digitalized and non-digitalized foreign-trading firms (exporters or importers) varied across regions. Moreover, our findings suggest that innovation and the adoption of coping strategies (remote work, online sales, or delivery services) are plausible channels through which pre-pandemic digitalization influences firms' resilience to the pandemic.

This paper contributes to the growing literature on the role of digitalization in mitigating major shocks. Among others, Bertschek et al. (2019) find that ICT-intensive firms were more resilient to the economic crisis of 2008-2009. Similarly, Nose and Honda (2023) show that digitally enabled firms had greater resilience to aggregate shocks during the last two decades, and Katz et al. (2020)

provide evidence that countries with better broadband connectivity experienced lower economic losses from the 2003 SARS (severe acute respiratory syndrome) outbreak.

Since the onset of COVID-19, digitalization has attracted greater attention, and several studies have examined it in high-income countries (e.g., Bai et al., 2021; Deole et al., 2023; Jaumotte et al., 2023; Oikonomou et al., 2023; Gaspar et al., 2024). These studies generally report greater resilience among digitalized firms to economic disruptions from the pandemic. In the context of developing countries, Abidi et al. (2023) find a smaller decline in sales among digitally enabled firms than among digitally constrained firms in the Middle East and Central Asia. Similar evidence is documented in other studies employing panel data that also include emerging and developing economies (Calza et al., 2023; Copestake et al., 2024; Khan, 2025).

The findings of Bürgel et al. (2023) differ from those of others: they find that pre-pandemic digitalization did not generally enhance crisis resilience among German small and medium-sized firms, but it had positive effects among firms highly exposed to globalization. Similarly, Gopalan et al. (2025), using cross-country firm-level data from both developed and developing economies, document that the survivability of enterprises during the pandemic depended positively on their integration into global value chains, whereas, Constantinescu et al. (2025) show that stronger digital infrastructure reduced the impact of the pandemic for firms in sectors amenable to remote work, regardless of their export status. And Beglaryan et al. (2025) find that offering online services before the pandemic did not shield Armenian small and medium enterprises from its impacts. Thus, the evidence on the impact of digitalization on firm resilience is somewhat mixed, and there is a scarcity of evidence from individual SSA countries.

The rest of this chapter is organized as follows: Section 2.2 describes the empirical strategy. Section 2.3 presents the data and descriptive statistics. Empirical results and conclusions are provided in sections 2.4 and 2.5, respectively.

2.2. Empirical strategy

Our analysis consists of three steps. First, we explore how COVID-19 induced changes in sales using:

$$Y_{it} = \alpha_i + \beta COVID_t + u_{it} \quad (2.1)$$

where Y_{it} is the rate of change of sales revenue for firm *i* in period *t,* adjusted for inflation by converting nominal sales values to real terms using the Consumer Price Index. $COVID$ is a dichotomous indicator that is 0 for the pre-pandemic period and 1 for COVID-19. Firm fixed effects are represented by α_i, and u_{it} is the error term. This model allows us to estimate the average impact of COVID-19 on the rate of change in sales revenue.

In the second step, we employ the difference-in-differences (DID) model to examine the differential impact of the pandemic on the rate of change of real sales revenue:

$$Y_{it} = \alpha_i + \beta COVID_t + \delta(COVID_t * Website_i) + \eta X_{it} + \varepsilon_{it} \quad (2.2)$$

where $Website$ is 1 for firms that had a website in 2019 and 0 otherwise; X represents time-varying firm characteristics; and ε_{it} is the error term.

Our interest lies in the estimated coefficient of the interaction term $\delta(COVID_t * Website_i)$. It measures the pandemic's differential impact on digitalized firms relative to non-digitalized firms. In other words, it shows whether digitalized firms are more resilient to the pandemic than their non-digitalized counterparts.

The third step involves the estimation of mechanisms through which pre-pandemic ownership of websites lessens the effects of the pandemic on the rate of change of sales revenue. We consider three channels: innovation, access to finance, and the use of coping strategies, i.e., online sales, remote work arrangements, and delivery or carry-out services, as follows:

$$Z_i = \alpha + \gamma Website_i + \eta X_i + \varepsilon_t \quad (2.3)$$

where Z_i denotes the mechanisms by which website ownership mitigates the pandemic's effects on the rate of change in sales revenue for firm *i*, and X is a vector of control variables. We treat each of the three channels as dummy variables denoting whether the firm invested in innovation, has financial access, and uses any of the coping strategies. All other terms are as defined before. Due to data limitations, the mechanism measures correspond only to the COVID-19 period.

The main challenge in estimating Equation (2.2) is the firms' endogenous adoption of digitalization. To partially account for this, our DID estimation is based on the digitalization status of the firm before the onset of COVID-19. One identifying assumption is the unanticipated nature of the pandemic; thus, the adoption of digital technology (i.e., websites) can be assumed to be predetermined. It is unlikely that firms prepared themselves for COVID-19 through instantaneous investment in digital technologies and a systematic change in business operations. Although one may argue that using pre-COVID-19 digitalization is a reasonable framework to identify the differential impact of the pandemic on firm outcomes (Bai et al., 2021; Comin et al., 2022; Kawaguchi et al., 2022; Copestake et al., 2024), there could be an endogenous adoption of websites during the pandemic. To address this concern, we exclude firms that had no website at the onset of the pandemic but invested in new equipment, software, or digital solutions after the outbreak. This group accounts for about 10 percent of our final sample.

Another concern is that digitalized and non-digitalized firms may be systematically different, and that digitalized firms are more resilient to the pandemic than non-digitalized firms, due to factors unrelated to digitalization. This would violate the parallel trends assumption: that is, firms that became digitalized before the pandemic would have experienced the same development during COVID-19 as the non-digitalized firms (i.e., the control group) would have if they had not been digitalized. We indirectly examine the parallel trends assumption using three rounds of data spanning 2013 to 2021: ES 2013, ES 2019, and the 2021 wave of the ES COVID-19.[7]

Furthermore, as noted, we use an entropy-balancing technique to create a balanced sample of observations across digitalized and non-digitalized firms. This approach, developed by Hainmueller (2012), is commonly employed in the economics literature (e.g., Neuenkirch & Neumeier, 2016; Ogrokhina & Rodriguez, 2019; Balima & Sy, 2021; Piper, 2022; Apeti, 2023). Entropy balancing consists of two steps. The first step is to calculate weights for the control group. These weights are chosen to meet predefined balanced constraints based on the sample moments of pretreatment characteristics (Neuenkirch & Neumeier, 2016; Apeti, 2023). In our analysis, the

[7] No ES was conducted in Zambia between 2013 and 2019.

balance conditions impose equal covariate means and variances across the treated and control groups.[8] In the second step, we use the weights from the first step in our DID model.

The entropy balancing method offers notable advantages over other matching techniques, such as propensity score matching (PSM). One of the most important features of this approach is that it achieves a high degree of covariate balance between the treated and control groups by creating a synthetic control group that closely mirrors the treated group. With PSM, control units are matched to treated units using estimated propensity scores, and units for which balance is not achieved are discarded, reducing the sample size. In contrast, entropy balancing assigns a scalar weight to each unit in the control group while ensuring the weights remain close to the base weights—allowing users to leverage the entire sample (Neuenkirch & Neumeier, 2016; Choudhuri & Desai, 2021). In addition, entropy balancing does not require specifying an empirical model for the outcome variable or the treatment, thereby minimizing bias from misspecification (Balima & Sy, 2021; Apeti, 2023).

The choice of covariates for entropy balancing is based on evidence on firm characteristics that predict their success during shocks. Larger firms, for example, have advantages over smaller firms as they can draw on a broader pool of resources (Apedo-Amah et al., 2020; Cirera et al., 2021; Ganotakis et al., 2023). Older firms, meanwhile, are better positioned to deal with crises due to more established relationships with customers and suppliers and greater access to information (Fernández-Cerezo et al., 2023; Muzi et al., 2023). Moreover, foreign-owned firms have relatively more straightforward access to modern technology (Amin & Soh, 2020). Female-led enterprises face several constraints (Bue & Martínez-Zarzoso, 2024), making them more likely to experience adverse effects of the pandemic than male-led enterprises (Njiwa et al., 2023). These variables are also correlated with firms' adoption of digital technologies (Torres et al., 2023; Avalos et al., 2024; Zhu & Dong, 2025). Accordingly, our entropy balancing relies on the following pre-pandemic characteristics: firm age (in log), firm size (1 if small and medium enterprise and 0 if large enterprise), top manager's gender (1 if female), foreign ownership (1 if yes), industry dummies, and region dummies.

[8]Our results are robust to using only the first moment condition.

While our main regression includes firm fixed effects to control for time-invariant heterogeneity, we replace these with industry fixed effects when plotting the predictive margins based on Equation (2.1) and Equation (2.2). This allows us to isolate how the average impact of COVID-19 and the role of digitalization vary across industries. The results of the main models are identical across the two specifications. Our main specification includes two time-varying control variables: firm age (in log) and a dummy for a female top manager. In the mechanism analysis and alternative estimations without firm fixed effects, we also include baseline variables for firm size, foreign ownership, industry type, and region.

Finally, the possible mitigation role of digitalization may depend on the nature of the industries under consideration. To this end, we classify industries as high-contact or low-contact and examine whether the findings differ. This classification is based on the relative degree of contact with customers or among employees (Kaplan et al., 2020; Albanesi & Kim, 2021; Aum et al., 2021). Following Gopalan et al. (2025), we also examine whether the impact varies by firms' participation in global value chains, distinguishing between foreign trading firms (i.e., exporters or importers) and domestic-oriented firms (neither exporters nor importers).

2.3. Data and descriptive statistics

This study draws on ES 2019 and the third wave of the ES COVID-19, conducted from July 28 to September 8, 2021.[9] Both surveys cover registered enterprises with at least five employees. The target sectors include manufacturing, construction, services, transport, storage, and communications.[10] The 2019 survey included 601 firms. Among them, 522 firms were successfully tracked down and interviewed in 2021, of which 463 were still in operation.

[9]We do not use the first and second rounds of the ES COVID-19. The first round was conducted from June 16, 2020, to July 17, 2020, that is, close to ES 2019, during the initial wave of the pandemic. It is too soon to expect an impact of digitalization. The second round was carried out from December 19, 2020, to February 18, 2021, which is close to the third ES COVID-19, making the time gap insufficient for meaningful distinction in our analysis.

[10]Additional information about the data can be found at https://microdata.worldbank.org/index.php/catalog/3763/related-materials

In addition, we use ES 2013 when evaluating parallel trends. We do not include it in the main analysis, as many firms in the 2013 survey are missing from ES 2019 and ES COVID-19. Only 45 percent of the firms interviewed in 2019 had participated in the 2013 survey, while the remaining 55 percent were newly incorporated into the 2019 sample.

Table 2.1 presents a descriptive summary of the variables used in the study, excluding the information technology industry, whose activities are closely tied to digitalization. We also exclude firms that had no websites before the pandemic but invested in digital solutions after the pandemic outbreak, as our focus is on the role of pre-pandemic digitalization. In addition, we exclude a couple of firms with extreme outcome values.[11] We thus end up with 301 firms.

The outcome is the rate of change in firms' sales revenue. The ES provides sales figures for the most recent fiscal year and the fiscal year two years prior, while the ES COVID-19 reports the year-over-year rate of change in sales revenue by comparing each month to the same month in the previous year. We use the ES data to calculate the average annual sales growth rate over the two years, applying the compound growth rate formula. This serves as a proxy for the year-over-year rate of change in sales, as reported in the ES COVID-19.[12] The average annual change in revenue was -3.2 percent in 2019 and -34 percent in 2021.

The measure of digitalization is a binary variable that takes the value 1 for enterprises that had websites prior to the pandemic and 0 otherwise. Approximately 60 percent of enterprises were digitalized in 2019. Nearly 80 percent of the sample comprises small and medium enterprises (SMEs) with 5 to 99 employees: the remaining 20 percent are large firms. The average age of firms was 18 years in 2019, while approximately 27 percent of the establishments were partly or entirely foreign-owned.[13] Just under 15 percent of the enterprises were managed by women. By industry, retail trade accounts for the largest share of enterprises, followed by manufacturing. More than

[11] To deal with extreme values, the rate of change in sales is trimmed at the 1st and 99th percentiles.

[12]This is based on the presumption that sales revenue in manufacturing and service industries does not vary significantly during the year, in contrast to sectors like agriculture, for which sales earnings may show substantial seasonal variations.

[13]A firm is defined as foreign owned if the share of foreign owners is at least 10 percent.

half of the firms are in Lusaka, the country's capital, while the remainder are evenly distributed across the three large cities covered by the surveys: Kitwe, Livingstone, and Ndola.

Website ownership varies across industries, as shown in Figure 2.1. It depicts the average proportion of enterprises with websites by industry in 2019. The food industry had the highest proportion of firms with websites (73 percent), followed by hotels and restaurants (72 percent). The transport, construction, and manufacturing industries reported rates of 64 percent, 63 percent, and 62 percent, respectively, whereas retail and wholesale trade reported rates of about 55 percent and 50 percent, respectively. The adoption of websites was the lowest among firms engaged in motor vehicle services.

Table 2.1: Descriptive statistics

	2019		2021	
Variable	Mean	SD	Mean	SD
Sales change	-0.032	0.214	-0.34	0.328
Website	0.608	0.489	0.608	0.489
SME	0.794	0.405	0.794	0.405
Age	18.037	12.295	20.037	12.295
Female manager	0.146	0.354	0.143	0.351
Foreign owned	0.272	0.446	0.272	0.446
Industry				
Manufacturing	0.209	0.407	0.209	0.407
Food	0.133	0.34	0.133	0.34
Construction	0.063	0.244	0.063	0.244
Services of motor vehicles	0.05	0.218	0.05	0.218
Wholesale trade	0.106	0.309	0.106	0.309
Retail trade	0.282	0.451	0.282	0.451
Hotels and restaurants	0.12	0.325	0.12	0.325
Transport	0.037	0.188	0.037	0.188
Region				
Kitwe	0.143	0.351	0.143	0.351
Livingstone	0.156	0.364	0.156	0.364
Lusaka	0.551	0.498	0.551	0.498
Ndola	0.15	0.357	0.15	0.357
Observations	301		301	

Notes: Sales change is the rate of change in sales revenue. The classification of industries follows ISIC Rev. 3.1, but the food industry is considered separately from other manufacturing industries. Wholesale trade, retail trade, and services of motor vehicles are also presented independently. The information technology industry is omitted because its activities are closely tied to digitalization. Except for sales change, firm age, and female manager, all other variables are measured at the baseline (2019).

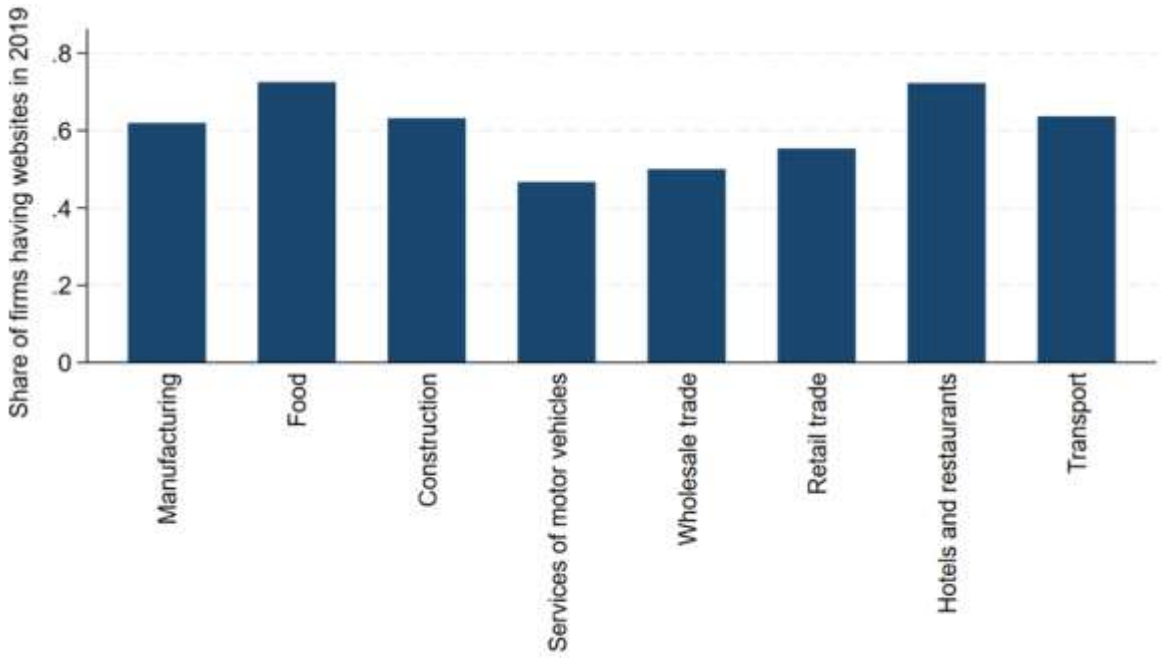


Figure 2.1: Share of firms having websites in 2019 by industrial group

Table 2.2 presents the means and standardized differences in means of covariates between digitalized and non-digitalized firms in 2019, before and after entropy balancing. Covariates are considered well-balanced if the values of standardized differences are less than 0.1 in absolute terms (Parish et al., 2018; Ogrokhina & Rodriguez, 2019; Larrain & Groene, 2023). As Table 2.2 reports, after balancing, the standardized differences are all close to zero. Since our entropy balancing includes second-order moment constraints, the variances are also well aligned. We report only the mean comparison for convenience; complete statistics are provided in Table A2.1 in the appendix.

Table 2.2: Covariate balancing for the digitalized and the non-digitalized group at the baseline (2019)

	Original sample			Entropy weights used	
	Digitalized (mean)	Non-digitalized (mean)	Standardized difference	Non-digitalized (mean)	Standardized difference
Log Age	2.700	2.621	0.113	2.702	-0.002
SME	0.710	0.924	-0.469	0.712	-0.003
Female manager	0.164	0.119	0.122	0.164	0.001
Foreign owned	0.350	0.153	0.412	0.349	0.001
Food	0.158	0.093	0.178	0.159	-0.001
Construction	0.066	0.059	0.025	0.066	0.000
Services of motor vehicles	0.038	0.068	-0.154	0.038	-0.001
Wholesale trade	0.087	0.136	-0.170	0.088	-0.001
Retail trade	0.257	0.322	-0.149	0.257	0.000
Hotels and restaurants	0.142	0.085	0.164	0.142	0.002
Transport	0.038	0.034	0.023	0.038	0.000
Livingstone	0.104	0.237	-0.436	0.104	-0.001
Lusaka	0.678	0.356	0.686	0.677	0.002
Ndola	0.109	0.212	-0.328	0.109	0.000
Observations	183	118		118	

Note: Manufacturing is the reference industry, and Kitwe is the reference region.

2.4. Results

2.4.1. The impact of COVID-19 pandemic on sales growth

Before examining whether digitalization strengthens firms' resilience to the pandemic, we analyze how firms' sales revenue changed during COVID-19 relative to the pre-pandemic period. Table 2.3 presents the effect of the pandemic on the rate of change in sales revenue, with columns (1-3) using the original sample and columns (4-6) using the weighted sample. Columns (1) and (4) have no fixed effects, columns (2) and (5) have industry fixed effects, and columns (3) and (6) have firm fixed effects. The estimates are surprisingly stable across the six models. They show a substantial negative impact of the pandemic on the outcome variable, corresponding to approximately a 30-percentage-point decline.

Table 2.3: Effect of COVID-19 on the rate of change in sales revenue

	Original sample			Entropy weights used		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID	-0.308***	-0.308***	-0.308***	-0.314***	-0.314***	-0.314***
	(0.023)	(0.023)	(0.023)	(0.030)	(0.030)	(0.030)
Observations	602	602	602	602	602	602
R-squared	0.237	0.251	0.381	0.271	0.288	0.425
Industry FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes

Notes: This table provides the effect of COVID-19 on the rate of change in sales revenue. The first three columns use the original sample, while the sample in the last three columns is based on the entropy balancing method of reweighting. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 2.4 presents the impact of the pandemic for two key firm characteristics: industry contact intensity (low-contact vs. high-contact) and integration into global value chains (foreign-trading vs domestic-only firms), using the weighted sample. While the impact size for low-contact and high-contact industries is similar to that for the full sample in Table 2.3, it is higher for non-trading (i.e., domestic) firms than for foreign trading firms.

In addition to the broad industry classification in Table 2.4, we evaluate the impact on individual industries in Figure 2.2. It shows the linear prediction plots of the rate of change in sales before and during the pandemic based on column (5) in Table 2.3. The pandemic's effects vary across industries, but the construction sector was disproportionately affected. According to Geda (2021), the massive contraction in the construction sector could be attributed to both a slowdown in infrastructure and urban expansion projects financed by loans and windfall gains from the mineral sector, which had already begun to decline before COVID-19, as well as to reductions in government-funded projects during the pandemic. There was also a considerable decline in the rate of change in sales revenue across other industries, with food manufacturing and motor vehicle services the least affected.

Table 2.4: Effect of COVID-19 on the rate of change in sales revenue based on the nature of firms

	Dependent variable: Rate of change in sales revenue			
	Low-contact	High-contact	Foreign trading	Domestic
COVID	-0.311***	-0.319***	-0.254***	-0.374***
	(0.044)	(0.039)	(0.035)	(0.044)
Observations	338	264	322	280
R-squared	0.426	0.423	0.369	0.483
Firm FE	Yes	Yes	Yes	Yes

Notes: We use the sample based on the entropy balancing method of reweighting. Low-contact industries include manufacturing, food, construction, services of motor vehicles, and wholesale trade. High-contact industries include hotels and restaurants, retail trade, and transport. Foreign trading firms are those engaged in exporting or importing, whereas domestic firms are those with no participation in international trade at the baseline. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

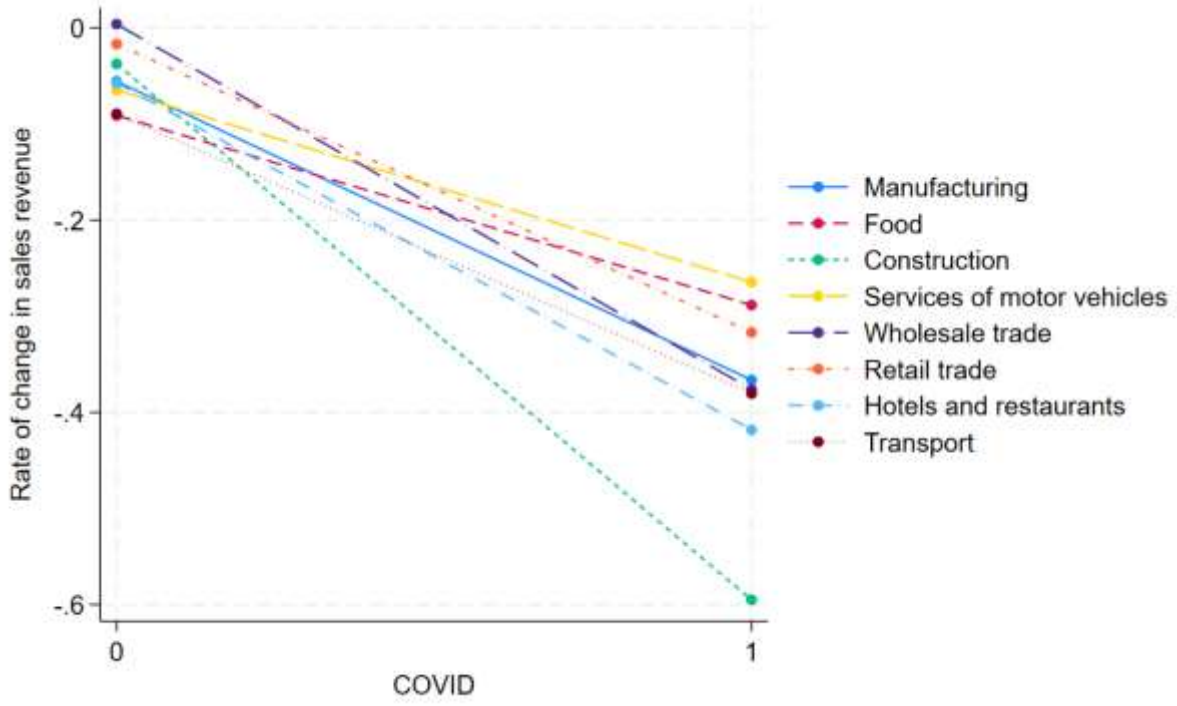


Figure 2.2: Change in sales revenue before (2019) and during COVID-19 across industries

2.4.2. The impact of digitalization on sales growth

Our findings thus show that the pandemic induced a sizable drop in sales. We now examine whether a firm's ex ante digital status affected its resilience to the pandemic. Tables 2.5 and 2.6 report the results from the DID estimations (see Tables A2.2 and A2.3 in the appendix for the complete results).

Table 2.5 shows that owning websites strengthens firms' resilience to the pandemic's adverse effects. The estimates are somewhat smaller when the weighted sample is used, 15 percentage points compared to 17 percentage points. However, there are only marginal differences across the three specifications. The results across all specifications consistently show that owning websites mitigated the pandemic's effects. This result is consistent with previous findings, for example, by Abidi et al. (2023). However, the magnitude of the coefficient in this study (15–17 percentage points) is higher than the 4 percentage points they report for the Middle East and Central Asia.

Table 2.5: Difference-in-differences estimation of COVID-19 and digitalization

	Original sample			Entropy weights used		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID	-0.412***	-0.408***	-0.362***	-0.388***	-0.383***	-0.324***
	(0.038)	(0.038)	(0.045)	(0.057)	(0.057)	(0.067)
Website	0.001	0.008		0.029	0.029	
	(0.027)	(0.027)		(0.029)	(0.032)	
COVID*Website	0.171***	0.171***	0.173***	0.148**	0.147**	0.147**
	(0.047)	(0.047)	(0.046)	(0.063)	(0.064)	(0.060)
Observations	602	602	602	602	602	602
R-squared	0.272	0.296	0.420	0.315	0.341	0.465
Firm Controls	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Region FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes

Notes: The first three columns use the original sample, while the sample in the last three columns is based on the entropy balancing method of reweighting. Columns (3) and (6) include firm fixed effects. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 2.6 reports disaggregated results on the mitigation effects of digitalization by industry contact intensity and firms' participation in international trade, using the weighted sample. Digitalization enhances firms' resilience to the pandemic's effects in low-contact industries, whereas it has no effect in high-contact industries. The estimated coefficient is also substantially higher for low-contact industries (0.2) than for all industries (0.15). Evidently, high-contact industries, such as hotels and transport, could not use the website to alleviate the drop in demand.

The ownership of websites also significantly improves the resilience of domestically oriented firms; the estimated coefficient is 0.25, whereas it is close to zero and insignificant for foreign-trading firms. However, as shown in Table 2.4, there is a substantial difference in the direct impact of COVID-19 on the two groups: -0.25 for foreign-trading firms and -0.37 for domestically oriented firms, with, as Table 2.6 shows, only partial mitigation by digitalization.

Table 2.6: Difference-in-differences estimation of COVID-19 and digitalization based on the nature of firms

Dependent variable: Rate of change in sales revenue				
	Low-contact	High-contact	Foreign trading	Domestic
COVID	-0.356***	-0.280***	-0.179*	-0.404***
	(0.108)	(0.064)	(0.092)	(0.069)
COVID*Website	0.198**	0.084	0.004	0.252***
	(0.092)	(0.075)	(0.081)	(0.077)
Observations	338	264	322	280
R-squared	0.480	0.457	0.388	0.545
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: We use the sample based on the entropy balancing method of reweighting. Low-contact industries include manufacturing, food, construction, services of motor vehicles, and wholesale trade. High-contact industries include hotels and restaurants, retail trade, and transport. Foreign trading firms are those engaged in either exporting or importing, while domestic firms represent firms with no participation in international trade at the baseline. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

To show the difference between industries, Figure 2.3 plots the average rate of change in sales revenue of digitalized versus non-digitalized firms during the pandemic. Consistent with the results presented in Table 2.6, digitalization plays an important role in mitigating the impact of COVID-19 in low-contact industries such as construction, wholesale trade, and manufacturing. At the same time, for hotels and restaurants, and transport, website ownership barely affects sales revenue.

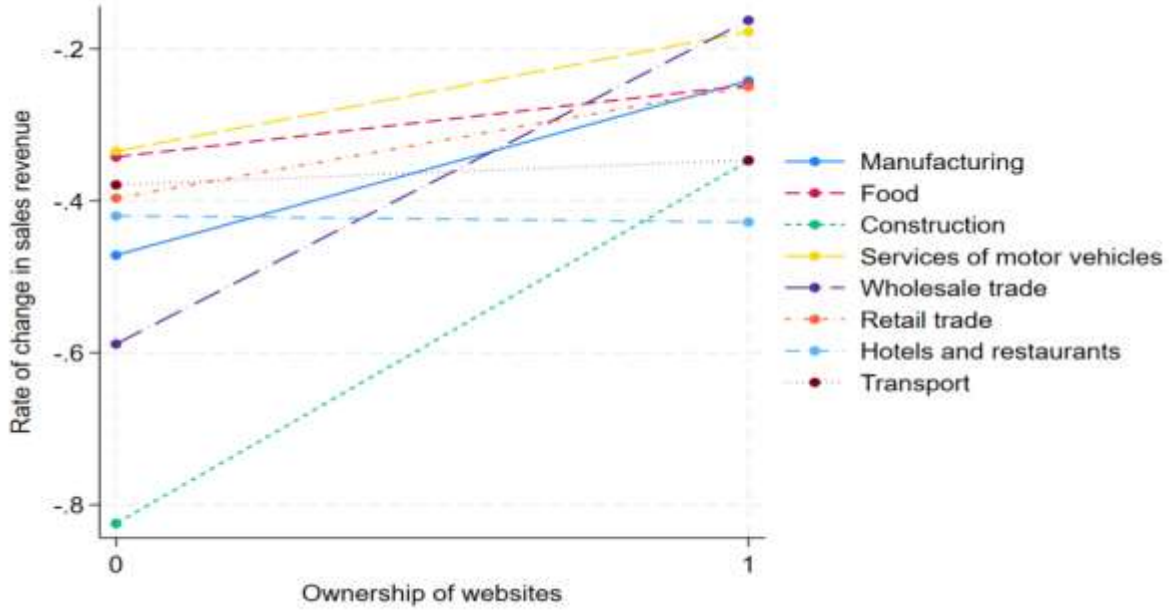


Figure 2.3: Mitigation role of digitalization during the COVID-19 pandemic across industries

2.4.3. Parallel trends and robustness analysis

In this section, we first show that the parallel-trends assumption is likely to hold and then conduct robustness checks to demonstrate the validity of our results.

Figure 2.4 plots the means of changes in sales for both digitalized and non-digitalized firms over three periods: 2013, 2019, and 2021, using the 201 observations available in all three surveys. The left-hand panel reports the standard model, while the right-hand panel reports the linear-trends model. The graph shows that the trajectories of the rate of change in sales revenue are reasonably parallel for the two groups before the pandemic outbreak. In other words, the assumption of parallel trends seems to hold. Given that panel history is limited and many firms are not observed throughout, the test provides only supportive evidence for the entropy balancing-based DID model.

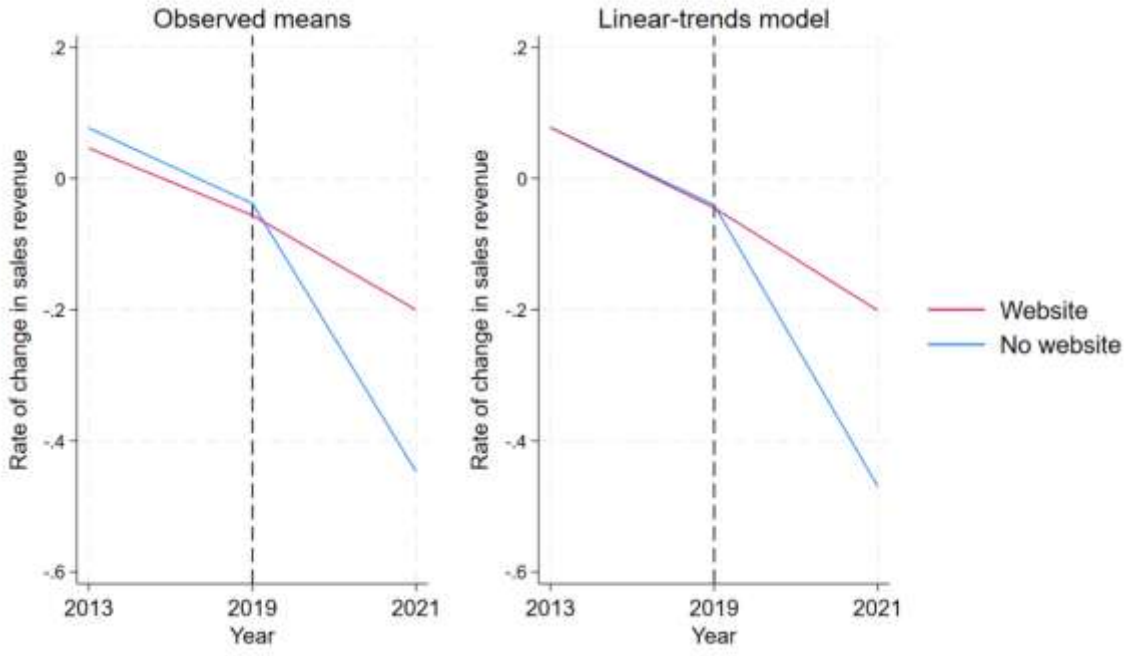


Figure 2.4: Graphical diagnostics for parallel trends

Next, to check for robustness of the results, we first apply an alternative reweighting approach: Kernel propensity-score weights. This approach entails matching control and treatment groups based on propensity scores (Villa, 2016). After dropping 38 unmatched observations, we re-estimated the DID model. The results are presented in Table 2.7. We found that website ownership mitigates the pandemic's impact, with coefficients comparable to those in the main model.

We then re-estimate the main model using unbalanced panel data, i.e., all available observations, which substantially increases the sample size (Table 2.8). As expected, the results are similar to those obtained with balanced panel data, in which effects are statistically significant for the full sample, low-contact industries, and domestically oriented firms. Thus, the loss of observations resulting from using a balanced sample in the main model does not affect our findings.

Table 2.7: Propensity-score matching difference-in-differences (PSM-DID)

Dependent variable: Rate of change in sales revenue					
	All	Low-contact	High-contact	Foreign trading	Domestic
COVID	-0.338***	-0.386***	-0.264***	-0.231**	-0.382***
	(0.051)	(0.077)	(0.059)	(0.091)	(0.052)
COVID*Website	0.156***	0.203***	0.086	0.032	0.247***
	(0.053)	(0.071)	(0.080)	(0.082)	(0.074)
Observations	564	314	250	296	268
R-squared	0.454	0.487	0.424	0.386	0.514
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Notes: The results are based on Kernel propensity-score matching DID. Low-contact industries include manufacturing, food, construction, services of motor vehicles, and wholesale trade. High-contact industries include hotels and restaurants, retail trade, and transport. Foreign trading firms are those engaged in exporting or importing, whereas domestic firms are those with no participation in international trade at the baseline. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 2.8: Estimation using unbalanced panel data

	Dependent variable: Rate of change in sales revenue				
	All	Low-contact	High-contact	Foreign trading	Domestic
COVID	-0.347***	-0.363***	-0.316***	-0.175**	-0.456***
	(0.075)	(0.116)	(0.062)	(0.088)	(0.073)
COVID*Website	0.158**	0.206**	0.091	0.008	0.273***
	(0.065)	(0.099)	(0.068)	(0.078)	(0.077)
Observations	709	387	322	367	341
R-squared	0.451	0.461	0.449	0.384	0.542
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Notes: The results are based on unbalanced panel data. We use the sample based on the entropy balancing method of reweighting. Low-contact industries include manufacturing, food, construction, services of motor vehicles, and wholesale trade. High-contact industries include hotels and restaurants, retail trade, and transport. Foreign trading firms are those engaged in exporting or importing, whereas domestic firms are those with no participation in international trade at the baseline. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

The descriptive statistics in Table 2.1 reveal that digitalized firms are more likely to be located in Lusaka. As a third robustness check, Table 2.9 presents results for a sample excluding firms in Lusaka. In general, the results for the pooled sample and low- and high-contact firms are consistent with those of the main model, with marginally higher coefficient estimates. The main differences are that the estimated impact of having a website is positive and statistically significant for foreign trading firms, and the impact of COVID-19 among non-digitalized foreign trading firms is large (- 0.54). One reason for the lack of significance in Table 2.6 for foreign trading firms is likely insufficient statistical power; many firms are based in Lusaka, and 90 percent of those involved in foreign trade had websites. However, it can be deduced from Table 2.6 and Table 2.9 that foreign trading firms in Lusaka experienced a much smaller loss due to COVID-19 than those in other regions. This may be attributed to greater market access during the pandemic; almost all international trunk highways go through Lusaka. Firms in other regions were affected by disruptions in both international and regional trade, whereas firms in Lusaka were affected by disruptions in international trade only.

Table 2.9: Excluding Lusaka-based enterprises

	Dependent variable: Rate of change in sales revenue				
	All	Low-contact	High-contact	Foreign trading	Domestic
COVID	-0.409***	-0.569***	-0.341***	-0.535***	-0.344***
	(0.064)	(0.124)	(0.078)	(0.106)	(0.080)
COVID*Website	0.180***	0.335***	0.138	0.227**	0.218*
	(0.065)	(0.114)	(0.089)	(0.087)	(0.121)
Observations	270	136	134	138	132
R-squared	0.506	0.515	0.544	0.480	0.559
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Notes: All columns exclude firms located in Lusaka, the capital city. We use the sample based on the entropy balancing method of reweighting. Low-contact industries include manufacturing, food, construction, services of motor vehicles, and wholesale trade. High-contact industries include hotels and restaurants, retail trade, and transport. Foreign trading firms are those engaged in exporting or importing, whereas domestic firms are those with no participation in international trade at the baseline. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Finally, we retain the 70 observations that did not have websites in 2019 but invested in new equipment, software, or other digital solutions during the pandemic. Here, they are included in the sample as a control group. As shown in Table 2.10, the estimated impacts for the pooled sample and low-contact firms are lower than those in the main model and are significant only at the 10 percent level. For domestically oriented firms, the estimate is significant at the conventional 5 percent level but smaller in magnitude than in the main model. These results reaffirm the importance of pre-pandemic digitalization. This is also evident when we include these firms in the treated group instead (see Table A2.4 in the appendix).

Table 2.10: Estimation without dropping firms that "digitalized" during the pandemic

Dependent variable: Rate of change in sales revenue					
	All	Low-contact	High-contact	Foreign trading	Domestic
COVID	-0.257***	-0.293***	-0.202***	-0.195***	-0.287***
	(0.045)	(0.055)	(0.071)	(0.060)	(0.060)
COVID*Website	0.080*	0.111*	0.035	0.001	0.154**
	(0.046)	(0.057)	(0.075)	(0.059)	(0.072)
Observations	672	378	294	352	320
R-squared	0.392	0.405	0.401	0.377	0.416
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Notes: We use the sample based on the entropy balancing method of reweighting. We don't drop firms that had no websites in 2019 but invested in equipment, software, or other digital solutions during the pandemic. Low-contact industries include manufacturing, food, construction, services of motor vehicles, and wholesale trade. High-contact industries include hotels and restaurants, retail trade, and transport. Foreign trading firms are those engaged in exporting or importing, whereas domestic firms are those with no participation in international trade at the baseline. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

2.4.4. Mechanisms

This section examines channels through which digitalization can enhance a firm's resilience to the pandemic. We test three channels: innovation, access to finance, and the use of coping strategies, i.e., online sales, remote work arrangements, and delivery or carry-out services. Specifically, we investigate whether ex-ante digitalized firms differ from their non-digitalized counterparts in these dimensions during the crisis.

The ES COVID-19 does not provide direct information on process innovation, so we focus solely on product innovation. It is defined as a binary variable equal to 1 if the firm has introduced a new product since the onset of the pandemic and 0 otherwise. Access to finance is also a binary variable: it is 1 if a firm is financially unconstrained and 0 otherwise. We follow Kuntchev et al. (2013) and Amin & Viganola (2023) and classify a firm as financially unconstrained if it did not apply for credit because it had sufficient internal funds, or if it applied for credit and the loan was approved. Firms may employ a single coping strategy or a combination of them, depending on the context. We use a binary indicator equal to 1 if a firm adopts at least one of the three strategies, and 0 otherwise. Since our mechanism measurements are restricted to ES COVID-19, the analysis in this section is based on only 301 observations.

Table 2.11 reports the results. Our findings suggest that firms that owned websites before the pandemic were about 30 percentage points more likely to innovate during the pandemic. This result aligns with Bertschek et al. (2019), who find that ICT-intensive firms were less affected by the 2008–2009 economic crisis, primarily due to innovation-driven productivity gains. However, we find no statistically significant relationship between firms' pre-pandemic digitalization status and access to finance during the crisis. This may reflect lenders' emphasis on real-time financial conditions and more stringent collateral requirements.

Not surprisingly, having websites before the pandemic enhances the adoption of relevant coping strategies. Firms with websites are about 15 percentage points more likely to use at least one coping strategy. The associations for the individual coping strategies are weaker but provide the same message (Table A2.5 in the appendix). Our findings are in line with Cariolle and Léon (2022), who, using firm-level data from 39 developed and developing countries, found that pre-pandemic ownership of websites increased firms’ propensity to adopt coping strategies, and Avalos et al. (2024), who documented that it was associated with increased use of diverse digital technologies in response to the pandemic in a sample of 65 countries.

Table 2.11 : Analysis of mechanisms, marginal effects

	Product innovation	Access to finance	Coping
Website	0.324***	-0.027	0.150***
	(0.042)	(0.067)	(0.054)
Observations	301	301	301
Controls	Yes	Yes	Yes

Notes: The table presents the association between pre-pandemic ownership of websites and three firm-level outcomes during the pandemic, estimated with probit models. We use the sample based on the entropy balancing method of reweighting. Coping includes online sales, remote work arrangements, and delivery or carry-out services. All models include firm age (in log), firm size (one if small and medium enterprise and zero if large enterprise), top manager's gender (one if female), foreign ownership (one if yes), industry dummies, and region dummies. The coefficients are reported as marginal effects. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

2.5. Conclusions and policy implications

The digital revolution has led to significant economic and social transformations in many countries. Sub-Saharan Africa has also witnessed a growing digital economy, although slowly. Using COVID-19 as a natural experiment and employing firm-level panel data from Zambia, this study investigates whether digitalization improved firms' resilience to this shock in a developing-country context.

We first show that COVID-19 had a substantial negative impact on firms' sales revenue; the average rate of change in sales revenue declined by approximately 30 percentage points. Using entropy balancing and difference-in-differences estimation, we show that firms with websites prior to the onset of the pandemic experienced smaller declines in sales revenue than firms without websites. These results are generally consistent with other studies in different contexts (such as Bai et al., 2021; Doerr et al., 2021; Copestake et al., 2024; Gaspar et al., 2024).

Our results suggest that pre-pandemic website ownership enhances firms' resilience through innovation and the adoption of relevant coping strategies during the pandemic. Digitalized firms are more likely to introduce new products, which may entail reorganization of their operations. Pre-pandemic digitalization is also associated with a greater likelihood that firms start or increase at least one coping strategy (online sales, remote work, or delivery services) during the pandemic.

However, the impact of digitalization differed greatly across industries. The effect was substantial in low-contact industries: the decline in the rate of change in sales for digitalized firms was about 20 percentage points lower, whereas the corresponding impact was about 15 percentage points for the pooled sample. Low-contact firms typically involve little direct customer interaction, enabling them to leverage websites for marketing, client communication, order management, and effective coordination during periods of restricted mobility. Digitalization could also allow them to implement telework schemes, thereby sustaining operations amid the crisis.

Among high-contact industries, having a website was insignificant. It is not surprising that websites had a limited effect on industries that require face-to-face contact, such as hotels and public transport. On the other hand, high-contact industries, such as retail trade and restaurants, may benefit from websites that enable home delivery. However, business-to-consumer (B2C) e-commerce is not widespread in Zambia. In 2020, it ranked 120th among 152 countries in UNCTAD's B2C e-commerce index (UNCTAD, 2021). Thus, website ownership offered minimal mitigation when the service delivery required in-person interaction. These results are consistent with the findings of Kawaguchi et al. (2022) but differ from those of Abidi et al. (2023), who report a greater impact of digitalization on high-contact firms than on low-contact firms in the Middle East and Central Asia. This could be due to greater access to infrastructure and digital literacy in the latter than in Africa. However, it may also be attributable to differences in the classifications of high-contact industries, since Abidi et al. (2023) only included wholesale and retail trade, hospitality, and tourism.

The impact of website ownership is also notably larger among domestically oriented firms, that is, firms not engaged in foreign trade, than among those involved in foreign trade. However, firms not located in Lusaka benefited from having websites. Among those in Lusaka and engaged in foreign trade, 90 percent had websites, which made it challenging to test for an effect. Nevertheless, our findings differ from those of Gopalan et al. (2025), who, using pooled data from a sample of mainly high- and middle-income countries, found that digitalization improved resilience only among firms integrated into global value chains.

Our study highlights the importance of digitalization in mitigating economic losses resulting from COVID-19. There have been, and there will be, other types of adverse shocks at the global,

regional, and individual-country levels for which digitalization played, or will play, a mitigating role. Moreover, combined with the emerging complementary technologies, such as AI, drone-based deliveries of goods and driverless cars, digitalization is expected to expand further, providing new coping mechanisms. However, the African continent has lagged in digitalization due to multiple constraints (Mpofu, 2023). Thus, a clear policy conclusion is to invest in ICT infrastructure, including cables and 4G and 5G networks. In this regard, the government of Zambia has made significant progress in expanding telecommunications sites, optic fiber networks, and international connectivity routes.[14]

Our results support increased government efforts to place digital strategies at the center of their policy agendas. Effective expansion of digitalization requires not only infrastructure but also social interventions to increase access to and use of digital technologies (Abidi et al., 2023; Mpofu, 2023). Anchored in Vision 2030, the Zambian government has designed policies such as the National ICT Policy (2023), which outlines a framework for leveraging ICT as a driver of economic transformation, and the National Digital Transformation Strategy (2023-2027), which advances this vision by embedding digital adoption across all sectors of the economy. A key concern in digital policy and strategy is inclusivity, as the adoption and use of digitalization is heterogeneous (Abidi et al., 2023). Hence, inclusive strategies and actions are necessary to maximize the benefits of digitalization.

We acknowledge that this study has some limitations. Measuring resilience is challenging, and we do not capture aspects such as the capacity to adapt to unexpected shocks. Moreover, our analysis relies on a single-country survey and should be replicated in other Sub-Saharan African countries. Another limitation is that our measure of digitalization—website ownership—may not fully capture an enterprise's overall level of digitalization. Finally, as with observational studies, establishing causality is challenging, and we may not have controlled for all omitted variable bias. Hence, further studies are needed, preferably employing datasets with various digitalization indicators.

[14] https://www.zicta.zm/market-reports/2024_annual_market_report.pdf

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Appendix

Table A2.1: Covariate balancing at the baseline 2019, complete results

	Before entropy balancing						
	Digitalized			Non-digitalized			
	Mean	Variance	Skewness	Mean	Variance	Skewness	Standardized difference
Log Age	2.700	0.485	-0.317	2.621	0.515	-0.802	0.113
SME	0.710	0.207	-0.928	0.924	0.071	-3.193	-0.469
Female manager	0.164	0.138	1.816	0.119	0.105	2.359	0.122
Foreign owned	0.350	0.229	0.630	0.153	0.130	1.933	0.412
Food	0.158	0.134	1.870	0.093	0.085	2.798	0.178
Construction	0.066	0.062	3.510	0.059	0.056	3.731	0.025
Services of motor vehicles	0.038	0.037	4.815	0.068	0.064	3.438	-0.154
Wholesale trade	0.087	0.080	2.921	0.136	0.118	2.129	-0.170
Retail trade	0.257	0.192	1.113	0.322	0.220	0.762	-0.149
Hotels and restaurants	0.142	0.123	2.050	0.085	0.078	2.982	0.164
Transport	0.038	0.037	4.815	0.034	0.033	5.151	0.023
Livingstone	0.104	0.094	2.598	0.237	0.183	1.235	-0.436
Lusaka	0.678	0.220	-0.760	0.356	0.231	0.602	0.686
Ndola	0.109	0.098	2.505	0.212	0.168	1.410	-0.328
Observations	183			118			

	After entropy balancing						
	Digitalized			Non-digitalized			
	Mean	Variance	Skewness	Mean	Variance	Skewness	Standardized difference
Log Age	2.700	0.485	-0.317	2.702	0.484	-1.127	-0.002
SME	0.710	0.207	-0.928	0.712	0.207	-0.934	-0.003
Female manager	0.164	0.138	1.816	0.164	0.138	1.819	0.001
Foreign owned	0.350	0.229	0.630	0.349	0.229	0.633	0.001
Food	0.158	0.134	1.870	0.159	0.135	1.868	-0.001
Construction	0.066	0.062	3.510	0.066	0.062	3.512	0.000
Services of motor vehicles	0.038	0.037	4.815	0.038	0.037	4.798	-0.001
Wholesale trade	0.087	0.080	2.921	0.088	0.081	2.918	-0.001
Retail trade	0.257	0.192	1.113	0.257	0.192	1.114	0.000
Hotels and restaurants	0.142	0.123	2.050	0.142	0.123	2.057	0.002
Transport	0.038	0.037	4.815	0.038	0.037	4.819	0.000
Livingstone	0.104	0.094	2.598	0.104	0.094	2.592	-0.001
Lusaka	0.678	0.220	-0.760	0.677	0.221	-0.756	0.002
Ndola	0.109	0.098	2.505	0.109	0.098	2.506	0.000
Observations	183			118			

Table A2.2: Difference-in-differences estimation of COVID-19 and digitalization (complete results)

Dependent variable: Rate of change in sales revenue						
	Original sample			Entropy weights used		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID	-0.412***	-0.408***	-0.362***	-0.388***	-0.383***	-0.324***
	(0.038)	(0.038)	(0.045)	(0.057)	(0.057)	(0.067)
Website	0.001	0.008		0.029	0.029	
	(0.027)	(0.027)		(0.029)	(0.032)	
COVID*Website	0.171***	0.171***	0.173***	0.148**	0.147**	0.147**
	(0.047)	(0.047)	(0.046)	(0.063)	(0.064)	(0.060)
Log Age		-0.023	-0.319**		-0.035*	-0.393**
		(0.020)	(0.148)		(0.020)	(0.177)
SME		-0.001			0.005	
		(0.028)			(0.028)	
Female manager		0.007	0.081*		-0.014	0.092*
		(0.031)	(0.048)		(0.032)	(0.051)
Foreign owned		0.039*			0.046*	
		(0.023)			(0.027)	
Food		0.015			0.010	
		(0.036)			(0.035)	
Construction		-0.102**			-0.107**	
		(0.040)			(0.044)	
Services of motor vehicles		-0.014			0.048	
		(0.043)			(0.045)	
Wholesale trade		0.047			0.016	
		(0.048)			(0.054)	
Retail trade		0.015			0.032	
		(0.034)			(0.040)	
Hotels and restaurants		-0.088**			-0.047	
		(0.040)			(0.043)	
Transport		-0.022			-0.018	
		(0.049)			(0.046)	
Livingstone		-0.056			0.016	
		(0.047)			(0.054)	
Lusaka		-0.053			-0.016	
		(0.039)			(0.049)	
Ndola		-0.036			-0.019	
		(0.044)			(0.053)	
Constant	-0.033	0.063	0.806**	-0.061**	0.029	1.000**
	(0.023)	(0.081)	(0.396)	(0.026)	(0.081)	(0.475)
Observations	602	602	602	602	602	602
R-squared	0.272	0.296	0.420	0.315	0.341	0.465

Notes: The first three columns use the original sample, while the sample in the last three columns is based on the entropy balancing method of reweighting. Columns (3) and (6) include firm fixed effects. Except for firm age and the female manager dummy, which are time-varying, all other covariates are measured at the baseline. Manufacturing is the reference industry, and Kitwe is the reference region. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table A2.3: Difference-in-differences estimation of COVID-19 and digitalization based on the nature of firms (complete results)

Dependent variable: Rate of change in sales revenue				
	Low-contact	High-contact	Foreign trading	Domestic
COVID	-0.356***	-0.280***	-0.179*	-0.404***
	(0.108)	(0.064)	(0.092)	(0.069)
COVID*Website	0.198**	0.084	0.004	0.252***
	(0.092)	(0.075)	(0.081)	(0.077)
Log Age	-0.361**	-0.462	-0.578**	-0.275
	(0.180)	(0.297)	(0.284)	(0.197)
Female manager	0.047	0.132*	0.034	0.124*
	(0.067)	(0.071)	(0.069)	(0.067)
Constant	0.937*	1.147	1.579**	0.638
	(0.480)	(0.785)	(0.796)	(0.507)
Observations	338	264	322	280
R-squared	0.480	0.457	0.388	0.545

Notes: We use the sample based on the entropy balancing method of reweighting. Low-contact industries include manufacturing, food, construction, services of motor vehicles, and wholesale trade. High-contact industries include hotels and restaurants, retail trade, and transport. Foreign trading firms are those engaged in either exporting or importing, while domestic firms represent firms with no participation in international trade at the baseline. All models include firm controls and firm fixed effects. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table A2.4: Estimation including firms that "digitalized" during the pandemic (as "treated" group)

Dependent variable: Rate of change in sales revenue					
	All	Low-contact	High-contact	Foreign trading	Domestic
COVID	-0.322***	-0.367***	-0.256***	-0.191**	-0.389***
	(0.066)	(0.108)	(0.064)	(0.093)	(0.070)
COVID*Website	0.147**	0.205**	0.075	0.013	0.233***
	(0.059)	(0.090)	(0.073)	(0.082)	(0.073)
Observations	672	378	294	352	320
R-squared	0.469	0.495	0.452	0.395	0.535
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Notes: We use the sample based on the entropy balancing method of reweighting. Firms that had no websites in 2019 but invested in equipment, software, or other digital solutions during the pandemic are included as "treated" group. Low-contact industries include manufacturing, food, construction, services of motor vehicles, and wholesale trade. High-contact industries include hotels and restaurants, retail trade, and transport. Foreign trading firms are those engaged in either exporting or importing, while domestic firms represent firms with no participation in international trade at the baseline. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table A2.5: Analysis of mechanisms for specific coping strategies

	Online sales	Delivery	Remote work
Website	0.137*	0.107	0.262***
	(0.080)	(0.068)	(0.044)
Observations	301	301	301
Controls	Yes	Yes	Yes

Notes: The table presents the association between pre-pandemic ownership of websites and three coping strategies (online sales, remote work arrangements, and delivery or carry-out services) during the pandemic, estimated with probit models. We use the sample based on the entropy balancing method of reweighting. All models include firm age (in log), firm size (one if small & medium enterprise and zero if large enterprise), top manager's gender (one if female), foreign ownership (one if yes), industry dummies, and region dummies. The coefficients are reported as marginal effects. Robust standard errors clustered at a firm level are in parentheses. ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

3. The impact of mobile broadband internet on literacy: Evidence from Nigeria

Abstract

This paper examines the impact of 3G mobile broadband coverage on basic literacy among children aged 5-12 years in Nigeria. Basic literacy is measured by a binary indicator of the ability to read and write. The analysis draws on three waves of panel data from the Nigerian General Household Survey (2010–11, 2012–13, and 2015–16), which are geographically matched to a mobile network coverage map. The study employs the Callaway and Sant'Anna (2021) difference-in-differences estimator, exploiting quasi-experimental variation from the staggered rollout of 3G infrastructure. We find a robust and statistically significant positive association between mobile broadband coverage and literacy attainment. The effects are particularly pronounced among boys, children from economically disadvantaged households, and those enrolled in school at baseline. Our findings also provide suggestive evidence of two indirect channels through which mobile broadband expansion might affect children's literacy: enhanced parental aspirations and increases in household income.

Keywords: Literacy, mobile broadband, Nigeria

3.1. Introduction

Globally, the percentage of people using mobile internet increased from 33 percent in 2015 to about 58 percent by the end of 2024 (GSMA, 2025), with smartphones providing the most convenient access to the service (Bahia & Suardi, 2019). This digital shift has brought substantial changes to education, fostering benefits such as greater creativity and broader access to learning. At the same time, it has also introduced several challenges, including the proliferation of misinformation and increased distractions (Bulman & Fairlie, 2016; Bala, 2025).

The use of information and communication technologies in education can be crucial, particularly in hard-to-reach areas, such as conflict zones. Digital technology expands educational opportunity for learners who otherwise would not have access to schools or well-trained teachers (Ashlee et

al., 2020; Antoninis et al., 2023). For instance, app-based instructions have the potential to enhance fundamental literacy skills, even among out-of-school children. However, the technology alone is insufficient without strong family and community support. The other issue is that education technology usually requires complementary investment in infrastructure such as power supply (Mutu 2023; Barnes et al., 2025). Still, its advantage lies in providing an effective alternative when other means are resource-intensive or prohibitively expensive (Rodriguez-Segura, 2022).

The impact of internet access or availability on educational outcomes may be direct or indirect. The direct impact primarily manifests itself through its effect on time use, not just for students but also for parents and teachers. In this regard, the advent of 3G technology could be a major blessing, as it offers faster, more efficient resources for children's self-learning and for instructional support from parents and educators. However, excessive time spent on social media may impede learning (Vigdor et al., 2014; Faber et al., 2015; Malamud et al., 2019). The indirect impact mainly operates through changes in income and labor-market variables, such as employment and sectoral skill demand, thereby shaping parents' decisions about their children's education (Bessone et al., 2020).

A body of literature documents that internet expansion, including mobile broadband, improves economic outcomes such as employment (Hjort & Poulsen, 2019; Chiplunkar & Goldberg, 2022; Caldarola et al., 2023; Pham & Caldarola, 2024), and welfare (Ma et al., 2020; Bahia et al., 2024). However, there is limited evidence on the impact of this technology on educational outcomes, particularly literacy, and the existing findings are mixed. A few studies reveal a significant positive effect of the internet on student test scores across both developed and developing economies. For example, Grimes and Townsend (2018) document such an effect in New Zealand, while Derksen et al. (2022) report similar findings for Malawi. Complementing these country-specific studies, Bala (2025) shows a positive association between national internet use and harmonized test scores, using a cross-country panel of 107 economies. In the African context, Elom et al. (2024) find that internet access enhances school enrollment, using panel data from 25 countries.

Despite the above evidence of potential benefits, the empirical findings largely point to a negative or neutral impact of internet access on educational attainment. For example, Malamud et al. (2019) and Okyere (2022) report negligible effects of the internet on educational achievement in Peru and Kenya, respectively. Others find a negative association between the two, particularly in advanced

economies (e.g., Belo et al., 2014; Vigdor et al., 2014), while Henriksen et al. (2022) document similar results for Brazil.

One explanation in the literature for negative associations between internet access and educational outcomes is the excessive use of the internet for entertainment rather than for learning (Vigdor et al., 2014; Malamud et al., 2019; Cambini et al., 2024). An alternative explanation is the choice between education and employment, where internet access expands employment opportunities while increasing the opportunity cost of schooling and lowering educational achievement. This trade-off is particularly pronounced among students in later grades, such as upper secondary levels (Pham & Caldarola, 2024). In sum, the educational impact of the internet remains inconclusive. The results seem to differ depending on the context.

Nigeria, Africa's largest mobile market, has seen a surge in mobile broadband coverage, increasing from 21 percent in 2010 to more than 57 percent in 2015—driven primarily by the liberalization of the telecommunications sector.[15] In contrast, fixed broadband penetration remained relatively limited, rising marginally from approximately 2 percent in 2010 to 5 percent by 2016. The implication is that a sheer majority of the population accesses the internet primarily through mobile devices rather than fixed-line connections (World Bank & GSMA, 2020). By mid-2024, the coverage of 3G and 4G mobile networks reached 99 percent and 84 percent, respectively (GSMA, 2024). However, just over 45 percent of the total population were using the internet at the beginning of 2025 (Statista, 2025).

Against this backdrop, this study examines the impact of mobile broadband coverage on literacy among children aged 5-12 years in Nigeria, where literacy is defined as the ability to read and write. Basic literacy skills are a key pillar of all other educational outcomes and are essential to personal and societal well-being. Without a minimum proficiency in reading and writing, children will struggle to succeed later in school and to acquire higher-level competencies needed for the increasingly evolving labor market in developing economies.[16] Consequently, low literacy

[15] Coverage refers to whether individuals reside within the range of a cellular signal, regardless of whether they use mobile internet services.

[16] Children who have not mastered reading by the end of primary education generally struggle to do so in later schooling (World Bank, 2019).

constrains human capital accumulation and productivity, posing a substantial challenge to achieving sustainable and inclusive growth (World Bank, 2019). In Nigeria, only 27 percent of children aged 7-14 years had foundational reading skills in 2022 (UNICEF, 2023).[17]

We geographically match the mobile broadband coverage map from Collins Bartholomew's Mobile Network Coverage Explorer with three waves of the Nigerian General Household Survey (GHS), collected between 2010 and 2016. The focus of this study is 3G mobile broadband technology, which enables users to browse the web directly on their phones. A broad consensus in the literature is that, although the rollout of mobile broadband may be influenced by underlying economic conditions—such as income levels or urbanization—it is largely determined by supply-side factors and by mobile network operators' infrastructure investment decisions.[18] As a result, the expansion of mobile broadband tends to occur unevenly across regions and over time, which provides quasi-experimental designs to estimate its impact on the outcome variable. Accordingly, we employ the difference-in-differences (DID) estimation technique developed by Callaway and Sant'Anna (2021), which accounts for treatment effect heterogeneity in settings with staggered treatment adoption while reducing biases in traditional two-way fixed effects models. The identification relies on a conditional parallel trends assumption, whereby untreated potential outcomes evolve similarly across treated and control units conditional on pre-treatment covariates.

Overall, our findings suggest that increased 3G mobile broadband coverage is associated with a statistically significant improvement in literacy of approximately 10 percentage points. The group average impact for early-treated children (treated between waves 1 and 2) and late-treated ones (treated between waves 2 and 3) is statistically significant, despite the group-specific effects being individually insignificant. We find a statistically significant aggregated impact at the third wave, but not at the second wave. The impact is also significant at the time of treatment, but it is statistically insignificant at the 5 percent level one wave after initial treatment, while its magnitude remains large. This result could be partly due to a ceiling effect, as basic literacy improves naturally with age and schooling. Our results generally remain consistent across alternative specifications.

[17] UNICEF's Multiple Indicator Cluster Surveys (MICS) define foundational learning skills as the learning outcomes expected for Grades 2 and 3 in numeracy and literacy for children aged 7 to 14 years.

[18] See, for example, Bahia et al. (2024).

The heterogeneity analysis further indicates that larger gains accrue to boys, children from less affluent households, and those enrolled in school at baseline.

This paper contributes to various strands of the literature. First, it adds to the scant yet mixed evidence on the educational impact of the internet. While existing studies largely focus on advanced economies with apparently better educational infrastructure (e.g., Belo et al., 2014; Vigdor et al., 2014; Grimes & Townsend, 2018; Cambini et al., 2024; Nordrum & Gracia, 2024), there is a dearth of information in the context of developing countries. Prominent studies focusing on developing economies highlight the effects of internet access in schools (e.g., Derksen et al., 2022; Okyere, 2022; Lakdawala et al., 2023). Elom et al. (2024) provide cross-country evidence on the effect of internet subscriptions and usage on school enrolment. Closely related to our study, Henriksen et al. (2022) investigate the effect of broadband expansion on various education outcomes in Brazil, relying on the rollout of local internet speed infrastructure that connects peripheral data centers to the backbone network. In contrast, the current paper examines the micro-level impact of mobile broadband coverage on literacy.

Second, we focus on the impact of mobile broadband availability, rather than internet access through subscriptions or actual usage. While the former provides a more exogenous source of variation (Bahia et al., 2024), the latter measure is more susceptible to endogeneity concerns as households' or individuals' decisions to use the internet are likely to be correlated with unobserved characteristics that also shape educational outcomes. Several studies have mainly focused on the extent to which internet usage affects educational attainment (e.g., Malamud et al., 2019; Hampton et al., 2021; Derksen et al., 2022; Cambini et al., 2024). In contrast, this paper is based on supply-side expansion of 3G to better identify the effects of interest.

Third, this analysis is based on panel data at the child level, which allows us to control for unobserved time-invariant individual heterogeneity. Some studies employ cross-sectional data on students' education outcomes (Okyere, 2022; Lakdawala et al., 2023), while others base their analysis on school-level data (e.g., Belo et al., 2014; Henriksen et al., 2022).

Finally, unlike previous research that focuses exclusively on children enrolled in schools (e.g., Vigdor et al., 2014; Malamud et al., 2019; Derksen et al., 2022; Okyere, 2022; Pham & Caldarola, 2024), our study covers all children aged 5 to 12 years. The approach adopted in this paper,

therefore, provides an understanding of how internet expansion influences literacy across a broader spectrum of the population in the specified age group. Among others, it allows us to provide evidence on whether 3G technology supports learning beyond formal education. UNICEF (2023) reports that more than one-quarter of primary-school-aged children remain out of school in Nigeria, ranking among the highest globally.

The remainder of this chapter is organized as follows. Section 3.2 deals with the data and descriptive statistics of the variables. Section 3.3 presents the empirical strategy. The empirical results are discussed in section 3.4, while section 3.5 provides conclusions and policy implications of the study.

3.2. Data and descriptive statistics

3.2.1. Data

We measure mobile broadband coverage using digital maps of 3G networks. The mobile broadband coverage data is drawn from Collins Bartholomew's Mobile Network Coverage Explorer, the official mapping partner of the Global System for Mobile Communications Association (GSMA). Annually updated digital maps are available in a raster format of 1km × 1km grid cells, constructed from submissions by mobile network operators. This dataset is widely used in studies examining the impact of mobile technologies on various socio-economic and political outcomes (e.g., Manacorda & Tesei, 2020; Guriev et al., 2021; Mensah et al., 2022). Not all operators are expected to submit data on time, though, as reporting is voluntary. To mitigate this limitation, we complement it with the data from OpenCelliD, the world's largest open database of cell towers. OpenCelliD is a crowd-sourced database that provides the geographic coordinates of cell towers, the underlying technology (e.g., GSM, UMTS, LTE), and the date when the cell tower was first added to the database.[19]

The GHS panel is a nationally representative survey collected as part of the World Bank Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). This study uses three waves of the GHS panel: 2010/11, 2012/13, and 2015/16. The survey comprises household,

[19] https://www.opencellid.org/

agriculture, and community questionnaires. While each household is visited once after the planting season (August to October) and again after the harvest season (February to April), much of the information is gathered during the post-harvest period.[20] The education roster was administered in both visits in waves 1 and 2, but only after harvest in wave 3. To ensure comparability across survey years, the literacy measure is, therefore, drawn exclusively from the post-harvest data. The approach followed in the GHS panel is to solicit information on all existing household members and new entrants, such as those born since the previous wave. The outcome variable in this study—whether children can read and write in any language—is collected for individuals aged five years and above. This information is provided either by the individuals themselves or by someone presumed to be more knowledgeable, typically the household head. While our literacy indicator is not based on objective assessments of reading and writing skills, and tends to overstate the true ability (Nath, 2007), it remains the most practical option when direct literacy tests are infeasible or unavailable (e.g., Lee et al., 2019; Fagbamigbe et al., 2021; Mtika & Abbott, 2025). Moreover, we are interested in changes over time among the same children, so overestimation of the level is unlikely to affect our estimates.

In the first wave of the GHS panel, 4,916 households were interviewed. In the second, 4,716 households were re-interviewed with an attrition rate of about 4 percent. The total number of households interviewed in the third wave was 4,581, with a retention rate of about 92 percent from the first wave and 94 percent from the second wave. Thus, altogether 4,407 households were successfully tracked during both post-planting and post-harvest visits over the three waves. The longitudinal structure of the data allows for in-depth analysis of changes over time while also controlling for unobserved individual heterogeneity that cannot be captured with cross-sectional data.

We spatially link the GHS panel data with the mobile network coverage maps. The GHS panel households are geocoded at the enumeration area level. Hence, all households in a particular enumeration area are assigned the same GPS coordinates, corresponding to the centroid of the enumeration area. To ensure confidentiality, household GPS locations in the original data are

[20] Further explanation about the survey can be found at https://microdata.worldbank.org/index.php/catalog/2734/related-materials.

randomly displaced up to 2 kilometers for urban and up to 5 kilometers for rural areas. Since the GPS coordinates are available only as point locations, we create a buffer zone around each point: 2 kilometers for urban and 5 kilometers for rural households. A household (or any household member) is assumed to be covered by a mobile broadband network if the corresponding buffer zone generated from the centroid of the household enumeration area is covered by one or more grid cells with a medium or strong 3G signal. The dataset does not show any records of 4G or 5G for the period under study. Figure 3.1 depicts the 3G mobile broadband coverage along with the GHS enumeration areas corresponding to the last two waves of the sample of the study.

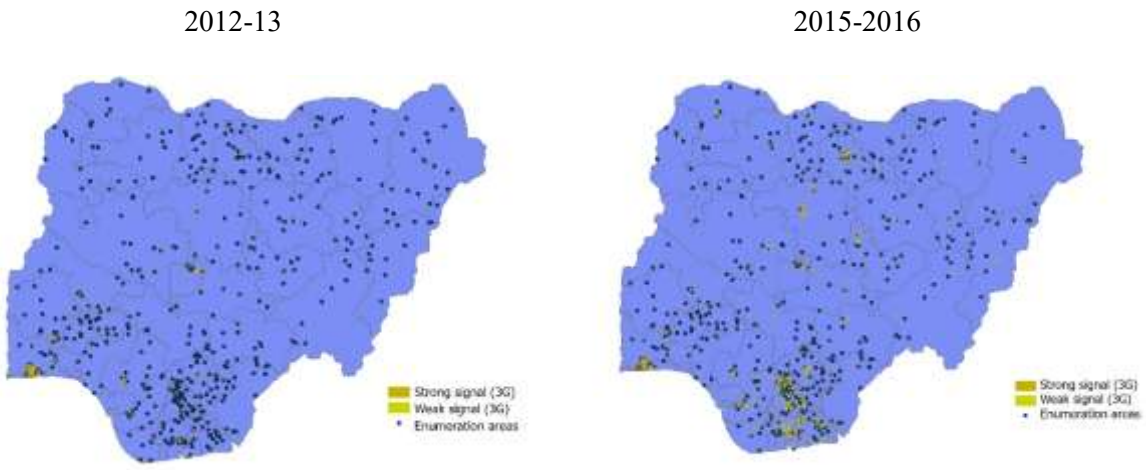


Figure 3.1: GHS enumeration areas and 3G mobile broadband coverage

3.2.2. Descriptive statistics

Table 3.1 presents descriptive statistics for the outcome variable and covariates used in the analysis, reported separately by the treatment group at baseline (2010–2011). Literacy is a binary variable that takes on a value of one if an individual can read and write in any language, and zero otherwise. Although the key variable of interest in this analysis is the 3G technology, we also control 2G networks, which primarily offer voice calls and text or multimedia messaging.

Age is measured in years, the variable ‘male’ identifies sex of the child taking a value of one for boys and zero for girls, and head literacy is equal to one if the household head can read and write, and zero otherwise. Other covariates include a binary variable whether a child has ever attended

formal or informal school (one if yes); household assets (in log of Naira)[21]; access to electricity (one if yes); area of residence (one for urban and zero for rural); and distance to the nearest market center in kilometers. The descriptive summary of the variables across the three waves is provided in Table A3.1 in the appendix.

As shown in Table 3.1, children in the early-treated group exhibit the highest literacy level, followed by the late-treated groups. Further, the rollout of 3G mobile broadband networks seems to start earlier for children in urban areas, those with better access to electricity, and who are members of economically better-off households (as indicated by higher asset values). Additionally, proximity to market centers slightly favors earlier treatment, suggesting prioritized investment decisions of operators in more accessible and economically active regions.

Table 3.1: Descriptive statistics at baseline by treatment group

	Never treated			Early treated			Late treated		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
The child is literate (1 if Yes)	2,584	0.245	0.430	615	0.525	0.500	295	0.346	0.476
Coverage 2G (1 if Yes)	2,584	0.555	0.497	615	0.963	0.190	295	0.969	0.172
Age of the child (in years)	2,584	7.438	1.891	615	7.159	1.781	295	6.475	1.633
The child is male (1 if Yes)	2,584	0.514	0.500	615	0.556	0.497	295	0.522	0.500
The child ever attained school (1 if Yes)	2,584	0.717	0.450	615	0.950	0.219	295	0.868	0.339
The household head is literate (1 if Yes)	2,584	0.563	0.496	615	0.795	0.404	295	0.766	0.424
lnasset	2,584	10.27	1.453	615	11.08	1.580	295	10.70	1.569
The household accesses electricity (1 if Yes)	2,584	0.143	0.350	615	0.537	0.499	295	0.363	0.482
Lives in urban areas (1 if Yes)	2,584	0.114	0.318	615	0.624	0.485	295	0.308	0.463
Distance to market	2,584	77.85	43.42	615	54.35	40.23	295	56.23	34.58

Notes: Child refers household member aged 5-12 years. *Early treated* are individuals treated between wave 1 and wave 2, while *late treated* denote those treated between wave 2 and wave 3.

[21] Household assets are measured as the total values of household assets, including consumer durables, transport equipment, and communication devices. The variable is log-transformed to reduce skewness and limit influence of extreme values.

3.3. Empirical strategy

As our focus is on mobile broadband network availability rather than usage, the empirical strategy follows an intention-to-treat framework. Unlike internet adoption, internet coverage is independent of individual or household decisions. However, mobile operators do not expand broadband coverage randomly. Instead, as Table 3.1 indicates, they are likely to target areas where economic benefits are expected. The implication is that households (individuals) living in areas with mobile broadband coverage tend to be distinct in several dimensions from those residing in locations without coverage (Bahia et al., 2024). To retrieve the effect of mobile broadband coverage on the reading and writing skills of children, this study leverages the temporal and spatial variation in exposure to the 3G network.

The two-way fixed effects (TWFE) model has often been employed in staggered rollout contexts to identify causal effects of treatment participation. However, the coefficients from this model may not represent a meaningful weighted average of unit-level treatment effects when the treatment effects are heterogeneous over time or across units (De Chaisemartin & D'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021). Moreover, the weights on the treatment effect parameters are sensitive to the timing of treatment, size of each group, and the number of periods under consideration (Goodman-Bacon 2021; Roth, 2022).

Callaway and Sant'Anna (2021) have developed an alternative approach that produces more plausible parameter estimates in the presence of heterogeneity in the treatment effects. One parameter is the group-time average treatment effect, which, for a group g that receives treatment in period g and in a post-treatment period $t \geq g$, is given by:

$$ATT(g,t) = E[\,Y_t(g) - Y_t(0) | G = g] \qquad (3.1)$$

where $Y_t(g)$ is the potential outcome variable, literacy in this paper, at time t if treated and $Y_t(0)$ is the corresponding potential outcome at time t if untreated. In essence, $ATT(g,t)$ represents the average treatment effects for units in group g at time t.

The group-time average treatment effect serves as a foundation for making further (partial) aggregations to highlight different dimensions of treatment effect heterogeneity. For $g=2,\ldots,\mathcal{T}$, $t=2,\ldots,\mathcal{T}$, and $t \geq g$, several such aggregations can be defined. One of the most important

aggregations is in terms of the period of treatment. Accordingly, the aggregate average treatment effect for each group g is given by:

$$\theta(g) = \frac{1}{\mathcal{T} - g + 1} \sum_{t=2}^{\mathcal{T}} \mathbf{1}\{g \leq t\} ATT(g,t) \qquad (3.2)$$

Another aggregation of interest is the change in the cumulative average treatment effects over calendar time. The average treatment effect at a particular time period t for groups that have been treated by time t is:

$$\theta(c) = \sum_{g=2}^{\mathcal{T}} \mathbf{1}\{g \leq t\} ATT(g,t) P(G = g | G \leq t) \qquad (3.3)$$

The third key aggregation is based on the length of exposure to the treatment. This follows an event-study approach to measure the dynamic treatment effects. The treatment effect for groups with exposure duration of e time periods is given by:

$$\theta(e) = \sum_{g=2}^{\mathcal{T}} \mathbf{1}\{g + e \leq \mathcal{T}\} ATT(g, g+e) P(G = g | G + e \leq \mathcal{T}) \qquad (3.4)$$

Apart from the above partial aggregations across different dimensions, the model also allows for the computation of a single overall treatment effect. A straightforward approach is to compute a simple ATT as a weighted average of all group-time average treatment effects, with weights proportional to group size. Unlike the two-way fixed effects model, this aggregation procedure does not suffer from the problem of negative weights, although it attaches greater weights to early-treated groups (Callaway & Sant'Anna, 2021).

As in the case of the TWFE model, the validity of the staggered DID approach depends on the assumption of parallel trends. That is, in the absence of treatment, the outcomes of the treated and control groups would have followed parallel trajectories over time. However, the latter framework allows for parallel trends assumptions to hold after conditioning on the observed covariates (Callaway & Sant'Anna, 2021). To this end, we incorporate a set of covariates commonly used in the literature; individual characteristics (age, gender, and school attendance), the literacy status of the household head, household assets, access to electricity, urban versus rural residence, and

distance to markets. Additionally, we control for 2G coverage to isolate the effect of the transition to 3G and ensure the estimates are not affected by existing 2G networks.

In the main results, we present the aggregated treatment effects across treatment groups, by calendar time, and by length of exposure to the treatment, corresponding to equations (3.2) - (3.4), along with the overall treatment effect estimate (i.e., simple ATT). The analysis follows the doubly robust estimation procedure, where the never-treated group serves as a control group. Unless otherwise specified, statistical significance is evaluated using bootstrap-based simultaneous confidence bands. Callaway and Sant'Anna (2021) demonstrate that, unlike conventional pointwise confidence intervals, these bands account for dependency across different group-time average treatment effect estimators and yield inferences robust to multiple testing. We cluster standard errors at the enumeration area level.

For a valid difference-in-differences estimation, all children are required to have no 3G coverage at baseline. Though the GSMA map does not show any coverage of this technology during the first wave of our GHS panel, the OpenCelliD dataset reveals a limited number of 3G cell towers during the same period. As a result, we exclude observations with such attributes, which account for less than 1 percent of our sample. An individual covered by a mobile broadband network in a particular wave remains covered in the subsequent waves, by construction.

3.4. Results and discussions

3.4.1. Main results

It is worth noting that we focus on the literacy impact of mobile broadband coverage. However, coverage does not necessarily imply internet access or adoption. Hence, we first investigate the association between 3G coverage and access or adoption for individuals aged 10 years and above. Internet access is defined as a binary indicator equal to one if the individual reports access to the internet from any source—personal subscription, household members, friends, neighbors, community centers, or others. Internet adoption, by contrast, refers to whether individuals subscribe to internet services via their own mobile devices. The results from the two-way fixed effects model and the staggered difference-in-differences model show a positive and statistically significant association between mobile broadband coverage and both internet access and adoption

(see Table A3.2 in the appendix). Thus, our measure of 3G coverage is strongly associated with access to internet, which is a prerequisite for our analysis.

Table 3.2 presents the aggregated treatment effects for the main model under the conditional parallel trends assumptions. The corresponding null hypothesis is that, conditional on observed covariates, treated and control groups would have followed the same trend in the absence of treatment. The average treatment effects in Table 3.2 are group-specific effects, calendar-time effects, and dynamic treatment effects (event study). The *early-treated* group comprises individuals covered by the 3G mobile network between the first and the second waves, while the *late-treated* group denotes those treated between the second and the third. The average impact estimated jointly for both early-treated and late-treated groups is statistically significant at the five percent level of significance, while the estimate for each group is statistically insignificant. It can be noted, however, that the magnitudes of the estimated ATT are higher among the late-treated than the early-treated.

The other aggregation provided in Table 3.2 is the calendar-time effect. This represents the cumulative average treatment effects among individuals who have been covered by 3G mobile broadband networks, evaluated at a particular point in time. While the impact at wave 2 is statistically insignificant, it is significant at wave 3 with a clearly higher coefficient estimate. This finding provides additional support for the greater ATT estimate among the late-treated group obtained under the group-specific aggregation. These results could be attributed to enabling factors such as the growing penetration of smartphones. In Nigeria, the mobile cellular subscriptions (per 100 people) rose from about 52 in 2010 to 64 in 2012 and 79 in 2016 (World Bank, 2026).[22]

The dynamic treatment effect (event study) estimates suggest that the instantaneous effect of mobile broadband coverage on the literacy indicator (at e=0) is statistically significant, while the impact one wave after the initial treatment (at e=1) is insignificant. This pattern may reflect a smaller number of observations or a ceiling effect: as children grow older or advance through school, basic reading and writing skills typically improve, reducing the gains attributable to internet availability. Unlike test scores, which may measure changes in cognitive achievements, a

[22] These figures refer to all subscriptions that offer voice services. The World Bank database and other relevant surveys don't provide information on smartphone subscriptions explicitly.

binary literacy indicator tends to be static once individuals master basic reading and writing skills. In other words, basic literacy exhibits limited within-individual variation over time unless we are interested in more granular measures such as reading fluency, reading comprehension, or writing speed. The saturation or fading out of the impacts of educational interventions is documented in literature from various perspectives (e.g., Bailey et al., 2020; Wan et al., 2021).

The results are summarized by Figures A3.1 and A3.2 in the appendix, which display graphical illustrations of group-time average treatment effects and aggregate treatment effects, respectively. Although some of the estimates reported in Table 3.2 are not significant at the five percent level, the figures highlight that the 95 percent confidence bands are almost entirely above zero. The statistically insignificant pre-treatment impact also suggests that the treated and comparison groups would have followed similar literacy trends in the absence of mobile broadband rollout, conditional on covariates.

Finally, ATT (simple) is 0.095 and significant. Thus, overall, our findings show that 3G coverage increases the likelihood of reading and writing by about 10 percentage points, which is about 20 percent for the early treated and close to 30 percent for the late treated. These results align with prior evidence on the impact of the internet on test scores (Derksen et al., 2022; Lakdawala et al., 2023). However, they contrast with the predominantly negative or null impact of high-speed internet on students' performance reported in developed countries' context (Vigdor et al., 2014; Faber et al., 2015; Cambini et al., 2024). Our results in Table 3.2 also provide evidence supporting the validity of the conditional parallel trends assumption.

Table 3.2: Impact of 3G mobile broadband network on literacy (children aged 5-12 years)

Dependent variable: Literacy (reading and writing)			
	Early treated	Late treated	Group average
Group-specific effects	0.082	0.135	0.103*
	(0.049)	(0.068)	(0.037)
	Wave=2	Wave=3	Calendar average
Calendar time effects	0.079	0.114*	0.096*
	(0.051)	(0.047)	(0.036)
	e=0	e=1	Post average
Event study	0.096*	0.090	0.093
	(0.037)	(0.067)	(0.044)
ATT (simple)			0.095*
			(0.036)
Outcome mean		0.418	
P-value for parallel trends		0.750	
Observations		8,413	

Notes: The table shows aggregated treatment effects by the timing of the treatment, by calendar time, by length of exposure to the treatment, and as the weighted average of group-time average treatment effects. Early treated are individuals treated between wave 1 and wave 2, while late treated denote those treated between wave 2 and wave 3. For the event study, e=0 denotes the treatment period and e=1 refers to one period after first exposure. The last column provides the overall average treatment effect along each aggregation method. The control group are never-treated observations. The p-value corresponds to the null hypothesis that the assumption of conditional parallel trends holds. Bootstrapped standard errors clustered at the enumeration area are in parentheses. * indicates statistical significance at the five percent level based on simultaneous confidence bands.

3.4.2. Robustness checks

To validate the results in the main model, we conduct a battery of robustness checks. We report the aggregate average treatment effects from staggered difference-in-differences estimation under four broad scenarios: (i) not-yet-treated units as the control group; (ii) unconditional parallel trends assumption; (iii) alternative age ranges within 5-12 years; and (iv) balanced sample. Except in case (i), the control groups are the never-treated observations. All models, except for case (ii), are estimated under the conditional parallel trends assumption. For comparison, we also provide the results for the two-way fixed effects model.

Table 3.3 reports the findings from using the not-yet-treated observations as the control group. Consistent with Table 3.2, the calendar time effects show that the impacts are statistically

significant only by the third wave. Furthermore, the event study aggregation reaffirms a statistically significant contemporaneous impact of mobile broadband coverage that ceases after one period. The magnitude of the aggregated group-time average treatment effect is the same as in the main specification. Hence, our results are not sensitive to using never-treated or not-yet-treated observations as the control group.

Table 3.3: Using not-yet-treated group as control group

Dependent variable: Literacy (reading and writing)			
Group-specific effects	Early treated	Late treated	Group average
	0.090	0.135	0.108*
	(0.044)	(0.068)	(0.038)
Calendar time effects	Wave=2	Wave=3	Calendar average
	0.090	0.114*	0.102*
	(0.043)	(0.047)	(0.037)
Event study	e=0	e=1	Post average
	0.104*	0.090	0.097
	(0.036)	(0.067)	(0.043)
ATT (simple)			0.101*
			(0.037)
Outcome mean		0.418	
P-value for parallel trends		0.750	
Observations		8,413	

Notes: See Table 3.2 for details. The control group are not-yet-treated observations.

Table 3.4 presents the results under the unconditional parallel trends assumption, which entails estimating the model without control variables. In aggregate, the findings confirm a statistically significant and positive impact of 3G broadband coverage on literacy. The effect is statistically significant at the five percent level for the early-treated group, but not for the late-treated group. Both the calendar time effects and the dynamic treatment effects are consistent with the corresponding results in the main model, despite the slight variations in the magnitude of the event study estimates.

Table 3.4: Estimation under unconditional parallel trends assumptions

Dependent variable: Literacy (reading and writing)			
	Early treated	Late treated	Group average
Group-specific effects	0.084*	0.100	0.090*
	(0.035)	(0.051)	(0.028)
	Wave=2	Wave=3	Calendar average
Calendar time effects	0.070	0.108*	0.089*
	(0.033)	(0.037)	(0.027)
	e=0	e=1	Post average
Event study	0.079*	0.118	0.098*
	(0.027)	(0.056)	(0.035)
ATT (simple)			0.088*
			(0.027)
Outcome mean		0.418	
P-value for parallel trends		0.743	
Observations		8,413	

Notes: See Table 3.2 for details. The p-value corresponds to the null hypothesis that the assumption of parallel trends holds unconditionally.

Table 3.5 presents results based on alternative age ranges for defining primary-school-aged children: 5–11, 6–11, and 6–12 years. The lower and upper bounds represent the potential ages at which children would begin school and eventually either attend or complete the final year of primary education, respectively. Overall, the effect of 3G mobile broadband coverage on literacy remains positive and statistically significant, with the corresponding magnitudes closely aligned to those obtained in the main specification. The findings reinforce the robustness of the results and suggest that the observed literacy gains are not an artifact of the specific age brackets adopted in this study (5-12 years).

Throughout this paper, the analysis is based on unbalanced panel data of children observed in at least two of the three waves of the GHS panel. In Table 3.6, we restrict the sample to children tracked in all waves. The number of observations is considerably reduced, that is, to 4987, because our sample is limited to children who were observed in all three waves while remaining between the ages of 5 and 12 years. The results from this balanced sample also confirm that 3G mobile broadband coverage is associated with improved literacy, with an overall ATT of 11 percentage points.

Table 3.5: Estimations across alternative definitions of primary-school-aged children

Dependent variable: Literacy (reading and writing)			
	5-11 years	6-11 years	6-12 years
Group-specific effects:			
Early treated	0.087	0.074	0.071
	(0.054)	(0.061)	(0.054)
Late treated	0.137	0.138	0.135
	(0.081)	(0.083)	(0.067)
Group average	0.107*	0.103*	0.101*
	(0.042)	(0.046)	(0.039)
Calendar time effects:			
Wave =2	0.094	0.093	0.075
	(0.059)	(0.065)	(0.054)
Wave=3	0.106	0.093	0.108
	(0.056)	(0.063)	(0.051)
Calendar average	0.100*	0.093	0.092*
	(0.040)	(0.043)	(0.038)
Event study:			
e=0	0.107*	0.109*	0.097*
	(0.043)	(0.046)	(0.039)
e=1	0.070	-0.001	0.060
	(0.077)	(0.094)	(0.079)
Post average	0.088	0.054	0.078
	(0.048)	(0.060)	(0.052)
ATT (simple)	0.099*	0.093*	0.091*
	(0.042)	(0.044)	(0.038)
Outcome mean	0.389	0.411	0.440
P-value for parallel trends	0.967	0.790	0.580
Observations	7,103	5,885	7,194

Notes: See Table 3.2 for details. For each aggregation method, the final row presents the corresponding overall average treatment effect.

Table 3.6: Balanced sample (children aged 5-12 years)

Dependent variable: Literacy (reading and writing)			
	Early treated	Late treated	Group average
Group-specific effects	0.096	0.135	0.117*
	(0.084)	(0.067)	(0.049)
	Wave=2	Wave=3	Calendar average
Calendar time effects	0.103	0.113*	0.108
	(0.101)	(0.049)	(0.065)
	e=0	e=1	Post average
Event study	0.120	0.090	0.105
	(0.055)	(0.074)	(0.059)
ATT (simple)			0.110*
			(0.055)
Outcome mean		0.403	
P-value for parallel trends		0.918	
Observations		4,987	

Notes: See Table 3.2 for details.

Table 3.7 provides a two-way fixed effects (TWFE) approximation to the staggered difference-in-differences estimation. Although the estimated coefficient from the TWFE is also statistically significant, its magnitude is notably smaller. This finding may point to treatment effect heterogeneity, which TWFE does not adequately account for. In other words, the result renders analytical justification for employing the Callaway and Sant'Anna (2021) approach, which is designed to address such heterogeneity in staggered adoption settings.

Table 3.7: Two-way fixed effects (TWFE) estimation result

Dependent variable: Literacy (reading and writing)	
3G	0.064**
	(0.028)
Individual FE	Yes
Year FE	Yes
Covariates	Yes
Outcome mean	0.423
Observations	8,794

Notes: This table shows the impact of mobile broadband coverage on literacy, using the two-way fixed effects (TWFE) method. We use the same set of covariates as in the main specification. Robust standard errors clustered at the enumeration area are in parentheses. *** p<0.01 ** p<0.05 * p<0.1

3.4.3. Heterogeneity analysis

Next, we examine whether the impact of mobile broadband on literacy varies depending on children's demographic, socioeconomic, and geographic characteristics. Figure 3.2 illustrates the results segmented by children's baseline enrollment status, gender, household wealth (proxied by asset accumulation), and geographical location (rural vs urban). This approach may enable us to investigate whether mobile broadband coverage benefits a specific group of children more than others. For convenience, we report only the overall average treatment effects (i.e., simple ATT).

Children who were enrolled in school at baseline (2010–11) experience larger gains than their non-enrolled counterparts, suggesting that school attendance facilitates the effective use of digital learning resources. In contrast, the impact appears to be statistically insignificant for those who were not in school. In other words, children who possess at least basic knowledge of how to use this technology will reap greater rewards. Out-of-school children may also experience relatively lower parental support.

Consistent with the findings of Nordrum and Gracia (2024), the impact seems to be larger for boys than for girls. This gender gap may reflect existing disparities in social norms, time use, or digital engagement. For instance, in developing countries like Nigeria, females are more likely to devote greater time to domestic chores than males. Hence, they may be at a disadvantage in leveraging mobile broadband expansions.

The effect of mobile broadband internet appears to be higher among children from poorer households compared to those from more affluent families. This finding highlights the role of mobile broadband internet in addressing educational disparities resulting from financial constraints. In this study, a household is categorized as poor if the asset value at the baseline is less than the sample median value. Our results are consistent with those of Caldarulo et al. (2023), who find larger gains in educational achievements from broadband adoption among lower-income students in the United States compared to wealthier ones. However, our findings show that the estimates for urban and rural sub-samples are statistically insignificant.

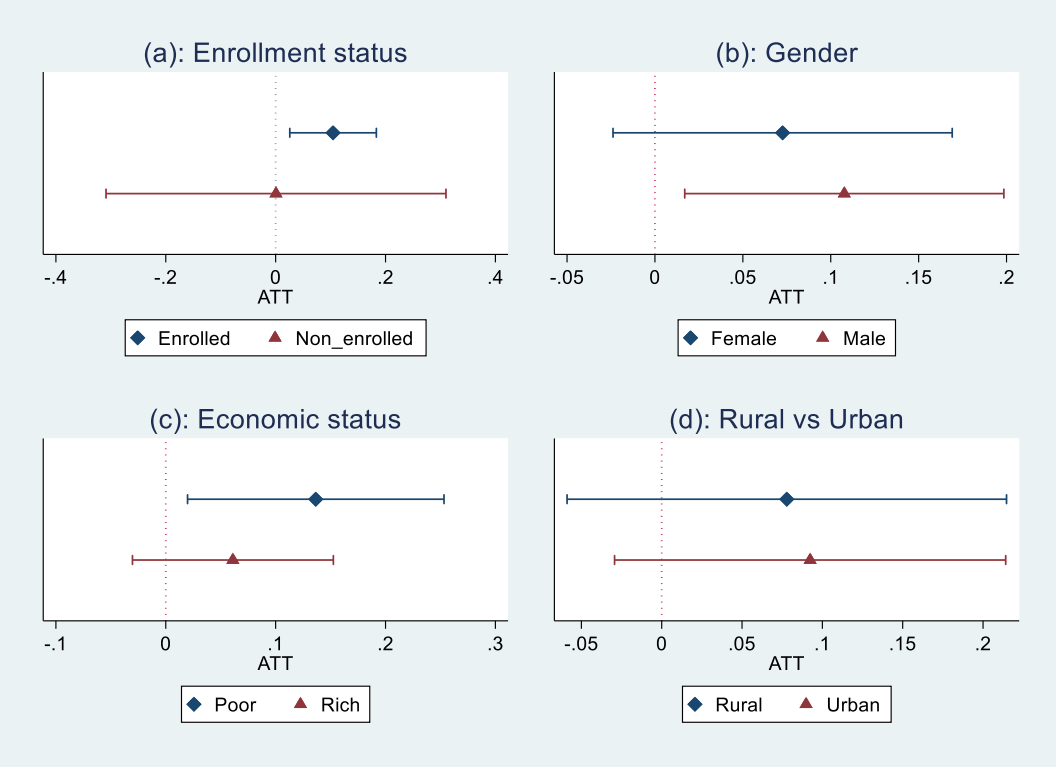


Figure 3.2: Heterogeneity analysis

Notes: This figure shows the ATT (simple), with 95 percent confidence bands, from the staggered difference-in-differences model of Callaway and Sant'Anna (2021). Bootstrapped standard errors are clustered at the enumeration area.

3.4.4. Mechanism

This section presents two interrelated channels through which mobile broadband coverage may affect the literacy status of primary-school-aged children and can be tested with our data: the aspirational channel and the income channel. We use household-level education expenditure as a proxy for parental aspirations. The income channel is represented by household consumption expenditure, which captures a household's ability to invest in children's education. Specifically, we construct consumption expenditure as the averages of post-planting and post-harvest household consumption. The main premise here is that mobile broadband coverage may improve literacy indirectly by increasing employment opportunities and income, which in turn empowers parents to make choices that improve the literacy level of their children.

Table 3.8 reports the results of the two hypothesized channels. Our findings show that mobile broadband expansion is associated with a 17 percent increase in the average education expenditure

at the household level. This result closely aligns with the findings of Orozco-Olvera and Rascon-Ramirez (2023) in Northern Nigeria. They document that mobile learning apps enhance children's literacy and numeracy, driven by improved parental attitudes and increased home learning.

Being covered by a 3G mobile broadband network is also associated with an approximately 8 percent increase in household consumption expenditure. Our findings are consistent with those of Bahia et al. (2024), who employ the same household survey—the Nigerian GHS— combined with mobile network coverage collected directly from the operators. Relatedly, Caldarola et al. (2023) find that 3G internet coverage boosted employment, especially for skilled workers, and facilitated structural transformation in Rwanda.

While children from higher-income households and those with parents who have strong educational aspirations are more likely to perform better in reading, these factors are not the sole determinants of literacy. The relationship is also influenced by factors such as parental education, school quality, teacher effectiveness, language of instruction, nutrition, health, and broader community conditions. Thus, parental income and aspirations are important predictors of reading achievement, but their effects are indirect and interact with broader individual, family, school, and societal factors.

Table 3.8: Potential indirect mechanisms

	Educational expenditure	Consumption
ATT (simple)	0.170*	0.075*
	(0.078)	(0.030)
P-value for parallel trends	0.607	0.761
Observations	13,120	13,120

Notes: This table presents the effect of mobile broadband coverage on household-level educational expenditure and consumption expenditure as potential mechanisms, using the Callaway and Sant'Anna (2021) difference-in-differences approach. Both outcome variables are deflated by the consumer price index (CPI) and are log-transformed. The covariates included in the models are household size, gender of household head (1 if male), household assets (in log), distance to market (in kilometers), and a binary variable for 2G coverage. The p-value corresponds to the null hypothesis that the assumption of conditional parallel trends holds. Bootstrapped standard errors clustered at the enumeration area are in parentheses. * indicates statistical significance at the five percent level based on simultaneous confidence bands.

3.5. Conclusions and policy implications

This paper analyzed the impact of 3G mobile broadband coverage on literacy among Nigerian children aged 5 to 12 years. Literacy is defined as the ability to read and write, a skill that children are expected to achieve by the end of primary school at the latest. Our analysis relies on a geographically matched mobile broadband coverage map and three waves of the Nigerian General Household Survey collected between 2010 and 2016. Leveraging the staggered rollout of 3G technology as a source of quasi-experimental variation, the study employed the Callaway and Sant'Anna (2021) difference-in-differences framework, which allows for heterogeneity in the treatment effects across time and cohorts.

Overall, our findings suggest that 3G mobile broadband coverage increases the probability that children in the specified age group can read and write in any language by about 10 percentage points, or between 20 percent and 30 percent. Although the average treatment effects segmented by the timing of treatment are statistically insignificant, the group average impacts are significant. In terms of calendar time, the cumulative aggregated average treatment effects at the third wave are statistically significant, but not at the second wave. This may be attributed to the increased use of smartphones over time. Furthermore, we find a positive and statistically significant contemporaneous impact of mobile broadband coverage. However, the effect is no longer statistically significant one wave after the initial exposure. This finding could be partly attributed to the expected improvement in literacy with increasing age and level of schooling, thereby limiting the marginal impact of the mobile broadband internet.

The effects of mobile broadband networks on literacy are more concentrated among boys, children from less affluent households, and those who were enrolled in school at baseline. The analysis of mechanisms, which our data allows us to test for, suggests that increased parental aspirations—captured by higher education expenditure—and improvement in household income are important pathways through which 3G coverage affects literacy. The former captures forward-looking parental investment or their willingness to devote scarce resources to children's education (Bernard et al., 2019; Eble & Maya, 2021), whereas the latter represents household resource constraint.

Our findings have important policy implications. The positive impact of 3G mobile broadband coverage on literacy, particularly among economically disadvantaged children, underscores the importance of expanding this infrastructure in fostering educational equity. This evidence supports ongoing digitalization efforts in the country. While the *National Policy on ICT in Education* (2019) emphasizes integration of ICT into the education system, the *National Digital Learning Policy* (2023) aims to ensure inclusive digital learning for all (Federal Ministry of Education, 2023).

Furthermore, the findings of this study highlight the need for complementary policies to ensure that the benefits of mobile broadband infrastructure are widely shared. In particular, given that the effects are more concentrated among boys than girls, broadband expansion may reproduce or widen gender inequalities unless it is accompanied by complementary policies or measures. These may include improving girls' access to digital devices, providing digital literacy and online safety training, and reducing domestic obligations that constrain the time devoted to learning. Offering targeted tutoring and mentoring may also be critical.

We acknowledge that our study has its own limitations. In particular, literacy is measured through self-assessment responses by the children themselves or knowledgeable household members. Additionally, due to data limitations, we are unable to validate our results using alternative indicators of educational achievement. Further research is needed, employing objective and standardized measurements of learning outcomes.

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Appendix

Table A3.1: Descriptive statistics across waves

	2010-11			2012-13			2015-16		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
The child is literate (1 if Yes)	3,494	0.303	0.460	3,332	0.455	0.498	1,968	0.581	0.493
Coverage 3G (1 if Yes)	3,494	-	-	3,332	0.184	0.388	1,968	0.304	0.460
Coverage 2G (1 if Yes)	3,494	0.662	0.473	3,332	0.821	0.383	1,968	1	0
Age of the child (in years)	3,494	7.308	1.871	3,332	8.989	1.860	1,968	10.06	1.668
The child is male (1 if Yes)	3,494	0.522	0.500	3,332	0.516	0.500	1,968	0.539	0.499
The child ever attained school (1 if Yes)	3,494	0.771	0.420	3,332	0.884	0.320	1,968	0.908	0.289
The household head is literate (1 if Yes)	3,494	0.621	0.485	3,332	0.638	0.481	1,968	0.634	0.482
lnasset	3,494	10.45	1.518	3,332	10.62	1.320	1,968	11.01	1.431
The household accesses electricity (1 if Yes)	3,494	0.231	0.422	3,332	0.285	0.451	1,968	0.265	0.441
Lives in urban areas (1 if Yes)	3,494	0.220	0.414	3,332	0.218	0.413	1,968	0.195	0.396
Distance to market	3,494	71.89	43.36	3,332	72.06	43.36	1,968	71.33	42.13

Table A3.2: The impact of mobile broadband coverage on internet access and internet adoption

	Internet access		Internet adoption	
	TWFE	CSDID	TWFE	CSDID
3G	0.053*	0.041*	0.049*	0.048*
	(0.010)	(0.015)	(0.008)	(0.011)
P-value for parallel trends		0.683		0.553
Covariates	Yes	Yes	Yes	Yes
Observations	41,855	39,571	41,855	39,571

Notes: This table presents the effect of mobile broadband coverage on internet access and internet adoption, using two-way fixed effects (TWFE) model and Callaway and Sant'Anna difference-in-differences (CSDID) model. Both specifications use the same set of covariates as in the main model. Standard errors clustered at the enumeration area are reported in parentheses: robust for TWFE model and bootstrapped for CSDID model. * indicates statistical significance at the five percent level, which relies on simultaneous confidence bands for CSDID model.

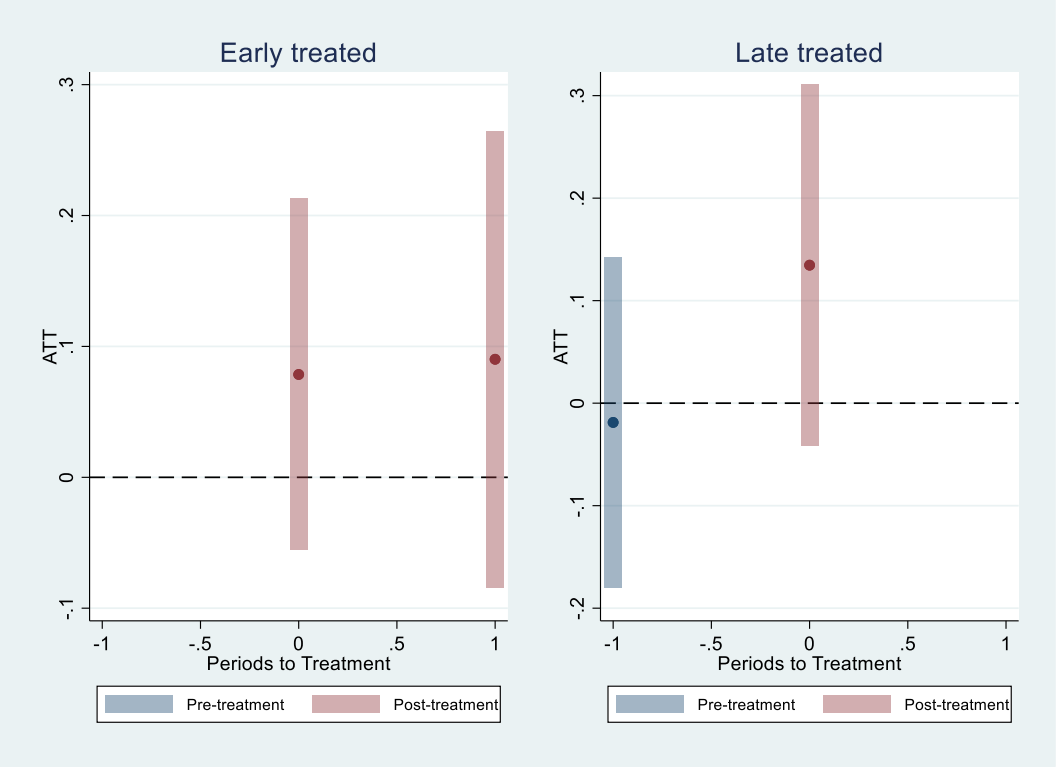


Figure A3.1: Group-time average treatment effects

Notes: The results are based on 95% simultaneous confidence band. Bootstrapped standard errors are clustered at the enumeration area level.

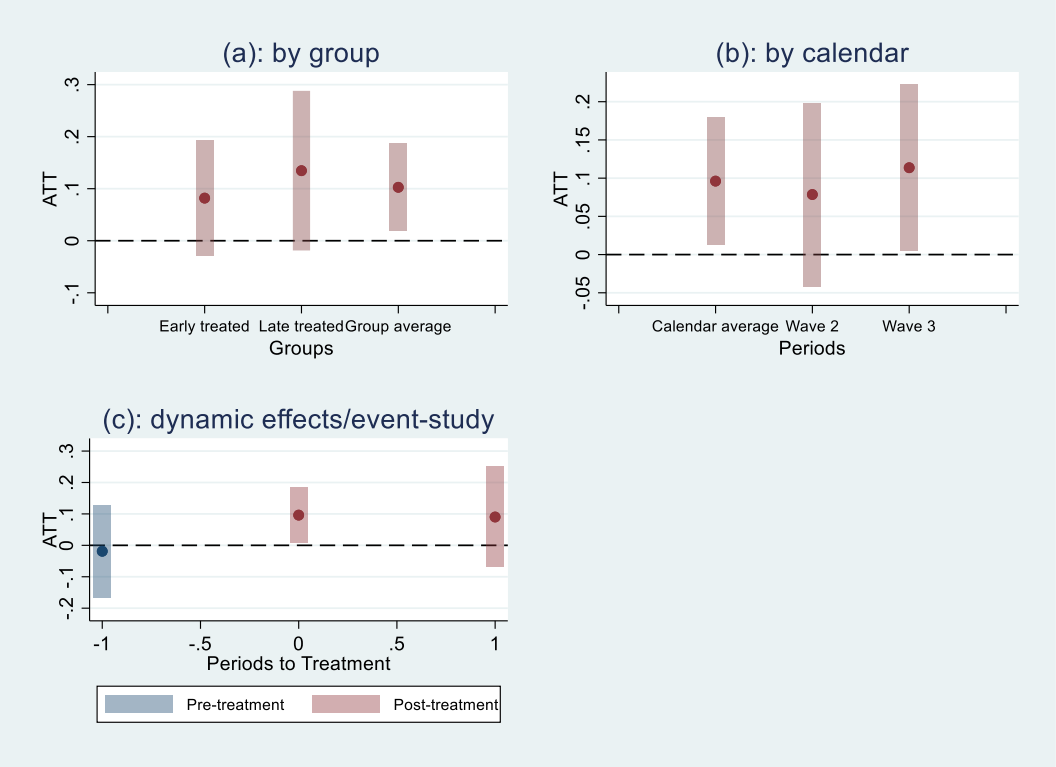


Figure A3.2: Aggregated average treatment effects by group, calendar time, and treatment duration

Notes: The results are based on 95% simultaneous confidence band. Bootstrapped standard errors are clustered at the enumeration area level.

4. Non-farm entrepreneurship and energy poverty: Evidence from Ethiopia

Abstract

This paper examines the effect of non-farm entrepreneurship on multidimensional energy poverty, using three waves of panel data from the Ethiopian Socioeconomic Survey. The findings from the two-stage least squares instrumental variable model, with a non-farm network as an instrument, suggest that ownership of non-farm enterprises reduces households' multidimensional energy poverty. The heterogeneity analysis reveals that the effects are more pronounced for those living in rural areas and headed by males, with no statistically significant effects in small towns or among female-headed households. The study identifies consumption (a proxy for income) and asset accumulation as the potential channels through which non-farm entrepreneurship influences energy poverty.

Keywords: Entrepreneurship; energy poverty; instrumental variables

4.1. Introduction

Energy is essential for achieving sustainable economic growth and social welfare (Adusah-Poku & Takeuchi, 2019; Agradi, 2023; Barkat et al., 2023). In this regard, the United Nations Sustainable Development Goal 7 aims to ensure access to affordable, reliable, sustainable, and modern energy for all (UN, 2015). Notwithstanding the efforts made thus far, much work remains to achieve this goal. According to the International Energy Agency (2024), about 750 million people – 80 percent of whom live in Sub-Saharan Africa (SSA)– lack access to electricity, while more than 2 billion people do not use clean cooking fuels.[23] This implies that many households rely on traditional fuel sources, resulting in indoor air pollution and subsequent health problems (Zhang et al., 2019; Kahouli, 2020; Nawaz, 2021).

[23] The full report can be accessed at https://www.iea.org/reports/world-energy-outlook-2024

Although there is no universally agreed upon definition of energy poverty, it typically refers to a lack of access to sustainable, safe, affordable, and environmentally friendly energy products and services (Nussbaumer et al., 2012; Koomson & Danquah, 2021). While the earlier versions of the energy poverty measure focused on the lack of access to modern energy for cooking and heating, it has now expanded to include additional indicators and dimensions including household energy services such as refrigeration, communication, and recreation (Mendoza et al., 2019). This development provides an opportunity to capture a more comprehensive aspect of energy poverty, which is fundamentally multifaceted in developing countries (Nussbaumer et al., 2012; Ssennono et al., 2021; Al Kez et al., 2024). However, a narrower definition still applies in industrialized nations, where households are often classified as energy-poor if they cannot effectively heat their homes or if the share of energy exceeds 10 percent of their total income (Alem & Demeke, 2020).

In developing countries, such as those in SSA, there are apparent supply-side bottlenecks due to the massive investment expenditure required by governments to provide electricity and other types of clean energy. These challenges are particularly evident in rural areas, where most of the population resides. However, demand-side constraints are equally essential as supply-side constraints (Blimpo et al., 2020). As cleaner energy sources are expensive, the transition to these forms of energy heavily depends on the purchasing power of the households (Akter & Bagchi, 2021; Koomson & Danquah, 2021). In this respect, the energy ladder hypothesis asserts that as income and awareness increase, households gradually shift from traditional biomass fuels to clean energy (Leach, 1992). Although empirical findings largely corroborate this theory, they also underscore the importance of other socioeconomic determinants (Hosier & Dowd, 1987; Khandker et al., 2012; Van der Kroon et al., 2013; Poddar et al., 2021; Martey et al., 2022).

Non-farm enterprises provide rural households with an alternative source of income and employment (Barrett et al., 2001; Rijkers & Soderbom, 2013), allowing them to accumulate assets. Thus, livelihood diversification through non-farm entrepreneurship (NFE) may promote households' energy transition process and reduce energy poverty amid increasing population size and limited farming land in agriculture-dependent developing nations (Koomson et al., 2023). Non-farm enterprises are income-generating activities not tied to crop and livestock production. They typically include agribusiness, services, trade and retail, tourism, construction, and mining. Non-farm entrepreneurship is thus understood as self-employment in the rural non-farm economy.

(Rijkers & Costa, 2012; Nagler & Naudé, 2017). It should be noted, however, that the term "non-farm" differs from "off-farm", where the latter describes all activities that take place outside of the household's own farm. As such, off-farm employment may, for example, include working as a laborer on someone else's farm (see Barrett et al., 2001; Gordon & Craig, 2001).

Despite evidence of the broader welfare implications of both non-farm employment and off-farm employment in the literature (for example, Haggblade et al., 2010; Bezu et al., 2012; Davis et al., 2017), their impact on energy poverty has received little attention. Exploring the latter relationship can enhance the understanding of rural transformation strategies for reducing reliance on traditional biomass fuels and improving investment in clean energy. This study investigates whether non-farm entrepreneurship reduces the multidimensional energy poverty level among households in rural and small towns, using three waves of the Ethiopian Socioeconomic Survey (ESS) panel data collected during 2011-12, 2013-14, and 2015-16. Ethiopia presents an interesting case study due to its persistently high level of energy poverty and a predominantly agrarian rural economy. According to Alem & Demeke (2020), about 26 percent of the country's urban households were multidimensionally energy-poor during the first decade of the 21st century. This figure is very likely to be much higher in rural areas. The same study documents state-dependence in energy poverty, where a household that is energy-poor in a particular period is more likely to be energy-poor in the next period.

In the context of this paper, NFE is defined as a dummy variable representing whether any household member owned any form of non-farm business during the 12 months preceding the surveys. Energy poverty is measured as a composite index computed from six weighted indicators, with the weights reflecting their relative contribution to household energy consumption and deprivation. These indicators span modern cooking fuel, indoor pollution, access to electricity, household appliances, entertainment appliances, and means of communication. Following the seminal work of Nussbaumer et al. (2012), this index has become a benchmark in energy poverty analysis in developing countries.

After addressing the endogeneity of non-farm entrepreneurship using a non-farm network as an instrument in a two-stage least squares framework, the results show that non-farm entrepreneurship reduces multidimensional energy poverty index by about 7 percentage points. The heterogeneity

analysis further suggests that the effect is more evident among households that live in rural areas and are male-headed, while the effects are statistically insignificant in small towns and among female-headed households. The results are robust across alternative estimation approaches, different measurements of non-farm entrepreneurship, and weighting systems for energy poverty. Consumption (a proxy for household income) and asset accumulation are the potential channels through which non-farm entrepreneurship affects household energy poverty.

This paper contributes to emerging literature on the impact of non-farm entrepreneurship on energy poverty. First, while a large body of literature emphasizes broad aspects of welfare or income poverty (e.g., Haggblade et al., 2010; Hoang et al., 2014; Alemu & Adesina, 2017), this study provides robust empirical evidence of the association between non-farm entrepreneurship and energy poverty. This aspect of poverty is worth considering given its far-reaching impact on health, productivity, and the environment.

Second, unlike the relatively better-explored impacts of off-farm employment, the current paper focuses on the understudied concept of non-farm entrepreneurship, which is a strong indicator of rural entrepreneurship. Closely related to the current study, Koomson et al. (2023) document a negative impact of non-farm entrepreneurship on household energy poverty in rural India, with the effect varying across castes. The present study offers evidence in the context of SSA, where persistent demand and supply constraints continue to limit access to clean energy. Other studies primarily focus on off-farm employment. For example, Martey et al. (2022) and Zheng (2023) document that off-farm employment is positively associated with the use of clean fuels and negatively with the consumption of traditional fuels in Ghana and China, respectively. Lin & Zhao (2021) also find that off-farm work reduces households' energy poverty in China.

Finally, following recent developments in energy poverty literature (for example, Nussbaumer et al., 2012; Koomson & Danquah, 2021; Cheng et al., 2023), this paper adopts the multidimensional energy poverty measure to capture the multifaceted nature of households' energy deprivations.

The remainder of this chapter is organized as follows. Section 4.2 presents relevant literature on non-farm entrepreneurship and energy poverty and then outlines the theoretical framework that links these two concepts. Section 4.3 deals with data and descriptive statistics. Section 4.4 outlines

the empirical strategy. Section 4.5 presents the results. Section 4.6 provides conclusions and policy implications of the study.

4.2. Literature review and theoretical framework

4.2.1. Non-farm entrepreneurship

Rural non-farm entrepreneurs can be opportunity entrepreneurs or necessity entrepreneurs, where the primary difference between the two lies in the underlying factors that motivate them to launch their business. While households operate non-farm enterprises based on profit-earning motives in the former case, their decisions are mainly driven by limited or a lack of access to traditional jobs in the latter (Reynolds et al., 2005). Opportunity entrepreneurs have a higher survival rate than necessity entrepreneurs because they are more likely to acquire relevant knowledge and skills, which in turn help them thrive in their operations (Block & Sandner, 2009).

4.2.2. Measuring household energy poverty

The energy poverty measure has been the subject of debate regarding the choice between unidimensional and multidimensional approaches, as well as objective versus subjective methodologies (Pelz et al., 2018). Two prominent unidimensional and objective measures of energy poverty are the expenditure-income approach and the low-income high-cost (LIHC) approach. These measures reflect households' energy-use conditions in terms of affordability. The expenditure-income approach is based on the proportion of energy expenditure to total income, where households are commonly considered energy-poor if their energy expenditure exceeds 10% of their income (Farrell & Fry, 2021). However, it could be misleading to classify as energy-poor those households that over-consume energy but don't face income constraints. Though the expenditure approach is praised for its objectivity and ease of quantification, it does not account for the difference between desired and actual energy expenditures (Churchill & Smyth, 2020). It is also prone to variations in energy prices (Thomson et al., 2017).

The LIHC approach defines households as energy-poor if their energy expenditure exceeds the national median and their income is below the poverty line. This approach is less sensitive to energy prices, but it may not accurately measure the extent to which households can afford modern energy (Churchill & Smyth, 2020).

Objective measures, such as those based on the expenditure-income approach and the LIHC method, may overstate or understate household energy poverty due to potential biases in reported income and expenses. Access to comprehensive data on household energy spending is also often limited. As a result, such measures are rarely applied in the context of developing countries (Herrero, 2017; Churchill et al., 2020; Koomson & Danquah, 2021).

The subjective approach (also called consensual approach) measures energy poverty based on households' self-reported assessments of material deprivation, with more emphasis on energy accessibility (Farrell & Fry, 2021). This approach considers more elements of household energy poverty compared with the objective approaches. However, it is not free of criticism as households may not identify themselves as energy-poor even if they are poor on an objective basis (Churchill et al., 2020).

While unidimensional energy poverty indicators are straightforward to handle and easy to interpret, they cannot capture the complex and multidimensional nature of energy poverty. Thus, the multidimensional energy poverty approach is widely used in developing countries. This approach combines accessibility with affordability and reflects both subjective and objective measures of household energy poverty (Koomson & Danquah, 2021; Zhang et al., 2021). The concept resonates with the notion of multidimensional poverty by UNDP, which is rooted in Amartya Sen's idea of deprivation. The concern with the multidimensional energy poverty framework is the lack of standardized indicators, deprivation scores, and cut-offs (Pelz et al., 2018; Sokołowski et al., 2020).

4.2.3. Theoretical framework: non-farm entrepreneurship and energy poverty

The energy ladder theory, together with its corresponding fuel-switching model, provides a basis for studies examining the energy transition process and household energy poverty. The central premise of this theory is that as income rises, households gradually shift away from traditional biomass (such as plant residues, firewood, charcoal) in favor of modern energy sources such as electricity, liquefied petroleum gas (LPG), and natural gas (Hosier & Dowd, 1987; Leach, 1992; Kowsari & Zerriffi, 2011; Van der Kroon et al., 2013). Though the energy ladder theory passes the empirical validity test, it makes two simplified assumptions: the availability of all forms of

energy and a complete transition away from the so-called 'inferior energy' whenever household wealth increases (Heltberg, 2004; Adamu et al., 2020; Mika et al., 2021).

A related approach, the fuel stacking model, asserts that households in developing countries do not entirely switch from traditional fuels to modern energy; instead, they use both types of energy sources simultaneously. In other words, the energy-switching process is only partial as modern and traditional energy forms are not perfect substitutes, and households tend to choose specific types of energy for specific tasks even when their economic status improves (Ado & Darazo, 2016; Omar & Hasanujzaman, 2021). The conclusion is that as household income or wealth increases, they are more likely to use clean energy types, yet they do not completely abandon the traditional ones.

Given the relatively higher costs of cleaner energy, full or partial energy transition depends heavily on the purchasing power of households (Akter & Bagchi, 2021). Non-farm enterprises provide households with diversified sources of income, which also boost savings (Zereyesus et al., 2017; Duong et al., 2021). This diversified income could pave the way for clean energy consumption and reduce energy poverty (Anang et al., 2020; Li & Xu, 2023). While the energy ladder hypothesis is commonly discussed in terms of income, a variant version is the accumulation of productive and non-productive durable assets. In other words, wealthier households are more likely to use clean energy for cooking, lighting, and other activities (Rahut et al., 2017; Duong et al., 2021; Koomson et al., 2023). Apart from the impact of non-farm entrepreneurship on energy poverty through income or wealth, it can also directly affect the energy poverty level among households. Entrepreneurs, for example, could be more aware of the benefits of cleaner energy due to their exposure to urban areas than non-entrepreneurs.

4.3.Data and descriptive statistics

4.3.1. Data

This study uses nationally representative panel data from three waves of the Ethiopian Socioeconomic Survey (ESS) collected in 2011-12, 2013-14, and 2015-16. ESS is collected by the Central Statistical Agency (CSA) of Ethiopia in collaboration with the World Bank under the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) project.

The surveys have three parts: a household questionnaire, an agricultural questionnaire, and a community questionnaire. The household questionnaire mainly deals with household demographic characteristics, education, health, time use and labor, food and non-food expenditure, dwelling conditions, non-farm enterprises, and other sources of income. The community questionnaire collects essential community-level information, including access to basic services, economic activities, infrastructure, community organizations, and local retail prices. The agricultural questionnaire primarily covers crop production, land ownership and use, farm labor, input use, irrigation, and livestock.[24]

The first wave of ESS covered only rural areas and small towns, while the sample expanded to include medium and large cities since the second wave. Given that non-farm entrepreneurship is fundamentally a livelihood diversification strategy of rural communities, the scope of this study is confined to rural areas and small towns (semi-urban). In the first wave, 3,969 households were interviewed. In the second wave, 3,776 households were re-interviewed, with a panel attrition rate of 5 percent. In ESS3, the total number of households from rural and small towns was 3699. This study is based on panel data of 11034 observations, after merging and accounting for missing data.

4.3.2. Measurement of variables

This section describes the variables used in the empirical analysis. Non-farm entrepreneurship is a binary variable representing whether a household operates any non-farm enterprises. These activities take the form of non-agricultural services, processing and sale of agricultural by-products, trading businesses, professional services, transportation services, or food services (see Tables A4.1 and A4.2 in the appendix). Energy poverty is measured as a composite index reflecting multiple dimensions of household energy deprivation. Table 4.1 presents the descriptions of all variables included in the main analysis.

[24] Detailed information about the survey can be accessed at https://microdata.worldbank.org/index.php/catalog/2783

Table 4.1: Description of variables

Variable	Description
Multidimensional energy poverty	Multidimensional energy poverty score
Non-farm entrepreneurship	Takes a value of 1 if the household owns or operates at least one type of non-farm enterprise, and 0 otherwise
Village_ NFE	Share of households in the village that own or run at least one type of non-farm enterprise
Age_head	Age of household head (in years)
Male_head	Household head is male (1 if yes)
Married_head	Household head is married (1 if yes)
Literate_head	Household head is literate: can read and write (1 if yes)
Household_size	Number of household members
Farm_work	Household engaged in farming (1 if yes)
Wage_employment	At least one household member employed for wage/salary over 12 months (1 if yes)
Idiosyncratic_shocks	Household faced any idiosyncratic shocks over 12 months (1 if yes). These include shocks such as death or illness of income earning family member, death of livestock, loss of property due to fire, loss of land, dwelling damage, etc.
Credit_access	Any household member borrowed on credit over 12 months (1 if yes)
Dist_urban	Distance from the community to the nearest major urban center (in kilometers)
Dist_road	Household distance (in kilometers) to the nearest major road
Village_electricity	Availability of electricity in the village (1 if yes)[25]
Small town	Enumeration area small town indicator (1 if yes)

[25] This is proxied by whether a health post or a primary school in the village is electrified. If there is no primary school or health post in the village, the nearest school or health post within 5 km is used.

Derivation of energy poverty

Following relevant literature (Nussbaumer et al., 2012; Crentsil et al., 2019; Koomson & Danquah, 2021; Sen et al., 2023, among others), the multidimensional energy poverty index or score is derived from six indicators categorized under five dimensions. These indicators include modern cooking fuel, indoor pollution,[26] electricity access, household appliances, entertainment/education appliances, and means of communication. Modern cooking fuels, indoor pollution, and electricity are assigned the highest weights to reflect their relative importance in multidimensional energy poverty. Indicators with relatively lower weights are also included since they provide useful information regarding household energy consumption levels. Table 4.2 presents the dimensions, indicators, cut-offs, and weights attached to each indicator of multidimensional energy poverty.

Table 4.2: Dimensions, indicators, deprivation cut-offs, and weights

Dimension	*Indicator*	*Deprivation cut-off (energy poor if…)*	*Weight*
Cooking	Modern cooking fuel	Uses any fuel besides electricity, LPG, kerosene, natural gas, or biogas	0.2
	Indoor pollution	Food cooked on a traditional oven/stove or open fire; and has no kitchen or uses traditional kitchen inside the housing unit	0.2
Lighting	Electricity access	Does not have access to electricity	0.2
Connected household appliances	Household appliance ownership	Does not have a fridge	0.13
Entertainment/education	Entertainment/education appliance ownership	Does not have a radio or television	0.13
Communication	Telecommunication means	Does not have a mobile phone or landline telephone	0.13

[26] The definition of indoor pollution takes into account the Ethiopian context of how and where "injera" or bread is baked. If households use traditional ovens or stoves for baking “injera” or bread, they are assumed to use traditional fuels.

The multidimensional energy poverty score is computed as the sum of the weighted deprivations. That is,

$$MEP_{it} = \sum_{j=1}^{n} w_j D_{ijt} \qquad (4.1)$$

where MEP_{it} is the multidimensional energy poverty score of household i at time t; D_{ijt} is a dummy variable that takes a value of 1 if household i is deprived in indicator j at time t and zero otherwise. w_j is the weight attached to each indicator such that $\sum_{j=1}^{n} w_j = 1$. The outcome variable in this study is a continuous index ranging from zero to one. A similar approach was employed in other studies (see, for example, Cheng et al., 2023; Koomson et al., 2023; Hasibuan & Hartono, 2024). The other alternative is to define energy poverty in binary form, where households are considered multidimensionally energy-poor if the deprivation score is 0.33 or above. Given that the emphasis of this study is rural and small towns, where a significant proportion of households are likely to be in energy poverty, adopting a binary indicator is not the best option.

4.3.3. Descriptive statistics

Though the primary unit of analysis in this study is the household, it is informative to provide a brief overview of non-farm enterprises over the survey periods. As households may operate more than one enterprise, uniquely matching household and enterprise data is not feasible. Hence, this discussion is presented for illustration only and does not form part of the main empirical analysis.

Table 4.3 presents the industrial classifications of non-farm enterprises. Across all waves, trade is the most common non-farm business. This could be explained by the ease with which such enterprises can be started, particularly for small trading businesses operating from home or on the street. Manufacturing, utilities—including electricity, gas, water supply—and transportation, storage, and communications also make up important components of non-farm income-generating activities. Agriculture-related enterprises and hotels and restaurants account for a smaller portion of the total. As shown in Table 4.4, only 13 percent of the enterprises were formally registered in 2011-12, which slightly increased to 17 percent in 2013-14, and 18 percent in 2015-16.

Table 4.3: Industrial classification of non-farm enterprises (in percent)

	2011-12	2013-14	2015-16
Agriculture	2.90	6.39	8.21
Manufacturing	20.98	16.44	21.33
Electricity, gas, and water supply	16.96	18.70	12.86
Wholesale and retail trade	32.96	27.10	30.96
Hotels and restaurants	4.46	2.13	2.41
Transport, storage and communications	10.42	19.31	13.51
Other services	1.49	2.68	2.68
Others	9.82	7.25	8.04
Total	100.00	100.00	100.00

Table 4.4: Ownership of license (in percent)

	2011-12	2013-14	2015-16
No	86.68	82.88	81.57
Yes	13.32	17.12	18.43
Total	100.00	100.00	100.00

Table 4.5 reports the descriptive statistics of the variables used in the main analysis. The choice of variables is guided by economic theory and previous studies (for example, Alem & Demeke, 2020; Lin & Zhao, 2021; Ma et al., 2023). Energy poverty remains widespread, with a slight decline from 0.8 during the first wave to 0.77 in the final wave. The prevalence of non-farm entrepreneurship fluctuates around 27 percent. The average age of household heads shows a natural increase over time from the initial age of 44 years in 2011-12. The share of male-headed households and married household heads stands at about 75 percent, while about 40 percent of the heads can read and write. Exposure to idiosyncratic shocks substantially increased from 25 percent in 2011-12 to 38 percent in 2015-16. Approximately one-quarter of the households obtained credit over 12 months prior to the surveys. While nearly three-quarters of households are engaged in farming, the share of those with at least one member employed as a salaried worker is less than 15 percent. There are about five members per household. On average, households are just over 16 km away from the main road. The distance from the community to the nearest urban center declined from about 82 km in the first wave to 77km in the third wave. Village electrification improved steadily from about 32 percent to 49 percent over the same period. This figure, however, should

be interpreted with caution because village electrification is proxied by the electrification status of the nearest primary school or health center. Households living in small towns account for about 11–13 percent of the sample, with the remaining share representing rural households.

Table 4.5: Summary statistics

	2011-12		2013-14		2015-16	
	Mean	SD	Mean	SD	Mean	SD
MEP	0.800	0.208	0.782	0.215	0.769	0.219
NFE	0.274	0.446	0.282	0.450	0.264	0.441
Village_NFE	0.274	0.271	0.283	0.268	0.263	0.272
Age_head	44.05	15.76	45.84	15.32	47.47	15.12
Male_head	0.752	0.432	0.739	0.439	0.734	0.442
Married_head	0.757	0.429	0.746	0.436	0.742	0.438
Literate_head	0.406	0.491	0.402	0.490	0.414	0.493
Household_size	4.821	2.383	4.913	2.362	5.053	2.369
Farm_work	0.758	0.428	0.753	0.432	0.726	0.446
Wage_employment	0.142	0.349	0.123	0.328	0.111	0.314
Idiosyncratic_shocks	0.249	0.432	0.202	0.402	0.381	0.486
Credit_access	0.234	0.424	0.270	0.444	0.235	0.424
Dist_road	16.76	22.06	16.84	22.62	16.31	21.56
Dist_urban	81.55	87.84	68	64.14	77.26	102.45
Village_electricity	0.318	0.466	0.447	0.497	0.490	0.500
Small town	0.126	0.332	0.112	0.316	0.114	0.318
Observations	3,793		3,593		3,648	

4.4.Empirical strategy

A challenge in estimating the impact of non-farm entrepreneurship on energy poverty is that the estimation may suffer from endogeneity, which could produce biased estimates. Possible sources of endogeneity include measurement errors, omitted variable bias, and reverse causality. As respondents are supposed to be knowledgeable about non-farm enterprise ownership and deprivation in a specific indicator, the measurement issue may not be a critical concern. However, there could be a reverse causality between energy poverty and non-farm entrepreneurship (Koomson et al., 2023). On the one hand, non-farm entrepreneurship may increase household income and savings (Zereyesus et al., 2017) and enhance the ability of households to spend on

modern energy, thereby reducing energy poverty (Koomson & Danquah, 2021). On the other hand, energy poverty might have a detrimental health impact, which redirects financial resources to healthcare (Kahouli, 2020; Llorca et al., 2020; Nawaz, 2021). This erodes the household income and savings needed for starting non-farm enterprises (Abbas et al., 2020). In addition, households with electricity, better appliances, communication devices, or improved cooking arrangements may be more likely to start or expand non-farm enterprises.

To deal with the endogeneity issue, this study employs the two-stage least squares instrumental variable approach. Following previous studies (Oseni & Winters, 2009; Hoang et al., 2014; Mathenge & Tschirley, 2015; Bui & Hoang, 2021; Lin & Zhao, 2021; Koomson et al., 2023), the non-farm network is used as an instrument. The non-farm network is represented by the proportion of non-farm entrepreneur households in the enumeration area. The prevalence of non-farm entrepreneurs in the village may enable households to share essential information about non-farm businesses. It could also be interpreted as the peer effect, where households tend to own or operate non-farm enterprises if many of their neighbors do (Koomson et al., 2023).

Areas with a higher concentration of non-farm enterprises may also exhibit better market access, road infrastructure, electricity, local demand, higher income levels, or more dynamic local economies. However, the validity of the exclusion restriction is reinforced by the following considerations: i) the instrument is constructed as a leave-one-out village-level mean that excludes the household in question, thereby reducing mechanical correlation with the outcome variable; ii) as shown in the descriptive statistics, more than 80 percent of the enterprises are unregistered or informal household businesses, which are not primarily driven by community-wide infrastructure. In other words, the instrument is less likely to capture village-level infrastructure development or other community characteristics that directly influence multidimensional energy poverty; and iii) the analysis controls for a rich set of household and village-level characteristics. Hence, conditional on these controls, village-level entrepreneurship is expected to influence multidimensional energy poverty only indirectly through household participation in non-farm entrepreneurship.

The first stage and the second stage models are given in Equation (4.2) and Equation (4.3), respectively.

First stage: reduced form equation

$$NFE_{it} = \lambda_i + \gamma Z_{it} + \varphi X_{it} + \pi_t + \varepsilon_{it} \qquad (4.2)$$

Second stage: structural equation

$$MEP_{it} = \alpha_i + \beta \widehat{NFE}_{it} + \theta X_{it} + \mu_t + \nu_{it} \qquad (4.3)$$

where, MEP_{it} is the multidimensional energy poverty score of household i at time t and NFE_{it} is a dummy variable taking on a value of one if a household owns any non-farm enterprise at time t. The outcome variable is measured as the sum of the weighted indicators. Hence, this index takes a value ranging from zero to one, with a higher score indicating greater deprivation. Z is the proportion of non-farm entrepreneurs in the enumeration area (excluding the household itself), which serves as an instrument. X is a vector of control variables including characteristics of the household head (gender, age, education, marital status), household size, access to credit, wage employment, engagement in farming, distance to road, exposure to idiosyncratic shocks, availability of electricity in the village, the proximity of the village to the nearest major urban center, and whether the household resides in small town or rural area. λ_i and α_i are household fixed effects, while π_t and μ_t are year fixed effects. ε_{it} and ν_{it} are the error terms.

4.5. Results and discussions

4.5.1. Main results

Table 4.6 presents the results of the main model. The dependent variable is the multidimensional energy poverty score. The first two columns are the findings from the fixed effects model. The preferred model for this study is the two-stage least squares instrumental variable(2SLS-IV) approach, where non-farm entrepreneurship at the village level is used as an instrument (column 4). The first stage result shows that the instrument is positively correlated with non-farm entrepreneurship. This may indicate the role of the non-farm network in owning or running non-farm enterprises. In other words, the higher the share of neighbors who own non-farm businesses, the greater the likelihood that a household will also engage in such ventures. A strong non-farm

network enables entrepreneurs to communicate more closely about relevant non-farm opportunities. Households could also engage in non-farm household enterprises due to the peer effect.

The instrument must satisfy the two validity conditions: relevance and exogeneity. The relevance criterion requires that the instrument be correlated with non-farm entrepreneurship. This condition is fulfilled as the value of the F-statistic from the first stage is greater than 10, the commonly used threshold (column 4, Table 4.6). The exogeneity condition requires that the instrument be uncorrelated with the error term. It can be argued that village-level non-farm entrepreneurship likely affects household energy poverty only through the household's decision to engage in non-farm enterprises.

The findings in Table 4.6 show that owning non-farm enterprises is negatively associated with energy poverty. Given that farming activities are inherently seasonal and vulnerable to climate change, non-farm businesses provide households with diversified income, thereby promoting modern energy consumption. Specifically, ownership of non-farm enterprises is associated with about a 7 percentage points decline in the multidimensional energy poverty index or score, which corresponds to about a 9 percent decrease relative to the sample mean. The results are consistent with the findings of Koomson et al. (2023), who document similar evidence from rural India. The size of the impact is larger for the 2SLS-IV model than for the fixed effects model. This may suggest that endogeneity causes a downward bias in the coefficient estimates.

Table 4.6 : Non-farm entrepreneurship and energy poverty (main model)

	FE		2SLS-IV	
	(1)	(2)	(3)	(4)
NFE	-0.018***	-0.017***	-0.072***	-0.074***
	(0.005)	(0.005)	(0.020)	(0.020)
Age_head		0.000		0.000
		(0.000)		(0.000)
Male_head		-0.003		-0.003
		(0.010)		(0.010)
Married_head		-0.005		-0.005
		(0.007)		(0.008)
Literate_head		-0.010*		-0.009*
		(0.005)		(0.005)
Household_size		-0.008***		-0.007***
		(0.001)		(0.002)
Farm_work		-0.001		-0.001
		(0.004)		(0.005)
Wage_employment		-0.013**		-0.013**
		(0.006)		(0.006)
Idiosyncratic_shocks		-0.003		-0.003
		(0.003)		(0.003)
Credit_access		-0.003		-0.000
		(0.004)		(0.004)
Dist_road		0.001		0.001
		(0.001)		(0.001)
Dist_urban		-0.000		-0.000
		(0.000)		(0.000)
Village_electricity		-0.008**		-0.008*
		(0.004)		(0.004)
First stage				
Village_NFE			0.572***	0.571***
			(0.033)	(0.033)
F Statistic			300.4	300.7
HH FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	11,034	11,034	10,893	10,893
Depvar_mean	0.784	0.784	0.784	0.784

Notes: Columns 1 and 2 show the results of the fixed effects (FE) model, while columns 3 and 4 are based on the two-stage least squares instrumental variable (2SLS-IV) approach. Robust standard errors clustered at a household level are in parentheses. *** p<0.01 ** p<0.05 * p<0.1

4.5.2. Heterogeneity analysis

In this section, I explore the possible heterogeneous effects of non-farm entrepreneurship on multidimensional energy poverty in terms of the gender of the household head and the location of the household. Table 4.7 reports the results for male-headed and female-headed sub-samples. The findings reveal that this effect is statistically significant with a negative coefficient for households headed by males but statistically insignificant when headed by women. This gender-based heterogeneity could be attributed to several economic, social, and institutional factors. In the first place, male-headed households are more likely to run larger and more profitable businesses in sectors like transport and manufacturing, which yield higher returns and boost investment in clean energy. Female-headed households, on the other hand, are more likely to engage in low-profit and informal businesses such as petty trade and small-scale food processing. Moreover, male-headed households may have better access to financial resources to start and expand their businesses. For instance, informal financial institutions may be more willing to lend to men who are often better entitled to own land or other assets. Men may also have better mobility and access to urban markets, which could facilitate the investment in modern energy sources.

Table 4.7: Non-farm entrepreneurship and energy poverty (male-headed vs female-headed HHs)

	2SLS-IV	
	Male-headed HH	Female-headed HH
NFE	-0.078***	-0.052
	(0.022)	(0.050)
First stage		
Village_NFE	0.615***	0.417***
	(0.038)	(0.070)
F Statistic	264.1	35.16
HH FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes
Observations	7,927	2,630
Depvar_mean	0.775	0.808

Notes: This table presents the heterogeneous effect of NFE on energy poverty based on the gender of the household head. Robust standard errors clustered at a household level are in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 4.8 presents the heterogeneity analysis across rural and small towns separately. The effect of non-farm entrepreneurship on multidimensional energy poverty is negative and statistically significant in rural areas, but insignificant in small towns. This finding could be explained by lower baseline access to electricity and modern energy sources in rural areas than in small towns. Non-farm entrepreneurship in rural areas can introduce new income streams, enabling households to invest in cleaner energy sources. In small towns, there are typically more formal employment opportunities, and households may already have better energy access. Hence, the additional income from non-farm enterprises may not significantly change their energy consumption patterns. In other words, energy infrastructure in small towns might be relatively better than in rural areas, reducing the marginal impact of non-farm income on energy poverty.

Table 4.8: Non-farm entrepreneurship and energy poverty (rural versus small towns)

	2SLS-IV	
	Rural	Small towns
NFE	-0.069***	-0.115
	(0.021)	(0.072)
First stage		
Village_NFE	0.584***	0.454***
	(0.035)	(0.096)
F Statistic	277.4	22.43
HH FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes
Observations	9,638	1,255
Depvar_mean	0.820	0.513

Notes: This table presents the two-stage least squares instrumental variable (2SLS-IV) results for rural and small towns separately. Robust standard errors clustered at a household level are in parentheses. *** p<0.01 ** p<0.05 * p<0.1

4.5.3. Robustness checks

To check the validity of the results, I conducted a battery of robustness checks. First, I adopt the 2SLS-IV approach proposed by Lewbel (2012), which generates internal instruments based on heteroskedastic covariance restrictions. It also allows for supplementing the external instruments

with internally generated instruments to improve the efficiency of the IV estimator. Moreover, the combination of internal and external instruments could make it possible to conduct the Sargan-Hansen tests of overidentifying restrictions, which do not apply to exactly identified equations with only external instruments (Baum & Schaffer, 2024). This approach has been employed in prior studies on energy poverty (for example, Churchill et al., 2020; Farrell & Fry, 2021; Martey, 2022; Cheng et al., 2023).

Table 4.9 reports the results of the Lewbel 2SLS-IV estimation contextualized for panel data models. The instrument used here is a combination of internally generated instruments and the external instrument—village-level non-farm entrepreneurship. The findings are quite consistent with the results of the main model, even in terms of the magnitude of the effect. The p-value of the Hansen J Statistic suggests that we cannot reject the null hypothesis that the overidentifying restrictions are valid.

Table 4.9: Lewbel 2SLS-IV estimation

Dependent variable: Energy poverty	
NFE	-0.071***
	(0.019)
First stage	
Village_NFE	0.570***
	(0.032)
F Statistic	29.76
Hansen J Statistic	5.008
Hansen P-value	0.891
HH FE	Yes
Year FE	Yes
Control variables	Yes
Observations	11,034
Depvar_mean	0.784

Notes: The results are based on the Lewbel 2SLS-IV model. A combination of internally developed instruments and the external instrument is used. Robust standard errors clustered at a household level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Second, I employ alternative weighting approaches to construct the multidimensional energy poverty score. In one approach, in line with previous studies (Sadath & Acharya, 2017; Cheng et al., 2023), equal weight is given to each indicator. Alternatively, an index constructed using Item Response Theory (IRT) is also reported. Unlike simple averages, IRT assigns weights to items based on difficulty and discrimination parameters. The difficulty or severity parameter shows the difficulty of obtaining the item or how extreme the deprivation is, whereas the discrimination parameter represents the degree to which each item discriminates between the deprived and non-deprived respondents (Vollmer & Alkire, 2022). Table 4.10 presents the results of the fixed effects model and 2SLS-IV estimation for each weighting scheme. The findings are consistent with the corresponding results in the main model, but the coefficients are marginally higher. The results are, therefore, not sensitive to the weighting system employed to compute the multidimensional energy poverty score.

Table 4.10: Using alternative weights for the indicators

Dependent variable: Energy poverty				
	Equal weights		Weights using IRT	
	FE	2SLS-IV	FE	2SLS-IV
	(1)	(2)	(3)	(4)
NFE	-0.021***	-0.090***	-0.024***	-0.101***
	(0.005)	(0.020)	(0.005)	(0.020)
First stage				
Village_NFE		0.571***		0.571***
		(0.033)		(0.033)
F Statistic		300.7		300.7
HH FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	11,034	10,893	11,034	10,893
Depvar_mean	0.780	0.780	0.799	0.799

Notes: Energy poverty is calculated using equal weights for each deprivation indicator for columns 1 & 2, and using the weights from the Item Response Theory (IRT) for columns 3 & 4. The findings of the fixed effects model are shown in columns 1 & 3. Columns 2 & 4 show the results of the two-stage least squares instrumental variable (2SLS-IV) model. Robust standard errors clustered at a household level are in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Third, a different proxy is used for non-farm entrepreneurship. In the main regression, it was defined as ownership of non-farm enterprises. An alternative way of defining non-farm entrepreneurship is in terms of the time spent on non-agricultural activities. In this case, it is defined as a dummy variable that takes a value of one if any household member has spent non-zero hours on non-agricultural businesses owned by the household during the seven days preceding the date of the interview. The results are presented in Table 4.11. The findings confirm the results of the main model, but the corresponding effect sizes are larger for 2SLS-IV and smaller for the fixed effects model, respectively.

Table 4.11: Using a different proxy for non-farm entrepreneurship (NFE)

	Dependent variable: Energy poverty	
	FE	2SLS-IV
NFE	-0.008**	-0.151***
	(0.004)	(0.043)
First stage		
Village_NFE		0.279***
		(0.036)
F Statistic		61.36
HH FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes
Observations	11,036	10,893
Depvar_mean	0.784	0.784

Notes: NFE has a value of 1 if any HH member spent non-zero hours in HH-owned non-agricultural business during the last 7 days of the survey and zero otherwise. Robust standard errors clustered at a household level are in parentheses. ***p<0.01 ** p<0.05 * p<0.1

4.5.4. Mechanism

The relationship between non-farm entrepreneurship and multidimensional energy poverty can be explained through several mechanisms. Table 4.12 presents the results of two interrelated channels in the context of the energy ladder hypothesis: income (proxied by real consumption expenditure) and asset accumulation. The findings are based on the fixed effects model. The asset index is

constructed from household ownership of durable assets using principal component analysis. Items included in the energy poverty measure, such as cooking stoves, mobile phones, televisions, radios, and refrigerators, are excluded from the computation of the index. The findings show that non-farm entrepreneurship is positively correlated with real consumption expenditure and the accumulation of durable assets. Therefore, this evidence suggests that consumption expenditure (used as a proxy for income) and durable asset accumulation are the potential channels through which non-farm entrepreneurship affects household energy poverty.

Table 4.12: Mechanism (consumption and asset accumulation)

	Consumption	Asset index
NFE	0.091***	0.178**
	(0.021)	(0.074)
HH FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes
R-squared	0.073	0.010
Observations	10,641	11,034

Notes: This table presents the fixed effects estimation results of the mechanism through which NFE affects energy poverty. Both models use the same set of control variables as in the main specification. Consumption is in logarithmic form. Robust standard errors clustered at a household level are in parentheses. *** p<0.01 ** p<0.05 * p<0.1

4.6.Conclusions and policy implications

This study investigated the impact of non-farm entrepreneurship on multidimensional energy poverty using panel data from three waves of the Ethiopian Socioeconomic Survey: 2011-12, 2013-14, and 2015-16. The study is prompted by the understudied role of rural non-farm entrepreneurship in energy poverty reduction, which is a vital component of the Sustainable Development Goals. For this study, energy poverty is measured in a multidimensional framework that reflects a wide range of deprivations faced by a typical household in developing countries.

The findings from the two-stage least squares instrumental variable model suggest a negative effect of non-farm entrepreneurship on multidimensional energy poverty, where the results are robust to alternative estimation approaches, different weighting schemes for constructing energy poverty,

and alternative measurements of non-farm entrepreneurship. The results show a statistically significant effect of non-farm entrepreneurship on energy poverty among rural households, but not for small towns. Furthermore, the effects are more concentrated among male-headed households. The findings indicate that consumption expenditure (a proxy for income) and asset accumulation are the main pathways through which non-farm entrepreneurship influences energy poverty.

The main policy implication of this study is the importance of promoting the establishment and growth of rural non-farm enterprises in poverty reduction initiatives. Given the seasonality and vulnerability of farming activities to climate shocks, diversified income from non-farm enterprises may enhance households' spending on clean energy. Hence, incentives aimed at improving the survival and productivity of such enterprises could be of paramount importance. These may include access to credit, digital finance, road, electricity, working premises, and markets. Formalization of the enterprises may also pave the way for the provision wide ranges of support packages, thereby improving their productivity. Given that the analysis provides statistically insignificant results among female-headed households, there is a need to address gendered constraints related to access to capital, mobility, time burden, market access, business licensing, skills, and social norms.

This study has some limitations related to the data. In particular, the dataset lacks detailed information on households' expenditure across various energy sources and their corresponding prices. It also does not capture whether households rely on a single or multiple energy options. Future research could incorporate such information to enrich the evidence base and strengthen policy implications.

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Appendix

Table A4.1: List of non-farm activities employed to construct a binary non-farm entrepreneurship

Activity	Description
Nonagri_home	Owned a non-agricultural business or provided a non-agricultural service from home or a household-owned shop
Agri_byproduct	Processed and sold any agricultural by-products
Owntrading_market	Owned a trading business on a street or in a market
Offer_market	Offered any service or sold anything on a street or in a market
Professional	Owned a professional office or offered professional services from home
Transport	Driven a household-owned Transport or pick-up truck to provide transportation or moving services
Bar_restaurant	Owned a bar or restaurant
Others_small	Owned any other non-agricultural business, even if it is a small business run from home or on a street

Table A4.2: Descriptive summary of non-farm activities employed to construct a binary non-farm entrepreneurship

	2011-12		2013-14		2015-16	
	Mean	SD	Mean	SD	Mean	SD
Nonagri_home	0.082	0.275	0.095	0.293	0.089	0.284
Agri_byproduct	0.078	0.268	0.082	0.274	0.077	0.267
Owntrading_market	0.053	0.224	0.055	0.227	0.039	0.193
Offer_market	0.041	0.199	0.038	0.190	0.041	0.197
Professional	0.004	0.061	0.001	0.037	0.002	0.047
Transport	0.003	0.058	0.006	0.076	0.007	0.084
Bar_restaurant	0.006	0.078	0.005	0.073	0.006	0.076
Others_small	0.049	0.217	0.057	0.231	0.061	0.240
Observations	3,793		3,593		3,648	

5. Conclusions

Digitalization has evolved at a faster rate than any other innovation in human history (UN, 2020). The COVID-19 pandemic accelerated the use of digital technologies, including telework and e-commerce (Copestake et al., 2024; Constantinescu et al., 2025). Digital technologies also provide new opportunities for education by supporting both learners and teachers. Primarily, it increases access to learning and teaching resources (OECD, 2023). Nonetheless, excessive use of digital technologies, such as the internet, may come with its own costs, including exposure to misinformation (Bala, 2025). Aside from growing evidence on the wide-ranging impacts of digitalization, there is an increasing interest in the welfare effects of diversification into rural non-farm enterprises (Kolawole, 2021; Asiimwe et al., 2025). However, its specific impact on energy poverty remains underexplored.

This dissertation employed micro-level data to analyze the impacts of digital technologies on firms' resilience and children's literacy, and to explore the link between non-farm entrepreneurship and energy poverty in the context of sub-Saharan Africa. The first paper examined whether pre-pandemic ownership of websites mitigated the adverse effects of the COVID-19 pandemic on Zambian firms. The findings suggest that the pandemic led to a significant decline in firms' sales revenue. However, digitalized firms experienced lower revenue losses. The effects appear to be primarily driven by the adoption of relevant coping strategies during the pandemic, including the use of online sales and remote work platforms.

The second paper investigated the impact of mobile broadband coverage on children' s literacy in Nigeria. The results suggest that 3G mobile broadband networks increase the likelihood that children can read and write in any language. These findings highlight the potential role of early-stage exposure to digital technologies in human capital development. The mechanism analysis demonstrates that increased parental aspirations and household income are potential pathways through which the availability of mobile broadband internet enhances children's reading and writing skills.

The third paper examined the impact of non-farm entrepreneurship on energy poverty, with a particular focus on households in rural and small towns in Ethiopia. The findings suggest that non-farm entrepreneurship reduces households' multidimensional energy poverty levels. The results

further provide evidence that increases in household income and asset accumulation are potential mechanisms underlying this effect.

Overall, the findings of this dissertation render important policy implications. First, the results call for systematic integration of digitalization across all sectors and its embedment into national policies and strategies, while giving critical attention to inclusivity. Second, expanding mobile broadband infrastructure remains critical, particularly in developing countries where access to educational resources is limited. However, connectivity alone does not automatically improve learning outcomes; complementary investments in schools, teachers, and education systems remain essential. Policies should also focus on improving digital literacy and access to affordable devices.

Third, greater efforts are needed to promote the establishment and sustainability of non-farm enterprises, thereby improving households' access to modern energy sources and enhancing their welfare. Improving the survival and productivity of such enterprises can help households generate higher and more stable income. Beyond investment in complementary infrastructure, policies should be designed to ensure the gains are shared equitably across genders. Finally, future research could employ alternative measures of digitalization, literacy, and energy poverty while extending the analysis to include a large number of developing countries.

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