Three essays on resource and development economics in Sub-Saharan Africa: evidence from Senegal

By

Kadoukpè Gildas Magbondé

Thesis Presented for the Degree of

DOCTOR OF PHILOSOPHY

In the

School of Economics

UNIVERSITY OF CAPE TOWN

March 2025

Supervisors:

Associate Prof. Djiby Thiam

Prof. Natascha Wagner

University of Cape Town

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Declaration

I, Kadoukpè Gildas Magbondé, hereby declare that the work on which this dissertation/thesis is based is my original work and has not been previously submitted at this or any other university, either as a whole or in part. All the materials consulted during the study have been duly acknowledged.

Signature: ____________________ Date: __________________

Student Name: **Kadoukpè Gildas Magbondé**

Abstract

The thesis provides empirical evidence of the contribution of basic infrastructure resources to economic development in Senegal. In addition to the introduction and conclusion, three distinct papers make the backbone of the thesis, the first two being impact evaluation studies. The first paper combines difference-and-difference and propensity score matching and uses quantile regressions to examine the welfare effects of rural electrification. The latter is embedded within the first phase of the Emergency Programme for Community Development (PUDC I) implemented by the Senegalese Government. The study uses a panel dataset of 1,115 rural households observed before and after the roll-out of the program. Findings reveal that rural electrification is an agent of household well-being upgrading, irrespective of the electricity source, whether off-grid or on-grid. Electrified households seem to have enjoyed higher agricultural employment and non-food expenditure compared to the observationally similar households that are not connected to electricity. Social benefits manifested through an increase in school enrolment, school attendance, and time spent by children studying at home, with the increase in school attendance being more pronounced for girls than for boys. Furthermore, poor households and those that have access to a marketplace drew the most substantial benefits from access to electricity.

The second paper focuses on water infrastructures. It employs a panel dataset of 1,319 Senegalese rural households to empirically document the welfare effect of piped water adoption. Unlike the first paper which considers both economic and social outcomes, the second paper mainly centers on the economic benefits of piped water adoption, which are employment and household expenditure growth. This is because many previous studies have already looked at the social implications associated with access to water resources. The current gap in the literature is mainly observed with the economic impacts of access to water supply infrastructures installed in rural and under-serviced communities within the developing world. A key finding reveals that the adoption of piped water triggered agricultural employment in the PUDC rural areas. Such benefits appear to be greater within households that have access to road infrastructure, alongside access to water resources. The empirical analyses further suggest that non-poor households seem to benefit more from access to water infrastructures than poor households. Finally, when comparing the welfare effect of

government-led PUDC water supply with that of community-led initiatives, our findings suggest that the former is much effective than the latter in improving economic outcomes.

Using an array of empirical strategies including descriptive statistics, propensity score matching, quantile regressions, and Blinder-Oaxaca counterfactual decomposition, the third paper unravels the nexus between power outages, firm productivity, and gender-based productivity gap. For many developing countries, power outages represent additional costs for firms, given their need to invest in alternative inputs (i.e., generators) to maintain or enhance performance. Moreover, firms managed by females are often claimed to be more severely hit by such outages given the structural and institutional constraints women face in many developing countries. Understanding these interactions is the purpose of this paper. The World Bank's Enterprise Survey (WBES) dataset which comprises 601 Senegalese establishments surveyed in 2015 is used. The results highlight that female-owned firms underperform compared to male-owned firms and that the scale inefficiency stands out as the root of Senegalese firms' low productivity. A key finding is that unexpected and repetitive interruptions of electricity are sources of Senegalese firms' counter-performance and a driver of a broad gender-based productivity gap within firms.

Acknowledgment

“Without them, I would not have had the energy to see this project through to completion.”

Thomas Piketty (2014, p.x)

Any path toward a doctoral journey is not always straightforward. Mine has been winding. However, I am extremely grateful to the special people who supported and challenged me along the way. First and foremost, my deepest appreciation and heartfelt gratitude go to my supervisors Professors Djiby Thiam and Natascha Wagner for all the guidance, outstanding support, and timely feedback that shaped this thesis. This doctoral endeavor would not have been achieved without your support, help, expertise, and constant encouragement.

Special thanks to the International Development Research Centre (IDRC) for their invaluable doctoral scholarship and to Professor Djiby Thiam for additional funding provided, without which the thesis would not have been undertaken nor completed. I would be remiss in not mentioning Professor Mamadou Abdoulaye Konté and Professor Samba Mbaye from Gaston Berger University (UGB) who encouraged and supported my application to the IDRC fellowship and my candidacy to the University of Cape Town’s School of Economics.

To my wife, Ayélé Odile Sossou for your unparalleled support, genuine encouragement, and endless love to complete my doctoral odyssey, and to my son Lucas Duhamel for rooting for me along the way. You had both endured my absence from home during my doctoral journey and built unwavering resilience. May this doctoral achievement serve as a rewarding tribute to your immeasurable sacrifice and boundless support.

I am sincerely grateful to my parent for their unequaled investment in my education, embracing the notion that, schooling a child equalizes educating a nation. Your endless love, your motivation, and moral support fueled my doctoral journey and made me who I am today. To my brothers Bienvenue and Audrey, and to my sisters Ruth, Armelle,

and Caroline whose infallible love has been supportive. A warm word for my colleagues Victor and Esubalew for providing guidance when I first landed in Cape Town for the doctoral journey.

Dedication

To my parents Cossi Théodore Magbondé and Céline Ogougbé for opting to get me educated.

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List of abbreviations

ADB	:	Asian Development Bank
ANSD	:	Agence National de la Statistique et de la Démographie
ASER	:	Agence Sénégalèse d’Electrification rural [Senegalese Agency of Rural Electrification]
CRDES	:	Centre de développement économique et social [Centre for Economic and Social Development]
DEA	:	Data Envelop Analysis
ECREEE	:	Center for Renewable Energy and Energy Efficiency
GDP	:	Gross Domestic Product
ICT	:	Information and Communication Technologies
IDRC	:	International Development Research Centre
IEA	:	International Energy Agency
IFAN	:	Institut Fundamental d’Afrique Noire [Fundamental Institute of Black Africa]
LSMS	:	Living Standard Measurement Survey
MEA	:	Ministère de l’Eau et de l’Assainissement du Sénégal [Ministry of Water and Sanitation]
NGO	:	Non-Governmental Organization
OFOR	:	Office des Forage Ruraux
PASER	:	Plan d'Action Sénégalais d'Electrification Rurale [Senegalese Rural Electrification Action Plan]
PNER	:	Programme National d'Électrification Rurale [National Rural Electrification Programme]
PSE	:	Plan Senegal Emergent [Emerging Senegal Plan]
PSM	:	Propensity Score Matching
PUDC	:	Programme d’Urgence de Développement Communautaire [Emergency Programme for Community Development]
RCT	:	Randomised Trial Control
SDG	:	Sustainable Development Goals
SENELEC	:	Senegalese electricity generation company
SHS	:	Solar Home System

SME	:	Small and Medium-Sized Enterprises
SONES	:	Société Nationale des Eaux du Sénégal [National Water Company of Senegal]
SSA	:	Sub-Saharan Africa
UN	:	United Nations
UNICEF	:	United Nations International Children's Emergency Fund
USAID	:	United State Agency for International Development
USD	:	United State Dollars
WHO	:	World Health Organization

Chapitre 1 - General Introduction

"To function well, society needs public services."

Acemoglu, D.& Robinson, J. (2012, p.90)

1.1 Background

Electricity and water are critical to human progress and economic development, particularly in their roles within firms and households. Households primarily use electricity for lighting and various productive purposes, such as powering appliances and facilitating income-generating activities. Water, essential for sustaining life, is indispensable for cooking, washing, and cleaning. Consequently, both electricity and water are crucial for household well-being (Deveto et al., 2012; Khandker et al., 2014). In firms, electricity and water are fundamental inputs in the production process. The availability of reliable electricity and clean water directly boosts output by promoting capital accumulation. Additionally, both resources indirectly enhance productivity, thereby contributing to increased output. Electricity, in particular, has the unique advantage of improving the productivity of labor and physical capital as it facilitates the use of information and communication technologies (Falentina & Resosudarmo, 2019). Reliable electricity reduces production costs for firms, enabling them to expand their production capacity (Allcott et al., 2016).

Given the importance of water and electricity to firms and households, building infrastructure to enhance the supply of both resources is a core priority for policymakers in developing countries. Electricity and water infrastructure constitute basic components of a nation's overall infrastructure, yielding macroeconomic effects such as enhanced productivity and economic growth (Aschauer, 1989; Holtz-Eakin, 1994; Kodongo & Ojah, 2016; Song & van Geenhuizen, 2014). The importance of basic infrastructure for economic development extends beyond productivity growth. Access to essential infrastructure services is closely linked to reduced poverty levels. Economic growth driven by infrastructure investment leads to poverty alleviation. Furthermore, productivity improvements in the non-agricultural sector, resulting from basic infrastructure development, lead to wage increases and better remuneration, thereby

reducing multidimensional poverty (Zhang et al., 2023). In the current era of climate change, infrastructure also enhances countries' resilience to climate shocks and stresses (ADB [Asian Development Bank], 2012). Modern, efficient, and climate-smart infrastructure promises transformative impacts. Investing in basic infrastructure not only boosts efficiency but also ensures that capital assets remain viable in the future despite climate change.

Emphasizing electricity and water services, which form the basis of this thesis, provides deeper insights into the implications of supplying basic infrastructure. The theory of change associated with access to electricity highlights the economic and social benefits that electricity-deprived rural households could achieve if they had access to electricity services (Khandker et al., 2013, 2014; Lenz et al., 2017). The availability of electricity encourages households to purchase electrical appliances (such as light bulbs, radios, televisions, blenders, microwaves, stoves, and refrigerators) and motivates social institutions (like health centers and schools) to use electricity in their service delivery. The productive use of electricity results in outputs such as cleaner light with fewer pollutants, increased lighting, improved access to information and communication technologies, and enhanced productive motive power. These outputs ultimately lead to improved household well-being in terms of education and health outcomes (social benefits) and increased income and employment opportunities (economic benefits).

Health centers' enhanced efficiency and households' shift from using polluting biomass and kerosene (for lighting and cooking) contribute to better health outcomes for electrified households. The availability of cleaner light allows children to study late at night, and the time saved from not having to collect firewood can be reallocated, leading to better educational outcomes for children. As adults, particularly women, take advantage of the opportunities provided by electricity, they engage in income-generating activities through labor market participation. These employment effects, combined with improved human capital and productivity growth derived from electricity services, result in higher income, expenditure, and consumption.

These theoretical insights on the welfare effects of access to electricity have been confirmed by several empirical studies (Arraiz & Calero, 2015; Barron & Torero, 2014; Bensch et al., 2011; Chakravorty et al., 2014; Diallo & Moussa, 2020; Dinkelman,

2011; Khandker et al., 2014; Kudo et al., 2015; Litzow et al., 2019; Rao, 2013; Rathi & Vermaak, 2018; van de Walle et al., 2013).

The reliability of electricity is as critical as its availability. An unstable and inconsistent electricity supply has detrimental implications for household well-being (Chakravortya et al., 2014; Lenz et al., 2017). Power disruptions negatively affect the welfare of electrified households by reducing income and consumption (Lenz et al., 2017; Sedai et al., 2021). Furthermore, an expanding body of literature underscores the adverse effects of unreliable electricity on firm performance (Abdisa, 2018; Allcott et al., 2016; Falentina & Resosudarmo, 2019; Fisher-Vanden et al., 2015; Moyo, 2012; Oseni & Pollitt, 2015). Frequent and unexpected power outages increase production costs, cause firms to incur losses, and result in substantial declines in profits and productivity (Allcott et al., 2016; Fisher-Vanden et al., 2015; Steinbuks & Foster, 2010).

In addition to electricity, this dissertation examines water as another critical resource, recognizing its significant role in shaping social welfare and economic opportunities. The essential nature of water for human life establishes access to clean water as a fundamental human right, which policymakers worldwide endeavor to safeguard (Carrard et al., 2019; Ortiz-Correa et al., 2016). The scarcity of water resources has significant adverse effects on the social and economic outcomes for those who lack access. The absence of drinking water is well-known to lead to poor health, water-borne diseases, and psychological stress. In developing countries and rural areas, children and women often bear the burden of fetching water, typically from distant sources (Devoto et al., 2012; Winter et al., 2021). Consequently, investment initiatives aimed at improving water access in these rural and underserved communities are expected to free up time for women to engage in income-generating activities and for children to focus more on their education (Devoto et al., 2012; Koolwal & van de Walle, 2013; Lokshin & Yemtsov, 2005). In this context, providing drinking water to households previously without access would substantially save time and enhance women's participation in productive occupations and livelihood activities, both on-farm and off-farm (Winter et al., 2021). Children in households with access to potable water would have more time for their studies and experience significant improvements in their health. These well-being benefits associated with access to drinking water have been validated by empirical studies (Dhital et al., 2022; Ortiz-Correa et al., 2016; Winter et al., 2021).

1.2 The current trend of electricity and water infrastructures in Senegal

A well-established fact is that developing countries invest less in infrastructure facilities (Foster & Briceno-Garmendia, 2010; Litzow et al., 2019). Basic infrastructures including roads, information, and communication technologies (ICT), sanitation, electrical power, and water services remain scarce in the Global South. To illustrate, while 54 percent of the world uses the internet, the figure is only 19 percent for low-income countries (UN, 2023). In Sub-Saharan Africa, eight out of ten people do not have access to potable water and one out of eight has access to piped water (WHO & UNICEF, 2021). Almost 55 percent of Sub-Saharan African populations lack access to electricity services (IEA, 2019). In addition to the insufficient level of investment in infrastructure in the Global South, urban and rural areas are unequally furnished with infrastructure. For instance, rural areas are under-electrified compared to urban zones because of the inadequacy of public policies, the unprofitability of grid extension, the low population density which does not guarantee economies of scale and the limited production capacity (Diouf, et al. 2019).

Countries with poor infrastructures have limited capacity to accelerate their transformative development process. From Agénor's (2010) perspective, the actual level of infrastructures in the developing world has not reached the optimal level that is compatible with economic growth, resulting in nefarious effects. The harmful effect can also be a consequence of incomplete infrastructure. For instance, having electricity to manufacture goods but lacking roads to access the market would limit the expected growth effect. Given that the components of the infrastructure network complement each other's, only the join availability of these complements would generate efficient gains (Agénor, 2010).

A critical remark is that building and maintaining infrastructure systems appear singularly strenuous in the Global South. Among the factors responsible for the slackness of infrastructure development are the lack of financial resources and political will, poor institutions, the lack of institutional capacity, and the pressure of fiscal consolidation (Narayanan et al., 2017). In addition, the lack of maintenance favors the growing depreciation of the existing infrastructure capital. All these impeding factors must be addressed to accelerate infrastructure building in the Global South. One way

to circumvent the lack of institutional capacity is building public-private partnerships (ADB, 2012).

Access to water and electricity service is not universal in Senegal. To illustrate, only 65,7 percent of rural households have access to potable water, with a national access rate of 78,7 percent (ANSD, 2021). When it comes to energy service, while 53 percent of rural households are denied access to electricity, the urban rate of access to electricity (Dakar excluded) is settled at 89 percent (ANSD, 2021). Yet, the reliability of electricity pauses a serious problem in Senegal as well. Power outage frequency is on the rise, impeding firms' production and investment. For example, within a typical month, firms register an average of 27 outages, with around 4 hours per day (Cissokho, 2019).

Historically, the Government of Senegal initiated various reforms and policies to enhance access to water and electricity facilities in the 1990s. The sanitation sector was separated from the hydraulics sector, the latter being subdivided into rural and urban hydraulics. To increase efficiency in service delivery, the OFOR (*Office des forages ruraux*) was created in 2014 to lead rural areas' water supply and management (MEA, 2021). The stream of reforms has made it possible to switch from a monthly pricing system to a modern system in which pricing is based on the volume of water consumed (metering). It has further based the provision of public drinking water services on public-private partnerships (PPPs) through leasing contracts. To increase efficiency, the PPPs involve entrusting the management of the public drinking water service to private actors, while the financing of the hydraulic equipment falls into the responsibility of the delegating authority (the State).

To reach the target of a 60 percent electrification rate in rural areas by 2022 (World Bank, 2018; MPE, 2021) and close the urban-rural gap, several energy initiatives were implemented in the Senegalese electricity sector. This effort included the establishment of the Senegalese Agency of Rural Electrification (ASER) in 1998 to lead the Senegalese Rural Electrification Action Plan (PASER) (Diouf et al., 2013) and to activate rural electrification initiatives. The Urgency Plan for Rural Electrification, in line with the Emerging Senegal Plan (PSE), electrified nearly three thousand villages by 2015 (World Bank, 2018). In the same year, the country implemented the first phase of the Emergency Community Development Program (PUDC I), which provided water

and electricity infrastructure to rural communities. Under this program, villages were electrified through the extension of the national grid and decentralized mini-solar power plants. Landlocked, remote, and impoverished villages were equipped with mini photovoltaic power stations. The water interventions included the renovation of old boreholes and the construction of new ones, as well as the provision of drinking water.

1.3 Research gap and objectives

Despite the extensive literature on the impact of basic infrastructure on household welfare and firm productivity, previous studies are not clear-cut, necessitating answers to the following research questions in more nuanced ways: (i) What are the welfare effects associated with access to electricity in rural areas? (ii) What are the economic benefits linked to the adoption of piped water by rural households? (iii) What are the effects of inadequate electricity infrastructure on firm productivity and the productivity disparity between female- and male-owned firms? Providing precise and nuanced answers to these inquiries is crucial for Senegal and other developing countries. Firstly, a comprehensive analysis of the welfare effects of rural electrification is essential to gain deeper insights into the welfare impacts of different electricity sources (such as solar and grid electricity), the types of benefits (both social and economic), and the distributional effects of electricity access. As a policy implication, the findings regarding the welfare effects of rural electrification can guide policymakers in selecting energy sources (fossil fuel vs. renewable energy-based) to prioritize, and in determining the scale and focus of electrification programs targeted at different segments of the population (both poor and non-poor households). Secondly, examining the economic benefits of adopting piped water is crucial for better understanding the potential implications of water access on key socio-economic indicators such as women's empowerment, inequality, poverty alleviation, and overall rural development. Such a study provides an opportunity to compare the welfare effects of community-led initiatives with longstanding government-led water infrastructure efforts. Finally, Given that female-owned and female-managed firms in Senegal create more jobs than their male counterparts, a gender-based analysis of the productivity impacts of power outages would significantly influence employment policies in Senegal.

Overall, the thesis seeks to build on the stock of knowledge regarding the contributions of basic infrastructure services to economic development. It makes meaningful

contributions to the literature by addressing the three research questions mentioned above. Each research question is addressed by one paper. Though the three papers that make the backbone of the thesis are distinct and self-contained, they share a common ground. They relate to basic infrastructure, either electricity or water infrastructure, and have in common Senegal as a study area. Additionally, while the third paper explores existing observational data, the first and the second papers evaluate the impact of a real intervention implemented by the Senegalese government, namely the PUDC.

As each paper addresses one research objective, the dissertation is structured in three distinct chapters. The first paper conducts an impact evaluation study. It evaluates the welfare effects of a rural electrification embedded in the Emergency Programme for Community Development (PUDC). The analysis investigates the economic and social effects inherent to the PUDC's rural electrification. It further analyses the differential effects based on energy sources (on-grid and off-grid electricity), the distribution of household expenditure, and households' access to the market. Combining the difference-in-difference approach and propensity score matching technique as main empirical strategies, the study compared outcomes of interest between electrified households and observationally similar non-electrified households.

The second paper runs an impact evaluation study as well with a focus on water. It uses data collected to evaluate the impacts of PUDC to provide empirical evidence of the welfare effects of piped-water adoption by rural households in Senegal. The paper assesses the effects of piped-water adoption on employment and household expenditure. It further looks at the effects around the distribution of household expenditure, not just average, and investigates the interacting effects of water and electricity infrastructures, through a bundling process. A notable contribution of the paper is that it compares the welfare effects of a government-led water intervention, say PUDC water infrastructure, to community-led water services, say non-PUDC water infrastructure. To compare households with piped water to observationally similar households without piped water, the paper relies on an array of empirical strategies. It combines the difference-and-difference method with the propensity score matching technique to evaluate the welfare impacts of PUDC water infrastructure and uses only propensity score matching to isolate the welfare impacts of non-PUDC water infrastructure. Quantile regressions are further used to analyse the distributional effects of piped-water adoption.

The final paper links up unreliability of electricity to firm productivity and gender. It mainly focuses on the contribution of poor electricity infrastructure to the widening of the gender productivity gap between female-owned and male-owned firms in Senegal. Unlike the first two papers, which investigate the positive effect associated with access to basic infrastructures, the third paper considers the implications of poor and unreliable electricity supply services on firm productivity. Specifically, this study tests the female-underperformance hypothesis within firms and examines the impacts of power outages on firm productivity as well as the gender-based productivity gap. Based on cross-section data from the World Bank's Enterprise survey dataset, the paper makes use of a wide range of empirical strategies. These range from descriptive statistics, quantile estimations, to Blinder-Oaxaca decomposition.

1.4 Organization of the thesis

The research undertaken for this thesis comprises five chapters. The thesis opens with an introductory chapter that presents the economic relevancy of basic infrastructures, the current state of access to water and electricity in Senegal, the research gaps and objectives. The second chapter examines the welfare effects of rural electrification in Senegal. The third chapter investigates the impacts piped water adoption has on employment and household expenditure in Senegal. The fourth chapter explores the nexus between power outages, firm productivity, and gender in Senegal. The thesis closes with the fifth chapter which summarizes the main findings and policy implications and further acknowledges the limitations and suggests critical areas for future research.

Chapitre 2 - Impact of access to electricity on the well-being of rural households in senegal[1]

"Without access to electricity, the pathway out of poverty is narrow and long."

World Bank (2017, p.xi)

Abstract

This study examines the welfare impacts of rural electrification using a panel dataset from 1,115 rural households in Senegal, observed in 2016 and 2020. Combining the quasi-experimental methods of propensity score matching (PSM) and difference-in-differences (DiD), we show that electrified households increased their non-food expenditure and non-agricultural employment by 39.5 percent and 39.2 percent, respectively, compared to observationally similar non-electrified households. Children in electrified households are 45.3 percent more likely to be enrolled in school, 44.7 percent more likely to attend school, and study 63.3 percent more, with the increase in school attendance being more pronounced for girls compared to boys. Furthermore, poor households and those that have access to a marketplace drew the most substantial benefits from access to electricity. In sum, the findings show that access to electricity increases household well-being and thus encourage the speeding-up of universal access to electricity in rural areas both with on-grid and off-grid technologies.

Keywords: Rural electrification; access to electricity; rural households; household well-being; propensity score matching; difference in differences; Senegal

[1] This chapter is currently resubmitted to Journal of Development Effectiveness after a minor revision.

2.1 Introduction

Recent estimates show that 675 million people worldwide did not have access to electricity in 2021 (IEA et al., 2023). Most of these electricity-deprived populations live in rural areas in Sub-Saharan Africa (SSA) (Foster & Briceno-Garmendia, 2010; Litzow et al., 2019). We study whether the provision of electricity to rural populations has measurable positive impacts on household well-being. In Senegal, where the study at hand is located, we observe a significant disparity between urban and rural regions with respect to access to electricity. In 2015, only 43 percent of the rural population had access to electricity (MEP, 2021), while 90 percent of the urban population was connected (World Bank, 2018; MPE, 2021). However, more than half of the total population lives in rural areas with agricultural activities being the main source of income and poverty being still acute (ANSD, 2020). Nearly 54 percent of the rural population lives below the national poverty line, while the urban poverty rate is 20 percent (ANSD, 2021). To address this disparity and foster widespread dissemination of public services within rural communities, the government of Senegal initiated the Emergency Program for Community Development (PUDC) which aims at providing rural communities with access to reliable electricity services. One of the main objectives of the program is to reduce rural-urban differences in terms of access to electricity, and to support rural-based structural transformation with the creation of local jobs and the improvement of socio-economic conditions.

The first phase of the program (PUDC I) was operational from 2016 to 2020, and resulted in a rural access rate of 55 percent, and an urban access rate of 96 percent (MEP, 2021; World Bank, 2018). In Figure 2.1 we show electricity access rates per region before and after the implementation of PUDC I.

This article provides empirical evidence of the effect that access to electricity in the context of PUDC I has on the well-being of rural households in Senegal. From a theoretical perspective, access to electricity has the potential to remove important constraints that electricity-deprived households are faced with: the allocation of time to firewood collection and the extensive use of kerosene for lighting and biomass for cooking (Litzow et al., 2019). In addition, electrified households acquire appliances such as refrigerators, electric stoves for cooking, radios, televisions, mobile phones, bulbs, and other electrical devices, resulting in outputs such as improved home food preservation and cleaner cooking, improved access to information, cleaner light and a

greater quantity of lighting, and more energy for productive use. Concomitantly, children and women, who are responsible for firewood collection, save time (intermediate outcome); children can also study longer due to the light, and adults are encouraged to take part in the labor market, develop income-generating activities, and take advantage of opportunities offered by rural businesses. These intermediate outcomes lead to improved overall outcomes such as income, expenditure, employment, and children's education, resulting in greater well-being. The theory of change identifies all these pathways through which access to electricity may increase welfare. For details see Figure A.1 in the Appendix. Moreover, existing studies similarly recognize the importance of electricity for the well-being of households (Wagner et al., 2021; Khandker et al., 2014).

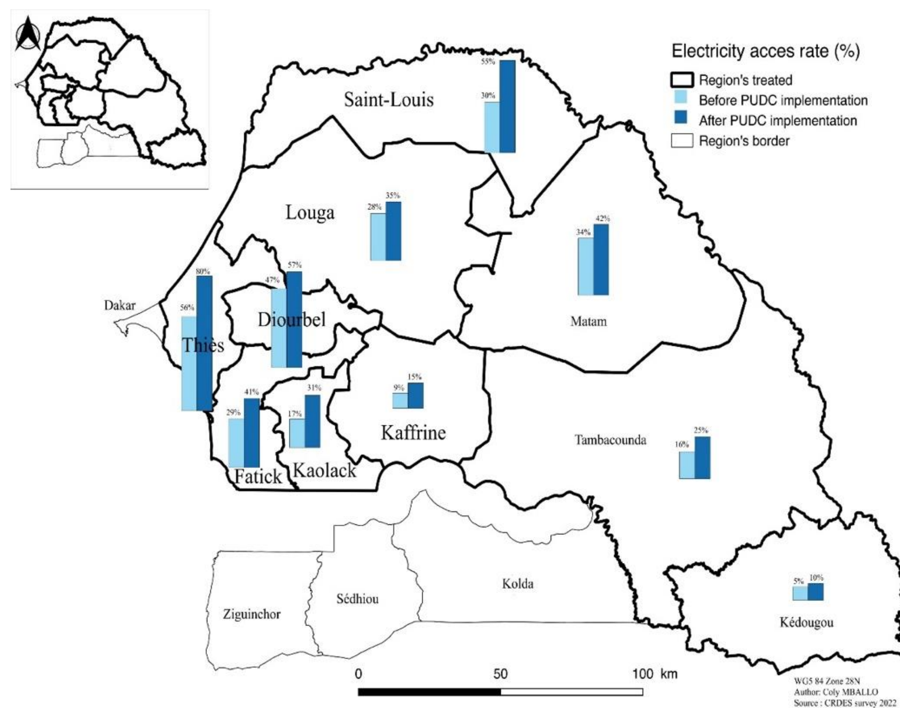


Figure 2-1. Access to electricity before and after PUDC I.

Source: CRSE (2020)

The current study makes three major contributions to the literature. First, we investigate the importance of contextual factors – types of electricity sources and access to marketplaces – on the nexus between access to electricity and household well-being. We further consider a wide array of socioeconomic variables, including economic and social outcomes, to capture household well-being. Second, we examine the

distributional effects of access to electricity, that is whether poor households benefit disproportionally from the use of electricity. The third contribution lies in the focus on Senegal, where very few studies have been carried out about rural electrification (Peters & Sievert, 2016). Despite the existence of earlier studies about rural electrification in Senegal (Diouf et al., 2013; Gafa & Egbendewe, 2021; Mawhood & Gross, 2014; Peters & Sievert, 2016; Salat et al., 2021), only Peters & Sievert (2016) assess its impact on household well-being. Contrary to their work, which looks at seven African countries (including Senegal), we carried out an in-depth country-specific analysis.

Similar to Smith & Todd (2005), we combine propensity score matching (PSM) and difference-in-differences (DiD) to estimate the mean effects and we use quantile DiD to estimate the distributional effects of access to electricity on household welfare. Based on a panel dataset of 1,115 rural households observed in 2016 and 2020, our results show that electrified households increased their non-food expenditure and non-agricultural employment by 39.5 percent and 39.2 percent, respectively, compared to observationally similar non-electrified households. These findings are in line with Khandker et al. (2013; 2014) and Chakravorty et al. (2016), who found that rural electrification increased household expenditure in Bangladesh, Vietnam, and the Philippines. Similarly, Dinkelman (2011) and Litzow et al. (2019) reported an increase in employment following electrification in South Africa and Bhutan, respectively. Next, we identified social benefits; children in electrified households are 45.3 percent more likely to be enrolled in school, 44.7 percent more likely to attend school, and study 63.3 percent more, with the increase in school attendance being more pronounced for girls compared to boys. These findings are in line with Khandker et al. (2013, 2014). Furthermore, poor households and those that have access to a marketplace drew the most substantial benefits from access to electricity. Overall, the findings suggest that rural electrification under PUDC I was effective, encouraging a further speed up towards universal access to clean energy in Senegal.

The remainder of the article is organized as follows. Section 2 introduces the rural electrification program of the PUDC I in Senegal. Section 3 provides a brief review of related literature. Section 4 describes the data used and Section 5 introduces the methodology used. The main findings are discussed in Section 6. Section 7 concludes and offers policy recommendations.

2.2 Rural Electrification within the Framework of the PUDC I

The Emergency Program for Community Development (PUDC) is a development program that was initiated by the Government of Senegal in 2015 and became operational in 2016. The government's main objectives with PUDC were (i) to reduce regional disparities by providing infrastructure to rural populations, (ii) to combat rural poverty, (iii) and to reinforce labor productivity in rural areas. Populations in rural areas were offered electric, road and hydraulic infrastructure, as well as postharvest equipment. These interventions are implemented to accomplish the *Plan Senegal Émergent* (PSE), introduced in 2014, to position Senegal as an emergent country by 2035.

The program was run in two phases. The first phase (PUDC I), from 2015 to 2018, was financed exclusively by the Government of Senegal with a budget of around USD 90 million. The second phase (PUDC II), from 2019 to 2022, was jointly financed with around USD 400 million by the Senegalese government, the Islamic Development Bank, the African Development Bank, and the Saudi Fund for Development.

This study focuses on PUDC I, particularly on the rural electrification project that is an integral part of the National Rural Electrification Program (PNER), implemented by the Senegalese Agency for Rural Electrification (ASER), which outlines the plan to achieve universal access to electricity in rural Senegal. Within the framework of PUDC I, 420 villages were electrified through the extension of the national grid as well as decentralized mini-solar power plants. Landlocked, remote, and poor villages were offered mini photovoltaic power stations. Villages that are located closer to tar roads or not further away than one kilometer from the main power lines created by the PNER or other interventions were electrified through the national grid (World Bank, 2018). Concerning the price structure, in solar-powered villages, once the photovoltaic power stations were installed, households could decide whether they want to be connected, and once they are supplied with electricity they are charged a monthly flat fee. In turn, households that access electricity from the grid are charged according to the electricity consumption bracket they fall into as set by SENELEC, the national electricity agency of Senegal.

2.3 Literature Review

The literature review is split into three parts. First, we present existing findings about economic benefits, followed by social benefits, and conclude with gaps in the existing literature and our contribution.

2.3.1 Economic benefits of rural electrification: Employment and income

The extension of the national grid to rural areas creates as a *first* economic benefit: employment opportunities, allowing adults in electrified households to spend more time on income-generating activities (Lenz et al., 2017).

Existing empirical studies have shown that employment in electrified households has substantially improved due to the national grid extensions (Litzow et al., 2019; Samad & Zhang, 2017; Dasso & Fernandez, 2015; Van de Walle et al., 2013; Lipscomb et al., 2013; Grogan & Sadanand, 2013; Dinkelman, 2011). Access to electricity increased the probability of obtaining a job by 3 percent in Bhutan (Litzow et al., 2019), and in India, men have substituted casual work for regular work (Van de Walle et al., 2013). Dasso and Fernandez (2015) show that in Peru access to electricity increased male employment by 2.6 points – men worked more in the agricultural sector and fewer had a second job; women worked an extra 0.35 hours per week – they increased their participation in the labor market (self-employment) and worked less in the agricultural sector. Similarly, Dinkelman (2011) and Rathi and Vermaak (2018) identify that access to electricity allows women to participate in the labor market and improve their productivity in India and South Africa respectively. Also, access to electricity increased female presence in the labor market by 2.3 percent in Bangladesh (Samad & Zhang, 2017). The probability of women having a paid job increased by 23 percent in Nicaragua (Grogan and Sadanand, 2013). Rural women reallocate part of the time they devote to domestic chores to productive use, and to participate in the labor market (Burney et al., 2017). Importantly, women do not need to look for firewood any longer, liberating time for productive activities (Grogan & Sadanand, 2013). As a consequence, rural electrification has the potential to reduce social inequalities and improve women's empowerment (Dasso & Fernandez, 2015).

Yet, not all existing studies identify positive employment effects from access to electricity (Chakravorty et al., 2016; Grogan, 2016; Grogan & Sadanand, 2013; Peters & Sievert, 2016; Samad & Zhang, 2017). The continued use of biomass for cooking

may still occupy a large amount of women's time (Litzow et al., 2019). Another potential reason for this lack of an effect is that the scope of the market for goods and services in rural areas is thin, which disincentivizes micro firms to increase their productive capacity or to recruit additional workers (Peters & Sievert, 2016). Rathi and Vermaak (2018) show that rural areas have a low absorption capacity, which limits their potential to create employment or absorb the supply of additional labor that results from access to electricity.

While positive employment effects may not affect all household members, the *second* economic benefit of access to electricity is the improvement of overall household income. Several studies show that access to electricity increases income (Khandker et al., 2009; Rao, 2013; Khandker et al., 2014), consumption (Khandker et al., 2009; Van de Walle et al., 2013) and expenditure at the household level (Khandker et al., 2013; Khandker et al., 2014; Chakravorty et al., 2016; Adusah-Poku & Takeuchi, 2019). Following the extension of the grid in rural India, Khandker et al. (2014) reported an increase in household income and expenditure by 38 percent and 18 percent, respectively. Van de Walle et al. (2013) documented an increase in household expenditure of 7 percent due to access to electricity. Likewise, Adusah-Poku and Takeuchi (2019) found an increase of 12 percent to 22 percent in household expenditure in Ghana, and Chakravorty et al. (2016) reported an increase in income and expenditure of 42 percent and 38 percent, respectively, in households connected to the grid in the rural Philippines. In turn, Arráiz and Calero (2015) for the case of Peru, Bensch et al. (2011) and Lenz et al. (2017) for Rwanda, and Aklin et al. (2017) for India do not identify income effects stemming from access to electricity. When electricity is not used productively, but rather used to power radios and televisions, no increases in income are found (Arráiz & Calero, 2015; Bensch et al., 2011; Lenz et al., 2017). The source of electricity also matters for income effects; given its intermittent nature, solar electricity may not offer sufficient energy to initiate income-generating, energy-consuming activities, making it unsuited for increasing the income of electrified households (Aklin et al., 2017).

2.3.2 Social benefits of rural electrification: education

Access to electricity can affect children's schooling outcomes in three different ways. First, by providing clean, stable, and sufficient light, access to electricity enables children to devote more time to studying at home in the evening (Khandker et al., 2009;

Bensch et al., 2011). Second, the substitution of dirty energy sources such as firewood with clean energy frees children from firewood collection, allowing them to study more with the potential to improve school outcomes (Guarcello, Lyon & Rosati, 2004; Akpandjar & Kitchens, 2017). Third, the use of electricity at school further contributes to the children's schooling outcomes (Lenz et al., 2017).

Diallo and Moussa (2020) have shown that the average years of schooling increased by 1.79 percent in Côte d'Ivoire due to the adoption of solar home systems (SHS). Arráiz and Calero (2015) demonstrated that within households using solar systems children allocate more time to homework, which translates into additional years of schooling. Gustavsson (2007) reported that children in households with access to solar technologies (SHS) increased their evening study time.

However, the effects of electricity on children's school outcomes are far from being clear-cut. The conclusions drawn seem to depend on the type of technology employed (national on-grid, solar home systems, mini-grids, and solar lights). Studies focusing on solar electricity and utilizing randomized controlled trials (RCT) to identify the causal effect of access to electricity (Furukawa, 2014; Kudo et al., 2019; Stojanovski et al., 2021) show mixed results. Access to solar electricity was found to enable children in Uganda and Bangladesh to devote more time to studying at home (Furukawa, 2014; Kudo et al., 2019) and to attend school more regularly in Bangladesh (Kudo et al., 2019). However, it is reported that solar technologies did not improve school performance in Bangladesh and Zambia (Kudo et al., 2019; Stojanovski et al., 2021). Unlike studies that focus on decentralized solar technologies, those based on national grid extensions are more likely to identify positive education outcomes (Khandker et al., 2009; Bensch et al., 2011; Khandker et al., 2014; Arráiz & Calero, 2015; Samad & Zhang, 2017; Peters & Sievert, 2016; Aguirre, 2017). For example, Khandker et al. (2014) have shown that rural electrification in India through the extension of the national grid improved children's education, with the effect being more pronounced for girls than for boys. The enrolment rate, time allocated to studying at home, and average years of schooling were found to have increased by 6 percent, 1.4 percent, and 0.3 percent, respectively, for boys, and by 7.4 percent, 1.5 percent, and 0.5 percent, respectively, for girls. Khandker et al. (2013) reported similar results for Vietnam; school enrolment increased by 6.3 percent for boys and 9 percent for girls. The primary school completion rate increased by 0.13 percent for boys and one percent for girls.

Saing (2018) in Cambodia and Van de Walle et al. (2013) in India also reported effects in favor of girls.

2.3.3 Existing gaps and own contribution to the literature

The existing literature has four major gaps. First, very few studies jointly consider on-grid and off-grid technologies and their impact on household well-being (Rao et al., 2015). On-grid infrastructure has greater production capacity and can power refrigerators and heavier machinery, off-grid solutions are primarily utilized for lighting, television, and radio (Peters & Sievert, 2016). Another difference between the two is the connection costs, with solar technologies generally exhibiting lower costs (Peters & Sievert, 2016). Yet, the Senegalese national grid is affected by power outages (ANSD, 2021). The distinctive features of both sources of electricity are likely to lead to differentiated effects that deserve scrutiny. For developing countries in general (Kudo et al., 2019), and Senegal in particular (World Bank & CREEE, 2019), where the energy policy aims to extend the national grid to accessible areas (often urban areas) and provide solar energy to landlocked ones (rural areas), a comparative analysis of both sources of electricity will help policymakers in setting up the energy supply system.

Second, access to markets is a necessary condition for realizing the benefits attached to the use of electricity but hardly studied (Khandker et al., 2013). The availability and accessibility of marketplaces incentivize rural micro-businesses to offer more employment opportunities and expand their production (Peters & Sievert, 2016; Peters, et al., 2011). As electrified households are expected to expand their production (agricultural and non-agricultural), access to marketplaces provides them with outlets for their output, thereby increasing their income and welfare. We assess the extent to which access to marketplaces strengthens the welfare effect of access to electricity.

Third, despite extensive literature on the welfare effects of rural electrification, only very few studies examine its contribution to poverty reduction with contradictory results (Khandker et al., 2013; Khandker et al., 2014; Samad & Zhang, 2017; Arráiz & Calero, 2015; Lenz et al., 2017; Saing, 2018). While Arráiz and Calero (2015) found no impact of access to electricity on poverty, Khandker et al. (2013) and Lenz et al. (2017) observed substantial benefits for both low and high-income households from electricity access in Vietnam and Bangladesh. Khandker et al. (2014) and Saing (2018) documented that the welfare derived from rural electrification accrues to high-income

households as they are more likely to afford the connection fees. To provide further insides, the study at hand addresses the distributional effects of rural electrification.

Fourth, past studies linking the well-being of households to electricity access in the case of Senegal are rare. Most of the existing studies on rural electrification in Senegal examined either the determinants of energy poverty (Gafa & Egbendewe, 2021), the drivers of low access to electricity and the barriers to successful energy policy (Diouf et al., 2013; Mawhood & Gross, 2014) and the importance of electrification to rural attractiveness (Salat et al., 2021). To the best of our knowledge, Peters & Sievert (2016) is the only study that has incorporated welfare aspects, yet in a multi-country setting. We complement their work with an in-depth, country-specific analysis of Senegal. Examining the case of Senegal is particularly interesting since in the last two decades, Senegal moved from a rural electrification rate of 8 percent in 2000 (World Bank & CREEE, 2019) to 55 percent in 2020 (MPE, 2021). The rapid increase in access to electricity holds the potential to provide a lesson for other developing countries in Africa and beyond.

2.4 Methodology

Given the general nature of the concept of well-being, we measure it mainly by socioeconomic variables in order to understand the economic and social benefits that result from access to electricity. Social variables include children's education and household health. The variables linked to education are school attendance and enrolement, and the time children devote to studying at home. The prevalence of respiratory diseases in households would be an appropriate basis on which to measure household health before and after electrification, because the use of biomass as a source of energy pollutes indoor and outdoor ambient air, exposing household members to respiratory diseases (Barron & Torero, 2017). However, due to the unavailability of data on respiratory diseases, we measure household health by looking at the prevalence of illnesses in general in households, a yardstick that is widely used in the literature (Diallo & Moussa, 2020; Litzow et al., 2019). Economic variables used to measure benefits are employment and household expenditure, which are also widely used in the literature (Khandker et al., 2013; Khandker et al., 2014; Chakravorty et al., 2016; Adusah-Poku & Takeuchi, 2019). Household expenditure is preferred over household income as a variable, because in developing countries respondents are reticent about declaring their real income (Meyer & Sullivan, 2011).

Considering that this chapter is investigating the causal effect of rural electrification on the well-being of households, the construction of a solid counterfactual is the first requirement. In reality, evaluating the impact of a programme on a set of indicators means comparing the same indicators for a similar unit, a household in this case, "with" and "without" the programme. Yet, a household cannot be a participant and, at the same time, a non-participant in the same programme, i.e., an electrified and non-electrified household. This poses the problem of lack of data for the counterfactual. The outcomes of an electrified household if it had not been electrified, and that of a non-electrified household if it had been exposed to electric light, are not observable. If the programme was randomised, impact evaluation could be made by comparing the outcome variables of electrified households to those of non-electrified households. However, electrification programmes are rarely randomised, and the non-random placement of a programme results in a significant difference between the treatment and the control groups, based on observable and non-observable characteristics. In this context, observable and non-observable characteristics would affect the placement of the programme, including the participation of households. For example, the extension of the national grid to certain villages is determined by the economic or agricultural potential of these areas (Khandker et al., 2014; Grogan, 2016), their high population density (Grogan, 2016; Lipscomb et al., 2013), and their connections with politicians (Dinkelman, 2011; Khandker et al., 2014). Vulnerable populations could also be targeted when the programme's objective is to reduce poverty. Moreover, following the extension of the grid, the levels of income (Phoumin & Kimura, 2019; Ahunov, Kakhkharov & Mozumder, 2022) and education (Acharya & Marhold, 2019) affect a household's decision on whether to connect to the national grid or not. The size of the household is also a key variable that influences electricity consumption (Acharya & Marhold, 2019; Sánchez-Sellero & Sánchez-Sellero, 2019).

We use the propensity score matching (PSM) method to reduce the selection bias. Widely used in the literature (Khandker et al., 2009; Litzow et al., 2019; Rao, 2013; Rathi & Vermaak, 2018; Arráiz & Calero, 2015), PSM is efficient in reducing the bias provoked by observable heterogeneities. It is also an efficient tool for constructing counterfactuals for statistical purposes (Rosenbaum & Rubin, 1983). To estimate the effect of the treatment on treated individuals by using PSM, it is pertinent to first estimate the equation of the treatment, which in this case is the probability of a

household to get connected to electricity (equation 1). This leads to obtaining exogenous treatment from observable characteristics. Let E (the variable that measures household status) equal 1 if the household is electrified and 0 if it is not. E being a binary variable, equation 1 is estimated using the logit model.

$$E = \beta_0 + \beta_1' X_{i,j} + \beta_2' V_{i,j} + \varepsilon_{i,j} \qquad (1)$$

β_0 , β_1' and β_2' are the parameters to be estimated, i is any households of the dataset, electrified or non-electrified, j is matched non-participants (non-electrified households), $\varepsilon_{i,j}$ is the term for idiosyncratic errors, $X_{i,j}$ represents the observed characteristics of the household and V_{ij} the observed characteristics of the village. The choice of these variables is justified in Appendix D.

Once equation 1 is estimated, it is used to predict the probability (or propensity score) of a household connecting to electricity. This probability is used to match non-electrified against electrified households through the kernel matching algorithm. The impact of rural electrification (Γ_{PSM}) on the outcome Y is then obtained via the difference between the outcomes for electrified households and for non-electrified households in the matched control group, as shown in equation 2.

$$\Gamma_{PSM} = \frac{1}{N}\left[\sum_{i\epsilon T} Y_i^T - \sum_{j\epsilon C} w(i,j)\, Y_j^C\right] \qquad (2)$$

N is the total number of participants, and $w(i,j)$ represents the weight used to aggregate the outcomes for electrified households (i) and non-electrified households (j). Y_i^T and Y_j^C are, respectively, the outcomes of households in the treatment group and households in the matched control group.

In addition to the PSM estimator, we used the inverse probability weighted (IPW) estimator. This functions by reweighting the outcomes of the two groups so as to have a similar distribution of observed characteristics. The outcomes of electrified households are weighted by $1/P$, whereas the outcomes of non-electrified households are weighted by $1/(1-P)$. The impact of the treatment on treated individuals, as determined from the PSM and IPW estimators, constitutes a basic estimation of the effect that access to electricity has on the well-being of rural households.

This chapter adopts the approach used by Heckman, Ichimura and Todd (1997), which combines the PSM and DiD methods as the main identification strategy. The PSM method, as described earlier, relies on two hypotheses: the hypothesis of independence between outcomes and treatment, and the common support hypothesis. The latter supposes that units with the same observable characteristics have the same probabilities of being participants and non-participants at the same time (Heckman, LaLonde & Smith, 1999). Implicitly, the PSM method is based on the strong hypothesis that no unobserved differences are concurrently correlated with the treatment and the outcomes. Consequently, the PSM and IPW estimators cannot deal with the unobserved characteristics of households. And this is what justifies the combination of the PSM and DiD methods.

The PSM-DiD estimator has the virtue of controlling unobserved, time-invariant heterogeneities (Smith & Todd, 2005). Based on Litzow et al. (2019), we postulate that unobserved variables likely to affect the adoption of electricity and the outcomes at the same time are time-invariant insofar as they do not have enough time to vary, considering the high increase in the rate of access to electricity in rural areas in Senegal. The short time period between the collection of PUDC I baseline data in 2016 and follow-up data four years later makes the variability of unobserved heterogeneities implausible. It ensures that the preferences of households, their innate capacities, and their knowledge of the potential advantages of electricity are fixed. Moreover, we can be sure that the PSM-DiD estimator corresponds to the nature of our data; it made it possible to exploit the richness of our data since we have baseline and follow-up data at our disposal. The PSM-DiD estimator is also reputed for reducing the endogeneity bias that could emanate from the simultaneous or reciprocal effect between outcomes and treatment (Ding et al., 2018).

Earlier studies used the method of instrumental variables to correct the endogeneity bias (Grogan, 2018; Van de Walle et al., 2013; Chakravorty et al., 2016; Khandker, 2014; Samad & Zhang, 2017; Phoumin & Kimura, 2019). Instruments such as the proportion of electrified households in the community (Khandker, 2014), distance to the grid or an electricity pole (Grogan, 2018; Samad & Zhang, 2017), distance between the municipality and the hydroelectric dam (Grogan, 2016), the adoption of electrical appliances (Phoumin & Kimura, 2019) and the land gradient (Dinkelman, 2011) have been used in the literature. However, we use the PSM-DiD estimator instead because

our database does not contain valid exogenous instruments. Although we do have information on the adoption of electrical appliances and the number of electrified households per village, these variables did not predate rural electrification and, consequently, are not exogenous to electricity access.

The estimated impact of access to electricity stemming from the PSM-DiD estimator is obtained from equation 3.

$$Y_{ijt} = \lambda_0 + \lambda_1 t + \lambda_2 E_{ijt} + \lambda_3 t E_{ijt} + \beta_1' X_{i,\mathrm{j}} + \varepsilon_{ijt} \quad (3)$$

where Y_{ijt} is a variable for the well-being of household i in the village j, at time t; t is a binary variable equal to 0 for the baseline survey and 1 for the follow-up survey. The variable of treatment E_{ijt} takes on the value 1 if the household is connected to electricity and 0 if it is not; ε_{ij} represents unobserved characteristics; λ_0, λ_1, λ_2 and λ_3 are parameters to be estimated. λ_0 measures the average outcomes of the control group; λ_1 measures the average outcome difference in the control group between the baseline period and the follow-up period; λ_2 measures the average outcome difference between the treatment group and the control group; and λ_3 is the average effect of the treatment on treated individuals ($\Gamma_{\mathrm{PSM}}^{\mathrm{DD}}$); β_1' represents the matrix of parameters that incorporate the characteristics of households and villages as well as fixed regional effects.

In order to take the heterogeneous effects of rural electrification into account, we carried out two series of additional analyses. First, we estimated the impact of rural electrification on the well-being of households according to two contextual variables – access to market and household poverty status. The variable measuring access to market is equal to 1 for households with access to the market, and 0 without access. The variable measuring poverty status is also a binary variable, which takes on the value of 1 if the household is poor, and 0 if it is not. A household is categorised as poor if its expenditure is below the median expenditure of the sample, otherwise it is categorised as non-poor. In the sub-sample analysis, treated households are divided into households with access to the market and households without it, on the one hand, and poor and non-poor households on the other. Equation 3 is then estimated in each sub-sample. This heterogeneity analysis makes it possible to identify household categories that benefited more from rural electrification than others. It was reinforced by taking into account the effect of rural electrification on the total expenditure of households at each distribution point of the same variable. The importance of such an analysis lies in the fact that the

effect of the average treatment on the treated individuals does not supply enough information on the location of such an effect along the distribution of household expenditure. The quantile regression then becomes useful to this end.

Let $Y^T(\tau)$ and $Y^C(\tau)$ be the total expenditure per capita with quantile τ for electrified and non-electrified households, respectively. For example, for τ=0.50, the average treatment effect on this quantile would represent a difference in the outcome on the 5th quantile between electrified and non-electrified households. Equation 4 gives the average treatment effect (QTE) on quantile τ under pure randomisation.

$$QTE = Y^T(\tau) - Y^C(\tau) \qquad (4)$$

Since the rural electrification program of the PUDC I is not randomised and our data is observational, additional hypotheses are still required on the selection bias and the counterfactual. The counterfactual is represented by the change in (Y) observed over time on the qth quantile of the control group increased by the qth quantile of (Y) observed before implementing the programme in the treatment group. Assuming that the counterfactual distribution of total expenditure per capita in the group of electrified households is given by $\left(Y_1^C(\tau) - Y_0^C(\tau)\right)$ for $\tau \in [0.1]$, the rural electrification effect on a quantile obtained with the DiD estimator (QTE^{DD}) is represented by equation 5. DiD quantile regression (QTE^{DD}) is used to estimate the impact of access to electricity on different quantiles τ.

$$QTE^{DD} = Y_1^T(\tau) + \left(Y_1^C(\tau) - Y_0^C(\tau)\right) \qquad (5)$$

2.5 Data and Variables

2.5.1 Sample and data collection

We use panel data from 1,115 rural households collected by the Research Centre for Economic and Social Development (CRDES) in 2016 and 2020. The baseline data were collected before the deployment of the program in 2016 using a two-phase sampling approach (CRDES, 2016). In the first phase, the treatment group was formed by selecting villages eligible for PUDC I from a government-provided list, while potential control villages comprised those not listed as PUDC-eligible. CRDES conducted visits to both eligible treatment and potential control villages, gathering data on economic activities, infrastructure, and population size to gain a comprehensive understanding of

the observable characteristics of these villages and allow for similarity tests. The subset of potential control villages whose observable characteristics showed no statistical differences from those of the eligible treatment villages was categorized into the control group (CRDES, 2016).

In the first phase, 270 villages were selected across the treatment and control villages. The sample size was determined by the minimum detectable effect (MDE). The MDE varies between 0.20 and 0.15 for a sample size that varies between 200 and 350 (CRDES, 2016). Initially, a sample size of 250 villages was chosen; to incorporate attrition, the size was increased by 8 percent, resulting in 270 villages, with 135 treatment and 135 control villages, distributed across 10 regions (Diourbel, Fatick, Kaffrine, Kaolack, Kedougou, Louga, Matam, Sain-Louis, Tambacounda, Thiès). Figure A2 in Appendix A presents the study setup and sample.

Next, ten households were chosen from each village using a random walk method (CRDES, 2016). Due to the dispersed layout of rural residences, enumerators were instructed to ensure that all households within the village boundaries had a positive probability of being selected in the sample. If boundary demarcations were unclear, guidance was sought from village chiefs. In total, 2,580 households were surveyed in 2016 to establish the baseline situation.

The follow-up survey in 2020 covered seven of the ten originally surveyed regions due to financial constraints. Villages in the regions of Kédougou, Matam, and Tambacounda were not included; the seven regions surveyed in 2020 (Diourbel, Fatick, Kaffrine, Kaolack, Louga, Saint-Louis, and Thiès) covered 163 villages, of which 74 were in the treatment group and 89 in the control group; 1,500 households were surveyed during the follow-up (CRDES, 2021). A visual representation of the location of the villages is presented in Figure A3 in Appendix A; treated and control villages are represented by blue and black dots with regions covered by the second round of data appearing in bold.

Since we are faced with sample attrition from 2,580 to 1,500 households it might result in biased estimates. In Appendix B we present an attrition analysis showing that attrition is unrelated to treatment and largely unrelated to household characteristics (except for one). Yet, it is associated with village characteristics. The latter is not

surprising given that all excluded villages lie in three very distant regions of Senegal. It implies that the external validity of our results has to be taken with a grain of salt.

Data collection was facilitated through CsPro installed on enumerators' phones and tablets, ensuring that high-quality data was collected. In each surveyed village, one questionnaire was directed to the village chief to assess village characteristics such as the economy, social life, the environment, taxes, and the availability of infrastructure. Household questionnaires were administered to the heads with the assistance from two or three household members to assure accuracy. If the household head was absent, the questionnaire was administered to a substitute person with a similar level of information. The household questionnaire gathered data on household composition, the level of education of household members, agricultural and non-agricultural activities and income, fixed assets, expenditure, food security, health, housing, and access to electricity.

After data cleaning, the sample was reduced to 1,444 households, observed in 2016 and 2020, with 833 households in the treatment group and 611 in the control group. The treatment group contained 748 electrified households and 85 households without electricity. Of the electrified households of the treatment group, 244 households were electrified before 2015–2016, and so obtained electricity through interventions other than PUDC I. These households and the 85 households without electricity were excluded from the treatment group. Of the 504 households connected to electricity through PUDC I, 182 were connected to the national grid and 322 used solar technologies. These 504 electrified households were finally compared to the 611 households in the control group, which accounts for the 1,115 households considered in this article.

2.5.2 Variables and descriptive statistics

Given the general nature of the concept of well-being, we have to identify how we measure it and we opted for a range of socio-economic variables to capture the economic and social benefits associated with access to electricity. Social variables are children’s educational outcomes that include school enrolment, attendance, and the time devoted to studying at home.Economic variables under study are employment and household expenditure, which are widely used in the literature (Khandker et al., 2013; Khandker et al., 2014; Chakravorty et al., 2016; Adusah-Poku & Takeuchi, 2019). Employment refers to the count of household members engaged in work, including

positions in the private or public sectors, or those who are self-employed, during the week preceding the surveys. Occupational sectors were categorized into agricultural and non-agricultural sectors, with the latter comprising mining, manufacturing, education, health, and services. Note that employment encompasses various types of work and is not limited to formal job contracts or conventional employment arrangements as found in developed countries settings. Moreover, we subscribe to Deaton's (1997) perspective that expenditure offers a more reliable measure of household welfare compared to income, particularly within the framework of household surveys conducted in developing countries.

Descriptive statistics of the study's main outcomes are summarized in Table 2.1. There are no significant differences between the mean outcomes of electrified and non-electrified households at baseline in terms of expenditure, employment, and schooling. However, we observe significant mean differences in the outcomes between the two groups of households in the follow-up data. Except for food expenditure per capita and agricultural employment, the other economic outcomes are significantly higher for electrified households at follow-up. The same applies for the schooling outcomes. There are no significant differences at baseline, yet at follow-up electrified households fare better for all outcomes under consideration.

The descriptive statistics of the observable characteristics are presented in Table C.1 in Appendix C. Column 3 of Table C.1 shows that households in the sample have an average of 12 members and are led by heads who are on average 51 years old; around 96 percent of the household heads are male, 65,7 percent work in the agricultural sector and only 7.2 percent received formal education. The average number of households per village is 60 (denoted in logarithmic terms in the table). Although these villages pay taxes (90.4 percent), they are equipped with little infrastructure, and only 1.4 percent and 10 percent of villages have a physical market and electricity at their disposal, respectively. Moreover, the distance to the regional capitals is on average 47 km.

Comparing the characteristics between electrified and non-electrified households we note that they differ with respect to the observed characteristics (Column 4 of Table C.1). The heads of electrified households are older (52 years old) than their counterparts in households without electricity, whose average age is 50 years. Furthermore, the heads of the electrified households (10 percent) are more educated than heads of the non-electrified households (5.2 percent). Households with access to electricity live in

bigger villages and are more likely to have a marketplace (12.5 percent). Due to these differences, the two groups of households cannot be directly compared.

Table 2-1. Descriptive statistics of the outcome variables in 2016 and 2020

	Baseline data (2016)				Follow-up data (2020)			
	Households without electricity	Electrified households	Total sample	Δ	Households without electricity	Electrified households	Total sample	Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Economic outcomes								
Expenditure per capita								
Food expenditure	12.18	12.12	12.15	-0.060	9.825	9.837	9.830	0.012
	(0.028)	(0.033)	(0.021)	(0.043)	(0.034)	(0.044)	(0.027)	(0.041)
Non-food expenditure	10.71	10.76	10.73	0.052	8.710	9.063	8.882	0.352^{***}
	(0.057)	(0.066)	(0.043)	(0.087)	(0.046)	(0.042)	(0.032)	(0.063)
Total expenditure	12.50	12.50	12.50	0.003	10.17	10.35	10.25	0.178^{***}
	(0.031)	(0.034)	(0.023)	(0.046)	(0.031)	(0.036)	(0.024)	(0.048)
Employment								
Agricultural employment	0.342	0.400	0.366	0.058	0.861	0.858	0.860	-0.002
	(0.039)	(0.048)	(0.030)	(0.061)	(0.046)	(0.055)	(0.035)	(0.072)
Non-agricultural employment	0.530	0.544	0.537	0.014	0.519	0.863	0.743	0.344^{***}
	(0.033)	(0.037)	(0.024)	(0.049)	(0.034)	(0.022)	(0.019)	(0.039)
Total employment	0.618	0.632	0.624	0.013	1.006	1.279	1.152	0.273^{***}
	(0.031)	(0.035)	(0.023)	(0.047)	(0.038)	(0.030)	(0.024)	(0.048)
Panel B. Social outcomes								
Education								
School enrolment	1.825	1.735	1.781	-0.089	0.725	1.009	0.864	0.283^{***}
	(0.057)	(0.059)	(0.041)	(0.082)	(0.032)	(0.037)	(0.024)	(0.048)
Boys' School enrolment	1.317	1.304	1.311	-0.012	0.341	0.547	0.444	0.205^{***}
	(0.091)	(0.083)	(0.061)	(0.123)	(0.030)	(0.037)	(0.024)	(0.047)
Girls' School enrolment	1.178	1.068	1.126	-0.109	0.394	0.554	0.477	0.159^{***}
	(0.092)	(0.095)	(0.066)	(0.132)	(0.030)	(0.033)	(0.022)	(0.045)
School attendance	0.954	0.881	0.917	-0.072	0.716	1.013	0.860	0.297^{***}
	(0.063)	(0.066)	(0.046)	(0.092)	(0.032)	(0.037)	(0.025)	(0.049)
Boys' school attendance	0.543	0.613	0.579	0.069	0.342	0.550	0.446	0.208^{***}
	(0.085)	(0.084)	(0.060)	(0.120)	(0.030)	(0.037)	(0.024)	(0.048)
Girls' school attendance	0.661	0.444	0.552	0.216	0.393	0.545	0.472	0.151^{***}
	(0.097)	(0.079)	(0.063)	(0.126)	(0.030)	(0.033)	(0.023)	(0.045)
Study time	5.235	5.122	5.178	-0.113	4.888	5.265	5.076	0.377^{***}
	(0.090)	(0.095)	(0.065)	(0.131)	(0.050)	(0.050)	(0.036)	(0.071)
Boys' study time	4.861	4.815	4.837	-0.045	4.583	4.818	4.706	0.234^{***}
	(0.130)	(0.134)	(0.093)	(0.188)	(0.050)	(0.055)	(0.038)	(0.075)
Girls' study time	4.939	4.693	4.820	-0.246	4.578	4.852	4.724	0.274^{***}
	(0.131)	(0.110)	(0.086)	(0.172)	(0.057)	(0.049)	(0.038)	(0.075)

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors are denoted in brackets; all outcome variables are expressed in logarithms. The sign Δ reflects the difference between the average outcomes of electrified households and those of households without electricity.

2.6 Empirical identification

2.6.1 Program placement and selection biases

Since program placement by PUDC was not random and we do not observe electrified households in multiple states of the world, a simple comparison of mean outcomes as presented in the descriptive statistics is biased. Since government officials choose to build electrical infrastructure in villages based on their characteristics such as the economic or agricultural potential (Khandker et al., 2014; Grogan, 2016), population density (Grogan, 2016; Lipscomb et al., 2013), and connection with politicians (Dinkelman, 2011; Khandker et al., 2014), electrified villages are likely to be systematically different from areas without electricity, leading to program placement bias. Moreover, households self-select to connect to the provided electricity. As the program being evaluated was placed at the village level, each of the treatment groups decided whether to use electricity or not.

With the observational data at hand and the non-random design of the intervention, we had to resort to the combination of propensity score matching (PSM) with difference-in-difference (DiD) to estimate a statistical counterfactual and reduce both program placement and selection biases.

2.6.2 Brief introduction to PSM, IPW and PSM-DiD

As a first step, we use propensity score matching (PSM) and inverse-probability weighting (IPW) to estimate the effect of access to electricity on household welfare. PSM is widely used in the literature (Khandker et al., 2009; Litzow et al., 2019; Rao, 2013; Rathi & Vermaak, 2018; Arráiz & Calero, 2015), efficient in reducing bias induced by observable characteristics between the treatment and the control group (Ding et al., 2018). Further details about PSM are provided by Rosenbaum & Rubin (1983).

We estimate a household's probability of getting connected to electricity, that is the propensity score, with a logit model.

$$E_{i,j} = \beta_0 + \beta_1' X_{i,\mathrm{j}} + \beta_2' V_j + \varepsilon_{i,\mathrm{j}} \quad (4)$$

$E_{i,j}$ is a binary variable equal to 1 if the household is connected to electricity and zero otherwise. As observed household traits, denoted by $X_{i,\mathrm{j}}$, we include the household size, age, gender, level of education and occupation of the household head, and the distance (in km) from the residence to the closest water point and rural road. Village characteristics, denoted by V_j, include the number of households (in log), the percentage of women (in log), the availability of a physical market, the availability of electricity, the payment of taxes, the distance between the village and the regional capital (in km) and the availability of forest resources. The predicted propensity scores are used to match electrified households with observationally similar ones without electricity through the kernel matching algorithm. We use kernel matching as it has been widely employed in the literature (Litzow et al., 2019; Ding et al., 2018; Saing, 2018). In addition, we employ the five-to-one nearest neighbor matching as a robustness check.

The impact of rural electrification on the outcome of interest (employment, expenditure, schooling outcomes) is obtained as the difference between the outcome of electrified households and that of households without electricity in the matched control group.

The inverse probability weighting (IPW) estimator reweights the outcomes of the electrified and non-electrified households based on the information content that the households provide according to their propensity score. The outcomes of electrified households are weighted by $1/P$, whereas those of households without electricity are weighted by $1/(1-P)$.

Like Heckman et al. (1997), we also combine the propensity scores from the PSM with a DiD approach as we have two rounds of data. The PSM-DiD estimator allows us to not only weigh the data but also control for unobserved time-invariant heterogeneities (Litzow et al. 2019; Smith & Todd, 2005). The short time period between the collection of baseline data in 2016 and the follow-up data in 2020 renders the assumption of time-invariant unobservables, such as household preferences, innate capacities, and their knowledge of the potential advantages of electricity, realistic.

Akin to the specification by Imbens and Wooldridge (2009) and Angrist and Pischke (2009), Equation 2 is estimated on the matched sample:

$$Y_{ijt} = \lambda_0 + \lambda_1 t + \lambda_2 E_{ijt} + \lambda_3 t E_{ijt} + \beta_1' Z_{i,\mathrm{j}} + \mu_j + \varepsilon_{ijt}, \quad (2)$$

where Y_{ijt} is a well-being outcome for household i in village j at time t; t is a binary variable equal to 0 for the baseline survey and 1 for the follow-up survey. t captures time-specific effects that affect all households at a given point in time. E_{ijt} is the binary treatment variable and $Z_{i,\mathrm{j}}$ includes both household and village characteristics as described above and is also included in the derivation of the propensity score. In addition, μ_j includes region-fixed effects to account for time-invariant characteristics of the regions, including geography, language, and cultural particularities. The error term ε_{ijt} captures unobserved characteristics. λ_0 measures the mean outcome of the control group at baseline; λ_1 measures the average change in outcome from the baseline to the follow-up period that is common to both groups; λ_2 measures the average change in outcome between the treatment and the control groups that is common in both time periods. We are interested in λ_3, the average effect of the treatment on treated individuals.

2.6.3 Heterogeneity analysis: electricity sources and access to marketplaces

To determine whether the sources of electricity and access to marketplaces matter for the nexus between electricity and household welfare, we conduct subsample analyses. The variable that measures the type of electricity takes a value of one if the household is connected to the national grid electricity and zero if it sources its electricity from solar technologies. Drawing from Von Carnap (2023), we define access to marketplaces as a binary variable, equal to 1 for households with access to a marketplace and 0 for those with limited access. A household has access to the market if it lives in a village that has a marketplace. We conduct the above-described analyses separately per sub-sample.

2.6.4 Quantile difference in difference (QDiD)

While Equation 1 provides the mean welfare effect of access to electricity, it does not nuance the impact across various levels of household expenditure. Assessing the distributional effects is relevant for aspects such as proper targeting and poverty alleviation. Quantile regressions reduce the impact of outliers and assumptions about functional form and enable us to explore aspects of the distribution beyond the mean (Meyer et al., 1995). Drawing on Saing (2018) and Meyer et al. (1995), we employ the

quantile difference-in-differences (QDiD) to estimate the distributional effects associated with access to electricity.

$$Y_{ijt}^{(q)} = \lambda_0^{(q)} + \lambda_1^{(q)}t + \lambda_2^{(q)}E_{ijt} + \lambda_3^{(q)}tE_{ijt} + \beta_1'^{(q)}Z_{i,j} + \varepsilon_{ijt}^{(q)} \quad (3)$$

The quantile estimates are obtained from Equation 2, where $\lambda_3^{(q)}$ measures the impact of access to electricity for quantile q. We estimate Equation 3 for deciles. We employ the Stata user-written package by Villa (2016) as it accommodates kernel propensity-score matching and does not require the computation of each decile individually. We use this package already to estimate Equation 2. As it jointly computes the treatment effects for all quantiles or rather deciles in our case.

2.7 Main results and discussion

2.7.1 Determinants of access to electricity and propensity scores

Findings from the logit model suggest that household characteristics such as size, education level, and the gender of the household head predict the probability of a household connecting to electricity. All three household traits are positively correlated with access to electricity. Gender and size of the household are only statistically significant at the 10 percent level and small in practical terms, education is large and highly statistically significant. For details, see Table C.1 in Appendix C. These results align with the prior literature. For instance, Acharya & Marhold (2019), Khandker et al. (2014), and Litzow et al. (2019) noted that households with educated and older heads are more likely to connect to electricity. Similarly, Dinkelman (2011) and Chakravorty et al. (2014) found that larger household sizes are associated with a greater probability of having electricity.

In line with the earlier discussed attrition analysis, village characteristics are largely associated with a household's decisions to connect to electricity. A higher percentage of women in a village is associated with a lower probability of household access to electricity. The low bargaining power of women may explain why villages with a high share of women are less likely to get electrified. The distance between the village and the regional capital, and the number of households within the village are positively associated with the electricity access rate. These findings echo those of Ding et al. (2018) and Grogan & Sadanand (2013), who respectively showed that remoteness and population density determine electrification program placement. The logit model also

indicates that access to a marketplace and forest, along with the village's ability to pay taxes, positively and significantly contribute to household adoption of electricity. These latter two are additional factors of integration and are thus likely to facilitate the installation of electricity infrastructure.

Figure 2.2 illustrates the resulting distributions of the propensity score per access to electricity status. The distribution of electrified households shifts more to the right compared to that of households without electricity reflecting the observed heterogeneities between the two groups. Yet, both distributions overlap and have thus an area of common support allowing us to calculate impact estimates for this common support.

Beyond the common support hypothesis, the independence assumption has been examined. The independence hypothesis is met when the matching variables are balanced between the treatment and the control group. Results of the balance tests indicate that observable characteristics are similar across both groups (Appendix C, Table C.2). Biases resulting from differences in the observed characteristics were largely reduced, except for the distance between the village and the regional capital.

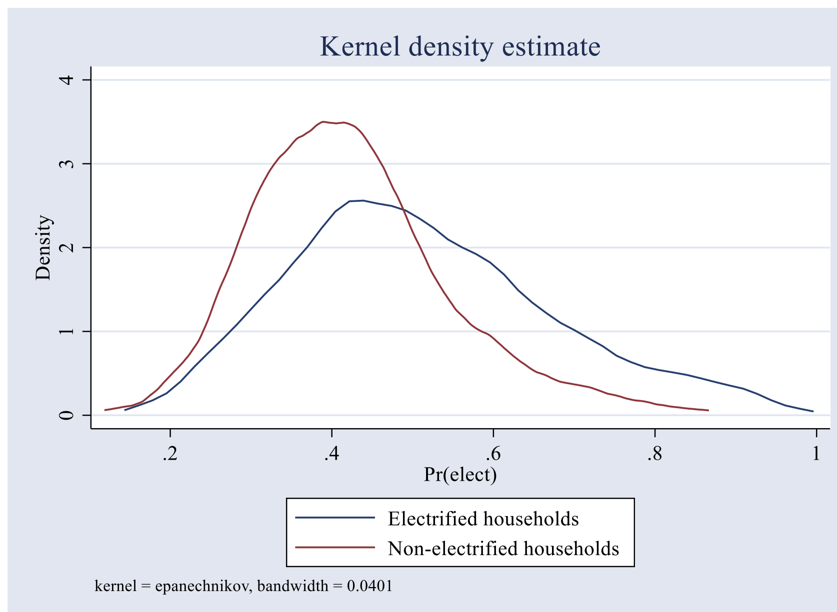


Figure 2-2. Distributions of propensity scores per access to electricity status.

Table 2-2. Impact estimates of access to electricity on economic outcomes – PSM and IPW

	Expenditures per capita			Employment			Schooling outcomes		
	Food	Non-food	Total	Agri-cultural	Non-agri-cultural	Total	School enrolment	School attendance	Study time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Kernel matching									
(a) PSM									
Access to electricity	0.152***	0.438***	0.281***	-0.062	0.329***	0.232***	0.160***	0.173***	0.245***
	(0.066)	(0.072)	(0.056)	(0.093)	(0.054)	(0.061)	(0.057)	(0.057)	(0.076)
Observations	898	827	899	393	620	750	620	610	544
Non-electrified households	482	411	482	188	201	331	308	304	272
Electrified households	416	416	417	205	419	419	312	306	272
(b) IPW									
Access to electricity	0.189***	0.472***	0.316***	-0.085	0.335***	0.235***	0.136**	0.150***	0.270***
	(0.072)	(0.073)	(0.062)	(0.093)	(0.048)	(0.060)	(0.054)	(0.055)	(0.083)
Observations	898	827	899	393	620	750	620	610	517
Panel B. 5-to-1 nearest neighbor matching									
(a) PSM									
Access to electricity	0.187***	0.438***	0.320***	0.025	0.329***	0.282***	0.186***	0.178***	0.275***
	(0.070)	(0.077)	(0.059)	(0.082)	(0.059)	(0.067)	(0.061)	(0.062)	(0.085)
Observations	898	827	899	393	620	750	620	610	517
Non-electrified households	482	411	482	205	201	331	308	304	257
Electrified households	416	416	417	188	419	419	312	306	260
(b) IPW									
Access to electricity	0.189***	0.472***	0.316***	-0.085	0.335***	0.235***	0.136***	0.150***	0.270***
	(0.072)	(0.073)	(0.062)	(0.093)	(0.048)	(0.060)	(0.054)	(0.055)	(0.083)
Observations	898	827	899	393	620	750	620	610	517

Note: * p < .10, ** p < .05, *** p < .01. Robust standard errors are denoted in brackets. The table showcases the effects of access to electricity on household expenditure and employment.

But even for this characteristic, the bias was considerably reduced from 3.8 to 1.6, which is a reduction of 58.8 percent. The additional diagnostic tests show that the median bias was reduced from 13.3 to 1.6 for the entire sample after matching (Appendix C, Table C.3). Furthermore, there is a considerable reduction in the pseudo R^2, from 0.07 for the unmatched sample to 0.0002 for the matched sample. The post-matching logit model loses its predictive power implying that the observed characteristics are balanced between the electrified households and those without electricity. Last but not least, the success of the matching is supported by the propensity score distribution of both groups that are very similar after matching (Appendix A, Figure A.5).

2.7.2 Impact estimates of rural electrification – PSM and IPW baseline estimates

Table 2.2 presents the baseline impact estimates for economic and social outcomes. Panel A shows the kernel matching estimates for the basic PSM and the IPW and Panel

B is the same for the 5-to-1 nearest neighbor matching. Even at a glance, we see that the matching approach does not affect our findings. Similarly, PSM and IPW results are close in magnitude and similar in terms of statistical significance. We find positive and statistically significant outcomes for all economic and social outcomes variables except for agricultural employment. Table 2.1 indicates significant estimates, except for agricultural employment. Overall, the baseline estimates highlight that access to electricity positively affects expenditures, non-agricultural employment, school enrolment, attendance, and study time. Yet, as argued in section 5, we consider these estimates only as a first approximation of impact as they do not account for time-invariant unobservables.

2.7.3 Impact estimates of rural electrification – PSM-DiD main estimates

Our main results deriving from PSM-DiD estimation are presented in Table 2.3. Panel A presents the estimates for the economic outcomes, and Panel B for the social outcomes. Non-food expenditure and non-agricultural employment have increased by 39.5 percent ($e^{0.333}$-1) and 39.2 percent ($e^{0.331}$-1), respectively, implying that the increases in total expenditure and employment within electrified households seem to be respectively driven by the expansion of non-food expenditure and non-agricultural employment. Importantly, the difference in coefficient estimates between non-food and food expenditures of 0.233 (std. error 0.128) is statistically significant at the five percent level. Similarly, the difference between non-agricultural and agricultural employment of 0.392 (std. error 0.119) is statistically significant at the one percent level. Moreover, the estimates are in line with those from PSM and IPW estimations. The increase in non-food expenditure within electrified households is also supported by the literature (Khandker et al., 2013 & 2014, Chakravorty et al., 2016; Adusah-Poku Takeuchi, 2019; Diallo and Moussa, 2020). Similarly, an increase in employment following electrification has been documented by Dinkelman (2011), Litzow et al. (2019), Dasso and Fernandez (2015), and Van de Walle et al. (2013). Access to electricity enables the electrified households to take part in the labor market outside of the agricultural sector, and to initiate income-generating activities.

Table 2-3. Impact estimates of access to electricity on economic and social outcomes-PSM-DiD

Panel A. Economic outcomes	Expenditure per capita			Employment		
	Food	Non-food	Total	Agricultural	Non-agricultural	Total
	(1)	(2)	(3)	(4)	(5)	(6)
Access to electricity	0.100	0.333***	0.203***	-0.061	0.331***	0.260***
	(0.073)	(0.107)	(0.069)	(0.113)	(0.063)	(0.070)
Observations	2,210	2,094	2,216	736	1,303	1,594
R square	0.00	0.06	0.01	0.10	0.08	0.14
Panel B. Education outcomes						
	School enrolment	School attendance	Study time			
Access to electricity	0.374***	0.370***	0.491***			
	(0.116)	(0.119)	(0.161)			
Observations	905	886	763			
R square	0.24	0.04	0.04			

Note: PSM-DiD results. Robust standard errors are denoted in brackets. The average treatment effects on the treated for access to electricity on economic and social outcomes are shown. Household and village characteristics as well as region and time-fixed effects are included across specifications. Kernel matching is used for deriving the propensity scores. Household characteristics are the household size (discrete variable), the age of the household head (discrete variable), the sex of the household head (male=1, female=0), the level of education of the household head (educated=1; uneducated=0), the occupation of the household head (agricultural=1, non-agricultural=0) and distances (in km) from the households' place of residence to the closest water point. Village characteristics include the logarithm of the number of households, the logarithm of the percentage of women, the availability of a physical market (yes=1, no=0), the availability of electricity (yes=1, no=0), the payment of taxes (yes=1, no=0), the distance between the village and the regional capital (km) and the availability of forest resources (yes=1, no=0). Region fixed effects are measured through dummy variables that correspond to the seven regions under study, i.e. Diourbel, Fatick, Kaolack, Kaffrine, Louga, Saint-Louis, and Thiès. Time fixed effects are captured by a binary variable which takes on the value 0 for the baseline round and 1 for the follow-up round. * $p < .10$, ** $p < .05$, *** $p < .01$.

In rural areas of Senegal, electricity is used productively in services such as dressmaking, hairdressing, conservation of seafood products, the production and transformation of dairy and agricultural products, as well as in the production of ice cream and cooling water (World Bank & ECREEE, 2020). Electricity is also used for husking and milling grain (maize, sorghum, millet and rice), and for pumping groundwater to irrigate agricultural surfaces (World Bank & ECREEE, 2020). Electricity allows small trading such as kiosks, shops and retail businesses alongside the main rural roads to reinforce the rural economy. These non-agricultural activities are sources of additional income used by households to meet their non-food expenditures.

Panel B of Table 2.3 shows the impact on the social outcomes. All educational outcomes are positively and significantly affected. School enrolment, school attendance, and the time children devote to studying at home increase by 45.3 percent, 44.7 percent and 63.3 percent respectively. Again, these findings echo earlier findings by Arráiz and Calero (2015), Khandker et al. (2014 & 2013).

We further examine the impact of access to electricity on education across gender. Results are reported in Appendix C, Table C.4, Panel A. Impacts are positive and significant for girls, while they are positive albeit insignificant for boys. Girls in the electrified households have significantly increased their school enrolment, school attendance and study time by 31 percent ($e^{0.270}$-1), 44.4 percent ($e^{0.368}$-1) and 68.2 percent ($e^{0.520}$-1) respectively. Yet, according to the mean-comparison tests only the difference in coefficient estimates for school attendance of 0.229 (standard error 0.145) is statistically significant at the 10 percent level, implying that electrification liberates time for girls to attend school. Overall, our data shows the tendency of positive schooling effects for boys and girls. Yet, the sub-samples are rather small contributing to the lack of statistical significance. Our education-related finding contrasts with Saing (2017) who showed that rural electrification in Cambodia increased the probability of having ever been enrolled in primary school for boys but not for girls. In turn, Van de Walle (2013) and Khandker et al. (2013) similarly show more pronounced schooling benefits for girls.

2.7.4 Contextual factors: on-grid versus solar electricity

To further disentangle how electrification affects household wellbeing, we now distinguish between the source of electricity used by households, i.e. on-grid versus solar electricity. Estimates are presented in Table 2.4. Panel A shows the economic impacts of the national grid (a) versus solar power (b). For both types of electricity sources, the estimates are positive and significant for total (and non-food) expenditure and total (and non-agricultural) employment. Coefficient estimates associated with expenditures tend to be higher for access to solar technologies. Yet, employment-related coefficient estimates are higher for electricity provided by the national grid.

Table 2-4. Estimates on economic and social outcomes by electricity source – PSM-DiD

Panel A. Economic outcomes	Expenditure per capita			Employment		
	Food	Non-food	Total	Agricultural	Non-agricultural	Total
	(1)	(2)	(3)	(4)	(5)	(6)
(a). Electricity (national grid)						
Access to electricity	0.050	0.328**	0.173*	-0.183	0.389***	0.311***
	(0.098)	(0.148)	(0.094)	(0.157)	(0.082)	(0.095)
Observations	1,572	1,469	1,576	533	837	1,093
R square	0.00	0.05	0.01	0.10	0.08	0.13
(b). Electricity (solar)						
Access to electricity	0.126	0.335***	0.218***	0.011	0.296***	0.231***
	(0.083)	(0.123)	(0.078)	(0.128)	(0.073)	(0.082)
Observations	1,850	1,734	1,855	617	1,016	1,289
R square	0.01	0.05	0.01	0.11	0.06	0.12
Panel B. Social outcomes						
	School enrolment	School attendance	Study time			
(a). Electricity (national grid)						
	0.449***	0.377**	0.327			
	(0.154)	(0.159)	(0.220)			
	624	611	512			
	0.28	0.05	0.05			
(b) Electricity (off-grid)						
	0.332**	0.366***	0.579***			
	(0.131)	(0.164)	(0.183)			
	744	728	633			
	0.26	0.04	0.04			

Note: PSM-DiD results. Robust standard errors are denoted in brackets. The average treatment effects on the treated for access to electricity on economic and social outcomes are shown. Household and village characteristics as well as region and time-fixed effects are included across specifications. Kernel matching is used for deriving the propensity scores. For details about included controls, consult the note in Table 2.3. * $p < .10$, ** $p < .05$, *** $p < .01$.

We performed mean-comparison tests to assess whether the differences in coefficient estimates between grid and solar electricity are significant. The difference in non-food expenditures between the national grid and solar power is -0.007 (std. error 0.190) and insignificant. Similarly, the difference for non-agricultural employment is 0.093 (std. error 0.109) and insignificant. For non-agricultural and overall employment, the difference is (std. error 0.127) and (std. error 0.127), respectively. These findings suggest that in the context of rural Senegal both sources of electricity provide similar economic advantages.

The impact estimates for educational outcomes by source of electricity are reported in Panel B of Table 2.4. Again, both sources of electricity demonstrate positive and statistically significant effects on school enrolment and attendance. While no significant impact of access to electricity on study time was recorded for grid electricity,

a significant impact was found for solar electricity. The finding that access to grid electricity has no significant impact on children's study time contrasts with Khandker et al. (2014). This finding can be attributed to the relative instability of on-grid electricity, often characterized by frequent power outages. Recent estimates for Senegal suggest that 81 percent of rural electrified households experience two power cuts per day (ANSD, 2021). These persistent power interruptions are likely to limit children's ability to study in the evening. Tests for the difference in coefficient estimates between grid and solar energy suggest statistical similarity of the estimates. Thus, also in the social domain, both types of electricity provide similar impacts.

We further differentiate the grid versus solar power impacts by gender (Appendix C, Table C.4, Panels B and C). The findings presented in Panel B showing the impacts of access to the national grid are all positive yet insignificant for boys and girls alike. However, Panel C showing the results for access to solar power indicates positive and significant impacts for girls and positive albeit insignificant impacts for boys, suggesting that the overall effect of access to electricity on children's educational outcomes is mainly driven by access to solar power. Testing for the difference in coefficient estimates for girls between grid electricity and solar technologies identifies a statistically significant difference for study time (difference: -0.607, std. error: 0.356). This finding underscores that solar electricity is likely to be even more of an enabler compared to on-grid solutions when it comes to girls' study time.

Overall, the findings by the source of electricity suggest that the electricity provision by the Senegalese government yields similar impacts independent of the source of electricity. This implies that the technical solutions opted for depending on the local context match with the socially desirable output of similar benefits across households.

2.7.5 Contextual factors: access to a marketplace

Next, we are interested in whether access to electricity has differential effects depending on the initial connectedness of a location as measured by access to a marketplace. Results are presented in Table 2.5; Panel A shows the estimates for the economic outcomes. The impacts of electricity on total (food) expenditure and total (non-agricultural) employment are positive and significant for households that have limited access to marketplaces. For households that have access to a marketplace, it is non-food expenditures and non-agricultural employment that go up following access to

electricity. The mean-comparison test shows that electrified households that have access to a marketplace have significantly greater non-food expenditures compared to electrified households with no access to a marketplace (difference: 0.398, p-value $\leq$ 0.05). Electrified households with limited access to a marketplace seem to benefit from food expenditures compared to those with access to a marketplace (difference: 0.226, p-value $\leq$ 0.1). In turn, employment differences between electrified households with and without access to a marketplace are not statistically significant.

Turning to social outcomes, the results reported in Panel B of Table 2.5 show that the three outcomes linked to education increased significantly for electrified households that have access to a marketplace. This is not the case for electrified households with limited access to a marketplace. For the latter households, social benefits manifest solely through an increase in school enrolment and attendance. Children's study time did not significantly increase for households with limited access to a marketplace. Yet, the mean-comparison tests for these outcomes suggest that there is only a significant difference for school attendance (difference: 0.446, p-value $\leq$ 0.1), suggesting that electrified households with access to a marketplace significantly increased the school attendance of their children compared to the ones with limited access to a marketplace.

In sum, access to a marketplace is an enabling factor for rural electrification to fully derive its potential. Electrified households with access to a marketplace tend to have higher non-food expenditures and their children have better school attendance. These findings suggest that access to a marketplace facilitates the sale of agricultural products, enabling electrified households to generate higher income. Since rural households typically produce crops for their own consumption and sell the surplus, the presence of a marketplace also allows them to purchase non-food goods and specialize in the production of manufactured goods (Von Carnap, 2023). Accessibility of marketplaces can also enhance the absorptive capacity of local microbusinesses, leading to the creation of jobs (Peters & Sievert, 2016; Peters et al., 2011).

Table 2-5. Estimates of access to electricity by access to a marketplace – PSM-DiD

Panel A. Economic outcomes						
	Log. Expenditures per capita			Employment		
	Food	Non-food	Total	Agricultural	Non-agricultural	Total
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Households with limited access to the market						
Access to electricity	0.219**	0.175	0.243**	-0.036	0.364***	0.281***
	(0.101)	(0.143)	(0.094)	(0.165)	(0.090)	(0.103)
Observations	1247	1177	1250	471	735	919
R^2	0.01	0.05	0.02	0.09	0.10	0.15
(b) Households with access to the market						
Access to electricity	-0.007	0.573***	0.182*	-0.116	0.269***	0.168
	(0.115)	(0.177)	(0.108)	(0.161)	(0.098)	(0.105)
Observations	959	913	962	264	564	671
R^2	0.00	0.05	0.01	0.08	0.05	0.11
Panel B. Educational outcomes						
	School enrolment	School attendance	Study time			
(a) Households with limited access to the market						
Access to electricity	0.372**	0.132	0.507*			
	(0.184)	(0.186)	(0.259)			
Observations	571	561	471			
R^2	0.21	0.04	0.03			
(b) Households with access to the market						
Access to electricity	0.417***	0.578***	0.570***			
	(0.155)	(0.162)	(0.211)			
Observations	331	323	289			
R^2	0.28	0.08	0.07			

Note: PSM-DiD results. Robust standard errors are denoted in brackets. The average treatment effects on the treated for access to electricity on economic and social outcomes are shown. Household and village characteristics as well as region and time-fixed effects are included across specifications. Kernel matching is used for deriving the propensity scores. For details about included controls, consult the note in Table 2.3. * $p < .10$, ** $p < .05$, *** $p < .01$.

2.7.6 Distributional effects of access to electricity

Next, we turn to distributional effects. We first explore heterogeneous treatment effects by poverty status based on a sub-sample analysis to assess to what extent poor households benefit from access to electricity. A household is categorized as poor if its expenditure is below the median expenditure of the sample, otherwise it is categorized as non-poor. The estimates in Appendix C, Table C.5 indicate that while non-poor households have a greater and statistically significant participation in non-agricultural employment, poor households experienced both increased non-agricultural employment and non-food expenditure. Yet, the mean-comparison test only identifies a significant difference in non-food expenditures between poor and non-poor electrified households (difference: 0.511, p-value ≤ 0.01). Concerning schooling outcomes, poor

households seem to benefit the most from rural electrification, however, the mean-comparison tests show that household poverty is not statistically significantly related to the benefits of electrification.

In addition to the sample split analysis, we also considered the distributional effects of access to electricity. Results are reported in Table 2.6 and support the findings of the heterogeneity analysis reported so far. Households whose expenditure per capita is below the median expenditure have considerably increased their non-food expenditure compared to those with expenditure per capita above the median, irrespective of the source of electricity used. Poor households thus derived disproportionally higher economic benefits from access to electricity compared to non-poor ones. A plausible explanation would be that access to electricity alleviates several binding constraints for poor households by providing lighting and allowing for income-generating activities such as the transformation of agricultural goods resulting in extra income that can be used to buy non-food goods.

2.8 Conclusion

Pursuing the objective of universal access to electricity, the Senegalese government has been implementing its energy policy with the objective to reduce energy poverty to a minimum, and to upgrade productivity while reducing poverty in rural areas. In this context, accessible rural areas have been electrified through the national grid, whereas enclaved areas have been provided with solar infrastructure through the Emergency Program for Community Development (PUDC). The implementation of the first phase of PUDC offered the opportunity to examine the implications of rural electrification for household welfare.

The study relied on a panel dataset composed of baseline and follow-up data collected in 2016 and 2020. Since program placement was not random, we combined propensity score matching and difference-in-differences (PSM-DiD) to isolate the causal effect of rural electrification on economic and social outcomes.

Findings suggest that electrified households gained economic benefits by engaging in non-agricultural activities and increasing their non-food expenditure. In addition, electrified households also benefited from social advantages, such as increased school enrolment, school attendance, and study time, with greater impacts on girls' school

attendance. While poor households seem to have benefited the most from rural electrification in terms of increased non-food expenditure, access to a marketplace reinforced the impact of access to electricity on both the economic and the social outcomes. Despite its contributions to the literature, our analysis also has some limitations. First, we are faced with considerable attrition as three regions could not be re-survey during the follow-up. While we show that in terms of household characteristics, this does not have an impact, village characteristics differ.

Table 2-6. Distributional effects of rural electrification – DiD quantile regressions

	Identification strategy: DiD quantile regressions								
	Panel A. Access to electricity			**Panel B.** Access to electricity (national grid)			**Panel C.** Access to electricity (solar power)		
	Log. Expenditure per capita								
Quantiles	Food	Non-food	Total	Food	Non-food	Total	Food	Non-food	Total
$Q_{0.1}$	0.221	0.560***	0.428***	0.367*	0.272	0.496**	0.231	0.684***	0.394***
	(0.173)	(0.176)	(0.152)	(0.208)	(0.263)	(0.213)	(0.202)	(0.202)	(0.171)
$Q_{0.2}$	0.183	0.383**	0.161	0.116	0.129	0.080	0.189	0.534***	0.198
	(0.118)	(0.158)	(0.101)	(0.143)	(0.207)	(0.134)	(0.123)	(0.188)	(0.121)
$Q_{0.3}$	0.029	0.462***	0.082	-0.011	0.446**	0.015	0.118	0.540***	0.136
	(0.093)	(0.140)	(0.091)	(0.139)	(0.204)	(0.113)	(0.112)	(0.181)	(0.102)
$Q_{0.4}$	0.019	0.264**	0.068	-0.094	0.334*	0.033	0.082	0.405***	0.120
	(0.082)	(0.130)	(0.080)	(0.107)	(0.189)	(0.093)	(0.095)	(0.138)	(0.084)
$Q_{0.5}$	-0.016	0.264**	0.095	-0.096	0.352*	0.110	0.021	0.314**	0.115
	(0.092)	(0.130)	(0.063)	(0.116)	(0.181)	(0.113)	(0.098)	(0.139)	(0.075)
$Q_{0.6}$	0.004	0.181	0.150**	-0.002	0.362**	0.113	0.051	0.105	0.017*
	(0.072)	(0.142)	(0.076)	(0.100)	(0.175)	(0.108)	(0.088)	(0.172)	(0.091)
$Q_{0.7}$	0.071	0.176	0.036	0.035	0.304*	0.073	0.031	0.081	0.051
	(0.069)	(0.129)	(0.066)	(0.091)	(0.176)	(0.102)	(0.080)	(0.139)	(0.078)
$Q_{0.8}$	-0.047	0.258*	0.103	0.018	0.182	0.104	-0.031	0.147	0.086
	(0.084)	(0.141)	(0.090)	(0.101)	(0.193)	(0.126)	(0.076)	(0.182)	(0.115)
$Q_{0.9}$	0.087	0.163	0.193*	0.105	0.336	0.187	0.156	0.001	0.245**
	(0.082)	(0.213)	(0.104)	(0.114)	(0.262)	(0.145)	(0.095)	(0.249)	(0.123)

Note: * p < .10, ** p < .05, *** p < .01. Standard errors are denoted in brackets.

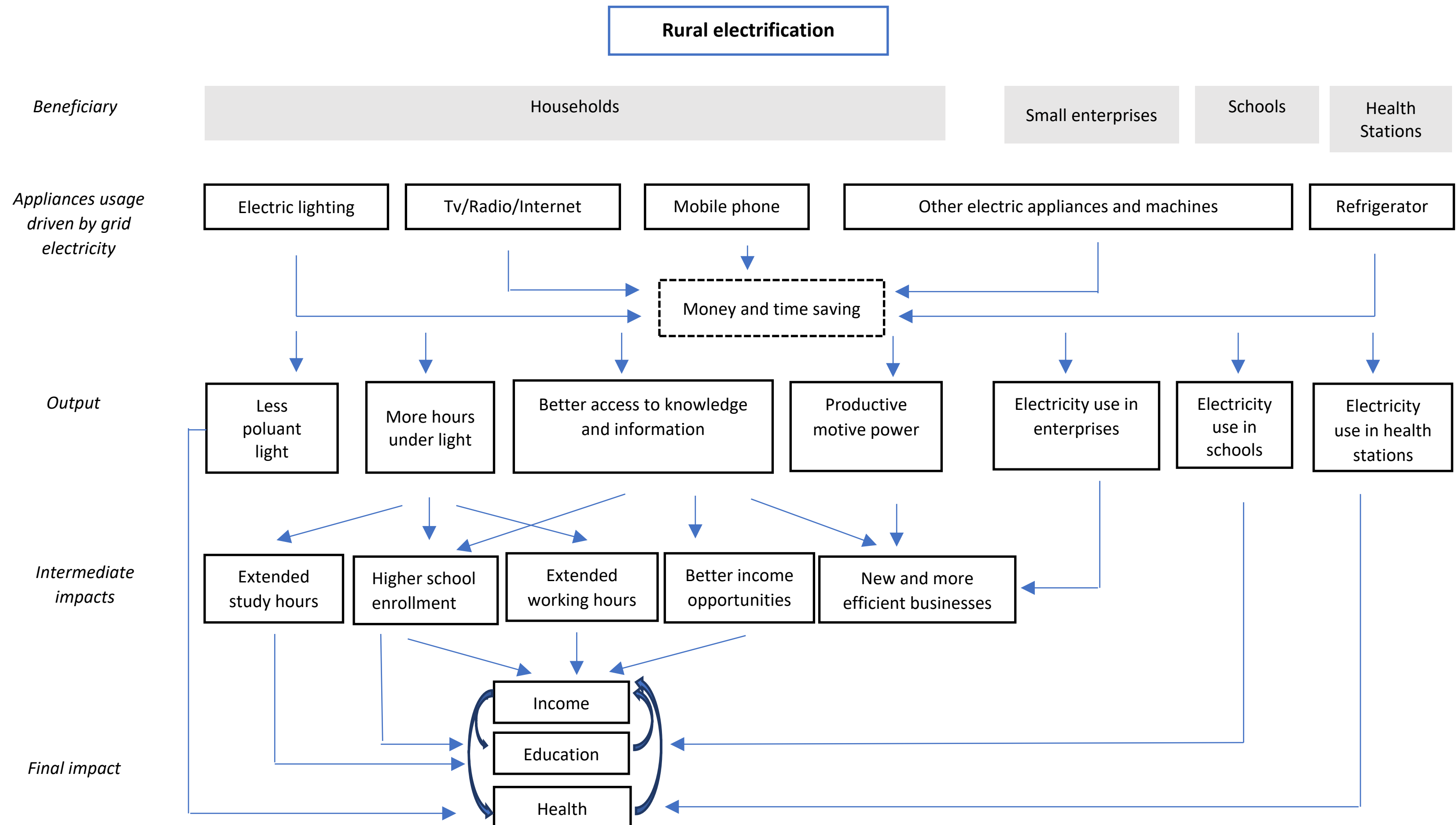
Attrition also has implications for our sample size. Our sub-sample analyses are performed on small datasets and therefore, only very strong findings are identified as being statistically significant. More evidence will be needed on differential effects along the gender, infrastructure, and distributional dimensions. Second, program placement was not random, and we had to resort to quasi-experimental methods. Our findings rest on the assumption that unobservable characteristics are time-invariant. Although we believe that this hypothesis is valid in the specific case of Senegal and for the structure of the data explored, future studies might want to aim for further refining the identification strategy. Third, no gender-related analysis could be conducted accounting for the gender of the household head due to the small size of the study sample. Future studies might want to address this aspect.

Despite all these limitations, the difference-in-differences estimates are reliable, given the validity of the parallel trend assumption (refer to Appendix E for detailed information). We further consider the identified findings important for policy making in Senegal and possibly beyond. We show that similar impacts can be achieved by grid extension and the provision of solar power. This is an important finding for policymakers suggesting that they can opt for the technically ideal solution with no negative implications in the economic and social domain. Next, we highlight the role of existing infrastructure in reinforcing the benefits of access to energy. Last but not least the overall findings show that access to electricity increases household well-being and thus encourage the speeding-up of universal access to electricity in rural areas both with on-grid and off-grid technologies.

2.1 Appendix

Appendix A: Additional figures

Figure A.2 Theory of change of electricity access.



Sources: Adapted from Lenz et al. (2017, p. 9)

Figure A.2 Study set-up

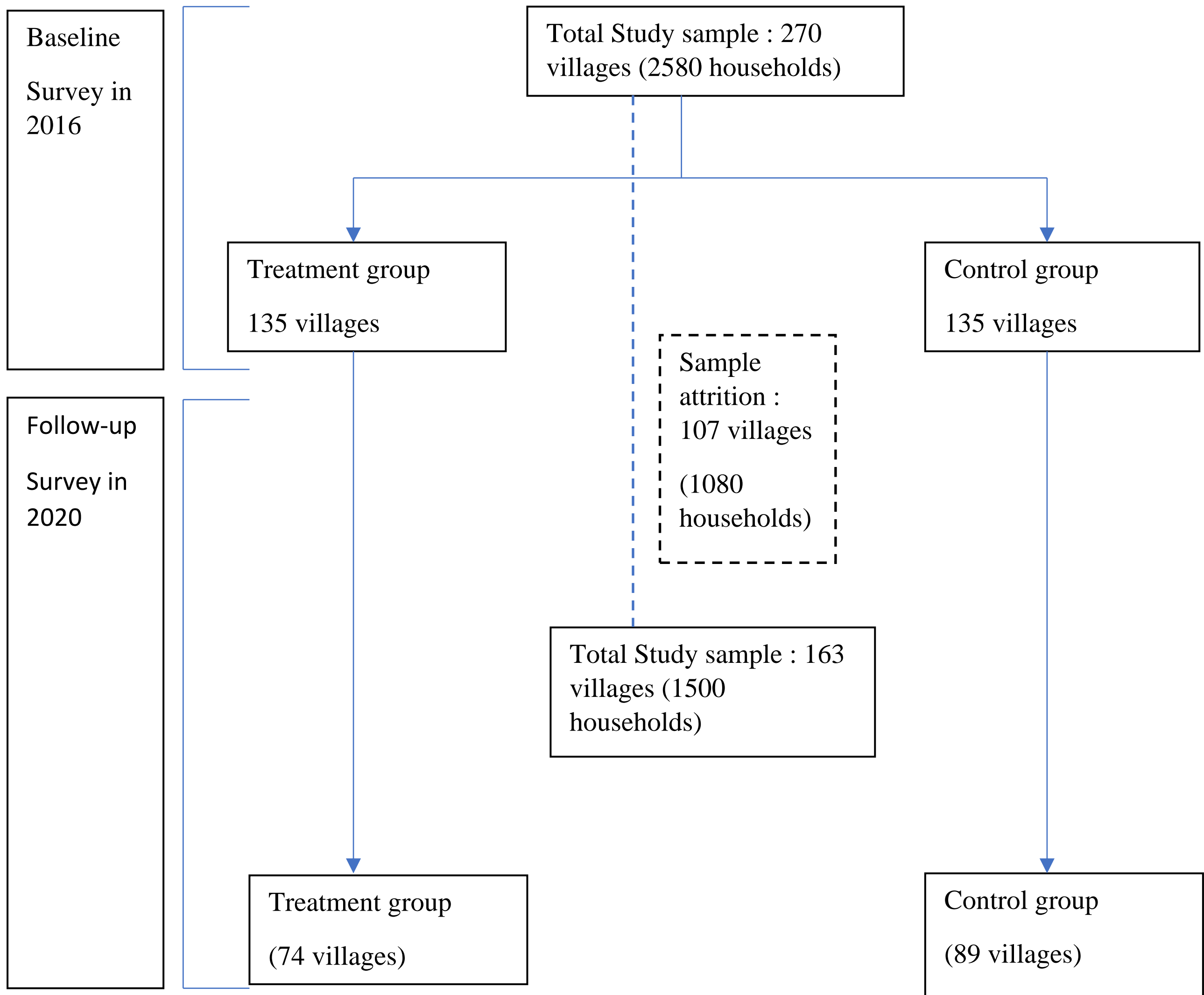
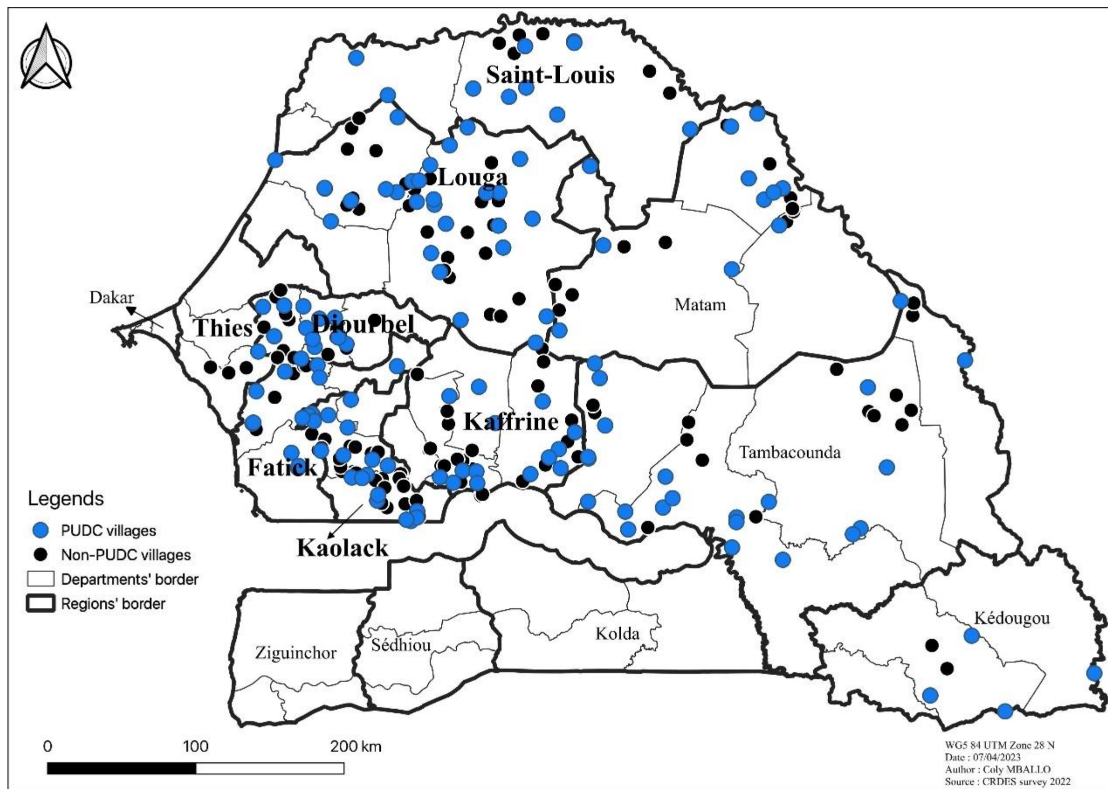
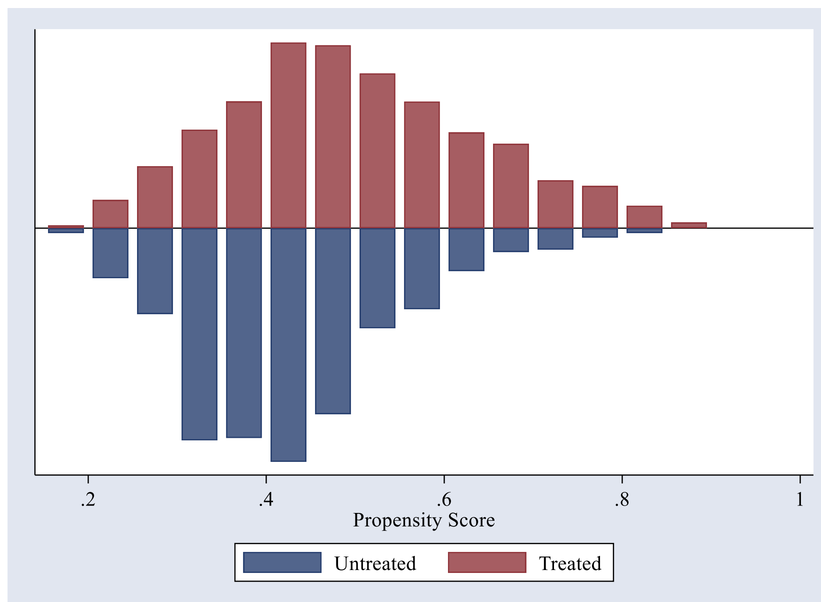


Figure A.3 Treatment versus control villages.



Source: CRDES baseline survey, 2023.

Figure A.5 Propensity score distributions according to the access-to-electricity status after matching.



Appendix B: Attrition analysis

We address attrition using the same approach as Zhang and Xu (2016) and Zhang (2012). Specifically, we examine whether the probability of not participating in the follow-up survey is correlated with the treatment variable, which is access to electricity. From the baseline dataset, we generate a dummy variable that takes a value of 1 if a household did not participate in the follow-up survey and 0 otherwise. This dummy variable is then regressed on household and village characteristics, including the treatment variable. Attrition would be a problem if it were correlated with the treatment variable.

Table B.1 Regression results of households' probability of being absent in the follow up-survey

	(1) Estimate	(2) Standard error
A. Household characteristics		
Household has access to electricity (Yes=1, No=0)	0.003	0.103
Size of household (discrete variable)	-0.004	0.007
Age of hh (discrete variable)	0.000	0.003
Gender of hh (Male=1, Female=0)	0.116	0.223
Educational level of hh (Educated=1; Uneducated=0)	-0.241	0.177
Occupation of hh (Farmer=1; Not Farmer=0)	-0.572^{***}	0.106
B. Village characteristics		
Log. number of households (discrete variable)	-0.347^{***}	0.054
Log. Percentage of women	-2.157^{***}	0.280
The village has a physical market (Yes=1; No=0)	0.376^{**}	0.164
The village pays taxes (Yes=1; No=0)	-1.301^{***}	0.124
Distance between the village and the regional capital (km)	0.016^{***}	0.001
The village has a forest 5 km away (Yes=1; No=0)	1.014^{***}	0.102
Observations	2224	
LR $chi^2(12)$	620.21	
R^2	0.205	

Note: * p < .10, ** p < .05, *** p < .01. Whether a village has electricity is not integrated into village traits to avoid its correlation with the treatment variable. hh abbreviates household head.

The results from the logit model in Table B1 indicate that the coefficient associated with the treatment variable is not statistically significant, suggesting that the probability of not participating in the follow-up survey is not correlated with a household's access to electricity. This result suggests that sample attrition does not sort on access to electricity. Furthermore, it is noteworthy that household characteristics are not significant predictors of attrition (except for the occupation of the household head). Yet, village characteristics are significant predictors of attrition suggesting that our findings are internally valid but have to be taken with a grain of salt when it comes to the external validity. It is not surprising that village characteristics are a significant predictors of

attrition given that all villages lie in the same three regions that considerably more remote and disconnected compared to the villages in the re-surveyed regions.

Appendix C: Additional tables

Table C.1 Observed characteristics (before matching) per access-to-electricity status.

Observed characteristics	Average before matching				
A. Household characteristics	households without electricity	Electrified households	Total sample	Δ	Logit model
	(1)	(2)	(3)	(4)	(5)
Size of household (discrete variable)	11.99 (0.232)	12.43 (0.290)	12.19 (0.182)	0.444 (0.367)	0.021^{*} (0.011)
Age of the household head (discrete variable)	50.64 (0.556)	52.16 (0.575)	51.33 (0.401)	1.525^{**} (0.805)	0.008^{*} (0.005)
Sex of the household head (Male=1, Female=0)	0.963 (0.007)	0.950 (0.009)	0.957 (0.006)	-0.013 (0.012)	-0.272 (0.338)
Education of the household head (Educated=1; Uneducated=0))	0.052 (0.009)	0.097 (0.013)	0.072 (0.007)	0.044^{***} (0.0155)	0.622^{**} (0.264)
Occupation of household head (Farmer=1; Not Farmer=0)	0.641 (0.019)	0.676 (0.020)	0.657 (0.014)	0.035 (0.028)	0.101 (0.147)
B. Village characteristics					
Log. number of households (discrete variable)	3.974 (0.036)	4.236 (0.042)	4.092 (0.027)	0.262^{***} (0.055)	0.247^{***} (0.083)
Log. Percentage of women	3.831 (0.005)	3.811 (0.007)	3.822 (0.004)	-0.019 (0.009)	-1.673^{***} (0.482)
The village has a physical market (Yes=1; No=0)	0.063 (0.009)	0.125 (0.014)	0.014 (0.008)	0.061^{***} (0.017)	0.623^{**} (0.278)
The village is electrified (Yes=1; No=0)	0.048 (0.008)	0.154 (0.016)	0.096 (0.008)	0.106^{***} (0.017)	0.822^{***} (0.249)
The village pays taxes (Yes=1; No=0)	0.933 (0.010)	0.869 (0.015)	0.904 (0.008)	-0.064^{***} (0.017)	0.754^{***} (0.231)
Distance between the village and the regional capital (km)	46.68 (1.449)	47.57 (1.077)	47.10 (1.077)	0.891 (2.160)	0.003^{*} (0.001)
The village has a forest 5 km away (Yes=1; No=0)	0.410 (0.020)	0.460 (0.022)	0.433 (0.014)	0.050^{**} (0.029)	0.418^{***} (0.137)

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors are denoted in brackets. Δ reflects the difference between the average outcomes of electrified households and those of households without electricity. In the logit model, the dependent variable is the binary treatment variable taking a value of 1 if the household has access to electricity and 0 otherwise.

Table C.2 Balance test on observed variables after matching

	Electrified households	Non-electrified households	Bias (%)	Reduction of bias (%)	p-value	Variance ratio
	(1)	(2)	(3)	(4)	(6)	(7)
A. Household characteristics						
Household size (discrete variable)	12.66	12.60	0.9	92	0.890	1.19
Age of the hh (discrete variable)	51.97	51.99	-0.2	98.5	0.978	0.90
Sex of the hh (Male=1, Female=0)	0.957	0.953	2.4	-75.3	0.734	0.87
Educational level of hh (Educated=1; Uneducated=0)	0.082	0.088	-2.7	75.7	0.720	1.01
Occupation of hh (Farmer=1; Not Farmer=0)	0.697	0.690	1.6	62.9	0.811	1.00
B. Village characteristics						
Log. Number of households (discrete variable)	4.137	4.138	-0.1	99.6	0.986	1.12
Log. Percentage of women	3.81	3.824	-10.0	38.7	0.132	1.23
The village has a physical market (Yes=1; No=0)	0.086	0.091	-1.9	87.4	0.802	0.96
The village is electrified (Yes=1; Non=0)	0.135	0.135	0.2	99.4	0.983	1.00
The village pays taxes (Yes=1; No=0)	0.875	0.864	3.8	77.8	0.614	0.94
Distance between the village and the regional capital (km)	48.09	47.53	1.6	58.8	0.808	1.29*
The village has a forest 5 km away (Yes=1; No=0)	0.433	0.428	1.0	93.0	0.882	1.00

Notes. The sign * becomes worrying if the variance ratio is situated in the [0,5, 0,8] or (1,25, 2) interval; ** indicates bad matching, i.e. a variance ratio below 0,5 or above 2. Hh abbreviates household head.

Table C.3 Results of diagnostic tests after matching

	Non-matching sample	Matching sample
	(1)	(2)
Pseudo R^2	0.07	0.0002
LR Chi^2	70.92	2.71
p-value of Chi^2	0.000	0.997
Average bias	13.7	2.2
Median bias	13.3	1.6
B	54.6*	10.9
R	1.58	1.47
Concern (%)	50	8
Bias (%)	0	0

Table C.4 Impact of access to electricity on education for boys and girls – PSM-DiD

	School enrolment		School attendance		Study time	
	Boys	Girls	Boys	Girls	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
Access to electricity	0.219	0.270**	0.139	0.368***	0.280	0.520***
	(0.136)	(0.131)	(0.048)	(0.134)	(0.204)	(0.195)
Observations	588	627	578	611	481	501
R^2	0.24	0.15	0.04	0.02	0.02	0.03
Panel B: Electricity (national grid)						
Access to electricity	0.284	0.248	0.110	0.307	0.175	0.103
	(0.173)	(0.174)	(0.172)	(0.187)	(0.250)	(0.296)
Observations	402	421	395	409	318	324
R^2	0.26	0.18	0.03	0.03	0.04	0.03
Panel C: Electricity (off-grid)						
Access to electricity	0.179	0.282*	0.155	0.398***	0.358	0.710***
	(0.153)	(0.145)	(0.155)	(0.148)	(0.235)	(0.214)
Observations	478	511	470	496	392	415
R^2	0.26	0.17	0.04	0.03	0.02	0.05

Note: PSM-DiD results. Robust standard errors are denoted in brackets. The average treatment effects on the treated for access to electricity on economic and social outcomes are shown. Household and village characteristics as well as region and time fixed effects are included across specifications. Kernel matching is used for deriving the propensity scores. For details about included controls, consult the note to Table 2.3. * p < .10, ** p < .05, *** p < .01.

Table C.5 Estimates of access to electricity by poverty status – PSM-DiD

	Log. Expenditures per capita			Employment		
	Food	Non-food	Total	Agricul-tural	Non-agricultural	Total
	(1)	(2)	(3)	(4)	(5)	(6)
Economic outcomes						
Panel A: Poor households						
Access to electricity	-0.038	0.291**	0.122*	0.047	0.255***	0.108
	(0.082)	(0.121)	(0.068)	(0.160)	(0.095)	(0.104)
Observations	1141	1070	1146	342	631	774
R^2	0.03	0.11	0.00	0.13	0.05	0.11
Panel B: Non-poor households						
Access to electricity	0.114	-0.220	0.028	0.099	0.422***	0.607***
	(0.092)	(0.188)	(0.086)	(0.206)	(0.102)	(0.114)
Observations	769	757	770	263	568	624
R^2	0.01	0.02	0.01	0.05	0.09	0.18
Social outcomes						
Panel C: Poor households						
	School enrolment	**School attendance**	**Study time**			
Access to electricity	0.412***	0.437***	0.551***			
	(0.143)	(0.149)	(0.202)			
Observations	452	443	392			
R^2	0.30	0.05	0.07			
Panel D: Non-poor households						
Access to electricity	0.117	0.213	0.432			
	(0.210)	(0.215)	(0.281)			
Observations	371	365	307			
R^2	0.12	0.01	0.01			

Note: PSM-DiD results. Robust standard errors are denoted in brackets. The average treatment effects on the treated for access to electricity on economic and social outcomes are shown. Household and village characteristics as well as region and time fixed effects are included across specifications. Kernel matching is used for deriving the propensity scores. For details about included controls, consult the note to Table 2.3.
* $p < .10$, ** $p < .05$, *** $p < .01$.

Appendix D: Selection of independent variables for the Logit model

This section justifies the choice of variables included in the Logit model. The selection of these variables is informed by the extensive literature on the determinants of access to electricity.

A household's decision to connect to electricity is primarily dependent on whether the area or village is supplied with on-grid electricity infrastructure. This is mostly true for the extension of the national grid or the construction of solar mini-grids rather than for stand-alone solar technologies. For instance, households can adopt solar home systems (SHS) even if their residential areas are not supplied with electricity. We use a binary variable that is equal to 1 if the village is electrified and 0 if not.

The placement of electricity infrastructure is mainly determined by specific features of the electrified areas. Demographic characteristics are one of the features based on which officials decide to extend the national grid (Jimenez, 2017; Lipscomb et al., 2013; Grogan, 2016). A large population features a high demand for electricity, which guarantees economies of scale and the recovery of initial investment costs. Densely populated areas are, therefore, more likely to have electricity infrastructure. We capture village-level demographic characteristics by village population and the percentage of women living in the village. The latter is expected to be positively related to electricity adoption to the extent that women are responsible for firewood collection and therefore more likely to opt for electricity adoption (Ulsrud, 2020).

In addition to population density, the economic and agricultural potentials of the electrifying localities also play a role in the distribution of electricity infrastructure (Grogan, 2016; Jimenez, 2017; Lipscomb et al., 2013; Khandker et al., 2014). We measure village economic potential by the availability of a physical market and whether the village pays taxes to local and state officials. The argument is that the availability of a market facilitates transactions, as buyers and sellers can easily meet each other. Such markets incentivize rural micro-businesses to offer more employment opportunities and expand their production. The growing economic activities incentivize authorities to levy taxes and invest more in infrastructure. Agricultural activity is measured by whether a village has a forest in the surrounding area. The availability of a forest may indicate good soil quality and the existence of arable land.

We also control for the distance of the villages to regional capital cities to account for remoteness. The location of the village can pose challenges to the extension of electricity infrastructure. Typical characteristics of remote rural areas are lower population density, scattered demand, and high grid transmission costs, making the provision of electric infrastructure unprofitable (Jimenez, 2017). Strategies often include electrifying areas close to power transmission lines with on-grid electricity and providing more remote areas with off-grid technologies (World Bank, 2018).

Household characteristics also determine the adoption of electricity once electricity infrastructure is supplied. We control for the educational level, occupation sector, gender, and age of the household head and the size of the household. Households with educated heads are likely to adopt electricity because education raises awareness of the benefits of electricity access and increases the need for electric light for activities such as reading and using laptops. Empirical evidence supports the positive effect of education on access to electricity, whether through off-grid technologies (Ahmed et al., 2022; Etongo & Naidu, 2022; Smith & Urpelainen, 2014) or on-grid electricity (Khandker et al., 2014; Litzow et al., 2019).

There is widespread agreement that affordability is a crucial predictor of a household's electricity connection status. Income enables households to cover connection costs and fees, and low connection rates among poor households are often due to insufficient financial resources and unpredictable income (Jimenez, 2017). Though we were not able to directly control for income, we do control for education and employment outcomes that are significant predictors of household income. We control for the occupation sector of the head of the households. Litzow et al. (2019) found that households with heads working in the non-agricultural sector are likely to adopt electricity.

The sex of the heads of households also counts. Female-headed households are expected to have a greater likelihood of electricity adoption given that women perform many energy-intensive tasks (Diallo and Moussa, 2020). In some instances, female-headed households, which are often single-parent families with lower income levels, may be less likely to adopt electricity (Ulsrud, 2020).

The relationship between the age of the household head and electricity adoption is also ambiguous. Guta (2018) found no significant effect of age on solar home system

adoption, while Khandker et al. (2014) and Litzow et al. (2019) reported a positive correlation between the age of the household head and grid electricity adoption. This contradiction may be due to older individuals' greater wealth and productive resources, while younger individuals may be more aware of off-grid solutions and have a greater need for electricity (Etongo & Naidu, 2022).

Household size can influence electricity adoption in different ways. Larger households might adopt electricity if most members are employed, ensuring greater income, and including educated individuals with a higher need for electricity. Conversely, larger households might discourage adoption if they are poor and unable to cover the increasing costs. The size of the household is empirically found to be positively related to the adoption of on-grid electricity (Blimpo et al., 2020; Fotso et al., 2023) and the use of solar technologies (Ahmed et al., 2022, Guta, 2018).

Appendix E: Results of the outcome placebo test

The double difference estimator is robust to time-invariant unobservable characteristics. However, it cannot eliminate the differences between the treatment and control groups that change over time. Therefore, one must assume no time-varying differences between the treatment and control groups. This is the classical parallel trend assumption. In the absence of equal trends between the treatment and control groups, the estimates obtained with double difference would be biased.

The validity of the underlying assumptions can be tested in four different ways. The first approach is to compare the outcomes between the treatment and control groups before the implementation of the program. We were not able to run such a pre-intervention comparison, given that only one round of data collection has been performed. A second way to test the assumption of equal trends would be to perform the difference-in-differences estimation using different comparison groups. A third way consists of performing a placebo test by using a fake treatment group to compute difference-in-difference estimates. We were unable to perform this approach because the size of the study sample is not large enough to accommodate the construction of a fake treatment group and another control group. We, therefore, resorted to a fourth approach, which is a placebo test with a fake outcome.

The fake outcome considered is the amount of total financial credit received by a given household. Based on the theory of change of access to electricity, this outcome is less likely to be affected by the use of electricity and therefore must have equal trends before and after the intervention within both groups. The estimated impact of access to electricity on the amount of financial credit is reported in Table E1. Overall, the findings suggest that the adoption of electricity – either on-grid or off-grid electricity – has no impact on the total amount financial institutions lend to rural households. Therefore, the parallel trends assumption seems to be valid, and confidence can be retained regarding our impact estimates of the welfare effects of rural electrification.

Table E1 Estimates impact of access to electricity on the amount of financial credit – PSM-DiD

	Fake outcome**:** Log. Amount of financial credit		
	(1)	(2)	(3)
	Access to electricity	Access to on-grid electricity	Access to off-grid electricity
	0.250	0.214	0.288
	(0.157)	(0.224)	(0.176)
Observations	1053	719	885
R square	0.09	0.07	0.09

Note: PSM-DiD results. Robust standard errors are denoted in brackets. The average treatment effects on the treated for access to electricity on economic and social outcomes are shown. Household and village characteristics as well as region and time fixed effects are included across specifications. Kernel matching is used for deriving the propensity scores. For details about included controls, consult the note to Table 2.3. * $p < .10$, ** $p < .05$, *** $p < .01$.

Chapitre 3 - The economic impacts of rural water supply infrastructure in developing countries: Empirical evidence from Senegal[2]

"Or maybe they are less hungry because of the decline of heavy physical work—with the availability of drinking water in the village."

Banerjee, A & Duflo, E. (2011, p.57)

Abstract

The paper addresses the often-neglected economic impacts associated with the supply of hydraulic infrastructure in rural and under-serviced communities in developing countries. We rely on a rich panel dataset including 1,319 Senegalese rural households collected in 2016 and 2020, during the deployment of the first phase of the Emergency Program for Community Development (PUDC). By combining propensity score matching (PSM), inverse probability weighting (IPW), difference-in-differences (DiD), and quantile regression, we find that access to piped water improves employment in the agricultural sector but has no significant impact on household expenditures. The employment effect operates through access to a greater quantity of water and a reduction in the time women devote to water fetching chores. Moreover, when bundled with complementary infrastructure interventions such as the construction of rural roads, we find that access to water services generates an even higher impact. The quantile analysis shows that non-poor households seem to benefit more from the provided water supply infrastructure compared to poor households. Finally, when comparing the welfare effect of government-led PUDC water supply with that of community-led initiatives, our findings advocate for the widespread implementation of the former for reasons of cost-effectiveness. It should be noted that the follow-up survey did not include three remote regions. Despite experiencing a high attrition rate, we maintain confidence in our estimates, as we were able to minimize biases through the application of PSM.

Keywords: drinking water, well-being, impact evaluation, PSM-DiD, rural households, Senegal.

JEL classification: I38, Q25, J43

Competing Interests: None

[2] This chapter was submitted to *Environmental and Resource Economics* and revised two times. It has recently been resubmitted after a minor revision.

3.1 Introduction

Among the 25 percent of the global population who lack access to water services, most people live the rural areas of Sub-Saharan Africa (SSA) (WHO & UNICEF, 2021). Several factors may explain the low rural coverage with water infrastructure in SSA: the overall low performance of the water utilities is one of them (World Bank, 2017). Uneconomical water pricing structures hamper cost recovery and narrow the revenue basis that would be needed to attract the necessary investments. Even in instances where water is priced at market level, low consumption and the high prevalence of water from open sources make the cost of service delivery of quality water quite onerous. As a result, several utilities rely on public funds not only to secure the costs needed for the expansion of their services but also to guarantee reasonable operations and maintenance.

The enabling environment in which utilities operate is another factor contributing to the low prevalence of quality water infrastructure in developing countries. The expansion of water infrastructure to remote and sparsely populated communities that largely characterize rural SSA is hindered by low economies of scale (Abubakar, 2019), making the achievement of universal access to quality water and sanitation services (Sustainable Development Goal, SDG6) unattainable, especially in the medium term (UNICEF & WHO, 2023).

Governance challenges in the water sector are another factor of concern. Transparent processes would be necessary to secure long-term investments, particularly in the water sector that is characterized by considerable initial sunk costs, which are required to expand the network infrastructure. A recent OECD survey on water governance in African cities offers mixed results concerning perceptions about transparency and integrity in the water sector (OECD, 2021)[3]. While more than half of the respondent African cities confirm that clear procurement processes are applied when investment decisions are made, only a limited number of the surveyed cities (less than 25 percent) declare that random auditing, anti-corruption plans, and integrity charters are implemented. Failure to guarantee integrity not only undermines trust but also

[3] The following question was asked: which mechanisms have been put in place at the city level to enhance transparency and integrity for the management of water-related issues. The selected mechanisms were as follows: water budget auditing, water financial information disclosure, budget transparency principles, anti-bribery management systems, whistle-blower protection policies, clear procurement processes, random audits, and prevention of conflict of interest.

jeopardizes the quality of service delivery. Similar patterns can also be observed from the Afrobarometer surveys, in which 20 percent of the respondents from 34 countries declared having obtained water utility services only once some form of a bribe was paid (Howard & Han, 2020).

This predicament has severe consequences, as limited access to quality water exposes households to waterborne diseases, often being fatal for vulnerable individuals (Kumar et al., 2022; Adams, 2018; Ezeh et al., 2014; Ntouda et al., 2013). In households lacking indoor tap water, members have to dedicate a larger share of their time to fetching water from remote sources (Choudhuri & Desai, 2021; Kremer et al., 2011). For example, in rural Senegal, where this study is located, women and children walk distances ranging from 500 meters to 1 kilometer on average to access potable drinking water, spending an average of 30 minutes to one hour on a round-trip to and from a water source (ANSD, 2021). Concomitantly, water fetching has a high opportunity cost, since the activity reduces the time available for income-generating activities, employment, and educational pursuits (Adams, 2018; Choudhuri & Desai, 2021; Ortiz-Correa et al., 2016). Furthermore, it exposes women to sexual harassment, exacerbating the existing gender inequality gap in the global South (Dickin et al., 2021; Routray et al., 2017).

Senegal has made quite some progress in providing access to clean water to its populations over the past two decades (ANSD, 2021). Nearly 97 percent of Dakar's population and 82 percent of the remaining urban dwellers have access to potable water, while access in rural areas is available for 65.7 percent, resulting in a national access rate of 78.7 percent (ANSD, 2021). Despite noticeable progress –between 2016 and 2020, 238 boreholes and 159 water towers were built in rural areas (for more details see Appendix A)– ample disparities exist across regions with more remote areas tending to be most underserved (for details see Figure B1 in Appendix B).

This situation motivated the Senegalese Government to implement the Emergency Program for Community Development (PUDC) including a targeted water intervention in 2016 (see Appendix A for details about PUDC). This study sets out to identify whether the public investments mobilized for the supply of rural populations with quality water services have yielded any economic impact. In addition, we can identify whether there are differences in impacts between public and community-led interventions. The study offers a rigorous evaluation of the impact of access to quality water services on key economic outcomes (expenditures and employment, per sector)

in Senegal. The economic dynamics resulting from the implementation of the centrally administered hydraulic infrastructure under PUDC are compared with the ones associated with previous alternative water supply initiatives. We term these alternative initiatives: community-led initiatives or non-PUDC water supply programs[4]. Before PUDC rollout, baseline data were collected in 2016, followed by a 2020 survey, resulting in a panel of 1,319 households. Given the non-random implementation of PUDC and the pre-existence of community-led initiatives at baseline, quasi-experimental analysis techniques, such as propensity score matching (PSM) and inverse probability-weighting (IPW) are employed to evaluate the impact of PUDC water infrastructure on employment and household expenditure. Furthermore, based on Smith and Todd (2005), we combine PSM with a difference-in-difference estimator (DiD). Finally, quantile regressions are used to identify heterogeneous effects across the distribution of household expenditure. Both DiD quantile regression and Firpo's (2007) approach are applied to identify the distributional effects of PUDC and non-PUDC water infrastructure. The need to rely on PSM further arises from the high attrition rate we face between baseline and follow up (~42 percent) due to cost constraints. Thus, in interpreting our results, we need to consider that those areas that are more remote and have potentially benefitted the most have not been resurveyed making our impact estimates likely a conservative lower bound.

Our findings reveal that the PUDC water intervention stimulates agricultural employment, while non-PUDC water supply initiatives show no significant impact on both employment and expenditure. The exploration of the underlying mechanisms reveals that households connected to PUDC piped water consume larger amounts of water and women benefitting from the program allocate their saved time to farming and gardening. The PUDC water intervention is a large-scale development project with a huge budget to ensure not only the full operation but also the functional quality of the installed water infrastructure. PUDC hydraulic infrastructure was installed at the request of rural populations, guaranteeing the efficient and productive use of the installed water supply infrastructure through sustained maintenance. The demand-driven nature of PUDC water infrastructure and their maintenance, facilitating the population’s buy-in, may explain why the PUDC water intervention provides better

[4] These are NGO-supported initiatives that fund water supply infrastructure in remote and sparsely populated areas. NGOs such as GIZ and USAID have funded decentralized projects that facilitate the construction of boreholes and water towers for rural populations.

economic opportunities to the users. Participatory and demand-driven water infrastructure has been deemed effective as communities feel responsible for them, ensuring their sustainability (Barde, 2017). The quantile regressions further show a more pronounced effect of PUDC water infrastructure when combined with road infrastructure, with non-poor households benefiting more from the provided water.

We make two contributions to the existing literature. First, the study further enhances our understanding of the economic impacts associated with the adoption of piped water in a developing country context. This is important since it provides information on the value-for-money associated with public investments in water supply infrastructure (Trémolet, 2015; Prat et al., 2015; Mujica et al., 2015). For Senegal, the current literature has examined the social benefits associated with the expansion of water supply infrastructure (Daffe et al., 2022; Novak, 2014; Ntouda et al., 2013), the effect of access to tap water on water consumption (Briand et al., 2010), the various productive uses of water (Hall et al., 2014; Houweling et al., 2012), and the determinants of piped water adoption (Briand et al., 2009). To the best of our knowledge, no study has examined the economic effects associated with access to water services in Senegal so far. Yet, there is growing interest in the role of water in supporting economic transformations and rural-urban disparity in terms of access to utility services. We close this gap by assessing the extent to which access to water influences economic activities within rural settings. We disaggregate the effects along the expenditure distribution to capture heterogeneities. Understanding such disaggregated effects is important for designing policies that aim at reducing water poverty and inequality in access to quality water. Finally, we determine the effects of water-related services on economic dynamics when combined with other interventions such as access to electricity and rural roads.

Second, the study compares the impacts of government-led (PUDC) versus community-led (non-PUDC) water supply interventions in a developing country context, where a combination of stakeholders operates in the water sector. Whether government-led interventions crowd community-led interventions in or out is an important empirical question that can guide the governance structures adopted in the water sector. Previous studies have explored the factors contributing to the effectiveness of community-led water deployment infrastructure (Ankon et al., 2022; Daniel et al., 2023; Marks & Davis, 2012; Roekmi et al., 2018). Others have offered a direct comparison between

community and government-led water interventions (Barde, 2017; Newman et al., 2002). Barde (2017) and Newman et al. (2002) report that community-led water services enhance both water access and water quality in comparison to centrally supplied large-scale water infrastructure from public entities. With the increasing influx of donor-driven aid to fund small-scale water infrastructure in rural areas of developing countries, there is a revival of the notion that centrally supplied large-scale water infrastructure is ineffective in rural areas due to poor maintenance. The richness of our dataset provides a unique opportunity to contribute new insights to this debate.

The remainder of this article is structured as follows: Section 2 offers an exhaustive review of the related literature, Section 3 introduces the theoretical framework. Section 4 presents the data and the variables. The methodology is highlighted in Section 5, while Section 6 discusses the results. Finally, Section 7 concludes and offers policy recommendations for the deployment of future water supply initiatives.

3.2 Related literature review

Given the productivity gains that households connected to safe drinking water derive, greater economic outcomes (incomes, and employment) are expected to follow. Recent studies support this expectation (Winter et al., 2021; Zhou and Turvey, 2018). Using cross-sectional data based on 434 rural Zambian households, Winter et al. (2021) found that households connected to a piped system were likely to expand the size of their cultivated areas. The expansion of the cultivated area supports higher crop yield, which leads to higher on-farm employment and enhanced income from the selling of agricultural products. Zhou and Turvey (2018) showed that off-farm employment increased after households gained access to piped water in China. Renwick (2007) concluded that the supply of water services to rural households in Zimbabwe had led to a 27 percent increase in their income.

Yet, existing findings are not clear-cut. Access to piped water was found to have no significant impact on income, expenditure, and labor supply in several studies (Devoto et al., 2012; Koolwal & van de Walle, 2013; Lokshin & Yemtsov, 2003; Rauniyar et al., 2011; Viet & Vu, 2013). Using community-level panel data obtained from 106 communities observed between 1998 and 2002, Lokshin and Yemtsov (2003) found that water interventions in rural Georgia had no significant employment impact. Similar results were found for Pakistan by Rauniyar et al. (2011) based on cross-sectional data

from 2,602 households and using propensity score matching. Viet and Vu (2014) found no significant effects of piped water on employment and income in Vietnam, based on panel data and the combination of Propensity Score Matching (PSM) and Difference-in-Difference. Using a randomized design (based on a sample of 844 poor urban households), Devoto et al. (2012) identifies no significant improvement in household income following interventions in Morocco. A study carried out by Guzmán, Brown & Khatiwada (2016), based on panel data from 1,200 Ghanian households combining propensity score matching and analysis of covariance, showed that access to safe drinking water has no significant impact on households' income and assets.

Other studies have looked at social benefits from access to quality water such as health and education. The central message is that water containing pathogenic microorganisms (E. coli) and chemical substances poses a detrimental effect on users, necessitating targeted interventions aimed at improving water quality. Thus, most studies demonstrate that access to piped water (or improved water quality) has positive effects on health and education. Since the focus of this study is on economic effects, we placed the detailed discussion of the social benefits in Appendix C.

Only a few papers employed to randomized controlled trials (RCTs) (Prasad et al., 2023), as water intervention, tap water notably, are challenging to randomize (Devoto et al., 2012). The few existing RCTs available mainly focused on water treatment and hygiene (Dupas et al., 2016; Ercumen et al., 2015; Heitzinger et al., 2016; Kremer et al., 2011; Lindquist et al., 2014; Shaheed et al., 2018; Luby et al., 2018; Chard et al., 2019; Quattrochi et al., 2021; Stevenson et al., 2016). The remaining past studies have made use of a variety of quasi-experimental methodological approaches due to the absence of experimental data. These include the logit model and ordinary least squares (Renwick, 2007; Fink et al., 2011), fixed effect models (Komarulzaman et al., 2019; Koolwal & van de Walle, 2013; Winter et al., 2021; Zhang & Xu, 2016), propensity score matching (PSM) (Hasan & Gerber, 2016; Jalan & Ravallion, 2003; Rauniyar et al., 2011; Guzmán et al., 2016), double difference (DiD) (Chen et al., 2022), the combination of PSM and DiD (Klasen et al., 2012; Lokshin & Yemtsov, 2003; Viet & Vu, 2013), and the instrumental variable (IV) approach (Klasen et al., 2012; Mangyo, 2008; Ortiz-Correa et al., 2016; Zhang & Xu, 2016; Zhou & Turvey, 2018). Each quasi-experimental approach has its own limitations. With a simple logit model and ordinary least squares, one cannot claim causality. PSM is unable to eliminate selection bias

driven by unobserved factors. DiD is unable to control for time-varying heterogeneities. Although the IV approach remains a suitable method to correct for potential endogeneity bias, using poor instruments leads to biased estimates. We conclude from the existing literature that in the absence of exogenous and reliable instruments, the combination of PSM and DiD appears to be the most suitable empirical strategy.

Many of the above cited studies used cross-sectional data due to lack of panel data (Fink et al., 2011; Hasan & Gerber, 2016; Jalan & Ravallion, 2003; Klasen et al., 2012; Koolwal & van de Walle, 2013; Rauniyar et al., 2011; Ortiz-Correa et al., 2016; Trinies et al., 2016; Winter et al., 2021; Zhang & Xu, 2016). Yet, with cross-sectional data, time-varying characteristics are impossible to control for as well as dynamics over time and it becomes hard to establish causal relationships. These limitations are circumvented by studies that employ panel dataset consisting of baseline and follow-up data to explore the welfare effects of access to improved water sources (Chen et al., 2022; Devoto et al., 2012; Komarulzaman et al., 2019; Lokshin & Yemtsov, 2003; Mangyo, 2008; Viet & Vu, 2013; Zhang, 2012; Zhou & Turvey, 2018).

Across the existing literature external validity has hardly been discussed. The country-specific nature of the estimates associated with water quality standards and the processes that govern the distribution of water infrastructure allow for limited generalizations (Wapenaar & Kollamparambil, 2019). For instance, the effectiveness of water interventions was shown to be affected by local factors, such as private hygiene inputs, maternal education, and health facilities (Jalan & Ravallion, 2003; Mangyo, 2008; Wapenaar & Kollamparambil, 2019; Esrey et al., 1991; Gamper-Rabindran et al., 2010). Similarly, findings for rural areas may not necessarily be applicable for urban zones (Klasen et al., 2012). Statistical reasons may also contribute to limited external validity, especially when RCTs are piloted. Moreover, small samples that are not representative affect generalization (Deveto et al., 2012; Guzmán et al., 2016; Heitzinger et al., 2016; Hasan & Gerber, 2016; Stevenson et al., 2016; Quattrochi et al., 2021; Winter et al., 2021; Lokshin & Yemtsov, 2003).

A noticeable observation is that no previous studies have examined the economic impact of tap water in Senegal. The existing studies conducted in Senegal looked at i) the social benefits associated with access to potable water (Daffe et al., 2022; Novak, 2014; Ntouda et al., 2013), ii) the productive use of water (Hall et al., 2014; Houweling et al., 2012), and iii) the effect of access to tap water on water consumption (Briand et

al., 2010). Additionally, most of the existing studies report mean impacts rather than distributional effects. Thus, there is a need for an in-depth exploration of the economic implications of piped water adoption in Senegal. Moreover, we unpack heterogeneous effects in relation to income, gender, and educational status.

Furthermore, an important observation from the literature is that studies focusing on the welfare impact of water interventions often overlook the role of suppliers or implementers. The studies rather emphasize the observed improvements in water quality and availability in the users' vicinity. We are not aware of any comparative assessment of the welfare effects of community versus government-led water interventions. Community-led water infrastructure, supplied by NGOs, operates on a limited budget and may charge higher prices if they try to retrieve the investment costs. In contrast, government-led water infrastructure is provided by public water utilities (or their decentralized agencies), which charge lower prices due to economies of scale inherent in large-scale public investment. In turn, the longstanding tradition of a top-down approach to water infrastructure provision, coupled with the failures of centrally planned water interventions, has prompted the exploration of alternatives, such as community-led water infrastructure (Barde, 2017). The latter was expected to yield greater effects due to its participatory nature. Local communities are involved in the design, construction, and management of water projects, which fosters sustainability and community empowerment. Thus, it is key to understand which of water policy is more effective. This is eexactly what we can do by comparing the state-led Emergency Program for Community Development (PUDC) with community-led interventions supplied by private actors and non-governmental organizations (NGOs).

3.3 Theoretical framework

It is expected that access to on the premises tap water increases household welfare that mainly works through three channels: i) time-saving, ii) greater use of water, and iii) productivity gains. Households with indoor tap water have their time constraints alleviated as the drudgery of water collection is removed. The extra time gives these households the possibility to take up off-premises work and initiate income-generating activities. The presence of indoor tap water also allows to access a greater volume of water, thereby facilitating its productive uses. Importantly, the health and education benefits stemming from tap water further enhance productivity gains. All these effects –participation in the labor market, development of income-generating activities,

productivity gains, and more use of water– translate into more income, expenditure, and increased overall welfare. Figure B2 in Appendix B shows the likely pathways between access to water and economic outcomes.

We further formalize the gains in a model of time allocation, which we draw from the work of Koolwal & van de Walle (2013). The model explores the relationships between access to water, time spent on water collection, and economic dynamics; the model further allows to derive the conditions under which the adoption of indoor tap water results in welfare improvements.

We assume a typical household allocates its available time, normalized to unity, to two types of domestic labor $(t_1;\ t_2)$, market wage work (t_3), and leisure $(t_4 = l_4)$. Domestic labor $(t_1;\ t_2)$ is utilized to produce two types of domestic goods $(g_1;\ g_2)$; type 1 is related to water collection and is subject to an exogenous productivity gain, represented by a strictly positive parameter δ. Type 2 covers some additional domestic tasks such as firewood collection, tending to children's health and education, cooking, and washing. These chores are primarily performed by rural women in Senegal.

Market wage work (t_3) is remunerated at a market wage rate of w. The household purchases market-produced goods (g_3) with its total income, which comprises wage income (wg_3) generated by labor work (g_3) at the market wage rate of w, as well as other incomes (y). Assuming that the utility function $(U(.))$ is concave and increasing in the four arguments, g_1, g_2, g_3 and l_4, with diminishing marginal productivity ($U'(.) > 0$ and $U''(.) < 0$), the typical household solves the following maximization problem to derive the Marshallian demand functions for the four goods:

$$Max\ U(g_1, g_2, g_3, l_4) \text{ subject to } t_1 + t_2 + t_3 + l_4 = 1 \tag{1}$$

As the focus here is to unpack how changes in the productivity of type 1 domestic labor affect time allocation and consumption patterns, the typical household solves the following equivalent program: $\mathrm{Max\,U}(\mathrm{g}_1, \mathrm{g}_2, \mathrm{g}_3, \mathrm{l}_4)$ subject to $(\mathrm{w}/\delta)\,\mathrm{g}_1 + \mathrm{wg}_2 + \mathrm{g}_3 + \mathrm{wt}_4 = \mathrm{w} + \mathrm{y}$. Following Koolwal & van de Walle (2013), we define $g_1 = \delta t_1$, $g_2 = t_2$ and $g_3 = wt_3 + y$. The market wage rate (w) captures the relative price of both type 2 domestic labor and leisure, $w + y$ represents the full income while w/δ is the relative price of the type 1 good. The Slutsky decomposition can be derived as follows:

$$\frac{\partial g_i}{\partial(w/\delta)} = \left(\frac{\partial g_i}{\partial(w/\delta)}\right)_{u=\bar{u}} - g_1 \frac{\partial g_i}{\partial(w+y)} \; for\; i = 1,2,3. \qquad (2)$$

Thus, the change in the demand for the type 1 domestic good results from the substitution and the income effect. Assuming that the increase in the productivity of the type 1 domestic good affects its demand only through its relative price, and that type 1 domestic and market goods are normal goods, $(\partial g_i/\partial(w+y) > 0\; for\; i = 1,2,3)$, the consumption of type 1 domestic goods (water collected from outside the premises) increases with its productivity.

Furthermore, if the type 1 good is a complement to both the type 2 domestic and the market good, $(\partial g_i/\partial(w/\delta) < 0\; for\; i = 1,2,3)$, the increase in the productivity of type 1 domestic goods causes domestic and market goods to increase. Under these two conditions, access to indoor piped water increases the productivity of domestic goods, leading households to participate in the labor market and consume more market goods.

Overall, irrespective of the effect on time allocation, including market work, the increased productivity of domestic products unambiguously improves household well-being as long as the type 1 domestic good is valued. However, the expected welfare effects would be compromised if: (1) the time allocated to type 1 domestic goods does not increase with the productivity of type 1 domestic goods; (2) domestic goods are substitutes for market goods (the substitution effect might be superior to the income effect); (3) changes in productivity (δ) affect both income $(w + y)$ and the relative price $(w\;/\;\delta)$. Thus, the welfare effect of access to piped water remains theoretically ambiguous and asks for an empirical examination. We attempt to offer such an examination for the case of Senegal.

3.4 Data and variables

3.4.1 Data

We use a panel dataset consisting of 1,319 households. The baseline data were gathered in 2016, while the follow-up survey was conducted in 2020. The database provides information at both the household level (household composition, agricultural and non-agricultural activities and income, fixed assets, expenditure, food security, health, housing, and access to drinking water) and the village level (encompassing

environment, economy, social life, taxation, and infrastructure). We use the data to evaluate the economic benefits associated with the deployment of water infrastructure within PUDC.

The data collection was undertaken by the Research Centre for Economic and Social Development (CRDES) which employed a two-phase sampling method (CRDES, 2016). In the initial phase, the treatment group was established from the list of PUDC-eligible villages provided by the government to CRDES. Potential control villages encompassed all those that are not present in the list of PUDC-eligible villages. CRDES visited both the eligible treatment and potential control villages, collecting data on economic activities, infrastructure, and population size to develop a comprehensive overview of the villages and to ensure similarity between the potential control villages and the eligible treatment villages. The assessment of similarity was based on a simple comparison test. Essentially, the subgroup of potential control villages that was not statistically different from the eligible treatment villages was classified into the control group (CRDES, 2016).

In the second phase, ten households were selected per village within the treatment and control group. The selection of these ten households was based on a random walk method (CRDES, 2016). Given the dispersed nature of residences in rural Senegal, enumerators were instructed to ensure that selected households fall within the village limits. In cases where the boundaries were ambiguous, guidance was sought from the village chiefs. Data collection was done digitally on the enumerators' phones and tablets with CSPro. The use of electronic questionnaires ensured the quality of the collected data. In each surveyed village, one questionnaire was directed to the chief to assess village characteristics, the ten household questionnaires were administered to the heads of the households. Additional assistance from another two or three household members was sought to enhance the accuracy of the responses.

At baseline, 2,580 households and 270 villages were surveyed. The sample size was determined based on the minimum detectable effect (MDE). The MDE varied between 0.20 and 0.15 for a sample size ranging from 200 to 350 villages (CRDES, 2016). At a sample size of 250 villages no large gains in MDE could be attained anymore. Yet, to mitigate attrition effects, the sample size was increased by 8 percent. As a result, another 20 villages were added resulting in a sample of 270 villages, with 135 control and 135 treatment villages, distributed across 10 regions (i.e., Diourbel, Fatick,

Kaffrine, Kaolack, Kedougou, Louga, Matam, Sain-Louis, Tambacounda, Thiès). Figure B3 in Appendix B visualizes the geographical spread of treatment and control villages represented by green and red dots, respectively. Regions surveyed in both rounds are highlighted in bold. At follow-up, only seven regions (Diourbel, Fatick, Kaffrine, Kaolack, Louga, Saint-Louis, and Thiès) were covered due to financial constraints (CRDES, 2016). In total, 1,500 households across 163 villages, with 74 target villages and 89 control villages, were revisited during the follow-up survey (CRDES, 2021). A graphically representation of the study set up is shown in Figure B4 (Appendix B).

Undoubtedly, the reduction in sample size from 2,580 to 1,500 households during the follow-up survey may introduce attrition bias since the three dropped regions are more remote compared to the resurveyed regions and likely to be systematically different. We assess attrition formally in Appendix D. We identify significant differences between attrited and non-attrited households that are largely driven by village characteristics. To account for attrition, we resorted to matching techniques to obtain a comparable sample, resulting in the exclusion of 134 observations of which 38 participated in both survey rounds and 96 only in the baseline survey. The careful examination of attrition allowed us to reduce any possible bias to its minimum as shown by Table D4 in Appendix D. Moreover, the analysis supported our field-related knowledge that differences largely stem from remoteness and are introduced by the decision not the resurvey three regions and not by non-responses. We are therefore confident that we can handle the threats posed by sample attrition and that the resulting estimates are rather lower bounds of the effects (for more details see Appendix D).

Furthermore, we observe that some villages already had access to improved water before the intervention. These are the non-PUDC areas, and the water infrastructure being used is termed community-based water infrastructure as discussed earlier in the paper. This study setup requires a careful cleaning of the database. We dropped the 38 households identified by the attrition analysis as off the common support, resulting in a sample of 1,406 households distributed as follows: 949 had access to piped water in 2016 and 2020, 237 had access to piped water only in 2020, 133 did not have access to piped water in 2016 or 2020, 65 had access to tap water in 2016 and no longer had access to it in 2020, and for 22 households information about access to water was missing.

Given the data structure, two treatment groups are defined. The first treatment group (T_1) comprises 237 households that had access to tap water only in 2020, thus no access in 2016 (during the baseline). These households sourced their drinking water from the government-led water program under PUDC. The second treatment group (T_2) includes 949 households that had access to piped water in both survey rounds from community-led water services. The control group consisted of 133 households that did not have access to piped water in both surveys. The other 87 (65+22 households) observations have been dropped, resulting in a final sample size of 1,319 households observed in 2016 and 2020. Qualitative surveys and discussions with Senegalese policymakers and officials in charge of implementing the PUDC program support our stratification into the two treatment groups. Table E1 in Appendix E summarizes the data structure.

The treatment categorization into T_1 and T_2 was determined based on the information provided by the households regarding the type of water source they use. Senegalese households in rural areas get their water from various sources such as tap water on the premises, tap water from neighboring households, communal and public tap water, protected wells, and non-protected wells (Appendix B, Figure B5). Households with access to tap water are included in the treatment groups, while households consuming water from protected and non-protected wells constitute the control group. The terms "protected" and "unprotected" refer to underground water sources that do not originate from the extension of water supply pipelines. Households relying on other sources, such as water sellers and streams, were not considered in the study due to data limitations.

Being the primary water source for households in Senegal (ANSD, 2021), tap water is considered safe for drinking purposes (Jalan & Ravallion, 2003); it is potable water. Tap water is drinkable since taps are typically located inside or near the home (within 5 to 10 meters), thus minimizing bacterial contamination that may occur during the transportation of water (in open and unprotected buckets) over long distances. Additionally, having a water connection at home ensures access to drinking water in sufficient quantities, enabling rural households to fulfill their hygiene needs (Ahankari et al., 2021). In turn, underground water tends to be contaminated rendering it unsuitable for consumption (Rango et al., 2012). To illustrate, the level of unhealthy substances (salt, iron, and fluoride) in Senegalese underground water is estimated to exceed the acceptable limits set by the World Health Organization (USAID & SWP,

2021, p.5). Hence, we only consider tap water as potable water that is safe for consumption.

3.4.2 Main outcomes

The primary outcomes under consideration in this article are the logarithm of household expenditure per capita, expressed in the local currency (Franc CFA), and the proportion of employed household members. Household expenditures represent consumption expenditures over the four months preceding the surveys. Initially recorded on a quarterly basis, we transformed these expenditures into an equivalent annual figure by multiplying them by a factor of three. Subsequently, we calculated expenditures per capita by dividing the total expenditures by the household size and then took the logarithm of the result. The components of household expenditures consist of both food and non-food expenditures. Non-food expenditures include expenses for education, health, clothing, transportation, housing, construction, repairs, celebrations, and miscellaneous items (such as tobacco, alcohol, and gifts). We examine total household expenditure, as well as food and non-food expenditure, expressed in per capita terms.

A scholarly debate exists about the choice between expenditure and income as proxy for measuring household well-being. Deaton (1997) argues that expenditure is a superior indicator of household welfare compared to income, especially in the context of household surveys in developing countries. This preference arises because individuals may not fully disclose all their income during surveys (Meyer & Sullivan, 2011). Therefore, income-related information tends to be considered incomplete (Adams, 2018; Tirumala & Tiwari, 2022). For this reason, we opt for expenditure as a proxy for household well-being.

During the surveys, household members were asked whether they were employed or not. If yes, it was asked in which sector they worked. Responses classify respondents as self-employed, public servants, or private sector employees. Occupational sectors were further classified into the agricultural and non-agricultural sector, the latter encompassing mining, manufacturing, education, health, and services. Based on this information we identify the employment status within the household by calculating the ratio of employed household members to the total household size, representing the share of household members with jobs in the week leading up to the surveys. Importantly, in this context, employment does not exclusively refer to formal job contracts or formal

employment, as commonly understood in developed countries. Rather, it captures any form of occupation, whether formal or informal, as most rural workers engage in informal sector activities.

The primary economic outcomes considered are the logarithm of household expenditure per capita (both total and categorized into food and non-food expenditures) and the proportion of employment (comprising total, agricultural, and non-agricultural employment). Descriptive statistics for the main outcomes are presented in Tables 3.1 and 2 (Panel A) for PUDC-access (T_1) and community-led access (T_2), respectively, comparing the treatment groups, T_1 and T_2, to the control group. In Column 4 of Table 3.1, no statistically significant differences in mean outcomes are observed in 2016 for the eventual PUDC beneficiaries compared to the control group. However, in Column 8 of the same table, statistically significant differences emerge in the means of food expenditure per capita, the share of agricultural employment, and the share of total employment in 2020 after PUDC water access has been provided. This suggests that households that received treatment T_1 were initially comparable to the control group but diverged later, showing in the 2020 significant differences.

Moving to Table 3.2, Column 4 indicates significant differences in mean expenditure per capita (total, agricultural, and non-agricultural) already in 2016 as these households had already access to improved water in 2016. The significant difference persists in 2020, except for per capita non-food expenditure, which becomes insignificant.

Overall, these descriptives show that households who have access to potable drinking water (either treatment T_1 or T_2) had, on average, higher per capita total and food expenditure in 2020 compared to the control group. The share of agricultural and total employment was greater for households that received treatment T_1 in 2020. Yet, there is no employment difference in 2020 for households under treatment T_2 compared to the control group.

Table 3-1. Outcomes and observable characteristics by access to piped water status (T1)

	Treatment T1: Households that adopted piped water in 2020							
	2016				**2020**			
	Control group	**Treatment group**	**Total sample**	Δ	**Control group**	**Treatment group**	**Total sample**	Δ
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A. Outcome variables								
Log. Food expenditure per capita	10.82	10.86	10.85	0.043	10.78	10.91	10.86	0.129*
	(0.079)	(0.045)	(0.04)	(0.084)	(0.076)	(0.057)	(0.046)	(0.097)
Log. Non-food expenditure per capita	9.289	9.198	9.231	-0.090	9.949	9.998	9.974	0.039
	(0.128)	(0.101)	(0.079)	(0.166)	(0.087)	(0.076)	(0.058)	(0.120)
Log. Total expenditure per capita	11.12	11.15	11.14	0.029	11.21	11.31	11.27	0.093
	(0.076)	(0.050)	(0.042)	(0.088)	(0.071)	(0.055)	(0.043)	(0.091)
Share of agricultural employment	0.072	0.055	0.061	0.016	0.098	0.156	0.135	0.057***
	(0.011)	(0.007)	(0.006)	(0.012)	(0.012)	(0.014)	(0.010)	(0.021)
Share of non-agricultural employment	0.080	0.088	0.086	0.008	0.086	0.091	0.089	0.005
	(0.009)	(0.007)	(0.005)	(0.012)	(0.011)	(0.007)	(0.006)	(0.013)
Share of total employment	0.124	0.125	0.125	0.001	0.233	0.282	0.264	0.049**
	(0.012)	(0.008)	(0.007)	(0.014)	(0.022)	(0.016)	(0.013)	(0.027)
Panel B. Characteristics of households and villages								
Log. Household size	2.399	2.397	2.398	-0.002	2.356	2.438	2.409	0.082*
	(0.035)	(0.031)	(0.023)	(0.049)	(0.039)	(0.031)	(0.024)	(0.051)
Share of women	0.638	0.647	0.643	0.009	0.480	0.451	0.461	-0.029
	(0.045)	(0.037)	(0.029)	(0.060)	(0.022)	(0.015)	(0.012)	(0.026)
Share of children	0.280	0.276	0.277	-0.004	0.039	0.031	0.034	-0.008
	(0.028)	(0.021)	(0.017)	(0.035	(0.004)	(0.031)	(0.002)	(0.005)
Age of household head (HH)	52.53	50.61	51.32	-1.911	58.03	58.77	58.50	0.746
	(1.161)	(0.867)	(0.695)	(1.442)	(1.098)	(0.955)	(0.727)	(1.519)
Sex of HH (Male=1; Female=0)	0.976	0.972	0.974	-0.003	0.961	0.943	0.950	-0.017
	(0.013)	(0.010)	(0.008)	(0.017)	(0.017)	(0.015)	(0.011)	(0.024)
HH is educated (Yes=1; No=0)	0.109	0.090	0.097	-0.018	0.124	0.121	0.122	0.003
	(0.027)	(0.019)	(0.015)	(0.033)	(0.029)	(0.021)	(0.017)	(0.036)
Roof material (1=Cement, corrugated iron and tiles; 0= Other non-modern material),	0.421	0.371	0.389	-0.050	0.511	0.594	0.564	0.083
	(0.043)	(0.032)	(0.026)	(0.054)	(0.043)	(0.031)	(0.025)	(0.053)
Wall material (1=Cement, 0=Not cement)	0.398	0.266	0.315	-0.131**	0.421	0.459	0.436	0.038
	(0.043)	(0.029)	(0.024)	(0.051)	(0.042)	(0.032)	(0.025)	(0.053)
Toilet type (1=Flush toilet; 0=Pit toilet).	0.226	0.194	0.206	-0.031	0.338	0.379	0.364	0.041
	(0.037)	(0.026)	(0.021)	(0.045)	(0.041)	(0.031)	(0.025)	(0.052)
Log. Village population	5.930	6.324	6.180	0.393***	6.722	6.395	6.514	-0.327***
	(0.073)	(0.061)	(0.048)	(0.097)	(0.078)	(0.069)	(0.053)	(0.111)
Distance to the main road (km)	6.860	13.74	11.21	6.882***	6.528	7.050	6.862	0.522
	(0.849)	(1.041)	(0.750)	(1.514)	(0.569)	(0.606)	(0.438)	(0.915)
Distance to market (km)	6.652	6.162	6.342	-0.489	42.01	15.88	25.27	-26.12***
	(0.423)	(0.278)	(0.234)	(0.487)	(10.76)	(4.229)	(4.759)	(9.838)
Distance to the nearest health center (ordered)	2.234	2.352	2.309	0.118	2.751	2.966	2.888	0.214***
	(0.065)	(0.060)	(0.045)	(0.094)	(0.067)	(0.056)	(0.043)	(0.090)

Note: * p < .10, ** p < .05, *** p < .01. Robust standard errors are indicated in brackets. Δ represents the average outcomes of households with access to tap water (along with average observable characteristics) minus the average outcomes of households that consume underground water (along with average observable characteristics).

3.4.3 Observable characteristics

In addition to the outcomes of interest, the study incorporates observed characteristics at both household and village levels. Household-specific characteristics include household size, the proportion of women, the percentage of children under five years, the age of the household head (HH), the gender of the HH, the literacy status of the HH, and housing conditions, as indicated by the wall material, roof material, and type of toilet. Village-specific characteristics cover the population size, distance to the market, distance to the nearest health center, and distance to the main roads. The rationale behind the selection of these variables is provided in Appendix F – all are motivated by the existing literature.

Panel B of Tables 3.1 and 3.2 accounts for observable heterogeneities between treatment groups (T_1 and T_2) and the control group. Observed village characteristics show significant differences at baseline and follow-up in most cases. At the household level, households in the treatment group T_1 are statistically similar to households in the control group in both survey rounds, as shown in Columns 4 and 8 of Table 3.1 (Panel B). There are only two exceptions; treated households were more likely to have a cemented wall in 2016 and a larger size in 2020 compared to households in the control group. Table 3.2 presents the observed heterogeneities for treatment T_2 showing that at the household level most characteristics are significantly different from the control group at baseline and follow-up.

These observable differences highlight the need for a careful identification strategy that accounts for these pre-treatment heterogeneities between households that use tap water and households that do not. We turn to the empirical identification in the next section.

Table 3-2. Outcomes and observable characteristics by access to piped water status (T2)

	Treatment T2: Households that adopted piped water both in 2016 and 2020							
	2016				2020			
	Control group	Treatment group	Total sample	Δ	Control group	Treatment group	Total sample	Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Outcome variables								
Log. Food expenditure per	10.82	10.93	10.92	0.112*	10.78	10.95	10.93	0.172**
capita	(0.079)	(0.062)	(0.024)	(0.077)	(0.076)	(0.030)	(0.028)	(0.087)
Log. Non-food expenditure	9.289	9.583	9.558	0.304**	9.949	9.934	9.936	-0.015
per capita	(0.128)	(0.046)	(0.044)	(0.138)	(0.087)	(0.041)	(0.037)	(0.113)
Log. Total expenditure per	11.12	11.32	11.30	0.194***	11.21	11.35	11.33	0.128*
capita	(0.076)	(0.026)	(0.025)	(0.078)	(0.071)	(0.028)	(0.026)	(0.081)
Share of agricultural	0.072	0.054	0.056	-0.018	0.098	0.097	0.098	-0.0007
employment	(0.011)	(0.003)	(0.003)	(0.011)	(0.012)	(0.005)	(0.004)	(0.015)
Share of non-agricultural	0.080	0.091	0.090	0.010	0.086	0.091	0.091	0.005
employment	(0.009)	(0.003)	(0.003)	(0.010)	(0.011)	(0.004)	(0.003)	(0.011)
Share of total employment	0.124	0.124	0.124	0.0004	0.233	0.216	0.218	-0.017
	(0.012)	(0.004)	(0.004)	(0.013)	(0.022)	(0.007)	(0.007)	(0.021)
Panel B. Characteristics of households and villages								
Log. Household size	2.399	2.428	2.425	0.028	2.356	2.472	2.458	0.116***
	(0.035)	(0.015)	(0.014)	(0.045)	(0.039)	(0.015)	(0.014)	(0.044)
Share of women	0.638	0.630	0.631	0.007	0.480	0.476	0.477	0.004
	(0.045)	(0.018)	(0.017)	(0.054)	(0.022)	(0.007)	(0.007)	(0.022)
Share of children	0.280	0.243	0.248	-0.037*	0.039	0.033	0.033	-0.006*
	(0.028)	(0.009)	(0.008)	(0.027)	(0.004)	(0.001)	(0.001)	(0.004)
Age of household head (HH)	52.53	52.66	52.66	0.156	58.03	59.60	59.41	1.579
	(1.161)	(0.447)	(0.420)	(1.301)	(1.098)	(0.446)	(0.414)	(1.256)
Sex of HH (Male=1;	0.976	0.949	0.953	-0.027*	0.961	0.933	0.936	-0.028
Female=0)	(0.013)	(0.007)	(0.006)	(0.020)	(0.017)	(0.008)	(0.007)	(0.023)
HH is educated (Yes=1;	0.109	0.110	0.110	0.001	0.124	0.087	0.092	-0.036
No=0)	(0.027)	(0.010)	(0.001)	(0.029)	(0.029)	(0.009)	(0.009)	(0.027)
Roof material (1=Cement, corrugated iron and tiles; 0=	0.421	0.558	0.542	0.136***	0.512	0.09	0.684	0.197***
Other non-modern material),	(0.043)	(0.016)	(0.015)	(0.046)	(0.043)	(0.014)	(0.014)	(0.042)
Wall material (1=Cement,	0.398	0.458	0.451	0.059	0.421	0.565	0.548	0.144***
0=Not cement)	(0.043)	(0.016)	(0.015)	(0.046)	(0.042)	(0.016)	(0.015)	(0.045)
Toilet type (1=Flush toilet;	0.226	0.359	0.343	0.132***	0.338	0.456	0.441	0.117***
0=Pit toilet).	(0.037)	(0.015)	(0.014)	(0.044)	(0.041)	(0.016)	(0.015)	(0.045)
Log. Village population	5.930	6.560	6.485	0.629***	6.722	6.494	6.523	-0.228***
	(0.073)	(0.032)	(0.030)	(0.093)	(0.078)	(0.033)	(0.030)	(0.092)
Distance to the main road	6.860	10.35	9.940	3.495***	6.528	11.11	10.55	4.586***
(km)	(0.849)	(0.472)	(0.429)	(1.323)	(0.569)	(0.486)	(0.435)	(1.318)
Distance to market (km)	6.652	5.315	5.474	-1.337	42.01	27.12	28.95	-14.88*
	(0.423)	(0.178)	(0.165)	(0.510)	(10.76)	(2.865)	(2.841)	(8.647)
Distance to the nearest health	2.234	2.002	2.029	-0.232	2.751	2.815	2.807	0.064
center (ordered)	(0.065)	(0.025)	(0.024)	(0.074)	(0.067)	(0.028)	(0.026)	(0.080)

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors are indicated in brackets. Δ reflects the mean outcomes of households with access to piped water (along with average observable characteristics) minus the mean outcomes of households that consume underground water (along with average observable characteristics).

3.5 Methodology

3.5.1 Addressing selection bias

We denote Y_{1i} the outcome – either employment or expenditure – of household i with tap water ($T_i = 1$) and Y_{0i} the outcome of household i without it ($T_i = 0$). If both states Y_{1i} and Y_{0i} were known, the effect of access to water would be $\Delta Y = Y_{1i} - Y_{0i}$. In reality, both states cannot be observed. For the same household i only one state is observable: either Y_{1i} for households that use tap water or Y_{0i} for households that are not connected to water infrastructure. Therefore considering ΔY as the impact of access to tap water on household i is a biased estimate as Y_{0i} is a contrefeit conterfactual for Y_{1i}. The average effect would be $AE = E(Y_{1i}|T_i = 1) - E(Y_{0i}|T_i = 0)$. By adding and subtracting $E(Y_{0i}|T_i = 1)$ to AE – another way of estimating the counterfactual – the average effect becomes $AE = E(Y_{1i}|T_i = 1) - E(Y_{0i}|T_i = 0) + E(Y_{0i}|T_i = 1) - E(Y_{0i}|T_i = 1)$. With such transformation, the average effect (AE) has two components: the average treatment effect (ATE) which is $E(Y_{1i}|T_i = 1) - E(Y_{0i}|T_i = 1)$ and the selection bias which is $E(Y_{0i}|T_i = 1) - E(Y_{0i}|T_i = 0)$. The bias stems from the fact that the outcomes of the untreated households are different in both states, implying that $E(Y_{0i}|T_i = 1) \neq E(Y_{0i}|T_i = 0)$. Thus, the potential sources of selection bias need to be explored to provide an appropriate identification strategy.

The process of program placement and the household decision to connect to tap water determine the extent of selection bias. Utility infrastructure tends to be supplied endogenously in developing countries. Government agencies typically deploy rural infrastructure after careful consideration of intrinsic characteristics in the treatment areas, such as proximity to a city, political ties, and institutional structures (Grogan, 2016; Khandker et al., 2014; Ortiz-Correa et al., 2016). Previous evidence has emphasized the non-random placement of hydraulic equipment (Choudhuri & Desai, 2021; Gamper-Rabindran et al., 2010; Jalan & Ravallion, 2003). The argument often put forward is that policymakers build hydraulic infrastructure in areas already equipped with sanitary facilities (Jalan & Ravallion, 2003) and in poor and vulnerable areas, especially when aiming to close inequality gaps (Gamper-Rabindran et al., 2010). Government officials are likely to extend water infrastructure to densely populated areas to guarantee high economies of scale (Barde, 2017). Furthermore, remoteness is also a key determinant of water infrastructure placement or rather non-placement. The

high costs associated with the extension of water infrastructure to remote areas motivate the preference for areas closer to urban zones. All these characteristics that affect water infrastructure are observable by their very nature and can be controlled. Yet, unobserved characteristics at the village or community level may also influence the construction of water plants. These are often referred to as omitted variables that may simultaneously affect community development outcomes and treatment status.

The decision of households to connect to water infrastructure is endogenous as well. After the provision of hydraulic infrastructure, households decide whether or not to use it based on several variables, either observed or unobserved. Households' financial capacity (income) and educational level are key predictors of connection to water pipelines (Rahut et al., 2015; Adams et al., 2016). As both variables (education and income) may jointly influence the adoption of potable drinking water and households' well-being, they emerge as potential confounders in assessing the true effect of adequate drinking water on welfare outcomes. The size of the household and its composition are also crucial factors for households' access to adequate sources of drinking water (Adams et al., 2016; Arouna & Dabbert, 2010; Tshililo et al., 2022). Additionally, the households' ability to assess the advantages of having an improved water source on the premises and their preferences regarding health and time savings, are unobserved confounders (Rahut et al., 2015; Adams et al., 2016; Ortiz-Correa et al., 2016).

To ensure exogenous variability in treatment assignment, both randomized assignment and randomized promotion are often employed (Winter et al., 2021; Devoto et al., 2012). Randomizing infrastructure placement and household access to water would remove selection bias. In the absence of randomization, instrumental variables help correct selection bias. Ortiz-Correa et al. (2016) have instrumented access to potable water with a geophysical variable (measuring water availability) and the number of rivers in the village. Zhou & Turvey (2018) instrumented access to water with exogenous variabilities of irrigated land and hydro-geological traits. In cases where adequate instruments, satisfying the exclusion restriction and relevance assumptions, are not readily available, researchers have employed different empirical strategies to mitigate selection. These empirical strategies include propensity score matching (PSM) (Choudhuri & Desai, 2021; Jalan & Ravallion, 2003; Manalew & Tennekoon, 2019; Novak, 2014), the combination of PSM and the difference-in-difference approach

(Klasen et al., 2012; Lokshin & Yemtsov, 2003; Viet & Vu, 2013), and panel data quantile regression (Gamper-Rabindran et al., 2010). This paper addresses potential threats from selection bias by using PSM and DiD. Wee further complement it with quantile regressions.

3.5.2 Empirical strategies for access to non-PUDC water infrastructure (T2)

The empirical strategies employed in this article depend on the structure of our data and the type of treatment considered. For treatment T_2 , we mainly resort to propensity score matching (PSM) to estimate the mean impact of access to tap water. We further use it to account for the high rate of attrition bias (refer to Appendix D). PSM is applied both to baseline and follow-up data. The PSM approach addresses the selection bias by determining a statistical counterfactual based on three steps. First, propensity scores are determined using the Logit model: $P_i\ (T = 1) = \beta_0 + \beta_1' X_{i,j} + \beta_2' V_{i,j} + U_{i,j}$. The model estimates the probability that a household has access to clean and potable water. This probability is a function of the observable variables at the level of the household (X) and the village (V), and the non-observable variables measured by the idiosyncratic error term ($U_{i,j}$). Second, the predicted probabilities are used to match households from the treatment and control group. In the third and final step, considering that matched household pairs are identical from the point of view of observable variables, the mean impact of the program (λ_{PSM}) is calculated by taking the difference between the average outcome of the treatment group and that of the matched control group:

$$\lambda_{PSM} = \frac{1}{N} \left[\sum_{i \epsilon T} Y_i^T - \sum_{j \epsilon C} \Gamma(i,j)\, Y_j^C \right], \tag{3}$$

where $\Gamma(i,j)$ represents the weight used by the Kernel matching algorithm, Y_i^T the outcome of household i of the treatment group, Y_j^C the outcome of household j in the matched control group and N the size of the treatment group.

To test the robustness of the PSM results, the IPW estimator is used. This estimator allocates a different weight to the outcome in the treatment and control group so that both groups have similar observable characteristics. Outcome (Y_i) is weighted by $1/P\ (X)$ in the treatment group and by $1/(1 - P(X))$ in the control group. The average treatment effect (ATE_{IPW}) is then given by

$$ATE_{IPW} = \frac{1}{N}\sum_{i=1}\left(\frac{T_i \times Y_i}{P_i(X)} - \frac{(1-T_i)\times Y_i}{1 - P_i(X)}\right), \tag{4}$$

where N is the size of the matched control group.

Finally, we use quantile regression to assess the distributional effects of access to water services. Let Q^{τ}_{YT} and Q^{τ}_{Y1-T} be the total expenditure per capita for quantile τ for treated (T) and non-treated households (1-T), respectively. For τ=0,50, the average effect of this quantile measures the outcome difference of the 50th quantile between households that have access to clean water services and households in the control group. The impact of access to water in quantile τ is estimated based on the Firpo's (2007) quantile estimator:

$$\Delta^{\tau} = Q^{\tau}_{YT} - Q^{\tau}_{Y1-T} \tag{5}$$

3.5.3 Empirical strategies for access to non-PUDC water infrastructure (T2)

For the treatment group T_1, the PSM–DiD approach is used exploiting temporal variation in treatment as the households in treatment group T_1 gained access to clean water services only after the program was implemented (Heckman, Ichimura & Todd, 1997). The PSM estimator is invalid if treatment is affected by unobserved variables (innate capacities, aptitudes, and preferences). The PSM-DiD approach minimizes bias resulting from time-invariant unobserved traits and simultaneity bias that could emanate from the bi-directional causality between treatment and outcome (Ding et al., 2018). The following Equation is estimated on the matched sample to captures the average treatment effect:

$$Y_{ijt} = \lambda_0 + \lambda_1 t + \lambda_2 T_{1ijt} + \beta_1' X_{ij} + \varepsilon_{ijt}, \tag{6}$$

where Y_{ijt} represents the outcome variable, $X_{i,j}$ the vector for observed characteristics, t the binary time variable equal to 1 for the follow-up and 0 for the baseline survey, T_{1ijt} the treatment variable (T_1) for a household i in village j at time t and ε_{ijt} the idiosyncratic error term. β_1' and λ_i ($i = 1, \ldots, 5$) are parameters to be estimated. λ_0 measures the average outcome of the control group, λ_1 measures the average temporal

difference in outcomes between the baseline and follow-up, λ_2 is the average effect of access to tap water that we are mainly interested in.

As highlighted above, a factual reality of rural areas of developing countries is that women and children spend a great share of their time in firewood collection and water fetching when they lack both indoor sources of drinking water and electricity. Both domestic activities are onerous for rural households as they take away time from income-generating activities and affect intra-household allocation of resources (Choudhuri & Desai, 2021). As electricity and piped water are not substitutes, households still face a time burden if they only access one resource, either piped water or electricity. In that regard, access to electricity is expected to strengthen the expected gains from access to indoor piped water. In the theory of infrastructure-led development, one of Agénor's (2010) perspectives is that limited gains from infrastructure found in developing countries is driven not only by poor quality of infrastructure but also by their incompleteness. An instance of incomplete infrastructure is having good electricity and water infrastructure, but a poor road infrastructure. Given that the components of the infrastructure network complement each other, the joint availability of basic infrastructure is expected to generate bigger gains (Agénor, 2010). Therefore, we interact access to road infrastructure with piped water. Access to road infrastructure also facilitates access to the market and eases economic exchange, contributing to enhancing the expected benefits from piped water infrastructure. To account for the interactions of access to a bundle of infrastructure services, we introduce two additional variables in Equation 6 that capture access to electricity (E_{ijt}) and access to road infrastructure (D_{ijt}). E_{ijt} is equal to 1 if the household has access to electricity and 0 if it does not, D_{ijt} is the distance between the household and the closest main road. We interact these infrastructure variables with the treatment variable to estimate the average effect of access to tap water in electrified households and the average effect of access to tap water conditional upon the distance between the household and the closest main road.

To estimate the welfare impact of access to indoor tap water across the distribution of total expenditure, we employ a difference-in-differences (DiD) quantile regression (QTE^{DD}).

3.6 Main Results

3.6.1 Determinants of access to potable water

We start the discussion of the results by introducing the determinants of access to potable water. Table 3.3 presents the outcomes of the Logit models for treatments T_1 (Column 1) and T_2 (Column 2). In line with the earlier discussed attrition, we observe that village characteristics are the key determinants of access to potable water in both PUDC and non-PUDC villages. The coefficient associated with village size is as expected – positive and significant. Larger villages (in terms of population size) have a higher likelihood that households are connected to piped water, confirming the strategic placement of hydraulic infrastructure in sizable communities to ensure favorable returns on investments (Barde, 2017).

In contrast, the distance to the market exhibits a negative correlation with access to adequate drinking water, while the distance to the main road shows a positive correlation with access to potable water. The unexpected positive sign for the distance to the main road may be explained by the fact that in the case of the PUDC the water intervention targeted remote areas for placing the water infrastructure to expedite universal access to potable water and contribute to the achievement of SDG6.

In contrast to village characteristics, the relationship between household characteristics and access to potable water varies depending on the treatment. For households under treatment T_1, the age of the household head (HH) is negatively and significantly correlated with access to potable water. This negative coefficient can be explained by our definition of access to potable water, which predominantly involves public taps located outside households' residences. Households with older heads may not fetch water from a distant place and are thus less likely to access public taps. This finding aligns with Boone et al. (2011), who reported a negative and significant correlation between access to public taps and the age of the HH. For households under treatment T_2, the age of the HH is not found to be significant.

Table 3-3. Logit model results

	Treatment T_1	Treatment T_2
	Households with piped water in 2020 only	**Households with piped water in 2016 and 2020**
	Estimation technique: Logit model	
	(1)	(2)
Log. Household size	0.104	-0.026
	(0.362)	(0.259)
Share of women	0.093	-0.020
	(0.437)	(0.197)
Share of children	-0.184	-
	(0.680)	
Age of household head (HH)	-0.145*	-0.081
	(0.080)	(0.057)
Sex of HH (Male=1; Female=0)	-8.130	-4.866
	(4.52)	(3.365)
Age of HH×sex of HH	0.137*	0.078
	(0.080)	(0.057)
HH is educated (Yes=1; No=0)	-0.180	-0.466
	(0.412)	(0.331)
Roof material (1=Cement, corrugated iron and tiles; 0= Other non-modern material),	0.574*	0.790***
	(0.323)	(0.261)
Wall material (1=Cement, 0=Not cement)	-0.855***	-0.617***
	(0.322)	(0.263)
Toilet type (1=Flush toilet; 0=Pit toilet).	-0.002	0.567**
	(0.319)	(0.256)
Log. Village population	0.587***	0.756***
	(0.139)	(0.119)
Distance to the main road (km)	0.046***	0.035***
	(0.011)	(0.011)
Distance to market (km)	-0.053*	-0.063***
	(0.027)	(0.019)
Distance to the nearest health center (ordered)	0.042	-0.199
	(0.161)	(0.130)
Constant	5.029	2.613
	(4.588)	(3.448)
Total observations	370	1082
Treatment group observations	237	949
Control group observations	133	133
LR chi^2	62.22	96.12
Pseudo R^2	0.13	0.12

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors are denoted in brackets. The share of children was not adjusted for due to its lack of balance across both groups (treatment and control), exhibiting a bias close to 10%.

The housing conditions, including roof and wall materials and toilet type, play a crucial role in determining access to potable water. For households under treatment T_2, those using flush toilets are more likely to have access to potable water. This aligns with prior

research findings by Adams (2018) and Irianti et al. (2016). Irianti et al. (2016) identified for Indonesian data that households using improved toilets are more likely to have access to improved drinking water compared to those without toilet facilities. Similarly, Adams (2018) reported that households with improved toilet facilities allocate a higher percentage of income to water expenditure. Table 3.3 further illustrates that access to water is positively correlated with roof material and negatively correlated with wall material, regardless of the water supplier (PUDC or non-PUDC). The unexpected negative correlation with wall material may be attributed to the fact that having a cemented house is not necessarily an indicator of wealth compared to possessing a flush toilet or a roof made of tiles.

For both treatments, household size, composition (share of children and women), gender of the household head (HH), and literacy status of the HH are not found to be significant determinants of access to quality water. These findings indicat that these observable characteristics are well balanced across the treatment and control groups. Similar results have been reported by previous studies. For instance, Abubakar (2019) and Rahut et al. (2015) found no significant correlation between household size and access to piped water or public taps. Adams (2018) and Dhin Etia et al. (2022) even reported a negative correlation. While the need for a greater quantity of water may encourage larger households to adopt drinking water, the financial constraints of larger households may discourage them, as increased household size correlates with higher water expenditure. This balancing act between opposing forces may further explain the insignificant correlation between household size and access to drinking water. Similarly, and in line with Adams (2018) and Tshililo et al. (2022), the education level of the HH is not significantly correlated with access to drinking water. Like our findings, Arouna and Dabbert (2010) and Gebremichael et al. (2021) highlighted that the gender of the HH is not significantly correlated with access to drinking water in rural Ethiopia. The lack of correlation observed in our findings may be explained by the fact that we consider access to tap water in general without distinguishing between private and public taps. For instance, Briand et al. (2009) documented that female-headed households are more likely to obtain water from indoor pipes than from public taps in Dakar (Senegal). Similar results were reported by Briand and Loyal (2017) for Bamako (Mali).

In short, housing conditions, age of the HH, population size, and village remoteness emerge as significant determinants of a households' access to potable water implying that access to tap water is not exogenous, as highlighted in the literature. The observable characteristics identified as correlates of access to tap water may also be directly related to factors that affect the economic outcomes of interest, confounding the true impact of tap water. Therefore, careful analysis is required to reduce bias.

3.6.2 Distributions of propensity scores by treatment status

Figures 3.1 and 3.2 illustrate the distribution of propensity scores based on treatment status (T_1 and T_2) before the matching process. In Figure 3.1, the propensity scores of the control group are compared to those of the first treatment group (T_1), representing households connected to PUDC water infrastructure. Figure 3.2 presents the distribution of propensity scores of the control group in contrast to the second treatment group (T_2), which comprises households exposed to non-PUDC water infrastructure.

Upon initial observation, these figures reveal that households in the treatment groups do not share the same likelihood of connecting to tap water as the control group. The treatment groups display a higher probability of being connected to tap water compared to the control group. Put differently, the propensity score of the treatment groups is shifted to the right. While there is a common segment in both Figures 3.1 and 3.2 where the propensity score distributions of the control and treatment groups overlap, it is important to note that units outside this shared segment were excluded from the subsequent analysis as households with propensity scores close to one in the treatment group and those with scores close to zero in the control group are not comparable.

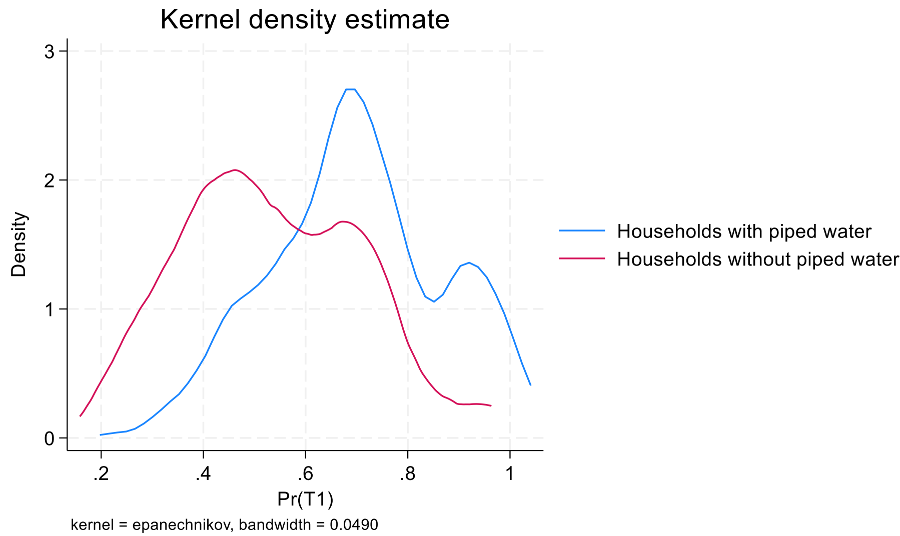


Figure 3-1. Distribution of propensity scores before matching by potable water adoption status (T_1)

Source: Authors, 2023.

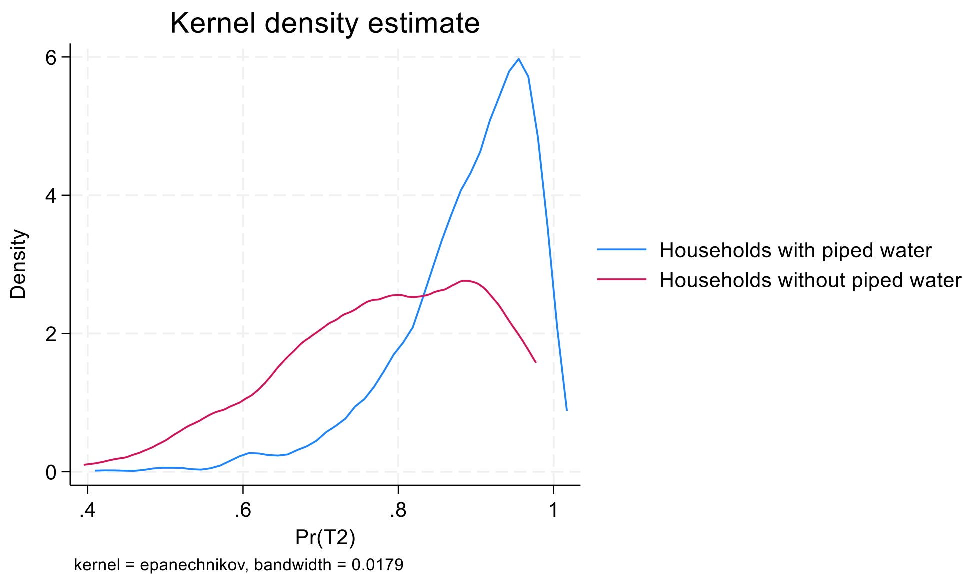


Figure 3-2. Distribution of propensity scores before matching by potable water adoption status (T_2)

Source: Authors, 2023.

Following matching and the exclusion of units outside the common support (as illustrated in Figures B6 and B7, Appendix B), the post-matching distributions of the treatment groups now overlap with that of the control group, supporting the effectiveness of the matching process. The success of the matching procedure is

contingent upon validating the un-confoundedness assumption, a validation that was conducted through a balance test.

The balance test, conducted via the standardized t-test, calculates the standardized bias for each matching variable. Standardized bias, expressed as a percentage of the square root of the average variance of the treated and non-treated households, gauges the extent to which a matching variable is balanced between the treatment and control groups. Minimal bias in a matching variable implies a balanced distribution between the two groups. Results of the standardized t-test are detailed in Tables E2 and E3 in Appendix E for treatments T_1 and T_2, respectively. These tables reveal a substantial reduction in bias after matching. The only exception is the distance to the main road that remains unbalanced in treatment T_1, while both the distance to the main road (in kilometers) and the proportion of women show imbalance for treatment T_2. However, this slight imbalance is deemed acceptable, as the standardized biases are below five percent (Caliendo & Kopeinig, 2008). A visualization of the standardized bias across covariates is depicted in Figure B8 and B9 of Appendix B (for T_1 and T_2, respectively), further supporting the success of the matching.

Additional diagnostic tests corroborate the bias reduction (Appendix E, Table E4). For treatment T_1, bias decreased from 85.1 (in the unmatched sample) to 23.3 (in the matched sample). Likewise, for treatment T_2, bias dropped from 79.4 to 14.2. The significant reduction in the Pseudo-R^2, approaching zero, serves as an indicator of the effectiveness of the matching process as well. Thus, we are confident that we can credibly employ the matched sample to assess the impact of the two treatments.

3.6.3 Mean impacts of access to tap water on expenditure and employment

3.6.3.1 PUDC water supply infrastructures

We start with the impact estimates using PSM and the inverse-probability weighted (IPW) estimators. Results are presented in Table E5 in Appendix E. Table E5 indicates a positive and statistically significant average treatment effect on the treated (ATT) for both per capita non-food expenditure and the share of agricultural employment. This finding is consistent across PSM and IPW estimates, suggesting that households connected to PUDC-based water infrastructure have experienced an increase in expenditure and agricultural employment. Yet, since PSM and IPW may not be robust

to unobservable characteristics, we prefer the PSM-DiD estimates, which are presented in Table 3.4.

Table 3-4. Estimated impacts of access to PUDC water (T_1) on employment and household expenditure

Outcomes	PSM-DiD					
	Log. Expenditure per capita			Employment share		
	Total	**Non-food**	**Food**	**Total**	**Agricultural**	**Non-Agricultural**
	(1)	(2)	(3)	(4)	(5)	(6)
Access to drinking water	0.164	0.189	0.184	0.064	0.079***	-0.003
(Yes=1; No=0)	(0.126)	(0.221)	(0.127)	(0.031)	(0.028)	(0.018)
Observations	661	618	659	665	538	665
R^2	0.125	0.141	0.143	0.165	0.154	0.04
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Kernel matching	Yes	Yes	Yes	Yes	Yes	Yes

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors are denoted in brackets. Time-invariant temporal effects are captured through a binary variable, taking the value 0 for the baseline round and 1 for the follow-up round.

Upon initial inspection, the results are similar to the IPW estimates, indicating that access to PUDC water supply infrastructure led beneficiary households to enhance both expenditure and agricultural employment. However, the ATT related to expenditure is no longer statistically significant, while the ATT related to agricultural employment remains significant. Moreover, the magnitude of the ATT linked to agricultural employment has increased in size. These differences reveal potential hidden bias primarily driven by unobserved heterogeneities. Taken together, the findings support the notion that access to PUDC water infrastructure (T_1) is associated with increased agricultural employment within households connected to piped water, compared to observationally similar units using water from wells.

The finding that access to potable water increases the proportion of employed household members in the agricultural sector aligns with earlier research by Winter et al. (2021). Access to water services empowers rural households to employ water productively for irrigation, stimulating smallholder farmers to engage in practices that enhance income, such as breeding cattle (Hall et al., 2014; Houweling et al., 2012). Additionally, the availability of on the premises potable water may relax time constraints for women.

To explore the channels of transmission, we examine women's and men’s daily time and monthly water consumption. As this information is available only in the follow-up dataset, we conduct an exploratory analysis with mean comparison tests. The results are detailed in Tables E8, E9, and E12 in Appendix E. Results from Table E8, showing women's time use, indicate significant shifts in their time use. Due to access to water, women’s time spent on water fetching decreases, while the time devoted to sleeping, leisure, gardening, and farming activities significantly increases. Such reallocation of time is not observed among men (Table E9). This is consistent with previous studies indicating that women save time when they no longer have to walk long distances to collect water (Choudhuri & Desai, 2021; Rahut et al., 2015; Winter et al., 2021; Guzmán et al., 2016; Hasan & Gerber, 2016). This extra time creates opportunities for participation in the labor market and the development of income-generating activities (Houweling et al., 2012; Koolwal & van de Walle, 2013).

An outcome of the exploratory analysis is that treated households consumed a greater quantity of water compared to the control group (Appendix E, Table E12). These results concur with findings from Winter et al. (2021) and Briand et al. (2010) who reported significant increases in water consumption. Winter et al. (2021) showed for Zambia that households that accessed tap water increased their water consumption by 32 percent using it for domestic and productive purposes. Predicting water demand functions for Senegal, Briand et al. (2010) found that getting a tap connection induced an expected increase in water use of 26 liters per capita per day.

Overall, the increased quantity of water and time use for purposes other than fetching water represent the primary channels through which access to PUDC tap water affects agricultural employment. It is noteworthy that findings from the current study are contrary to those of Koolwal & van de Walle (2013), Devoto et al. (2012), and Viet and Vu (2013), who found that access to piped water had no significant economic effects.

Next, we present results from incorporating interaction terms. The corresponding estimates are in Table 3.5. The positive coefficient associated with the treatment reinforces the finding that access to tap water is linked to increased agricultural employment. Additionally, the table reveals a positive but statistically insignificant coefficient for the interaction between access to water and access to electricity, regardless of the considered outcome. Among households with access to tap water, those with electricity do not exhibit a more pronounced improvement in well-being

compared to households without electricity. This may be attributed to electricity primarily serving basic functions such as lighting, phone charging, and powering radio and television in rural Senegal. Cooking with electricity is rare, and electrified households still spend time collecting firewood. However, the noteworthy observation is the negative and significant coefficient of the interaction between access to tap water and distance to the main road. The farther households are from main roads, the less they benefit economically from access to tap water. Consequently, road infrastructure plays a pivotal role in enhancing the well-being of households. Road infrastructure facilitates rural households' access to markets and stimulates economic transactions, thus contributing to the improvement of social welfare in rural areas.

Table 3-5. Impacts of access to PUDC water (T_1) on employment and household expenditure – interactions

	PSM-DiD					
Outcomes	**Log. Expenditure per capita**			**Employment share**		
	Total	**Non-food**	**Food**	**Total**	**Agricultural**	**Non-Agricultural**
	(1)	(2)	(3)	(4)	(5)	(6)
Access to drinking water (Yes=1; No=0) [ATT]	0.108 (0.143)	0.145 (0.251)	0.177 (0.143)	0.080** (0.035)	0.108*** (0.032)	-0.014 (0.020)
Access to drinking water × Access to electricity (Yes=1; No=0)	0.078 (0.112)	-0.023 (0.198)	0.080 (0.112)	0.005 (0.028)	-0.023 (0.022)	0.010 (0.016)
Access to drinking water × Distance to the main road (km)	0.007 (0.009)	0.011 (0.017)	-0.001 (0.009)	-0.003 (0.002)	-0.004** (0.002)	0.002 (0.001)
Observations	640	597	638	644	517	644
R^2	0.133	0.150	0.122	0.201	0.165	0.087
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kernel matching	Yes	Yes	Yes	Yes	Yes	Yes

Note: Note: * p < .10, ** p < .05, *** p < .01. The average treatment effects on the treated were estimated by employing a combination of the difference-in-difference method and the propensity score matching technique. Robust standard errors are reported in the brackets. In each estimated equation, observable household characteristics, village characteristics, and time-fixed effects are controlled for. Household observable traits included in the estimations are the age of the household head (HH), the sex of the HH (1=male; 0=female), the education status of the HH (1=Yes, 0=No), the age of women (continuous), the share of children (continuous), the roof material of the house (1=cement, corrugated iron, and tiles; 0=other non-modern materials), the wall material (1=cement, 0=not cement), and the type of toilet (1=flush toilet; 0=pit toilet). Village characteristics include population size, distance to the market (km), distance to the main rural road (km), and distance to the closest health center (ordered). Time-fixed effects are apprehended through a binary variable that takes the value 0 for the baseline round and 1 for the follow-up round.

3.6.3.2 Non-PUDC water supply infrastructure

Next, we examine the economic effects of non-PUDC tap water (T_2). Findings are presented in Tables E6 and E7 in Appendix E. Table E6 provides estimates from PSM and IPW for 2016, and Table E7 displays estimates for 2020, using the same estimation strategies. Table E6 consistently indicates a positive and significant average treatment effect on the treated (ATT) related to per capita non-food expenditure for both the PSM and IPW estimator in 2016. While the ATTs related to per capita total expenditure and food expenditure are significant with PSM, they become insignificant when estimated with IPW. From Table E7 we see that in 2020 only the ATT related to food expenditure is significant for both PSM and IPW. Overall, no clear pattern emerges regarding the effect of treatment (T_2) on household expenditure over the years. Although there was an increase in household non-food expenditure in 2016 and food expenditure in 2020, such an effect is not observed in total expenditure.

Regarding the employment effect of treatment (T_2), Tables E6 and E7 show no significant ATT across all measures of employment for both years, 2016 and 2020. Thus, access to non-PUDC tap water has not led to additional jobs within households. Taken together, we conclude that access to non-PUDC water supply infrastructure has no robust and significant impact on total employment and expenditure.

The ineffectiveness of non-PUDC water supply infrastructure revealed by our findings contrasts with previous works by Bisung & Elliott (2019), who documented that community or non-government-led water interventions are well-being increasing. Similar work reported that non-governmental water interventions lead to increased time and water expenditure savings, which are both kex ingredients to well-being (Devoto et al., 2012; Galiani et al., 2009; Winter et al., 2021). We also expected non-PUDC water infrastructure to enhance household well-being, given that community-led water interventions are often designed as an alternative to government-led water interventions. However, to ensure the provision of water infrastructure to rural households, community-led water interventions utilize financial resources from various stakeholders (the community itself, non-governmental organizations, and external private donors) to build the relevant infrastructure. The lack of financial resources for long-term maintenance of community-led infrastructure, coupled with insufficient community ownership and poor financial resource management, is likely to restrict the

efficacy of non-state water interventions (Humphrey, 2019; Jimenez-Redal et al., 2018; Klug et al., 2017). These factors may well explain the ineffectiveness of non-PUDC water facilities in Senegal. The PUDC water intervention, in contrast, is a large-scale project endowed with a substantial budget, guaranteeing also for the maintenance of the installed infrastructure. Importantly PUDC works with a demand-driven model, installing infrastructure at the request of rural populations, thereby ensuring the efficient and productive use of the installed water supply infrastructure and their maintenance.

The limited effectiveness of non-PUDC water infrastructure is further corroborated by findings from exploratory analyses on tariffs. We compared the average tariff (per cubic meter) across PUDC and non-PUDC water infrastructure and identified a noteworthy difference. The average self-reported tariff paid by households using non-PUDC water is higher than the average self-reported tariff for PUDC water infrastructure, as illustrated in Figure B10 (Appendix B). The elevated tariffs contribute to a reduced quantity of water consumed. We found no significant difference in the average quantity of water consumed on a monthly basis between households connected to non-PUDC water and households in the control group (Appendix E, Table E12). Consequently, it is not surprising that we find that households with non-PUDC water infrastructure still dedicate a considerable amount of time to water collection (Table E10 and E11).

3.6.4 Distributional effects of access to water services

Finally, we turn to distributional effects across the income distribution. the results are presented in Table E13 (Appendix E). Panel A shows the estimates of quantile regressions for treatment T_1, while quantile estimates for treatment T_2 are presented in Panels B and C for the years 2016 and 2020, respectively. In Panel A, we demonstrate that access to PUDC-water has no positive and significant effect across the entire distribution of total expenditure. Yet, a noteworthy impact has been identified in the 7th, 8th, and 9th quantiles for food expenditure, and in the 3rd and 4th quantiles for non-food expenditure. Concerning treatment T_2, the average treatment effect on the treated for access to non-PUDC water is significant from the 4th quantile to the 7th quantile for food expenditure in 2020 (Panel C of Table E13). Similar impacts were not recorded in 2016 (Panel B of Table E13).

To gain a comprehensive understanding of the distributional effects of access to water, we categorize households above and below the 50th percentile of household expenditure. The former represents non-poor households, while the latter stands for poor households. Based on this classification, significant increases in household expenditures are observed among non-poor households as indicated by both Panels A and B of Table E13. This group derived greater economic benefits (in terms of increased expenditure among various sub-groups) from piped water adoption compared to poor households, irrespective of the type of water infrastructure – whether PUDC or non-PUDC.

This contrasts with the expectation that poor households would derive the greatest economic benefits from piped water adoption. The findings from our distributional analysis are contrary to Sekhri (2014), who posited that access to water reduces rural poverty. However, our results align with Beyene et al.'s (2018) perspective, suggesting that if access to water promotes poverty reduction, it does so marginally, as access to water infrastructure alone is insufficient to guarantee a substantial drop in the poverty rate. Additional public investment in road infrastructure is necessary, as emphasized by also by our findings. Jalan and Ravallion (2003) underscored the need for investments in oral rehydration, medical treatment, hygiene, and nutrition, which are often lacking among poor households. Higher maternal educational attainment (Mangyo, 2008) and improved sanitary conditions (Gamper-Rabindran et al., 2010) are also relevant preconditions for the full manifestation of the well-being effects of access to tap water. Additionally, considering that access to water services is not free, poor households' limited financial capacity may be insufficient to cover water connection costs, jeopardizing the expected economic benefits (Carrard et al., 2019). Higher water bills for low-income households can lead to less disposable income for health-related expenditures, introducing an intra-household consumption trade-off that affects social welfare (Cory & Taylor, 2015). In this regard, a pro-poor pricing system within the water sector may be a viable option, contributing to the improvement of welfare for the poor (Ruijs, 2009).

It is worth recalling one of the major caveats of the current study which is the high attrition rate faced in the second round of data collection. High attrition rate engenders a significant drop in the sample size, which can reduce the statistical power of the study and make it harder to detect significant effects or differences. If not properly addressed,

the non-randomness of such attrition could lead to significant bias, as the remaining participants may differ systematically from those who dropped out, potentially skewing the results and affecting the generalizability of the findings. Fortunately, the differences between the attrited households and the remaining ones have been considerably minimized before further analysis (for more details see Appendix D). As a result, we were able to detect significant economic impacts of tap water adoption. Though we retain confidence in the estimates, caution must be exercised when interpreting our results. Since the program being evaluated was directed toward remote areas, from which households attrited, our impact estimates are likely to be around a conservative lower bound.

3.7 Conclusion and Policy Implications

This study scrutinizes the economic repercussions that access to water services might exert, specifically focusing on household expenditure and employment in rural Senegal. Employing a comprehensive panel dataset comprising 1,319 rural households observed in 2016 and 2020, as part of the Senegalese Emergency Program for Community Development (PUDC), the study distinguishes two water access treatments: access to PUDC tap water versus non-PUDC piped water. The former pertains to government-led water infrastructure, while the latter refers to community-led water services allowing for a unique comparative assessment of both types of infrastructure provision.

We employ a combination of empirical strategies, including PSM, IPW, and PSM-DiD, to ascertain the average impacts of water service accessibility. Additionally, we apply quantile regression in DiD and that developed by Firpo (2007) to capture the impacts across the distribution of household expenditure. The findings reveal that access to non-PUDC water yields negligible economic benefits for households, while PUDC water services exhibit positive and significant effects. Access to PUDC tap water is correlated with increased agricultural employment, facilitated by a higher water consumption rate and reduced time spent on water fetching. The analysis of distributional effects indicates that non-poor households derive more substantial economic benefits from quality water access compared to their impoverished counterparts.

Our findings call for more, large-scale, well-founded government-led initiatives, akin to PUDC, to effectively propagate water-supply infrastructure across rural Senegal. Such initiatives are likely to provide the needed push to the nation's pursuit of universal

access to water services in rural communities. In addition, the bundling of diverse interventions has been demonstrated to amplify the positive economic impacts of government-led water infrastructure. Therefore, policymakers should concurrently provide rural households with both road and water infrastructure, particularly given the secluded nature of many rural communities in developing countries. Constructing roads is paramount not only to facilitate access to water services but also to enhance economic benefits through improved market accessibility.

Importantly, we identify disparate economic benefits, with poor households benefitting less compared to their non-poor counterparts. This finding suggests that the overarching rural development policy of the Senegalese government to mitigate inequality and poverty through basic infrastructure provision needs to actively implement pro-poor policies. For instance, water infrastructure provision could be coupled with support mechanisms, such as subsidies or a pro-poor pricing structure, enabling impoverished households to bear the costs of water service. Similar initiatives, such as pro-poor pricing systems, have been successfully implemented in South Africa (Ruijs, 2009).

We cannot conclude without pointing towards the limitations of the current study. First, our findings can only be generalized to similar context, i.e. a rural African setting. While the external validity is limited, the roll out of the second phase of the program starting in 2021 offers the opportunity for future research to further explore economic effects and corroborate the external validity of the current findings. Second, in the absence of a randomized experiment we had to resort to quasi-experimental methods. While we applied the full toolbox with all relevant tests, we cannot fully rule out unobserved confounders. Future studies may want to refine the identification strategy. Third, we are faced with considerable attrition as three regions could not be re-survey during the follow up. Even though we account for possible impacts and attrition is not the result of non-response but of external, i.e. financial considerations, it has considerably reduced the sample size, which further limits our analysis. Fourth, due to the small sample we cannot explore gender-based impacts or other types of sub-sample analyses. Finally, we have to rely on self-reported data about household consumption expenditure, monthly water expenditure, and daily water consumption and do not have any information about the quality of the water infrastructure. Future studies should aim to address these limitations by incorporating more objective and detailed measurements, including technical information. Despite all these limitations, the

difference-in-differences estimates are reliable, given the validity of the parallel trend assumption (refer to Appendix G for detailed information). We find it worthwhile to emphazise that our findings point towards the relevance of large-scale, well-founded government interventions since the welfare effect of the government-led PUDC water supply is more pronounced compared to that of community-led initiatives.

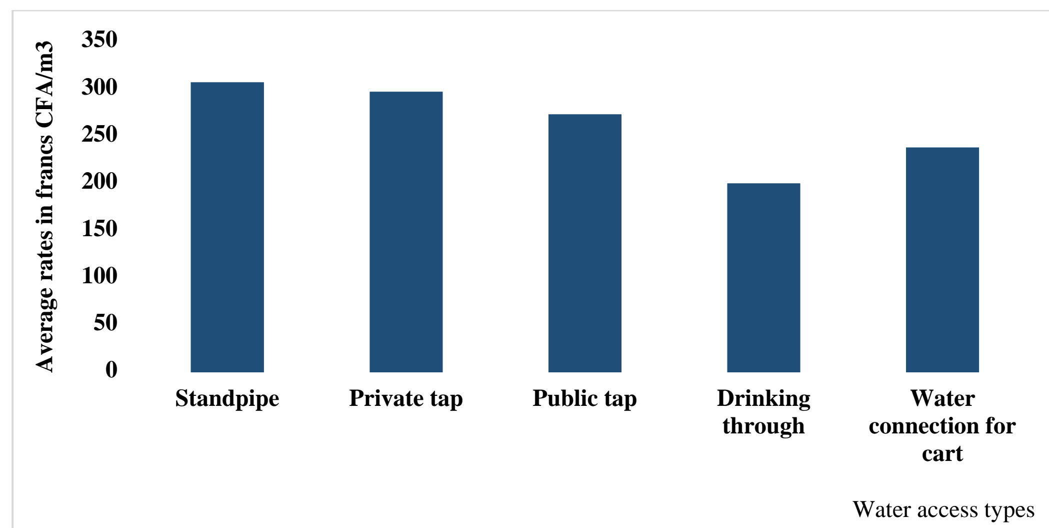
3.8 Appendix

Appendix A: The Water Sector in Senegal and the First Phase of the PUDC

State supremacy over the supply of water services in Senegal has, for a long time, been a source of inefficiency. Although the country's hydraulic potential (estimated at 4.750 m^3/person/year) remains higher than the reference value for a country to be categorized as physically water scarce (estimated at 1.000 m^3/person/year), the total water needs of the populations are not entirely covered by existing supply options (MHA, 2016). To improve access to clean water services for rural populations, Senegal initiated reforms during the 1990s. The sanitation sector was separated from the water one, and the latter was subdivided into rural and urban water supply entities. The National Water Company of Senegal (SONES) and the *Sénégalaise des Eaux* (SDE) (AFD, 2006) oversee urban water supply solely. They collect information on present and future urban water demands and design response mechanisms that guarantee the supply of water services to urban populations. For rural water supply, the Office of Rural Drilling (OFOR) was created in 2014 (MEA, 2021) to deal with the management of water resources in rural and decentralized zones. This clear separation between urban and rural water management architecture was made to cater to rural landscapes often characterized by a low density of the population, higher levels of poverty, more presence of farming communities, and weaker willingness to pay water bills. These institutional reforms have also led to a change in the water tariff structure and magnitude. Monthly flat rates were replaced with volumetric rates based on actual water consumption. Additionally, initiatives that promoted public-private partnerships (PPPs) were also initiated through contractual arrangements between the State and the private sector. The particularity of these partnerships, to increase efficiency, consists in entrusting the management of public service of water supply to private actors (SDE in urban areas, SEOH, AQUATECH, SOGES, and FLEXEAU in rural areas). The funding of hydraulic equipment remains the responsibility of the delegating authority (the State).

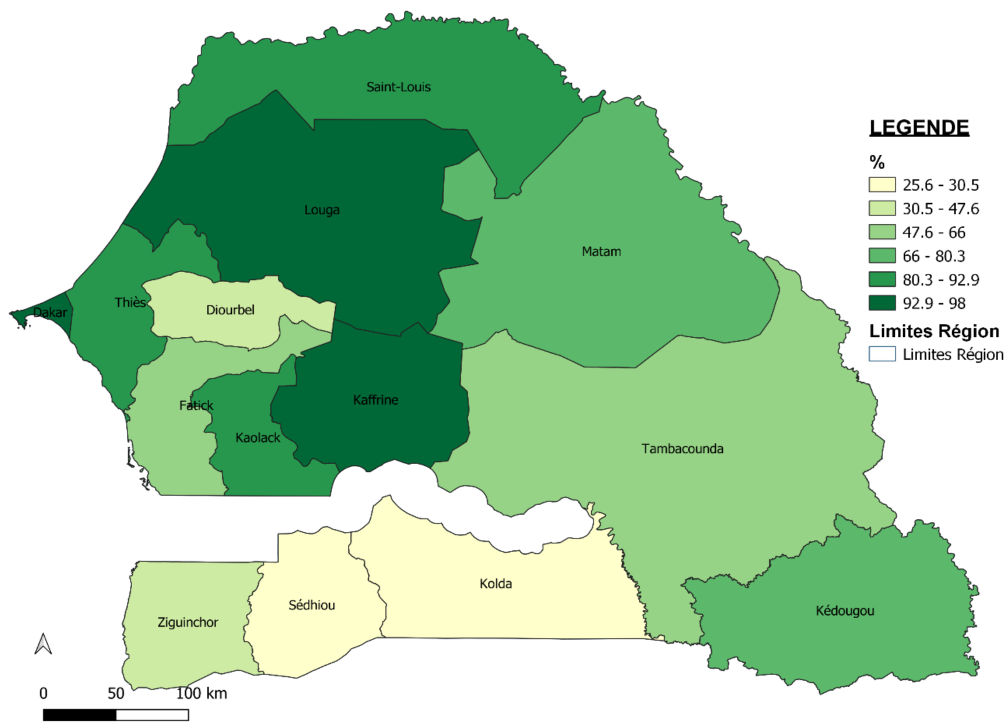
It is within the framework of this institutional system that the hydraulic section of the PUDC was initiated. The PUDC, a vast program for the development and structural transformation of the Senegalese economy, is part of the Plan Senegal Émergent (PSE) that seeks to position Senegal as an emergent country by 2035. Initiated in 2015, the

first phase of the program (PUDC I) was operational from 2016 to 2020. Placed at the village level, the PUDC I hydraulic interventions include the renovation and construction of new boreholes and water towers. Altogether, 238 boreholes and 159 water towers were built in the treatment villages. Drilling sites come with a five-thousand-litter storage tank that can meet the needs of more than five hundred people. This hydraulic infrastructure was built to service one or several villages at a time. Given the fact that the PUDC aimed primarily at reducing inequalities and poverty within rural areas, the water supply infrastructure was built in enclaved villages that expressed a strong need for access to water services to reduce poverty. However, once the equipment is installed or placed at the village level, households can decide whether they want to use the water that has been made available or not, provided they are charged according to consumption levels (Figure C 1). The type of water use depends on the needs expressed and the quantity required (domestic use, commercial use, market gardening, or drinking for animals).



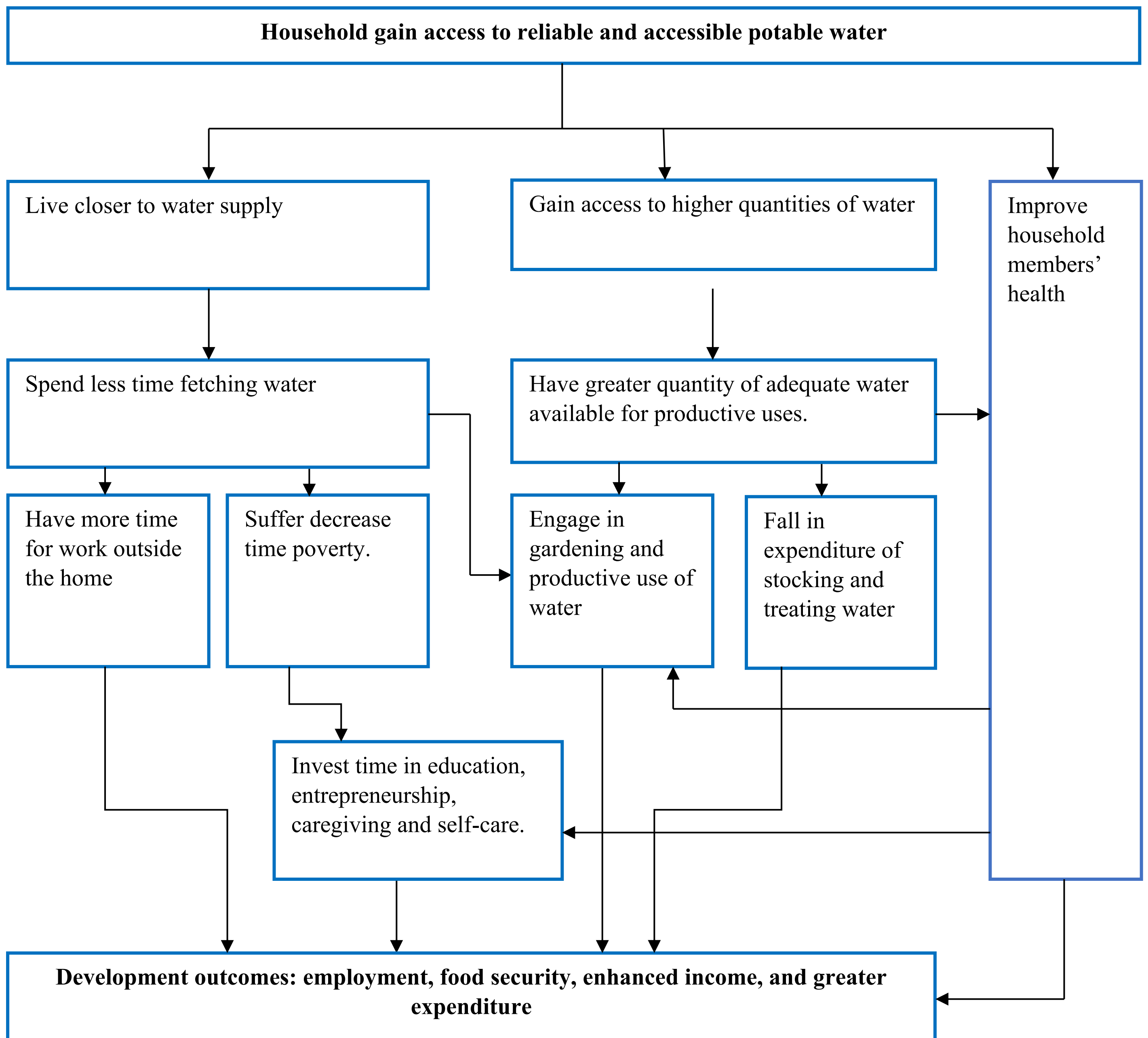
Source: MEA (2021, p.139)
Figure A1. Average access rates (per cubic meter) per type of water source

Appendix B: Additional figures



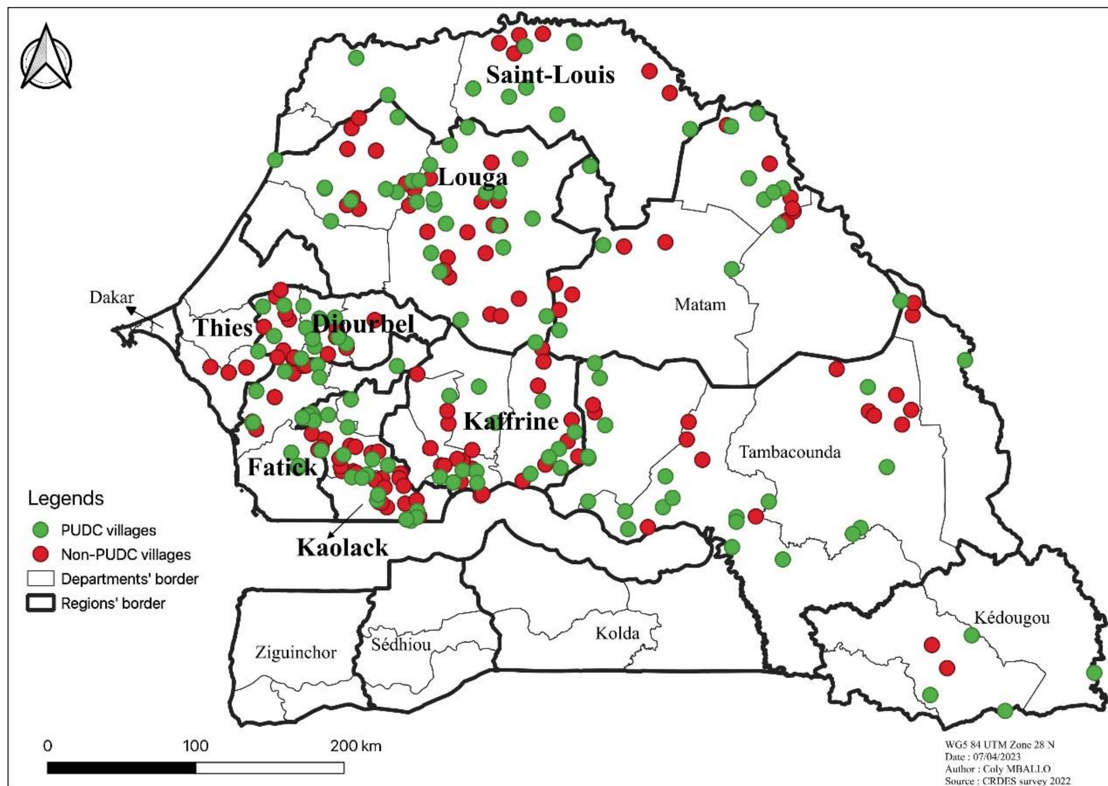
Source: ANSD (2021)

Figure B1. Rate of access to potable water by region in Senegal



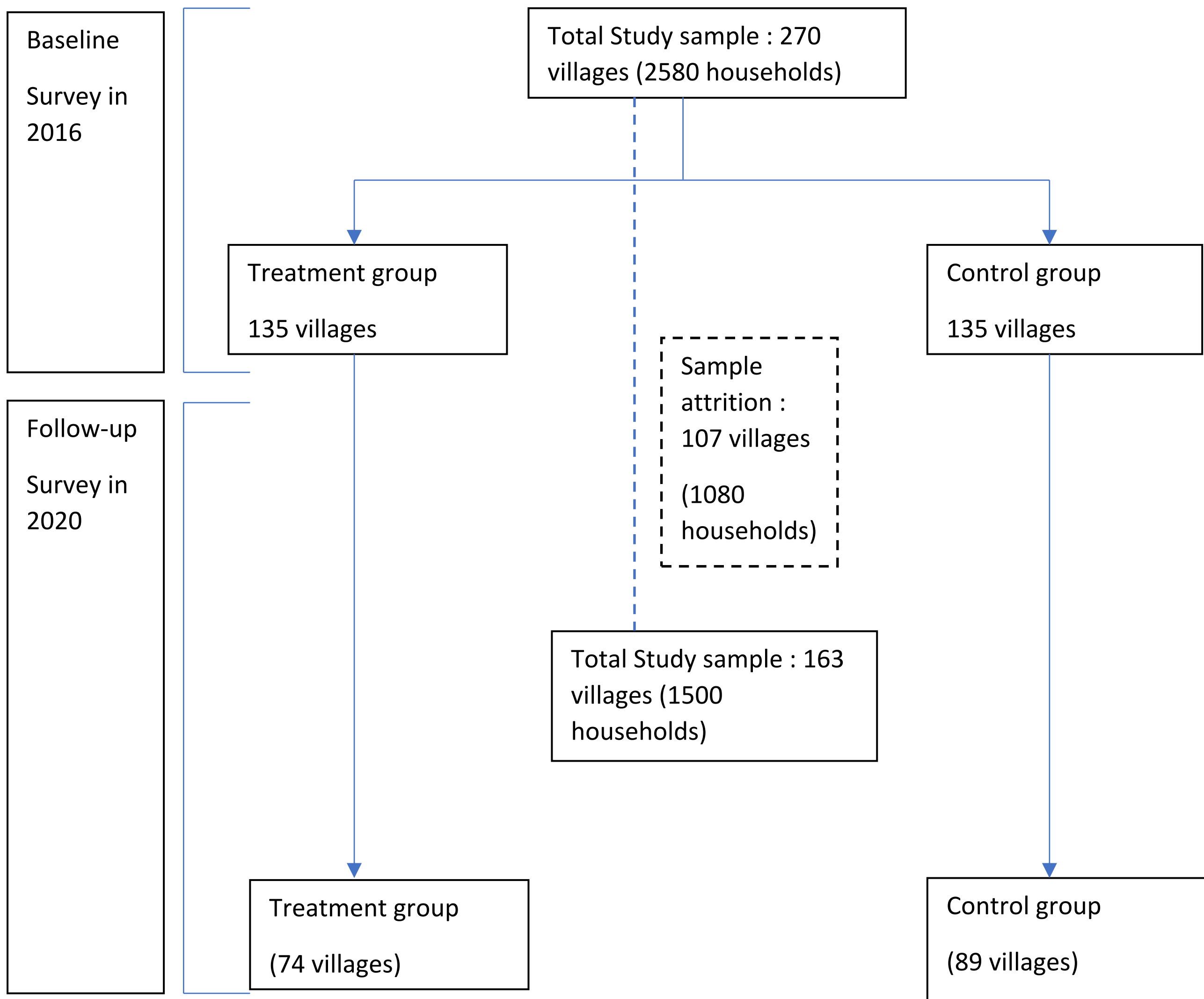
Source: Adapted from Winter et al. (2021)

Figure B2. Theory of change of access to adequate source of water

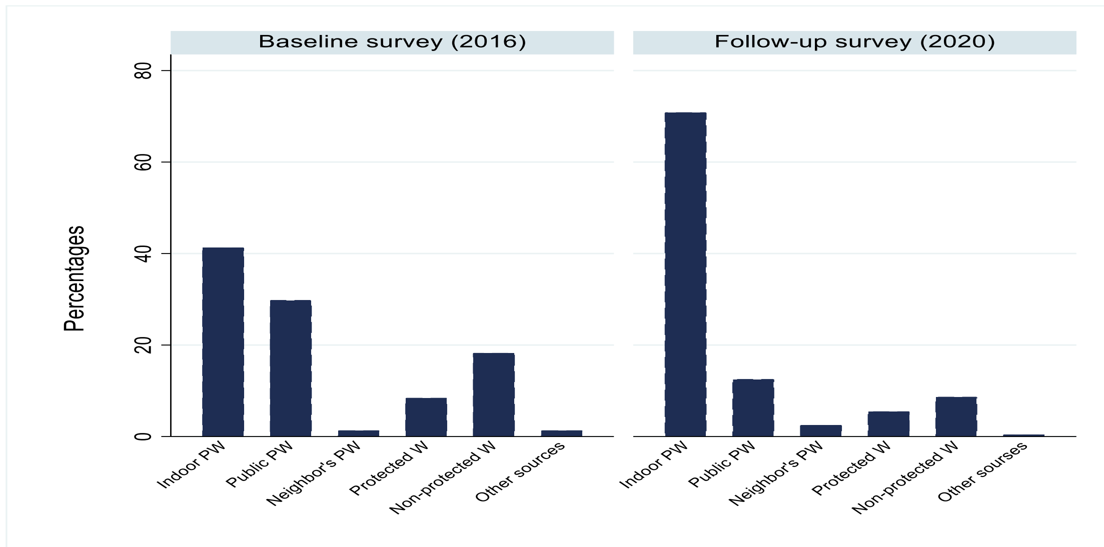


Source: CRDES baseline survey, 2023.

Figure B3. Treatment and control villages of PUDC I

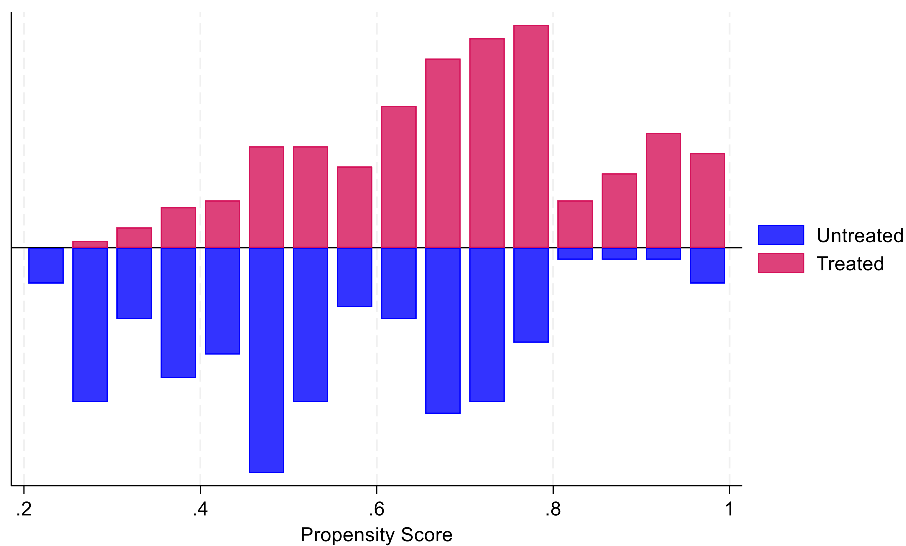


Source: Authors, 2023
Figure B4. Study set up

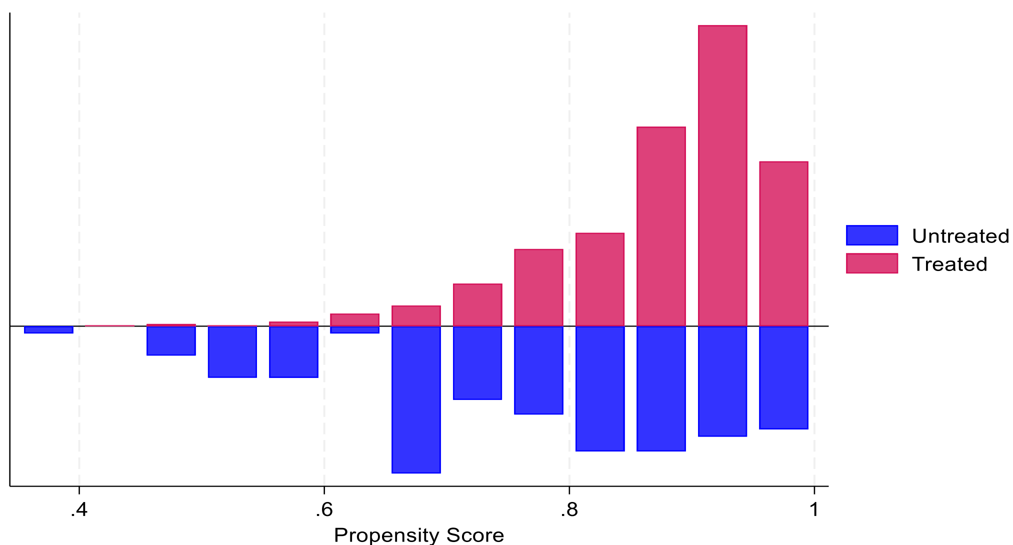


Note. The abbreviations PW and W stand for *piped water* and *wells* respectively. Other sources include river water, stream water, and water from hawkers.

Source: Authors' computations, 2023.
Figure B5. Distribution of households according to the source of water consumed

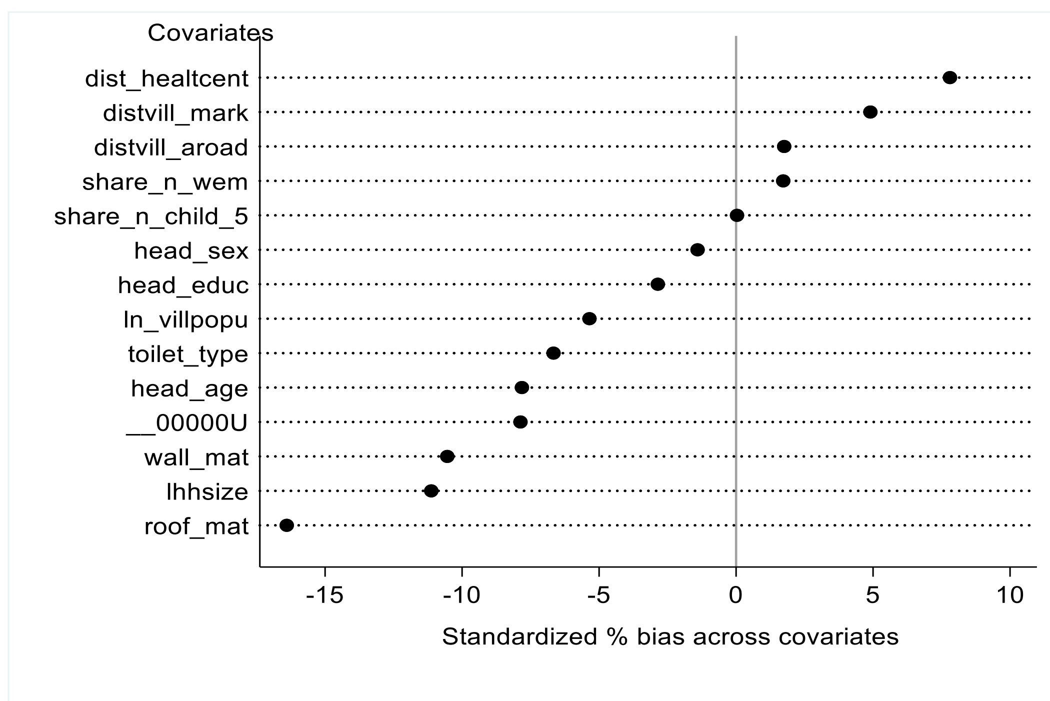


Source: Authors, 2023.
Figure B6. Distribution of propensity scores after matching by tap water adoption status ($\boldsymbol{T_1}$)



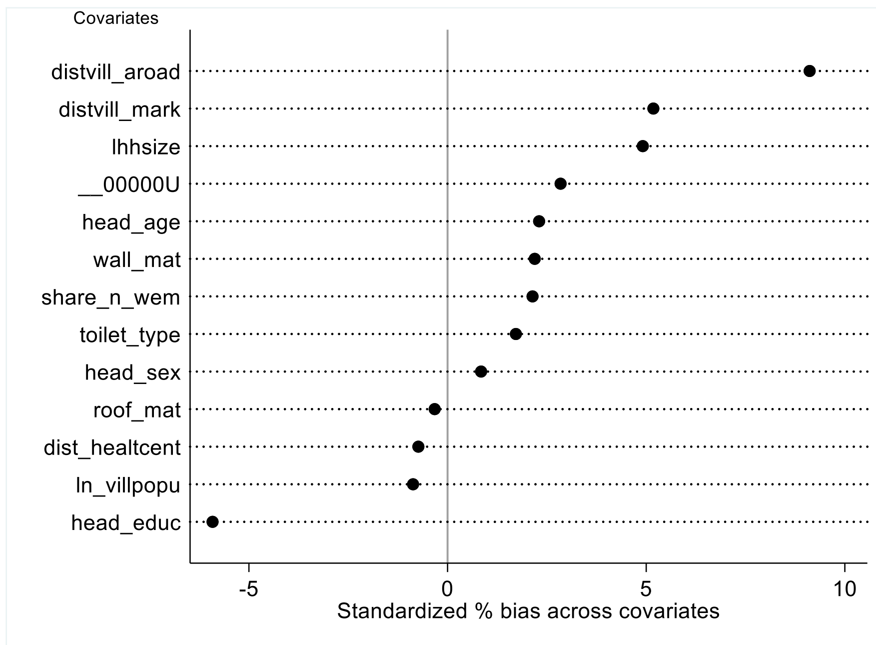
Source: Authors, 2023.

Figure B8. Distribution of the standardized bias across covariates after matching (T_1)

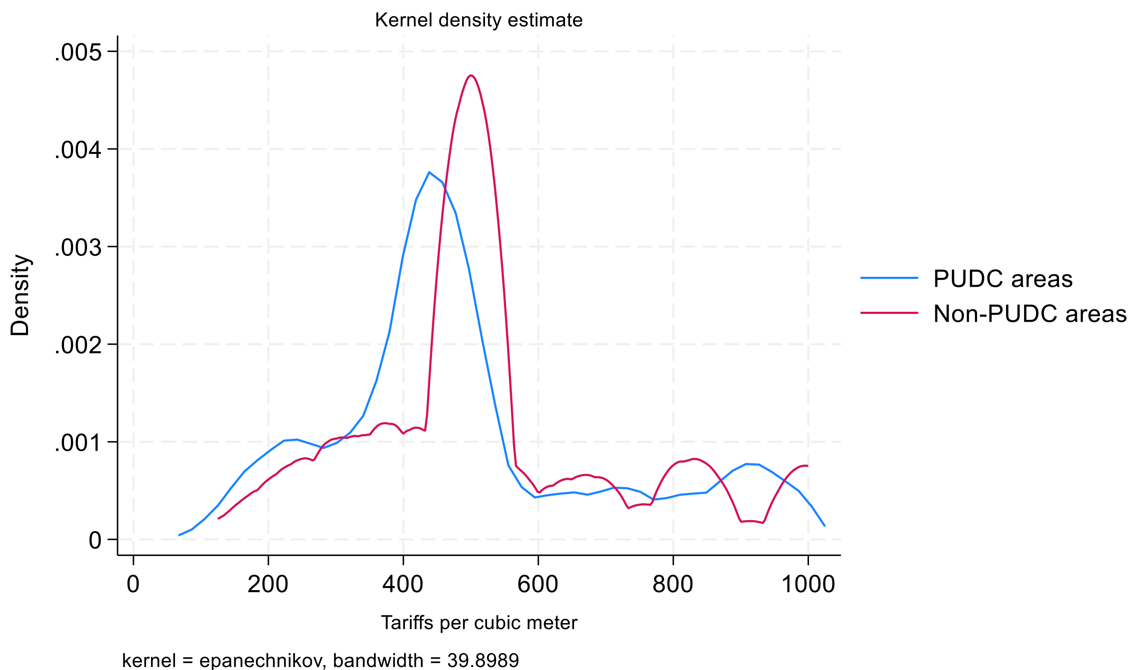


Source: Authors' computations, 2023.

Figure B9. Distribution of the standardized bias across covariates after matching (T_2)



Source: Authors' computations, 2023.



Note: The tariffs were calculated based on the monthly quantity of water consumed and the total costs incurred. Households reported both their monthly costs for water consumption and their daily water consumption in liters. We determined the tariffs by calculating the monthly water consumption in cubic meters. This involved multiplying the daily water consumption by 0.03 (30 days/1000 liters) and then dividing the monthly costs of water consumption by the monthly amount of water consumed (expressed in FCA per cubic meter). The mean comparison test between PUDC and non-PUDC areas indicates a significant difference, pointing towards higher costs in non-PUDC areas.

Source: Authors' computations based on the follow-up survey data, 2023.
Figure B10. Water tariffs in PUDC and non-PUDC areas

Appendix C: Social impacts of access to water services

The two major social outcomes associated with access to water are health and education. In this regard, previous studies assess the health-damaging effects arising from the use of water unfit for consumption (Akter, 2019; Brown et al., 2008; Corbo et al., 2008; He et al., 2008; Luby et al., 2015; Yamakawa et al., 1992; Brown et al., 2023; Devoto et al., 2012; Fink et al., 2011; Hasan & Gerber, 2016; Jalan & Ravallion, 2003; Klasen et al., 2012; Komarulzaman et al., 2019; Koolwal & van de Walle, 2013; Mangyo, 2008; Rauniyar et al., 2011; Trinies et al., 2016; Viet & Vu, 2013; Wapenaar & Kollamparambil, 2019; Rahman et al., 2021; Winter et al., 2021; Zhang, 2012). The central message is that water containing pathogenic micro-organisms (E.coli) and chemical substances poses a detrimental effect on users, necessitating targeted interventions aimed at improving water quality. Most studies demonstrate that access to piped water (or other forms of quality water) reduces child stunting and the prevalence of diarrhea among both children and adults. For example, using a simple OLS model and panel data from 4,500 rural households (in 152 villages) spanning from 1989 to 2006, Zhang (2012) identifies an 11 percent reduction in the incidence of illness among adults that is associated with access to improved water services. The weight-for-height of adults and children increased by 0.835 kg/m and 0.446 kg/m, respectively, following program implementation that targeted the deployment of water supply infrastructure. Employing propensity score matching, Jalan & Ravallion (2003) observed for the case of India that prevalence and duration of diarrhea spells were lower for households using piped water compared to observationally similar households that were not connected to piped water. Similar results were found by Trinies et al. (2016) in Mali, Winter et al. (2021) in Zambia, and Novak (2014) in Senegal. Another channel through which water scarcity affects human health is the way in which limited availability of water compels households to store this important resource under conditions that do not meet the required sanitary standards. Given the urgent need to secure water for the next day(s), unhealthy storage practices, combined with water containers used for transport and distribution that lack hygiene, result in the contamination and/or reduction of the water quality (Rufener et al., 2010).

Consequently, access to water does not necessarily have positive health impacts. Some studies report no impact on health (Hasan & Gerber, 2016; Rauniyar et al., 2011; Viet & Vu, 2013), while others condition the health effect of piped water on additional pre-

existing requirements (Jalan & Ravallion, 2003; Mangyo, 2008; Wapenaar & Kollamparambil, 2019). Access to water in sufficient quantity is deemed a necessary condition, but itdoes not guarantee improved health, either. For example, Jalan and Ravallion (2003) and Mangyo (2008) have shown that the effect of access to water on children's health is contingent on the income level of the household and the mother's educational level. Similarly, Wapenaar and Kollamparambil (2019) show that only when the primary caregiver (often the mother) has a minimum level of education exceeding 7 years that children's health improves following access to piped water. At this level of education, mothers are more likely to understand the vital need of investing in oral rehydration, medical treatment, hygiene, and nutrition to deliver enhanced welfare (Jalan & Ravallion, 2003). The presence of good-quality health services and latrines within communities also constitutes critical hygienic conditions that are necessary for water services to develop their full potential (Esrey et al., 1991; Gamper-Rabindran et al., 2010).

A second strand of the literature looks at the impact of access to water on education (Akter, 2019; Asadullah & Chaudhury, 2011; Bouchard et al., 2011; Gopu et al., 2022; Rocha-Amador et al., 2007). Children exposed to polluted water are expected to experience a decline in their cognitive ability, resulting in poor academic performance (Akter, 2019; Bouchard et al., 2011; Rocha-Amador et al., 2007). Analyzing a child-level dataset from Bangladesh, Akter (2019) found that excessive water salinity had an adverse impact on the grade advancement of 7–12-year-old children. Drawing on cross-sectional data, Bouchard et al. (2011) report that the use of water contaminated by manganese reduced the intelligence quotient (IQ) of 6-13-year-olds. Similarly, Rocha-Amador et al. (2007) found that exposure to fluoride through drinking water impaired the IQ of 6-to-10-year-old school children. The identified underlying mechanisms are: early childhood exposure to unsafe water (Akter, 2019) and the ostracization of children who become unhealthy due to the intake of unsafe water (Asadullah & Chaudhury, 2011). Based on cross-sectional data, Ortiz-Correa et al. (2016) concluded that children living within households connected to a piped water system gained 0.7 years of schooling in Brazil. Employing a panel dataset of 259 Indonesian districts from 1994 to 2014 and both static and dynamic fixed-effect models, Komarulzaman et al. (2019) found that districts with a greater share of households having access to on-premises water facilities displayed higher school enrolment and lower school absenteeism.

Choudhuri and Desai (2021) and Koolwal and van de Walle (2013) documented similar findings for India and across developing countries. Drawing on longitudinal data from the China Health and Nutrition Survey (CHNS) spanning from 1989 to 2011, Zhang and Xu (2016) found that early exposure to tap water increased the completed grade of education among youth by 1.1 years. Utilizing a DiD approach, Chen et al. (2022) similarly concluded that an extra year of exposure to piped water in early life increased the cognitive ability of 10-to-15-year-old children by 0.132. Other studies further support positive impacts of access to water on human capital (Chen et al., 2022; Choudhuri & Desai, 2021; Komarulzaman et al., 2019; Koolwal & van de Walle, 2013; Ortiz-Correa et al., 2016; Zhang & Xu, 2016).

Appendix D: Attrition analysis

Attrition is a non-negligible concern for the study at hand. We face a reduction in sample size from 2,580 to 1,500 households during the follow-up surveys. This is mainly driven by the fact that three regions are not re-surveyed in the second round (Kédougou, Matam, Tambacounda). These three regions differed systematically from those in the seven regions covered in both survey rounds (Diourbel, Fatick, Kaffrine, Kaolack, Louga, Saint-Louis, and Thiès). Importantly, the three regions were not r-surveyed due to financial constraints. Thus, while it is worrisome and reducing external validity, the main source of attrition is introduced by cost considerations and not non-compliance of initial survey respondents. Yet, the observed attrition can impact the estimates and, consequently, the analysis conducted if households systematically differ.

To assess attrition, we start by comparing the characteristics of households lost to follow-up with those households that participated in both rounds of data collection (Table D1). We find significant differences between households which participated in both rounds of data collection and those who participated only in the baseline survey as shown in Column 3 of Table D1. As already discussed, the large attrition rate is not random but a result of financial constraints. In a logit regression we further identify the determinants of attrition (Table D2). Unsurprisingly and in line with the systematic lack of follow-up data for three regions, village characteristics are the main determinants of attrition. The village population, distance to the market and main road are the key drivers of attrition. The further villages are located from the main road, the lower their probability of being selected for the second round of the survey. Thus, the data confirm

that the follow-up survey has targeted villages that are closer to cities (and the capital cities) to minimize survey-related expenditures.

Therefore, we resort to matching techniques to balance both groups of households. After the matching, 134 households – of which 38 participated in both rounds – that are off the common support were dropped. The results of the balance tests after matching are presented in Table D3 and indicate that most observed characteristics have been balanced, except for the household size, the share of women, the sex of the household head, the logarithm of village population and the distance to the nearest health center. Nonetheless, the balance tests further demonstrate a significant and sizable reduction of the attrition bias (Table D4).

Based on the results from the attrition examination and our knowledge from the field about the three regions that were not re-surveyed, we are confident that the sample attrition does not inflate our estimates but rather attenuate them and thus, they represent a conservative lower bound of the impact.

Table D1. Mean comparison test between households that participated in both round and those lost to follow-up at the baseline

	Attrition (Yes=1)	Attrition (No=0)	Mean difference
	(1)	(2)	(3)
Log. Household size	12.17	12.71	-0.540
	(0.210)	(0.168)	(0.266)**
Share of women	0.672	0.630	0.042
	(0.016)	(0.014)	(0.022)**
Share of children	0.262	0.248	0.013
	(0.008)	(0.008)	(0.011)
Age of household head (HH)	51.41	52.40	-0.989**
	(0.431)	(0.361)	(0.559)
Sex of HH (Male=1; Female=0)	0.942	0.953	-0.010
	(0.006)	(0.005)	(0.008)
Age of HH×sex of HH	51.41	52.40	-0.968
	(0.431)	(0.361)	(0.559)**
HH is educated (Yes=1; No=0)	0.087	0.107	-0.020
	(0.008)	(0.008)	(0.011)**
Roof material (1=Cement, corrugated iron, and tiles; 0= Other non-modern material),	0.417	0.517	-0.099
	(0.014)	(0.013)	(0.019)***
Wall material (1=Cement, 0=Not cement)	0.351	0.431	-0.079
	(0.014)	(0.013)	(0.019)***
Toilet type (1=Flush toilet; 0= Pit toilet).	0.240	0.327	-0.087
	(0.012)	(0.012)	(0.179)***
Log. Village population	6.155	6.474	-0.319
	(0.030)	(0.028)	(0.041)***
Distance to the main road (km)	21.45	11.30	10.14
	(0.643)	(0.448)	(0.762)***
Distance to market (km)	10.06	5.688	4.375
	(0.356)	(0.142)	(0.351)***
Distance to the nearest health center (ordered)	2.348	2.101	0.247
	(0.033)	(0.022)	(0.038)***

Note: * p < .10, ** p < .05, *** p < .01. Attrition is equal to 1 if a household had not been surveyed in the second round and 0 otherwise.

Table D2. Determinants of attrition in the second round of survey

	No participation in the follow-up survey (Yes=1)	
	Estimation technique: Logit model	
	Before matching	After matching
	(1)	(2)
Log. Household size	-0.009	-0.009
	(0.007)	(0.007)
Share of women	0.038	0.043
	(0.130)	(0.130)
Share of children	-0.044	-0.039
	(0.242)	(0.242)
Age of household head (HH)	-0.011	-0.011
	(0.016)	(0.016)
Sex of HH (Male=1; Female=0)	-1.201	-1.197
	(0.904)	(0.904)
Age of HH×sex of HH	0.014	0.014
	(0.017)	(0.017)
HH is educated (Yes=1; No=0)	0.081	0.083
	(0.152)	(0.153)
Roof material (1=Cement, corrugated iron, and tiles; 0= Other non-modern material),	-0.194*	-0.190
	(0.116)	(0.116)
Wall material (1=Cement, 0=Not cement)	0.079	0.073
	(0.118)	(0.118)
Toilet type (1=Flush toilet; 0= Pit toilet).	-0.100	-0.097
	(0.108)	(0.108)
Log. Village population	-0.162***	-0.158***
	(0.045)	(0.046)
Distance to the main road (km)	0.020***	0.021***
	(0.002)	(0.002)
Distance to market (km)	0.048***	0.046***
	(0.006)	(0.006)
Distance to the nearest health center (ordered)	0.028	0.031
	(0.048)	(0.048)
Constant	1.193	1.156
	(0.953)	(0.954)
Total observations	2474	2440
LR chi2	269.28	238.15

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors are indicated in brackets.

Table D3. Balance test on observable variables – Attrition (Yes=1)

	Attrition (Yes=1)	Attrition (No=0)	Bias (%)	Bias reduction (%)	p>t	Variance ratio
Observable characteristics before matching						
Log. Household size	12.2	12.6	-6.3	-	0.12	1.29*
Share of women	0.65	0.63	4.4	-	0.28	0.92
Share of children	0.26	0.24	4.1	-	0.32	0.95
Age of household head (HH)	51.4	52.4	-7.3	-	0.00	1.11
Sex of HH (Male=1; Female=0)	0.94	0.95	-5.7	-	-1.41	1.27*
Age of HH×sex of HH	48.3	49.9	-8.7	-	0.03	1.16
HH is educated (Yes=1; No=0)	0.08	0.10	-8.2	-	0.04	0.81
Roof material (1=Cement, corrugated iron and tiles; 0= Other non-modern material),	0.42	0.51	-19.5	-	-4.75	1.01
Wall material (1=Cement, 0=Not cement)	0.34	0.43	-17.4	-	-4.23	0.93
Toilet type (1=Flush toilet; 0=Pit toilet).	0.24	0.32	-17.8	-	-4.31	0.84
Log. Village population	6.17	6.44	-26.4	-	-6.45	1.00
Distance to the main road (km)	20.4	11.3	49.1	-	12.15	1.69*
Distance to market (km)	9.05	5.72	44.0	-	11.16	2.81**
Distance to the nearest health center (ordered)	2.32	2.10	22.7	-	5.66	1.79*
Observable characteristics after matching						
Log. Household size	12.2	11.9	5.0	20.5	0.24	1.28*
Share of women	0.65	0.68	-5.1	-17.1	0.25	0.79*
Share of children	0.26	0.27	-5.9	-43.9	0.185	0.85
Age of household head (HH)	51.4	51.3	0.7	90.7	0.87	1.10
Sex of HH (Male=1; Female=0)	0.94	0.91	11.1	-94.8	0.02	0.76*
Age of HH×sex of HH	48.3	47.1	6.7	23.5	0.15	0.96
HH is educated (Yes=1; No=0)	0.08	0.08	0.7	90.9	0.85	1.02
Roof material (1=Cement, corrugated iron and tiles; 0= Other non-modern material),	0.42	0.45	-5.7	70.6	0.19	0.98
Wall material (1=Cement, 0=Not cement)	0.34	0.36	-3.9	77.8	0.37	1.04
Toilet type (1=Flush toilet; 0=Pit toilet).	0.24	0.29	-11.0	38.1	0.01	0.94
Log. Village population	6.17	6.26	-8.1	69.4	0.06	0.77*
Distance to the main road (km)	20.4	19.5	4.8	90.3	0.30	1.00
Distance to market (km)	9.05	9.37	-4.2	90.4	0.41	1.25
Distance to the nearest health center (ordered)	2.32	2.26	6.2	72.9	0.18	1.42*

Notes. * indicates that the variance ratio is situated in the range [0.5, 0.8] or [1.25, 2] meaning that no perfect fit could be achieved; ** indicates bad matching, i.e. a variance ratio below 0.5 or above 2.

Table D4. Diagnostic tests after matching households that attrited with those that did not

	Non-matching sample	Matching sample
	(1)	(2)
Pseudo R^2	0.07	0.007
LR Chi^2	229.08	21.08
p-value of Chi^2	0.000	0.099
Average bias	17.3	5.6
Median bias	13.1	5.4
B	63.7*	20.2
R	1.59	1.02
Concern (%)	27	33
Bad (%)	7	0

Note: * indicates that B is above 25% and R is not included between 0.5 and 2.

Appendix E: Additional tables

Table E1. The data structure

Number of households	The first round of the survey (2016)	The second round of the survey (2020)	Status
949	Households with piped water	Households with piped water	**T1**
65	Households with adequate sources of water	Used underground water	Dropped
237	Used underground water	Households with piped water	**T 2**
133	Used underground water	Used underground water	Control group
22	Missing values		Dropped
1406	Total households		

Table E2. Balance test on observable variables – Treatment T1

	Treatment group	Control group	Bias (%)	Bias reduction (%)	p>t	Variance ratio
Observable characteristics before matching						
Log. Household size	2.397	2.399	-0.5	-	0.968	1.36*
Share of women	0.647	0.642	0.9	-	0.937	1.14
Share of children	0.276	0.281	-1.8	-	0.872	0.91
Age of household head (HH)	50.52	52.62	-15.4	-	0.167	0.96
Sex of HH (Male=1; Female=0)	0.972	0.976	-2.1	-	0.851	1.14
Age of HH×sex of HH	49.16	51.31	-14.0	-	0.210	1.00
HH is educated (Yes=1; No=0)	0.090	0.111	-6.8	-	0.536	0.82
Roof material (1=Cement, corrugated iron and tiles; 0= Other non-modern material)	0.371	0.420	-10.1	-	0.364	0.91
Wall material (1=Cement, 0=Not cement)	0.266	0.396	-27.8	-	0.012	0.74*
Toilet type (1=Flush toilet; 0=Pit toilet)	0.194	0.230	-8.7	-	0.433	0.85
Log. Village population	6.324	5.938	44.2	-	0.000	1.35*
Distance to the main road (km)	13.74	6.70	54.8	-	0.000	2.47**
Distance to market (km)	6.162	6.662	-11.1	-	0.309	0.79*
Distance to the nearest health center (ordered)	2.352	2.230	14.9	-	0.196	1.41*
Observable characteristics after matching						
Log. Household size	2.397	2.445	-11.1	-2366.4	0.253	1.04
Share of women	0.647	0.638	1.7	-94.1	0.856	1.15
Share of children	0.276	0.275	0.0	98.1	0.997	0.91
Age of household head (HH)	50.62	51.64	-7.8	49.2	0.413	0.94
Sex of HH (Male=1; Female=0)	0.972	0.975	-1.4	33.5	0.885	1.08
Age of HH×sex of HH	49.16	50.37	-7.9	43.8	0.410	0.95
HH is educated (Yes=1; No=0)	0.090	0.099	-2.9	58.2	0.758	0.88
Roof material (1=Cement, corrugated iron and tiles; 0= Other, non-modern material)	0.371	0.451	-16.4	-62.0	0.086	0.95
Wall material (1=Cement, 0=Not cement)	0.266	0.316	-10.5	62.0	0.255	0.82
Toilet type (1=Flush toilet; 0=Pit toilet)	0.194	0.221	-6.7	23.2	0.481	0.99
Log. Village population	6.324	6.371	-5.4	87.9	0.583	1.02
Distance to the main road (km)	13.74	13.51	1.8	96.8	0.884	0.79*
Distance to market (km)	6.162	5.942	4.9	55.9	0.569	0.99
Distance to the nearest health center (ordered)	2.352	2.288	7.8	47.4	0.42	1.20

Notes. * indicates that the variance ratio is situated in the range [0.5, 0.8] or [1.25, 2] meaning that no perfect fit could be achieved; ** indicates bad matching, i.e. a variance ratio below 0.5 or above 2.

Table E3. Balance test on observable variables – Treatment T_2

	Treatment group	Control group	Bias (%)	Bias reduction (%)	p>t	Variance ratio
Observable characteristics before matching						
Log. Household size	2.428	2.390	8.7		0.395	1.46*
Share of women	0.627	0.646	-3.3		0.740	1.30*
Age of household head (HH)	52.31	52.28	0.3		0.977	1.12
Sex of HH (Male=1; Female=0)	0.962	0.968	-2.9		0.769	1.15
Age of HH×sex of HH	50.26	50.39	-0.8		0.938	1.14
HH is educated (Yes=1; No=0)	0.104	0.112	-2.4		0.799	0.93
Roof material (1=Cement, corrugated iron and tiles; 0= Other non-modern material)	0.533	0.432	20.4		0.034	1.03
Wall material (1=Cement, 0=Not cement)	0.440	0.4	8.2		0.398	1.03
Toilet type (1=Flush toilet; 0=Pit toilet)	0.329	0.232	21.8		0.029	1.30*
Log. Village population	6.340	5.889	54.8		0.000	1.08
Distance to the main road (km)	8.375	6.008	27.1		0.008	1.70*
Distance to market (km)	5.879	6.788	-17.1		0.086	1.41*
Distance to the nearest health center (ordered)	2.077	2.088	-1.5		0.759	1.09
Observable characteristics after matching						
Log. Household size	2.428	2.404	5.4	37.6	0.296	1.20
Share of women	0.627	0.618	1.7	49.1	0.724	1.52*
Age of household head (HH)	52.31	52.01	2.3	-697.9	0.651	1.09
Sex of HH (Male=1; Female=0)	0.962	0.961	0.8	71.0	0.872	0.97
Age of HH×sex of HH	50.26	49.80	2.8	-266.9	0.579	1.07
HH is educated (Yes=1; No=0)	0.104	0.123	-6.2	-150.2	0.235	0.96
Roof material (1=Cement, corrugated iron and tiles; 0= Other non-modern material)	0.533	0.537	-0.8	96.3	0.880	1.01
Wall material (1=Cement, 0=Not cement)	0.440	0.431	1.8	78.2	0.723	1.02
Toilet type (1=Flush toilet; 0=Pit toilet)	0.329	0.324	1.2	94.7	0.824	1.01
Log. Village population	6.340	6.345	-0.6	98.9	0.903	0.88
Distance to the main road (km)	8.375	7.564	9.3	65.7	0.071	1.12
Distance to market (km)	5.879	5.624	4.9	71.9	1.284	1.70*
Distance to the nearest health center (ordered)	2.077	2.088	-1.5	92.1	0.759	1.09

Notes. * indicates that the variance ratio is situated in the range [0.5, 0.8] or [1.25, 2] meaning that no perfect fit could be achieved; ** indicates bad matching, i.e. a variance ratio below 0.5 or above 2.

Table E4. Diagnostic tests after matching

	Treatment T_1		Treatment T_2	
	Unmatched sample	Matched sample	Unmatched sample	Matched sampled
	(1)	(2)	(3)	(4)
Pseudo R2	0.120	0.010	0.096	0.0004
LR Chi2	54.51	5.96	70.12	8.16
P chi2	0.000	0.967	0.000	0.833
Average bias	15.2	6.2	14.4	3.0
Median bias	10.6	6.0	8.7	1.8
B	85.1*	23.3	79.4*	14.2
R	1.15	1.08	0.69	1.52
Concern (%)	33	7	36	14
Bad (%)	7	0	0	0

Note: * Indicates that B is above 25% and R is not included between 0.5 and 2.

Table E5. Impact estimates of access to drinking water (T_1) on employment and expenditure – PSM and IPW estimates

Outcomes	Propensity score matching (PSM)		Inverse-probability weighting (IPW)	
	(1)		(2)	
	ATT	Observations (treated/control)	AET	Observations (treated/control)
Log. Total expenditure per capita	0.156	314	0.150	314
	(0.099)	(198/116)	(0.095)	(198/116)
Log. Non-food expenditure per capita	0.222*	278	0.224*	278
	(0.135)	(173/105)	(0.134)	(173/105)
Log. Food expenditure per capita	0.169	314	0.150	314
	(0.108)	(198/116)	(0.100)	(198/116)
Share of total employment	0.038	316	0.036	316
	(0.031)	(117/199)	(0.034)	(117/199)
Share of agricultural employment	0.049***	316	0.050**	316
	(0.021)	(199/117)	(0.021)	(199/117)
Share of non-agricultural employment	0.002	316	0.001	316
	(0.158)	(117/199)	(0.014)	(117/199)

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (SE) are reported in parentheses in the columns presenting ATT and ATE.

Table E6. Impact estimates of access to drinking water (T_2) on employment and expenditure (round 2016) – PSM and IPW estimates

Outcomes	Propensity score matching (PSM)		Inverse-probability weighting (IPW)	
	(1)		(2)	
	ATT	Observations (treated/control)	AET	Observations (treated/control)
Log. Total expenditure per capita	0.284***	925	0.115	925
	(0.102)	(804/121)	(0.120)	(804/121)
Log. Non-food expenditure per capita	0.543***	909	0.465**	909
	(0.169)	(793/116)	(0.219)	(793/116)
Log. Food expenditure per capita	0.184***	925	-0.015	925
	(0.104)	(802/123)	(0.127)	(802/123)
Share of total employment	-0.010	920	-0.014	920
	(0.015)	(797/123)	(0.019)	(797/123)
Share of agricultural employment	-0.0001	545	0.012	545
	(0.015)	(472/73)	(0.014)	(472/73)
Share of non-agricultural employment	-0.087	925	-0.016	925
	(0.012)	(502/123)	(0.017)	(502/123)

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (SE) are reported in parentheses in the columns presenting ATT and ATE.

Table E7. Impact estimates of access to drinking water (T_2) on employment and expenditure (round 2020) – PSM and IPW estimates

Outcomes	Propensity score matching (PSM)		Inverse-probability weighting (IPW)	
	(1)		(2)	
	ATT	Observations (treated/control)	AET	Observations (treated/control)
Log. Total expenditure per capita	0.186	823	0.152	823
	(0.088)	(708/115)	(0.096)	(708/115)
Log. Non-food expenditure per capita	-0.054	730	-0.102	730
	(0.119)	(625/105)	(0.129)	(625/105)
Log. Food expenditure per capita	0.297***	819	0.277***	819
	(0.096)	(704/115)	(0.092)	(704/115)
Share of total employment	-0.034	825	-0.041	825
	(0.027)	(709/116)	(0.035)	(709/116)
Share of agricultural employment	-0.002	825	-0.005	825
	(0.016)	(709/116)	(0.017)	(709/116)
Share of non-agricultural employment	-0.001	825	0.003	825
	(0.014)	(709/116)	(0.011)	(709/116)

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors (SE) are reported in parentheses in the columns presenting ATT and ATE.

Table E8. Women's time use (T_1)

	Control group	Treatment T_1	Total	*p*-value
Leisure and social time	100.9(90.3)	175.3(142.6)	152.6(132.7)	0.05
Sleeping	877.86(301.8)	765.0(371.5)	799.3(355.07)	0.02
Cooking, laundry, cleansing	180.8(205.6)	176.6(133.9)	178.1(162.8)	0.84
Water fetching and wood collection	119.6(245.9)	47.0(81.6)	80.73(181.09)	0.01
Childcare	172.5(236.7)	38.84(21.89)	97.3(165.4)	0.11
Gardening and farming	253.6(162.5)	352.3(143.6)	317.3(156.9)	0.01
Trading, artisanal activities and transformation of agricultural products	216.45(150.7)	253.3(211.4)	237.5(185.6)	0.61

Note: The table reports the means expressed in minutes. Standard deviations are in parentheses. The *p*-value corresponds to the difference in the means test.

Table E9. Men's time use by treatment (T_1)

	Control group	Treatment T_1	Total	*p*-value
Leisure and social time	202.4(153.4)	183.3(178.9)	190.1(169.3)	0.65
Sleeping	857.1(363.3)	788.8(353.3)	811.6(357.5)	0.14
Cooking, laundry, cleansing	89.6(43.3)	59.7(1.26)	71.6(27.1)	0.28
Water fetching and wood collection	163.6(91.9)	105.5(77.9)	132.2(87.8)	0.11

Note: The table reports the means expressed in minutes. Standard deviations are in parentheses. The *p*-value corresponds to the difference in the means test. The average time devoted to gardening and farming, childcare, and non-agricultural activities such as trading, transformation of agricultural products and artisanal activities are not computed due to missing data.

Table E10. Women's time use by treatment (T_2)

	Control group	Treatment T_2	Total	*p*-value
Leisure and social time	100.9(90.38)	110.2(90.3)	109.1(90.1)	0.68
Sleeping	877.8(301.8)	822.9(358.7)	829.01(353.1)	0.20
Cooking, laundry, cleansing	164.3(123.9)	175.4(116.1)	174.0(117.1)	0.38
Water fetching and wood collection	119.6(245.9)	100.6(142.4)	105.3(173.4)	0.40
Childcare	172.5(236.7)	137.6(242)	141.7(239.7)	0.72
Gardening and farming	253.56(162.49)	217.4(136.6)	224.8(142.4)	0.22
Trading, artisanal activities and transformation of agricultural products	216.45(150.78)	256.2(191.9)	252.6(188.4)	0.49

Note: The table reports the means expressed in minutes. Standard deviations are in parentheses. The *p*-value corresponds to the difference in the means test.

Table E11. Men's time use by treatment (T_2)

	Control group	Treatment T_2	Total	p-value
Leisure and social time	202.4(153.4)	155.4(138.9)	160.4(140.9)	0.12
Sleeping	857.1(363.3)	885.9(334.6)	882.4(338.1)	0.45
Cooking, laundry, cleansing	89.6(43.3)	90.7(64.3)	90.8(59.9)	0.98
Water fetching and wood collection	163.6(91.90)	119.7(97.8)	126.7(97.61)	0.17

Note: The table reports the means expressed in minutes. Standard deviations are in parentheses. The *p*-value corresponds to the difference in the means test. The average time devoted to gardening and farming, childcare, and non-agricultural activities such as trading, transformation of agricultural products and artisanal activities are not computed due to missing data.

Table E12. Water consumption per treatment (T_1 and T_2)

	Control group	Treatment T_1	Total	p-value
Monthly water consumption (m^3)	8.52(7.22)	9.92(6.30)	9.49(6.42)	0.08
	Control group	Treatment T_2	Total	p-value
Monthly water consumption (m^3)	8.52(7.22)	9.55(7.31)	9.45(7.30)	0.18

Note: Standard deviations are in parentheses.

Table E13. Results from quantile regressions

	Panel A. T_1			**Panel B. T_2 (2016)**			**Panel C. T_2 (2020)**		
				Log. Expenditure					
Quantiles	**Total**	**NFE**	**FE**	**Total**	**NFE**	**FE**	**Total**	**NFE**	**FE**
$Q_{0.1}$	-0.610*	0.087	-0.175	0.433	0.372	0.181	0.000	-0.095	0.218
	(0.367)	(0.313)	(0.366)	(0.367)	(0.272)	(0.307)	(0.229)	(0.236)	(0.543)
$Q_{0.2}$	-0.142	0.385	-0.000	0.064	0.201	0.057	-0.113	-0.109	0.262
	(0.167)	(0.258)	(0.229)	(0.110)	(0.295)	(0.146)	(0.134)	(0.175)	(0.542)
$Q_{0.3}$	-0.075	0.608***	0.007	0.141	0.000	0.012	0.035	0.047	0.136
	(0.180)	(0.227)	(0.124)	(0.093)	(0.146)	(0.099)	(0.110)	(0.188)	(0.129)
$Q_{0.4}$	0.099	0.379*	0.111	0.126	0.185	0.035	0.121	0.000	0.213*
	(0.145)	(0.224)	(0.158)	(0.084)	(0.140)	(0.079)	(0.093)	(0.222)	(0.122)
$Q_{0.5}$	0.103	0.133	0.121	0.135	0.297*	0.093	0.131	-0.164	0.259**
	(0.129)	(0.226)	(0.122)	(0.084)	(0.153)	(0.076)	(0.090)	(0.206)	(0.104)
$Q_{0.6}$	0.185*	0.096	0.123	0.138	0.228	0.133	0.247**	-0.036	0.325***
	(0.103)	(0.292)	(0.138)	(0.089)	(0.190)	(0.079)	(0.095)	(0.182)	(0.100)
$Q_{0.7}$	0.308**	0.087	0.314***	0.125	0.179	0.105	0.291***	0.025	0.367***
	(0.140)	(0.243)	(0.104)	(0.095)	(0.168)	(0.094)	(0.104)	(0.169)	(0.115)
$Q_{0.8}$	0.300*	0.004	0.388**	0.153	0.360**	0.086	0.238*	0.128	0.287
	(0.159)	(0.283)	(0.160)	(0.091)	(0.155)	(0.099)	(0.144)	(0.251)	(0.179)
$Q_{0.9}$	0.146	-0.132	0.372**	0.280***	0.544***	0.036	0.254	0.079	0.310
	(0.511)	(0.382)	(0.178)	(0.101)	(0.188)	(0.093)	(0.292)	(0.515)	(0249)

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors are indicated in brackets. NFE and FE stand respectively for non-food expenditure and food expenditure.

Appendix F: Selection of independent variables for the treatment equations

This section addresses the selection and justification of independent variables used in the selection equation. In other words, it addresses the selection of potential determinants of access to a quality water source. These variables consist of a selection of both village and household characteristics. Building on the discussion of the non-random placement of hydraulic infrastructure in sub-section 6.1, we control for village characteristics such as population size and remoteness measures, including the distance of a village to the main road, the distance to the market, and the distance to the nearest health center. We anticipate a positive correlation between village population density

and access to potable drinking water. The rationale is that water infrastructure is constructed in areas with greater population density due to the larger economies of scale they offer, ensuring the recovery of initial investment costs (Barde, 2017). Moreover, in larger populations, the queuing time for water collection may be longer. Also, households in densely populated areas are likely to adopt piped water on the premises (Arouna & Dabbler, 2010). In turn, remote areas often receive less infrastructure due to the prohibitive costs of the network expansion, leading to less adequate water facilities (Barde, 2017). Consequently, we expect distance to the main road, the market, and the nearest health center to be negatively correlated with access to improved sources of drinking water.

Once villages are connected to water infrastructure, households decide whether to use it or not based on their characteristics. We control for the following observable household characteristics: the size of the household, the composition of the household (the gender of the household head, the share of women, and the share of children under five years of age), the age of the household head (HH), the education level of the HH, the occupation of the HH, and the household's housing conditions (type of toilet, wall material, and roof material). The selection of household characteristics is informed by the existing literature on the determinants of access to safe and appropriate drinking water in rural zones of developing countries. We detail our choices in the following paragraphs.

The size of the household is a crucial factor influencing households' decisions to connect to water through a piped system. Larger households are more likely to install piped water on the premises due to their increased need for a greater quantity of water and the challenges associated with collecting water from distant sources to meet their demands (Adams et al., 2016; Arouna & Dabbert, 2010; Briand et al., 2009; Rahut et al., 2015; Tshililo et al., 2022). Therefore, we anticipate a positive association between household size and the use of adequate drinking water (conditional on income, see below).

Household composition plays a significant role in water connectivity (Arouna & Dabbert, 2010). As women and children are the primary users of potable water for their hygiene, the absence of adequate drinking water exposes them to water-related diseases (Bisung & Dickin, 2019). The responsibility of fetching water also falls mainly on

women, and the lack of an indoor water source diverts their time away from active labor market participation (Koolwal & van de Walle, 2013). Consequently, we anticipate that households with a higher share of women and children are more likely to connect to an improved water system (conditional on income, see below). We use the gender of the household head, the share of women, and the share of children to capture household composition.

Age is also a predictor of a household's connection to a piped water system (Abubakar, 2019; Rahut et al., 2015). As household members age, they may lack the physical strength needed to collect water from distant sources, making them more likely to install water taps on the premises. Households with older household heads also tend to be better off. Therefore, we expect a positive correlation between the age of the household head and access to improved drinking water sources.

The education level of household members is another crucial parameter influencing a household's decision to install piped water on the premises, for at least two reasons. First, as the opportunity cost of water collection increases with alternative uses of time, educated household members would have a higher opportunity cost compared to the uneducated ones, preferring piped water on the premises (Rahut et al., 2015). Second, as the awareness of health benefits stemming from potable water increases with education, literate household members are more likely to make an informed decision to have piped water on the premises (Arouna & Dabbert, 2010). We measure the household's education level by the literacy of the household head, i.e. whether s/he is literate or not. Our hypothesis is that literate household heads are more likely to install piped water on the premises and rely less on water obtained from wells.

Empirical findings suggest that the occupation of the household head is significantly related to the quantity of water used in the household. For instance, Abubakar (2019) reported that households with heads employed in the agricultural sector use less water compared to those with off-farm activities in Nigeria. We expect a similar finding in this study.

Finally, one of the crucial determinants of the use of piped water in developing countries is a household's income level. Wealthier households are more likely to bear the costs of connection to the water system, while poorer households are less likely to

adopt tap water due to income constraints (Rahut et al., 2015; Carrard et al., 2019). We proxy the income level of households by their housing conditions. The argument is that wealthier households have better housing conditions compared to poorer households. To the extent that housing conditions are determined by the income level of households, they hold the potential to predict the household's water system connection status. Households with good housing conditions usually have flush toilets, requiring a greater quantity of water. We measure housing conditions by the type of toilet used (flush or pit), wall, and roof material.

Appendix G: Results of the outcome placebo test

In this section, we test the parallel trend assumption. The latter assumes no time-varying differences between the treatment and control groups. If this underlying identifying assumption is not valid, the estimates obtained with double difference would be biased. To determine the validity of the parallel trend assumption, we conducted a placebo test with a fake outcome. The fake outcome considered is the amount of total financial credit received by a given household. Based on the theoretical framework of the economic effects of piped water adoption, the total amount of credit households receive from banks or microcredit institutions has a lower probability of being affected by the use of clean water. Therefore, this outcome must have a parallel trend between both groups before the intervention. The estimated impact of access to PUDC clean water on the amount of financial credit is reported in Table G1. Overall, the findings suggest that the use of clean water has no impact on the total amount financial institutions lend to rural households. Therefore, the parallel trends assumption seems to be valid, and confidence can be retained regarding our impact estimates of the welfare effects of piped water adoption.

Table G1 Estimates of PUDC water (T_1) on the amount of financial credit – PSM-DiD

	PSM-DiD	
Fake outcome:	Log. Amount of financial credit	
	(1)	(2)
Access to drinking water (Yes=1; No=0) [ATT]	0.137	0.058
	(0.324)	(0.349)
Observations	324	309
R^2	0.05	0.11
Household characteristics	No	Yes
Village characteristics	No	Yes
Time fixed effects	No	Yes
Kernel matching	No	Yes

Note: Note: * p < .10, ** p < .05, *** p < .01. The average treatment effects on the treated were estimated by employing a combination of the difference-in-difference method and the propensity score matching technique. Robust standard errors are reported in the brackets. In each estimated equation, observable household characteristics, village characteristics, and time-fixed effects are controlled for. Household observable traits included in the estimations are the age of the household head (HH), the sex of the HH (1=male; 0=female), the education status of the HH (1=Yes, 0=No), the age of women (continuous), the share of children (continuous), the roof material of the house (1=cement, corrugated iron, and tiles; 0=other non-modern materials), the wall material (1=cement, 0=not cement), and the type of toilet (1=flush toilet; 0=pit toilet). Village characteristics include population size, distance to the market (km), distance to the main rural road (km), and distance to the closest health center (ordered). Time-fixed effects are apprehended through a binary variable that takes the value 0 for the baseline round and 1 for the follow-up round.

Chapitre 4 - Empirical evidence between power outages and firm performance nexus in Senegal[5]

'Productivity isn't everything, but in the long run it is almost everything'.

Paul Krugman (1994, p.204)

Abstract

Frequent power outages in developing countries brings about additional costs for firms, given their need to invest in alternative inputs (i.e. generators) to maintain or enhance performance. Moreover, female-managed firms often claim to be more severely hit by such outages given the structural and institutional constraints women face in many developing countries. Understanding these interactions is the purpose of this paper. Based on the World Bank's Enterprise Survey (WBES) dataset, which comprises 601 Senegalese establishments surveyed in 2014, the paper combines robust empirical strategies, including propensity score matching, Tobit model, Combes et *al*. 's (2012) statistical approach and Blinder-Oaxaca counterfactual decomposition technique. Findings confirm the female-underperformance hypothesis and suggest that power outages harm firm performance and enlarge gender-based productivity gaps. Our findings further highlight that the productivity gap is mainly driven by its structural component and lower within establishments that own generators.

Keywords: electricity infrastructure, power outages, gender, firm productivity, and Senegal.

[5] This chapter is currently under review with *Environment and Development Economics*.

4.1 Introduction

Electricity plays a critical role in economic development (Allcott et al., 2016; Falentina and Resosudarmo, 2019; Urrunaga and Aparicio, 2012). Stable and reliable electricity serves as an input in the production process and represents a source of output growth, income, and employment generation. Furthermore, the availability of reliable electricity facilitates the use of information and communication technologies (ICT) which enhances labor and capital productivity (Falentina and Resosudarmo, 2019).

Despite the importance of electricity for economic prosperity, developing countries lack reliable and sustainable electricity infrastructure due to low level of investment in the energy sector (Alam, 2013; Elliott et al., 2021; Oseni and Pollitt, 2015). The unrealiability of electricity in these countries, which is observable through power surges, load shedding, brownouts, and power outages (Moyo, 2013), constrains firms to incur higher electricity costs (Steinbuks and Foster, 2010) and additional costs from adopting alternative sources of electricity such as generators (Steinbuks and Foster, 2010). Notably, power disruptions harm firms' production, disrupt investment decisions, and dampen firm's capacity to take advantage of economies of scale (Geginat and Ramalho, 2018). In the long run, economic growth slows down (Alam, 2013; Allcott et *al*., 2016; Andersen and Dalgaard, 2013; Oseni and Pollitt, 2015).

This article provides empirical evidence of the nexus between power outages, firm productivity, and the gender-based productivity gap in Senegal. It does so by assessing the effect of power outages on firm productivity, testing the female underperformance hypothesis, and examining the impact of power outages on the gender-based productivity gap. The existing body of studies on the effects of power outages on firm productivity seems to have overlooked gender in their analyses (Abdisa, 2018; Allcott et al., 2016; Falentina and Resosudarmo, 2019; Fisher-Vanden et al., 2015; Grainger and Zhang, 2019; Moyo, 2013; Oseni and Pollitt, 2015). Similarly, previous studies that considered the gender-based productivity gap within firms have ignored the contribution of unreliable electricity infrastructure (Essers et al., 2021; Gui-Diby et al., 2017; Islam et al., 2020). Drawing on this, the current article addresses a significant research gap by investigating the extent to which power cuts serve as a primary determinant of the gender-based productivity gap. Although the occurrence of power outages is not influenced by gender, their impact is likely to vary depending on the

gender of the firm's owner or manager. In developing countries, where women must balance income-generating activities with unpaid domestic chores (Hallward-Driemeier and Rasteletti, 2010), power outages are more likely to have a disproportionately negative effect on women’s income-generating activities compared to men’s. The time-constraint women are subject to can also dictate differentiated management style and gender-related outcomes. Moreover, businesses owned or managed by women are significantly more susceptible to power outages compared to those owned or managed by men. This heightened vulnerability is due to the smaller size of female-owned businesses and their frequent operation within the service, retail, and informal sectors, where backup electricity solutions like generators are seldom used (Amin and Islam, 2014; Islam et *al*., 2020; Hallward-Driemeier, 2013; Falentina and Resosudarmo, 2019).

The article primarily focuses on Senegal, a context in which few studies have examined the relationship between firm productivity, gender, and the firm-level productivity gap (Cissokho, 2019; Seck et al., 2020). Cissokho (2019) analyzed the impact of power outages on the productivity of small and medium-sized enterprises, while Seck et al. (2020) investigated how gender discrimination in access to credit contributes to the productivity gap between male- and female-owned firms. Moreover, in Senegal, as in many developing countries, the unreliability of electricity is a significant issue. It has been identified as one of the primary constraints that deteriorate the business environment (see Figure A1 in the appendix). According to the 2014 World Bank’s Enterprise Survey, approximately 78.5% of firms reported experiencing an average of seven power outages per month, each lasting two hours (Table 4.1). Given that the number of female-owned firms is increasing and that they employ 16.2% more workers than their male-owned counterparts (Seck et al., 2020), it is crucial to assess the extent to which the unreliability of electricity infrastructure undermines the productivity of female-owned firms. This assessment holds substantial policy implications.

The article employs a variety of empirical strategies to achieve its objectives, using a sample of 601 Senegalese establishments. It integrates the Tobit model and propensity score matching (PSM) to analyze the impact of power outages on firm productivity. Additionally, it adopts the methodology of Combes et al. (2012) to test the female-underperformance hypothesis within firms. Subsequently, the study applies the counterfactual decomposition method, as proposed by Blinder (1973) and Oaxaca

(1973), to investigate the effect of power outages on the gender-based productivity gap. The findings suggest that female-owned firms underperform relative to male-owned firms. It is found that power outages have a negative relationship with firm productivity and a positive association with the gender-based productivity gap. Our findings further highlight that the productivity gap is mainly driven by its structural component and lower within establishments that own generators.

The remainder of the article is structured as follows. Section 2 provides an overview of the literature review. Section 3 describes the data used and Section 4 presents the empirical strategies. Section 5 presents and discusses the main findings. The conclusion and policy recommendations are drawn in section 6.

4.2 Related empirical literature

Power outages affect firms in several ways. Frequent discontinuity in the electricity supply impose additional costs on firms. The latter may be constrained to purchase generators, which are alternative sources of electricity, when faced with power disruptions. Such a coping strategy requires additional acquisition costs (for generators) and operating costs (purchase of diesel) to the detriment of productive activities (Steinbuks and Foster, 2010). In some instances, firms can adopt technologies that facilitate the processing and conservation of input materials (Alam, 2013) or energy-efficient technologies (Grainger and Zhang, 2019). The adoption of such energy-efficient technologies may cause a decline in productive capacity in the long term as such technologies are likely to be less sophisticated in terms of output growth (Grainger and Zhang, 2019). Furthermore, when faced with power shortages, firm may outsource the production of energy-intensive inputs (Fisher-Vanden et al., 2015) or squarely reduce their workforce (Allcott et al., 2016; Elliott et al., 2021; Grainger and Zhang, 2019). Regardless of the adjustment process, unexpected power disruptions generate extra costs for companies, leading to reduced production and profits.

Existing mpirical studies confirmed that power disruptions are detrimental to firm performance (Abdisa, 2018; Allcott et al., 2016; Amadu and Samuel, 2020; Cissokho, 2015, 2019; Cole et al., 2018; Diboma and Tamo Tatietse, 2013; Falentina and Resosudarmo, 2019; Fisher-Vanden et al., 2015; Grainger and Zhang, 2019; Iimi, 2011; Moyo, 2012; Oseni and Pollitt, 2015). In Pakistan, an hour of (unplanned) power outages was found to reduce firms' turnover and value added by 10 percent and 20

percent, respectively (Grainger and Zhang, 2019). Similar results were reported by Allcott et al. (2016) in India. Using a panel dataset of 23,000 Chinese firms from 1999 to 2004, Fisher-Vanden et al. (2015) show that power outages increase unit production costs by around 8 percent. Abdisa (2018) reports that Ethiopian firms incurred a 15 percent cost premium due to power outages. Cole et al. (2018) conclude that Sub-Saharan African firms can increase their sales by around 34 percent if the average power outages are reduced to the same level as those of South Africa.

Yet, empirical studies are not clear-cut. The adverse effects of power disruptions are not homogeneous. Losses due to power cuts appear to be larger for electricity-intensive manufacturing (Grainger and Zhang, 2019), small and medium-sized enterprises and and firms that operate without generators (Bardasi et al., 2011; Coleman, 2007; Islam et al., 2020; Oseni and Pollitt, 2015; Steinbuks and Foster, 2010).

A strand of the literature is interested in the firm-level gender-based productivity gap and its main determinants. Testing female-underperformance hypothesis is one of its core objectives. Theoritically, the female-underperformance hypothesis draws on two perspectives which are the liberal feminist theory and the social feminist theory (Fischer et al., 1993; Zolin et al., 2013). The liberal feminist theory holds that female entrepreneurs are less successful because women are confronted with financial and human capital discrimination (constraint-driven gaps, have difficulty accessing credit (Aidis et al., 2007; Muravyev et al., 2009), lower educational level (Campos and Gassier, 2017) and lower experience compared to men on average (Aterido et al., 2011; Campos and Gassier, 2017). From social feminist approach's perspective, gender-based disparities stem from differences in background and socialisation, which in turn determine preferences and choices (preference-driven gaps). Women may have a different vision of business and develop their businesses differently. It has been highlighted that women-owned businesses are more active in services (hotels and restaurants), retail (textiles, fruit, and food), informal sectors and operate frequently in small firms (Allcott et al., 2016; Amin and Islam, 2014; Bardasi et al., 2011; Islam et al., 2020; Coleman, 2007), which are less efficient and productive (Bardasi et al., 2011).

Yet, empirical works do not fit into one block. While the female-underperformance hypothesis was confirmed in some studies (Aterido and Hallward-Driemeier, 2011; Bardasi et al., 2011; Essers et al., 2021; Nordman and Vaillant, 2017; Islam et al., 2020),

it has been refuted in some existing studies (Zolin et al, 2013; and Gui-Diby et al., 2017). Using a sample of 128 developing countries, Islam et al. (2020) documented an unconditional gap of 11 percent and a conditional gap of 13 percent. Essers et al. (2021) found an unconditional gap of 12 percent among Ethiopian firms. A similar result was also reported by Bardasi et al. (2011) for sub-Saharan Africa. Using combined household survey and census data, Ggombe and Akampumuza (2018) found that turnover and net income per worker are respectively 20 to 22 percent and 22 to 25 percent lower among female-owned firms in Rwanda.

The empirical literature indicates a plethora of studies testing the female-underperformance hypothesis. Additionally, numerous past studies have investigated the determinants of firm productivity, including the reliability of electricity, and factors contributing to the gender-based productivity gap. However, there is a notable absence of research linking power disruptions to the gender-based productivity gap. Gender considerations are often overlooked in the exploration of power outages' effects on firm productivity, and the unreliability of electricity is rarely discussed in the context of factors influencing the gender-based productivity gap. The primary contribution of this article is its examination of the extent to which power cuts exacerbate the productivity gap between male- and female-owned firms.

4.3 Data and descriptive statistics

This article uses the 2014 World Bank's Enterprise Survey (WBES) dataset, which comprises 601 Senegalese establishments. The latters are the physical locations where business activities are conducted, industrial operations take place and services are provided. We use the WBES datase as it stands out as a consistent, publicly accessible, reliable, and rich dataset (Islam and Hyland, 2019) and widely used in the literature (Asiedu et al., 2021; Cole et al., 2018; Moyo, 2012; Oseni and Pollitt, 2015). Furthermore, it is extracted from a reliable questionnaire addressed to the managers of the surveyed establishments. The WBES dataset also contains information on the linkage between establishment productivity, gender, and electricity infrastructure. The current article uses the 2014 round (instead of the 2007 one) because it covers a representative sample of establishments in the private sector, compared to the 2007 WBES which focused selectively on establishments operating in the Dakar metropolis. In addition, the 2014 WBES data are based on random sampling stratified by region,

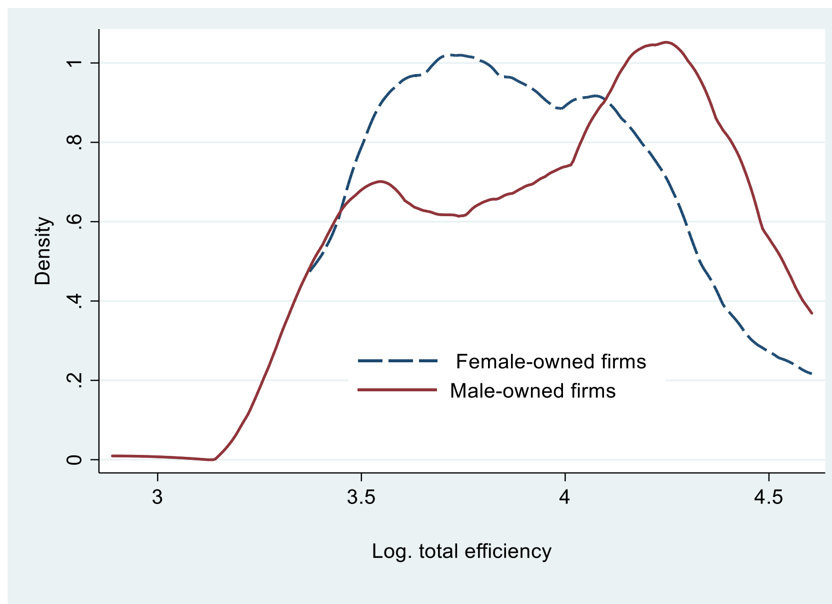
establishment size and establishment industry; such stratification allows for a more in-depth heterogeneity analysis.

Table 4.1 presents the descriptive statistics of the establishments' observable characteristics, including power outages and productivity by gender. Drawing on Hallward-Driemeier's (2013), gender is measured by a binary variable equal to 1 if the owner of the firm is female and 0 otherwise. Productivity is proxied with technical efficiency scores which are computed with Data Envelop Analysis (DEA) approach (refer to the following section for more development on DEA approach). Power outages is equally captured by a binary variable equal to 1 if the establishment experienced power outages in the year prior to data collection and 0 otherwise. The World Bank Enterprise Survey (WBES) dataset measures the unreliability of electricity infrastructure by the number of power outages experienced in a typical month, the average duration of a power outage, the total loss caused by power outages and whether an establishment experienced power outage (binary). These different metrics of power outage have been widely used in the literature (Asiedu et al., 2021; Cole et al., 2018; Moyo, 2012; Oseni & Pollitt, 2015). The current study measures power outages by a binary variable because this variable has more observations than the variables that measure the duration of power outages and the losses due to power outages. In addition, a binary variable is adapted to the propensity score matching for it eases the definition of the treatment group.

Column 1 of Table 4.1 shows that a great share of the surveyed establishments are small and medium-sized enterprises (SMEs) (90.6 percent), with an average current number of employees of 54. These establishments operate in the service and retail sectors (56 percent) and are predominantly owned by the private sector (99.3 percent). Nearly 81.2 percent of the establishments finance their productive activities with their own funds and only 0.13 percent of the establishment provide training for their employees. Most of the Senegalese establishments were exposed to unexpected power disruptions; around 78.5 percent reported to have experienced power outages in the year preceding the survey. These unforeseen power disruptions explain why most establishments (62.3 percent) have an alternative energy source - generators.

Column 4 of Table 4.1 indicates no significant difference in the establishments' observable characteristics across the gender line, except for efficiency scores, the use

of water, sectors and regions were the establishment operates. Women-owned establishments operate in the service and retail sectors (66 percent), use more water in their production activities (98.7 percent), and are more concentrated in Dakar city (71 percent). Furthermore, The male-owned establishments' average pure technical efficiency score is higher than that of the female-owned counterparts, leading to an unconditional productivity gap of 10 percent ($e^{-0.110} - 1$). The underperformance of female-owned establishments is confirmed by the distributions of gender-based efficiency scores in Figure 4.1.



Source: Authors,2022.
Figure 4-1. Productivity distribution by gender

Table 4.2 shows the descriptive statistics of observable characteristics for establishments that experienced power outages and those that did not. The table indicates a significant difference in the productivity between both types of establishments. Establishments located in Dakar were much more exposed to power outages than those in the other regions (Kaolack, Thiès and Saint Louis). Furthermore, establishments that experienced power outages are more likely to have purchased a generator (67.8 percent), compared with their counterparts that reported no power outages (42.2 percent). Both type of establishments have significant characteristics, therefore not directly comparable. This is where PSM comes in To help reduce these differences. The results from the Logit model used to derive propensity scores are

presented in Table A1 and the ones from the post-matching balancing test are shown in Table A2 in the appendix.

Table 4-1. Descriptive statistics of the establishments' characteristics by gender

	Total sample	Male-owned establishments	Female-owned establishments	Difference
	(1)	(2)	(3)	(4)
Productivity				
Log. Pure technical efficiency	3.982	4.002	3.892	0.110***
	(0.018)	(0.020)	(0.038)	(0.046)
Establishment characteristics				
Power outages (Yes=1)	0.785	0.782	0.800	-0.017
	(0.019)	(0.022)	(0.045)	(0.050)
Losses due to power outages (in percentage)	5.767	6.052	4.826	1.226
	(0.776)	(0.958)	(1.071)	(1.841)
Firm's age (years)	17.77	17.36	19.48	-2.116
	(0.733)	(0.823)	(1.596)	(1.854)
Percentage of foreign shareholders	9.247	8.160	13.98	-5.827
	(1.294)	(1.357)	(3.590)	(3.314)
Percentage of State's shares	0.652	0.616	0.812	0.652
	(0.269)	(0.296)	(0.650)	(0.269)
Manager' experience (years)	20.59	20.69	20.12	0.572
	(0.543)	(0.608)	(1.213)	(1.390)
Ownership of generator (Yes=1)	0.623	0.621	0.629	-0.007
	(0.023)	(0.025)	(0.053)	(0.059)
Exports (in percentage)	3.792	3.853	3.530	0.322
	(0.743)	(0.837)	(1.606)	(1.900)
Total employees at inception	31.83	32.89	26.89	5.995
	(8.28)	(9.819)	(10.50)	(21.73)
Usage of water (Yes=1)	0.958	0.951	0.987	-0.036*
	(0.009)	(0.011)	(0.012)	(0.024)
Current total employees	54.51	53.94	56.98	-3.045
	(11.43)	(13.31)	(19.78)	(29.331)
Employee training (Yes=1)	0.138	0.135	0.153	-0.018
	(0.016)	(0.018)	(0.041)	(0.043)
Share of assets financed with bank loan	5.574	5.422	6.243	-0.820
	(0.752)	(0.832)	(1.771)	(1.938)
Share of assets financed with own funding	81.18	81.96	77.78	4.183
	(1.411)	(1.541)	(3.460)	(3.619)
Establishments size (Small & medium=1)	0.906	0.887	0.910	0.023
	(0.014)	(0.035)	(0.015)	(0.057)
Sector (Manufacturing=1)	0.444	0.469	0.333	0.136**
	(0.023)	(0.026)	(0.052)	(0.061)
Region (Dakar=1)	0.590	0.561	0.716	-0.154***
	(0.023)	(0.026)	(0.050)	(0.060)

Note. Standard deviations are reported in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4-2. Descriptive statistics of the establishments' characteristics per power outages status

	Establishment with power outages (mean)	Establishment without power outages (mean)	Difference
	(1)	(2)	(3)
Productivity			
Log. Pure technical efficiency	4.246 (0.028)	3.910 (0.019)	0.336*** (0.040)
Establishment characteristics			
Owners' gender (1=Female)	0.173 (0.039)	0.189 (0.021)	-0.015 (0.045)
Firm's age (years)	17.75 (1.707)	17.83 (0.809)	-0.077 (1.825)
Percentage of foreign shareholders	8.109 (2.672)	9.883 (1.490)	-1.773 (3.201)
Pourcentage of State's shares	0.505 (0.505)	0.684 (0.310)	-0.178 (0.655)
Manager's experience (years)	20.92 (.173)	20.47 (0.611)	0.447 (1.322)
Ownership of generator (Yes=1)	0.423 (0.051)	0.678 (0.025)	-0.254*** (0.055)
Exports (in percentage)	4.384 (1.646)	3.590 (0.824)	0.793 (1.809)
Total employees at inception	13.32 (2.561)	36.70 (10.33)	-23.38 (20.17)
Usage of water (Yes=1)	0.978 (0.015)	0.953 (0.011)	0.025 (0.023)
Current total employees	27.48 (6.152)	61.08 (14.28)	-33.59 (27.62)
Employee training (Yes=1)	0.108 (0.032)	0.150 (0.019)	-0.042 (0.041)
Share of assets financed with bank loan	6.444 (1.912)	5.258 (0.793)	1.185 (1.824)
Share of assets financed with own funding	81.88 (3.070)	81.15 (1.572)	0.729 (3.434)
Establishments size (Small & medium=1)	0.913 (0.029)	0.908 (0.015)	0.004 (0.033)
Sector (Manufacturing=1)	0.434 (0.051)	0.438 (0.026)	-0.003 (0.058)
Region (Dakar=1)	0.445 (0.052)	0.625 (0.026)	-0.180*** (0.057)

Note. Standard deviations are reported in parentheses.
* p < .10, ** p < .05, *** p < .01

Table 4.3 delineates the distribution of total, pure, and scale technical efficiency scores according to selected binary characteristics. On average, the establishments exhibit a total efficiency score of 7.2 percent, indicating an efficiency gap of 92.8 percent. In other words, the average establishment has a total efficiency shortfall of nearly 93 percent relative to the most efficient counterparts. This efficiency gap diverges somewhat from the 80 percent gap documented by Seck et al. (2020) for Senegalese firms. This discrepancy may be attributed to the differing DEA models used; Seck et al. (2020) employed the output-oriented model proposed by Banker et al. (1984), whereas this study adopts the input-oriented model to estimate technical efficiency scores. Nonetheless, the average technical efficiency score of 7.2 percent approximates the 8 percent efficiency reported by Cissokho (2019) for manufacturing SMEs in Senegal.

The low average technical efficiency score can be attributed to the overrepresentation of SMEs in the dataset (90.6 percent). Most of these firms are from the production frontier, indicating significant potential for productivity enhancement. The poor performance of Senegalese SMEs may be more related to their size than to their sector of operation or their management and organizational practices. For instance, when examining pure efficiency scores (influenced by weak organizational and management practices), the efficiency gap between the average firm and its most productive counterpart on the production frontier is approximately 43 percent, which is less than the efficiency gap due to scale, estimated at nearly 90 percent. This suggests that improving scale efficiency could significantly enhance the productivity of Senegalese firms.

Table 4.3 further indicates that female-owned establishments have low average total efficiency and pure efficiency scores compared to male-owned establishments; female-owned establishments' average efficiency score is higher than their male-owned counterparts, although both display low scores. Table 4.3 further displays that establishments that have experienced power outages, which operate in regions other than Dakar, SMEs, manufacturing establishments, and establishments with an alternative energy source tend to have low technical efficiency scores.

Table 4-3. Distribution of technical efficiency scores

	Total efficiency	Efficiency pure	Scale efficiency
	(1)	(2)	(3)
Total sample	7.200	57.24	10.78
	(19.30)	(20.49)	(22.84)
Gender of the establishment's owner			
Female	7.163	51.95	11.55
	(2.009)	(2.106)	(2.49)
Male	7.275	58.50	10.70
	(1.075)	(1.130)	(1.259)
Power outages			
Yes	5.822	53.19	9.849
	(0.880)	(1.054)	(1.149)
No	12.32	72.30	14.28
	(2.960)	(1.918)	(3.051)
Ownership of generator			
Yes	7.002	51.52	10.57
	(1.198)	(1.174)	(1.381)
No	7.530	66.81	11.15
	(1.529)	(1.538)	(1.885)
Size of the establishments			
Small & Medium	5.053	57.26	8.414
	(0.777)	(1.001)	(0.962)
Large	30.80	57.00	41.31
	(6.191)	(4.646)	(6.229)
Region			
Dakar	10.30	54.78	15.12
	(1.504)	(1.418)	(1.728)
Other regions	2.900	60.65	4.775
	(0.730)	(1.312)	(0.996)
Sector			
Manufacturing	6.881	55.66	10.35
	(1.451)	(1.573)	(1.637)
Non-manufacturing	7.448	58.47	11.12
	(0.239)	(1.286)	(1.521)

Note. Efficiency scores are in percentage; standard deviations are reported in parentheses.

4.4 Empirical strategies

4.4.1 Effect of power outages on firm productivity

To estimate the effect of power outages on firm productivity, the technical efficiency (TE) scores of establishment i are regressed on the variable measuring power outages (P_i) as shown in Equation 1. The latter assumes θ_r and λ_s to be regional and sectoral heterogeneities, respectively, and $\varepsilon_{i,t}$ to be the idiosyncratic error term. α , γ, and β' are the parameters to be estimated. X measures the observable characteristics.

$$Log(TE_{\mathrm{i}}) = \alpha + \gamma P_i + \beta' X_i + \theta_r + \lambda_s + \varepsilon_{i,t} \quad (5)$$

Estimating Equation 4 using ordinary least squares (OLS) would result in biased estimates due to the likely endogeneity of exposure to power outages. From a firm's perspective, power outages are external shocks dependent on external suppliers, as firms generally cannot self-supply electricity, except in cases where they own generators. However, exposure to power cuts is likely endogenous. First, firms often possess backup energy sources, such as generators, to mitigate the impact of power cuts. Second, policymakers frequently enhance electricity infrastructure near highly productive firms, while neglecting to maintain infrastructure in areas with less productive firms. Additionally, high-productivity firms may choose to locate in regions with reliable electricity infrastructure to sustain their desired productivity levels, resulting in lower exposure to power cuts and higher productivity. From a macroeconomic standpoint, causality may operate in both directions (Moyo, 2012). Less productive firms pay lower taxes, leading to reduced fiscal revenue and weak incentives for policymakers to improve electricity infrastructure quality. Consequently, these firms are more frequently exposed to power shortages due to poor electricity infrastructure quality.

To downsize the endogenous bias related to exposure to electricity, we employ propensity score matching (PSM). Firms that are off the common support are excluded, resulting in a sample of comparable firms in terms of their exposure to power cuts. Drawing on Ji and Lee (2010) and Top et al., (2020), we estimate a Tobit model on the matched sample to better model the effect of power cut on firm productivity.

The technical efficiency (TE) scores, which measure firm productivity, are computed using Data Envelop Analysis (DEA). The latter uses either input-based model or output-based model to generate technical efficiency scores. Input-based models minimize inputs for a given level of output, while output-based models maximize output without requiring more of any of the observed input values. The DEA approach further considers the nature of returns to scale. For example, the DEA model developed by Charnes et al. (1978) assumes constant returns to scale. This assumption holds only when the decision-making units (DMUs) are operating at their optimal scale. Such an assumption appears difficult to maintain in practice as firms are faced with either

economies of scale or diseconomies of scale. Banker et al. (1984) proposed an alternative model based on variable returns to scale (VRS). We use the input-based Banker et al.'s (1984) model in this article to generate the technical efficiency scores. This model is opted for as most Senegalese companies are in the service sector where managers seem to have more control over inputs than outputs (Gafa and Egbendewe, 2021).

Banker et al.'s (1984) model decomposes technical efficiency (TE_{CSR}) into pure technical efficiency (TE_{VRS}) and scale efficiency (SE) under the assumption of constant returns to scale (Equation 2) (Xin-gang and Zhen, 2019). It also has the merit of ensuring that scale efficiency is not confused with technical efficiency measures (Coelli et al., 2005).

$$TE_{CSR} = TE_{VRS} \times SE \quad (2)$$

Let n be the total number of establishments $(; m = 1; \cdots m_0 \cdots ; n)$, for which we seek to determine technical efficiency scores. We also assume that each DMU uses a set of l inputs $(l = 1; \cdots ; k)$ to produce z outputs $(z = 1; \cdots ; s)$. Then x_{lm} is the vector of inputs used by unit DMU_m to produce an output vector y_{zm}. Based on the Charnes et al.'s (1978) definition of efficiency (Banker et al., 1984), the productivity (or technical efficiency) of unit DMU_m can be written as the ratio of outputs to inputs. u and v are weights assigned to each input and output under the constraint that the efficiency score of each DMU is less than unity. The technical efficiency score (TE_{m0}) of the decision unit DMU_{m0} is obtained by solving the linear program represented by System 3 (Charnes et al., 1978). System 4 presents the input-oriented VRS model used to determine the technical efficiency score (Banker et al., 1984).

$$\begin{cases} \text{Max } \mathrm{TE_{m0}}(\mathrm{v}, \mathrm{u}) = \dfrac{\sum_{z=1}^{s} u_z y_{zm0}}{\sum_{l=1}^{k} v_l x_{lm0}} \\ S/C \ \mathrm{TE_m} = \dfrac{\sum_{z=1}^{s} u_z y_{zm}}{\sum_{l=1}^{k} v_l x_{lm}} \leq 1; \ u_z \geq 0 \text{ and } v_l \geq 0 \end{cases} \quad (3)$$

$$\begin{cases} \text{Max } \mathrm{TE}_{\mathrm{m0}}(\mathrm{v},\mathrm{u}) = \dfrac{\sum_{z=1}^{s} u_z y_{zm0}}{\sum_{l=1}^{k} v_l x_{lm0} - v_0} \\ S/C\ \mathrm{TE}_{\mathrm{m}} = \dfrac{\sum_{z=1}^{s} u_z y_{zm}}{\sum_{l=1}^{k} v_l x_{lm} - v_0} \leq 1;\ u_z \geq 0 \text{ and } v_l \geq 0 \text{ and } v_0 \in \mathcal{R} \end{cases} \quad (4)$$

4.4.2 Testing the female underperformance

To test the female-underperformance hypothesis, the article relies on the Combes et al. (2012) statistical approach, initially developed by Melitz and Ottaviano (2008) to assess firm selection. Applied to productivity gap within firms, it mainly consists of comparing the distributions of female-owned and male-owned firms by generating three outcomes that are dilation, truncation and shift parameters. In our case, female-owned establishments' productivity distribution that is left-shifted, less dilated and left-truncated relative to that of male-owned establishments would imply, respectively, that female-owned establishments are less productive, homogeneous, and forced out of the market by competition.

For a formalisation purpose, we assume two cumulative distribution functions with a similar functional form (Γ). One for male-owned establishments (Γ_M) and the other for female-owned establishments (Γ_F). The distribution function Γ_M (Γ_F) is obtained by shifting Γ to the right by a parameter $A_M(A_F)$, left truncating a share $T_M(T_F)$ of Γ and dilating Γ by a factor $D_M(D_F)$. The female-owned and male-owned establishments 'distribution functions of the cumulative productivity are given below.

$$\Gamma_M(TE) = max\begin{Bmatrix} 0, & \dfrac{\Gamma\left(\dfrac{TE - A_M}{T_M}\right) - T_M}{1 - S_M} \end{Bmatrix} \quad (6)$$

$$\Gamma_F(Y) = max\begin{Bmatrix} 0, & \dfrac{\Gamma\left(\dfrac{TE - A_F}{D_F}\right) - S_F}{1 - T_F} \end{Bmatrix} \quad (7)$$

By defining $D \equiv D_F/D_M$, $A \equiv A_F - DA_M$, and $T \equiv (T_F - T_M)/(1 - T_M)$, where Γ_M (Γ_F) is a function of Γ_F (Γ_M), the relationship between Γ_M and Γ_F is given by the Equations 7 and 8.

$$\Gamma_M(TE) = \max\left\{0, \frac{\Gamma_F(D * TE + A) - \frac{-T}{1-T}}{1 - \frac{-T}{1-T}}\right\} if T_F < T_M \tag{8}$$

$$\Gamma_F(TE) = \max\left\{0, \frac{\Gamma_F\left(\frac{TE - A}{D}\right) - T}{1 - T}\right\} \tag{9}$$

Drawing on Combes et al. (2012), $\Gamma_M(\mathrm{TE})$ and $\Gamma_F(\mathrm{TE})$ can be transformed into quantile functions and the shift (S), dilation (D) and left truncation (T) parameters required to be applied to $\Gamma_M(\mathrm{TE})$ and $\Gamma_F(\mathrm{TE})$ can be derived. The parameter D represents the dilation ratio of the productivity distribution of female-owned establishments relative to male-owned establishments. Parameters T and S capture the intensity of truncation and the lag in the productivity distribution of female-owned establishment relative to their male counterpart, respectively.

4.4.3 Effect of power outages on the gender-based productivity gap

To explore the relation between power outages and productivity gap, we heavily rely on the Blinder-Oaxaca decomposition method (Blinder, 1973; Oaxaca, 1973). This technique has been extensively used in the literature to assess the agricultural productivity gap, the wage differential, the labour productivity gap, and the sectoral gaps (Essers et al., 2021; Goldstein et al., 2013; Islam et al., 2018, 2020; Oaxaca and Ransom, 1999; Palacios-López and López, 2015). The Blinder-Oaxaca method decomposes the productivity into endowment and structural effects and explores their determinants.

To formalise the model, we assume M and F to be two groups of firms owned by men and women respectively; TE is the productivity of the establishments, measured by technical efficiency scores and X is a set of their observable characteristics (including power outages). For each group of establishments, productivity is regressed on the variables X, where β are the parameters to be estimated and ε is the error term (equation 9).

$$TE_g = X_g'\beta_g + \varepsilon_{g,} \qquad g \in \{M, F\} \tag{10}$$

$$E(\varepsilon_g) = 0 \tag{11}$$

Starting from Equation 9, the productivity gap (PG) is defined as the difference in average productivity between male- and female-owned establishments (equation 11), provided that condition 10 is met. Rearranging Equation 11 gives Equation 12.

$$PG = E(TE_M) - E(TE_F) = E(X_M)'\beta_M - E(X_F)'\beta_F \tag{12}$$

$$PG = [E(X_M) - E(X_F)]'\beta_F + \mathrm{E}(X_F)'(\beta_M - \beta_F) + [E(X_M) - E(X_F)]'(\beta_M - \beta_F) \tag{13}$$

Equation 12 decomposes the productivity gap into three components. The first component $[E(X_M) - E(X_F)]'\beta_F$ measures the productivity gap due to differences in predictors (endowment effect). The second component $\mathrm{E}(X_F)'(\beta_M - \beta_F)$ measures the contribution of the differences in coefficients and intercepts. The third component $[E(X_M) - E(X_F)]'(\beta_M - \beta_F)$ is an interaction term that accounts for simultaneous differences in endowments and coefficients. As Equation 12 is formulated with reference to female-owned establishments, the first component captures the variation in average productivity of female-owned establishments if the latter has the same levels of predictors as male-owned establishments. The second component captures the expected variation in the average productivity of female-owned establishments if the estimated coefficients are adjusted to the same level as those for male-owned establishments.

4.5 Main results

4.5.1 Effects of power outages on firm productivity

As a first approximation, we estimate the Tobit model on the unmatched sample and reporte the results in Table 4.4. We find a negative correlation between power outages and firm productivity. The results of the Tobit model on the matched sample reported in Columns 1 to 5 of Table 4.5 confirms a negative coefficient for power outages. These results are consistent with estimates obtained with PSM and inverse probability weighting (IPW) estimators as indicated by Table A3 in the appendix. The negative

coefficient of power outages is not altered after the intégration of interaction terms as shown by Columns 6, 7 and 8 of Table 4.5. The harmful effect of power outages on productivity does not either depend on the sector and region of operation, or the size of the establishment as shown by the sub-sample analyses (Refer to Table A4 in the appendix). Our finding that power outages have a deleterious effect on firm productivity is consistent with past findings such as Moyo (2012), Allcott et al. (2016), Cissokho (2019), Falentina and Resosudarmo (2019), and Elliott et al. (2021). We were unable to confirm that owning a generator mitigates the harmful effect of unexpected power disruptions as shown by Moyo (2012) and Cissokho (2019). Owning a generator may not be enough to overcome the adverse effect of power disruptions. This may be the case if the establishments use heavy and energy-intensive equipment, so that the insufficient energy from the generator turns out to be an imperfect and poor substitute for energy from the national grid. Furthermore, the additional costs incurred using generators could contribute to reducing the performance of establishments.

Table 4-4.Tobit model on the unmatched sample

	Tobit model on the unmatched sample Dependent variable : Log. Total efficiency scores				
	(1)	(2)	(3)	(4)	(5)
Power outages (Yes=1)	-0.336***	-0.321***	-0.295***	-0.299***	-0.282***
	(0.034)	(0.035)	(0.030)	(0.031)	(0.031)
Constant	4.246***	4.311***	5.229***	5.277***	5.320***
	(0.028)	(0.033)	(0.121)	(0.122)	(0.123)
Observations	420	420	396	396	396
R squared	18.08	21.10	58.99	60.04	63.17
Control variables	No	No	Yes	Yes	Yes
Region (Dakar=1)	No	Yes	No	No	Yes
Sector (Manufacturing=1)	No	Yes	No	Yes	Yes

Note. Robust standard deviations are reported in the parentheses.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4-5. Results of Tobit model on the matched sample

Dependent variable	Tobit model on the matched sample Log. Total efficiency scores							
Interaction variables						Generator ownership (Yes =1)	State shareholder (Yes =1)	Foreign shareholders (Yes =1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Power outages (Yes=1)	-0.350***	-0.334***	-0.292***	-0.296***	-0.281***	-0.234***	-0.279***	-0.272***
	(0.035)	(0.037)	(0.030)	(0.030)	(0.031)	(0.043)	(0.031)	(0.032)
Power outages × Generator ownership						0.102		
						(0.063)		
Power outages ×State shareholder							-0.004	
							(0.003)	
Power outages × Foreign shareholders								-0.001
								(0.001)
Constant	4.256***	4.330***	5.256***	5.306***	5.325***	5.291***	5.310***	5.324***
	(0.029)	(0.035)	(0.121)	(0.122)	(0.123)	(0.122)	(0.142)	(0.123)
Observations	309	386	384	384	384	384	384	384
Pseudo R^2	21.64	24.13	61.62	62.76	62.60	66.22	67.7	65.92
Sector (Manufacturing=1)	No	Yes	No	Yes	No	No	No	No
Region (Dakar=1)	No	Yes	No	No	No	No	No	No
Control variables	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Note. Standard errors are indicated in parentheses.
* p < .10, ** p < .05, *** p < .01

1.1 Hypothesis of underperformance of women-owned firms

As a first approximation, we estimate the correlation between firm productivity and gender of the firm owner. The results are reported in Table 4.6. Columns 1 and 2 report estimations without interaction terms while Columns 3 to 8 present the results with interactions. Findings suggest that the conditional productivity gap (Column 2 of Table 4.8) is close to the unconditional productivity gap (Column 1 of Table 4.8). Furthermore, the productivity gap remains significant even after the interaction variables were included (Columns 3 to 8 of Table 4.8). We observe that the coefficients of the interaction terms are positive and significant. It ensues that the gender-based productivity gap gets smaller as the firm owns a generator, increases its size and get bank loans. Unlike Gui-Diby et al. (2017) and Seck et al. (2020), our findings suggest that the financial constraints women face due to their limited access to the credit market is among the determinants of women underperformance.

Findings from the the sub-sample analyses (reported in Table A5 in the appendix) indicate that the gender-based productivity gap is significant in small and medium-sized

enterprises (SMEs), in the service sector, and in regions other than Dakar, including Kaolack, Saint-Louis and Thiès.

The results from the quantile model of Combes et al. (2012) are now reported in Table 4.7. Findings indicate a negative and significant shift parameter for the total sample and the sub-sample, except for firms in the region of Dakar and larger establishments. This confirms once more the female-underperformance hypothesis.The dilation parameter is positive and significant (except for non-SME) while the truncation parameter is not significant thoughout. This implies that despite that male-owned establishments perform better compared to female-owned counterparts, the latters are heterogeneous and do not exit the market.

Table 4-6. Correlation between gender of establishment owner and firm productivity

Dependent variable	Tobit model on the unmatched sample Log. Total efficiency scores							
Interaction variables			Power outages (1=Yes)	Generator ownership (1=Yes)	Firm age (years)	Firm size	Employee training (1=Yes)	Bank-financed assets (in percentage)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender of the establishment owner (Female=1)	-0.11** (0.043)	-0.113*** (0.041)	-0.144** (0.074)	-0.231*** (0.056)	-0.139* (0.077)	-0.127*** (0.042)	-0.119*** (0.044)	-0.149*** (0.042)
Gender×Outages (Yes=1)			-0.039 (0.089)					
Gender × Generator				0.189** (0.079)				
Gender×firm age					0.001 (0.004)			
Gender×Employees						0.0005*** (0.0001)		
Gender×Training							0.050 (0.136)	
Gender×Bank loan								0.006** (0.002)
Constant	4.002*** (0.020)	4.382*** (0.0450)	4.388*** (0.044)	4.408*** (0.045)	4.376*** (0.045)	4.387*** (0.044)	4.383*** (0.045)	4.392*** (0.043)
Observations	416	359	359	359	359	359	359	359
Pseudo R^2	1.62	40.95	40.99	42.42	16.98	41.38	41.00	42.51
Additional control variables	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors are shown in the parentheses. The control variables are firm age, initial firm size at inception, current firm size, percentage of firm assets financed by bank loans, exports, percentage of state and foreign ownership, power outages, ownership of a generator and employee training.
* p < .10, ** p < .05, *** p < .01

Table 4-7. Results from Combes et al.'s (2012) quantile estimate

Dependent variable	Log. Total efficiency scores						
		Sector		Region		Firm size	
	Total sample	Manuf.	Non-manuf.	Dakar	Others	SME	Non-SME
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shift parameter A	-0.115***	-0.157*	-0.121**	-0.071	-0.165***	-0.140***	0.025
	(0.036)	(0.087)	(0.047)	(0.045)	(0.069)	(0.051)	(0.080)
Dilation parameter D	0.970	0.956	0.959	0.980	0.959	0.965	1.006
	(0.010)	(0.021)	(0.016)	(0.011)	(0.016)	(0.008)	(0.023)
Truncation parameter T	-0.113	-0.707	-0.707	-0.079	-0.152	-0.264	-0.070
	(0.160)	(0.728)	(0.548)	(0.287)	(0.252)	(0.190)	(0.196)

Note. Robust standard errors are shown in the parentheses. SME represents small and medium-sized establishments. The other regions are Kaolack, Saint-Louis and Thiès.
* $p < .10$, ** $p < .05$, *** $p < .01$

1.2 Effect of power outages on the gender-based productivity gap

Table 4.8 displays the estimates from the Oaxaca-Blinder counterfactual decomposition. Columns 1 to 3 present the estimates for the unmatched sample while Columns 4 to 6 present the estimates for the matched sample. Estimates from the unmatched sample display a significant productivity gap of the order of 0.11 log points, corresponding to a gap of 10.9 percent. This productivity gap is slightly reduced to 10.7 percent in the matched sample. Our findings thus support that the productivity gap varies between 10 percent and 11 percent. Such productivity gap is close to the ones reported by Essers et al. (2021), Islam et al. (2020) and Bardasi et al. (2011).

The endowment effect is not significant while the structural effect is positive and significant for both the unmatched and matched samples. The productivity gap is therefore determined by its structural component. Furthermore, the productivity gap increases with unexpected electrical disturbance as indicated by a positive and significant coefficient for power outages. We therefore retain that the productivity gap arises not from the fact that female-owned establishments experienced more power outages than male-owned ones, but rather from the fact that power cuts affect both groups differently. Consistent with Islam et al (2020), our findings further highlight that the productivity gap is lower within establishments that own generators.

Table 4-8. Results on the Oaxaca-Blinder decomposition

	Unmatched sample			Matched sample		
	Total	EE	SE	Total	EE	SE
	(1)	(2)	(3)	(4)	(5)	(6)
Log. Total efficiency scores (Male-owned firms)	4.006***			4.003***		
	(0.021)			(0.024)		
Log. Total efficiency scores (Female-owned firms)	3.889***			3.923***		
	(0.042)			(0.049)		
Productivity gap	0.1163**			0.114**		
	(0.048)			(0.055)		
Endowment effect (EE)	0.012			0.009		
	(0.028)			(0.031)		
Structural effect (SE)	0.104**			0.104**		
	(0.042)			(0.046)		
Firm age		0.002	0.192**		0.001	0.162
		(0.004)	(0.079)		(0.003)	(0.108)
Percentage of foreign shareholders		0.004	-0.047**		0.002	-0.020
		(0.005)	(0.024)		(0.004)	(0.022)
Percentage of State's shares		-0.0005	-0.005		-0.001	0.0005
		(0.001)	(0.006)		(0.003)	(0.007)
Manager' experience (years)		0.002	-0.193*		0.005	-0.288**
		(0.003)	(0.114)		(0.007)	(0.121)
Power outages (Yes=1)		0.004	0.157**		0.004	0.196***
		(0.016)	(0.068)		(0.021)	(0.060)
Ownership of generator (Yes=1)		-0.0004	-0.087*		0.0002	-0.107**
		(0.012)	(0.047)		(0.012)	(0.053)
Exports (in percentage)		0.0007	0.017*		0.002	0.026**
		(0.002)	(0.010)		(0.005)	(0.014)
Total employees at inception		-0.0007	-0.011		-0.0004	-0.010
		(0.002)	(0.007)		(0.0008)	(0.021)
Current total employees		-0.001	0.026*		-0.0003	0.016
		(0.003)	(0.014)		(0.002)	(0.033)
Employee training (Yes=1)		-0.001	-0.010		-0.0006	-0.004
		(0.006)	(0.022)		(0.003)	(0.022)
Share of assets financed with bank loan		-0.004	-0.052**		-0.005	-0.072**
		(0.011)	(0.021)		(0.012)	(0.029)
Constant			-0.231			0.427***
			(0.158)			(0.132)
Observations			359			
Regions		Yes	Yes		Yes	Yes

Note. Robust standard errors are shown in the parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

4.6 Conclusion and Policy Implications

Against the backdrop of poor-quality electricity infrastructure in developing countries, this article investigates the implications of power outages to firm productivity and gender-based productivity gap. Based on a sample of 601 Senegalese establishments, article combines the Tobit model and the propensity score matching approach to analyse the effect of power outages on firm productivity. It then tests the female-underperformance hypothesis using descriptive statistics and the statistical approach of Combes et al. (2012). It proceed to the counterfactual decomposition by Blinder (1973) and Oaxaca (1973) to examine the extent to which power outages affect the gender-based productivity gap. We find that power outages reduce firm performance. Our data indicate a significant productivity gap between male and female-owned estalishments which increases due to power outages. Importantly, our findings further highlight that the productivity gap is mainly driven by its structural component and lower within establishments that own generators.

Drawing on these findings, policymakers must channel substantial investment in electricity infrastructure. Given that the lack of performance of Senegalese firms is driven by inefficiency of scale, policymakers should give priority to investing in human capital to improve workers and entrepreneurs' productivity. Strengthening the managerial capacity of women entrepreneurs is a viable option (Hallward-Driemeier and Rasteletti, 2010).

Despite its contributions to the literature, the current study has not exhausted the debate, and therefore has limitations. Two main limitations stand out. First, the study uses cross-sectional data, which does not allow for a dynamic analysis. However, this does not call into question the quality of the study's findings, which are based on a sophisticated methodology and a rich database. Future studies should therefore explore panel data to apprehend the dynamic effect of power outages on firm productivity. Second, this study relies on matching methods to illustrate the causal effect of power outages on firm productivity and gender-based productivity gap. The lack of an exogenous instrument for power outages in the database prevents us from using the instrumental variable approach. The latter ought to be considered in future studies as well.

4.7 Appendix

Table A1 : Logit model

Model	Logit model
Dependent variable	Power outages (Yes=1)
	Coefficients
Firm's age (years)	-0.002
	(0.008)
Percentage of foreign shareholders	-0.005
	(0.006)
Percentage of State's shares	-0.022
	(0.027)
Manager' experience (years)	0.006
	(0.012)
Ownership of generator (Yes=1)	1.227***
	(0.286)
Export (percent)	-0.023**
	(0.008)
Current total employees	0.0005
	(0.001)
Employee training (Yes=1)	0.368
	(0.446)
Usage of water (Yes=1)	-1.147
	(0.811)
Share of assets financed with own funding	0.002
	(0.004)
Sector (Manufacturing=1)	-0.464
	(0.283)
Region (Dakar=1)	0.775***
	(0.276)
Constant	1.778*
	(0.928)
Observations	398
Pseudo R2	10.00

Note. Standard errors are shown in the parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A2: Balance tests on observables characteristics

	Treated	Untreated	Bias reduction (%)
	(1)	(2)	(4)
Firm's age (years)	17.61	17.65	96.6
Percentage of foreign shareholders	7.747	7.026	59.3
Percentage of State's shares	0.478	0.241	-32.8
Manager' experience (years)	20.39	19.81	-29.0
Ownership of generator (Yes=1)	0.662	0.664	99.2
Export (percent)	2.770	2.925	80.4
Current total employees	42.70	30.75	64.4
Employee training (Yes=1)	0.147	0.108	6.7
Usage of water (Yes=1)	0.967	0.959	68.5
Share of assets financed with own funding	80.86	10.38	33.9
Sector (Manufacturing=1)	0.436	0.527	-2307.1
Region (Dakar=1)	0.603	0.660	68.3

Table A3. Results on the matching methods

	PSM		IPW	
Outcome variable	Log. Total efficiency score			
	Kernel matching	5-to-1 nearest Neighbors matching	IPWRA	AIPW
	(1)	(2)	(3)	(4)
ATT	-0.331^{***}	-0.306^{***}	-0.310^{***}	-0.303^{***}
	(0.042)	(0.045)	(0.029)	(0.030)
Treated	81	81		
Untreated	305	305		
Observations	386	386	396	396

Note. Robust standard errors are shown in the parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A4. Effect of power outages on firm productivity – Sub-sample analyses.

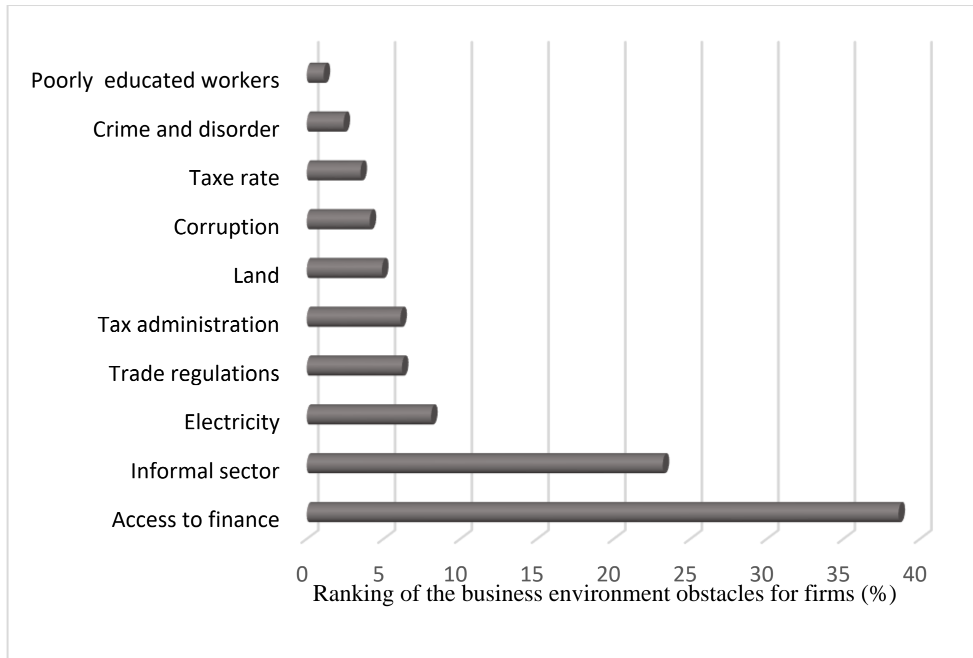
	Dependent variable : Log. Total efficiency scores					
	Sector		Region		Size	
	Manuf.	Non-manuf.	Dakar	Others	SMS	Non-SME
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Unmatched sample						
Power outages	-0.308***	-0.325***	-0.424***	-0.220***	-0.306***	-0.533***
(Yes=1)	(0.058)	(0.045)	(0.055)	(0.044)	(0.036)	(0.094)
Constant	4.291***	4.285***	4.333***	4.207***	4.311***	4.066***
	(0.052)	(0.039)	(0.054)	(0.038)	(0.032)	(0.086)
Observations	184	160	242	176	385	35
Pseudo R^2	26.75	33.04	20.35	20.56	20.83	23.80
Panel B. Matched sample						
Power outages	-0.345***	-0.324***	-0.442***	-0.233***	-0.320***	-0.563***
(Yes=1)	(0.059)	(0.047)	(0.057)	(0.045)	(0.037)	(0.121)
Constant	4.333***	4.287***	4.345***	-4.220***	4.332***	3.949***
	(0.053)	(0.041)	(0.056)	(0.039)	(0.033)	(0.147)
Observations	170	216	220	166	357	29
Pseudo R^2	28.93	20.95	24.31	21.19	27.29	31.52
Control variables	Yes	Yes	No	No	Yes	Yes
Region (Dakar=1)	No	No	Yes	Yes	Yes	Yes
Sector (Manufacturing=1)	No	No	No	No	No	No

Note. Robust standard errors are shown in parentheses. SME represents small and medium-sized establishments. The other regions are Kaolack, Saint-Louis and Thiès.
* p < .10, ** p < .05, *** p < .01

Table A5. Correlation between gender of establishment owner and firm productivity – Sub-sample analysis.

Dependent variable	Log. Total efficiency scores					
	Sector		Region		Firm size	
	Manuf.	Non-manuf.	Dakar	Others	SME	Non-SME
	(1)	(2)	(3)	(4)	(5)	(6)
Gender of the establishment owner (Female=1)	-0.044	-1.122*	-0.076	-0.150**	-0.128***	0.018
	(0.083)	(0.052)	(0.052)	(0.071)	(0.045)	(0.194)
Constant	4.054***	4.074***	3.936***	4.080***	4.120***	3.612***
	(0.063)	(0.034)	(0.044)	(0.036)	(0030)	(0.111)
Observations	170	214	242	165	355	29
Pseudo R^2	10.66	4.43	5.94	5.160	10.73	6.020
Region	Yes	Yes	No	No	Yes	Yes
Sector	No	No	Yes	Yes	Yes	Yes
Control variables	No	No	No	No	No	No

Note. Robust standard errors are shown in the parentheses. SME represents small and medium-sized establishments. The other regions are Kaolack, Saint-Louis and Thiès.
* p < .10, ** p < .05, *** p < .01



Source: World Bank’s Enterprise survey data, 2014.

Figure A1. Major constraints facing firms in Senegal.

Chapitre 5 - Summary of Findings and Conclusions

"All of my conclusions are by nature tenuous and deserve to be questioned and debated. It is not the purpose of social science research to produce mathematical certainties that can substitute for open, democratic debate in which all shades of opinion are represented."

Thomas Piketty (2014, p.776)

5.1. Summary of findings

Three studies make the backbone of the thesis, alongside the introductory and conclusion chapters. They explore the contributions of basic infrastructure resources to economic development in rural Senegal. Resting on this, the thesis makes three significant contributions to the literature. First, the dissertation sheds light on the welfere effects of electrification on rural households while considering contextual factors including the types of electricity sources and access to marketplaces. Second, it investigates the economic benefits that rural households might expect from piped-water adoption while comparing the impacts of government-led (PUDC) versus community-led (non-PUDC) water supply interventions. This is essentially relevant and insightful to draw some implications of piped-water adoption for rural transformations in terms of women empowerment, poverty, and inequality reduction. Third, the thesis contributes to our understanding of the effect of the unreliability of electricity infrastructure on the gender-based productivity gap at the firm level. Findings from the three main chapters were leveraged to advance some policy measures that would improve household welfare and firm productivity. Mainly, substantial investment must be channelled into basic infrastructure to increase water and electricity accessibility for firms and households.

The first chapter of the thesis highlights the overall contribution of water and energy services to economic development and discusses the current state of the water and

electricity sectors in Senegal. It further sheds light on the research gap and objectives and ends by outlining the organization of the thesis.

Chapter 2 evaluates the effect of electricity, offered through the Emergency Programme for Community Development (PUDC), on household welfare proxied with a range of economic and social outcomes. It does so by considering the source of electricity used by households – either on-grid and off-grid electricity – and exploring the role of access to market in the realization of the expected benefits from electricity access. The chapter further considers the distributional effects of rural electrification. The empirical findings from this chapter support the notion that rural electrification is a key agent for rural development and household well-being upgrading. A key empirical finding is that, regardless of the source of electricity either off-grid or on-grid, households exposed to electricity have increased their non-food expenditure and non-agricultural employment compared to observationally similar non-electrified households. The results of this research also underlined that school enrollment, school attendance, and time spent by children studying at home scaled up owing to the arrival of electricity in rural settings, with the increase in school attendance being more pronounced for girls than for boys. Furthermore, poor households and those that have access to a marketplace drew the most substantial benefits from access to electricity. Given that PUDC's rural electrification project has been instrumental in improving employment, expenditure, and education outcomes, findings from Chapter 2 encourage the extension of the electrification program in the whole country. In that regard, rolling out off-grid technologies into enclaved rural areas while extending the grid to accessible zones remain an optimal option. To keep pace with the green revolution, officials should prioritize a climate-smart approach and target poor households.

Findings from Chapter 2 rest on two-point household panel data collected to evaluate the welfare associated with the PUDC and an array of empirical strategies including difference-in-difference approach, propensity score matching, and quantile regressions. The contribution of the chapter to the literature resonates around three points. First, it explores the impact of contextual factors—specifically, types of electricity sources and access to marketplaces—on the relationship between electricity access and household well-being. Second, the chapter investigates the distributional effects of electricity access, examining whether poorer households disproportionately benefit from

electricity usage. Third, it focuses on Senegal, addressing a notable gap in the research on rural electrification in this region.

The third chapter investigates the welfare effects of piped water adoption, with a particular focus on economic benefits. To achieve this, the chapter set a range of objectives. It evaluates the effects of piped-water adoption on employment and household expenditure and examines the interactive effect of piped-water adoption with other basic infrastructure including electricity and road. The chapter further analyses the effects of piped-water adoption across the distribution of household expenditure and disentangles PUDC from non-PUDC interventions. The third chapter makes use of the same database as Chapter 2 and employs a bundle of empirical strategies including the difference-in-difference approach, the propensity score matching, and the quantile regressions. Findings suggest that households that adopted PUDC piped water have significantly increased their agricultural employment. Such effects were not observed regarding non-PUDC piped water. Findings are suggestive that non-poor households drew substantial welfare compared to poor households. Additionally, a key finding is that the lack of decent road infrastructure significantly reduces the welfare associated with piped-water adoption. As policy implications, policymakers must gear toward the universalization of access to drinking water. In addition, building road infrastructure is paramount to facilitating market access and bringing up the welfare effects of rural electrification.

The third chapter's contributions to the literature are threefold. The first novelty revolves around the exploration of the economic benefits of piped-water adoption because past studies seem to be much more inclined to social benefits. Second, Chapter 3 focuses on Senegal where most investigations on access water are more concerned with its productive use. Accessing a rich panel database and the country's progress toward universalization of access to water justify the choice of Senegal as the study area. Finally, Chapter 3 departs from earlier studies by exploring the heterogenous effect of piped-water adoption. The importance of this heterogeneity analysis could be captured in the interface of the policy implications. For instance, the tiny benefits drawn by poor households, explicitly convey the need to facilitate the poor's access to water. This may be achieved through subsidizing the poor's water consumption.

The fourth chapter aims at documenting the nexus between power outages, firm productivity, and gender-based productivity gap using a cross-section dataset gleaned from the World Bank's 2015 Senegalese Enterprise Survey. To achieve its goals, Chapter 4 uses descriptive Statistique and Combes et *al.*'s (2012) quantile approach to test the female-underperformance hypothesis. The Tobit model was further used to explore the linkage between power outages and firm productivity. Finally, the Blinder-Oaxaca counterfactual decomposition technique was solicited to confirm the female-underperformance hypothesis and infer the effect of power outages on the gender-based productivity gap. Power outages are more likely to affect differently female-owned firms compared to male-owned firms as the former operate in retail and service sectors, small and informal firms in which alternative sources of energy such as generators are barely adopted. As women are time-constrained, subjected to the daily allocation of their time between productive and incompressible unproductive occupations, unexpected power outages are more likely to play against women's income-generating activities. The key finding of the chapter suggests that the unreliability of electricity infrastructure has a detrimental effect on firms' productivity, irrespective of the sector in which firms operate. Power outages are found to widen the productivity gap between female-owned and male-owned firms. Such an effect is implicated in the structural component of the productivity gap. Put differently, the detrimental effect of power outages on the productivity gap stems from the gendered effect of power disruptions rather than the difference in the intensity of power outages experienced by both types of firms. Results from Combes et *al.*'s (2012) analysis underlined that female-owned firms remain in the market despite their low productivity compared to male-owned firms. Drawing on this finding policymakers ought to orient massive investment into the energy sector to improve the quality of the electricity being serviced to firms. As the Senegalese firms' inefficiency is widely driven by scale inefficiency, investment in human capital is a critical tangible well-meaning policy. The latter could be achieved by offering incentives to female-owned firms to provide on-job training to their employee to upgrade labor productivity.

5.1 Limitations and future research suggestions

One of the key limitations shared by the main three chapters is that they do not use the instrumental variable approach to control for time-varying unobserved characteristics. However, inferences made in the thesis are reliable as the empirical approaches used

therein are advanced including the difference-in-difference technique and propensity score matching, well known for their capacity to infer causal impacts.

Though the second and the third chapters draw their strength from the use of panel data and the evaluation of real development interventions, some limitations still transpire. For instance, access to electricity and piped water is measured at the extensive margin rather than the intensive margin. The panel dataset's short time frame and the lack of information on the duration of households' use of basic infrastructures impede the assessment of the dynamic effects of exposure to water and electricity services. Furthermore, regarding Chapters 2 and 3, the small sample size has prevented in-depth exploration of gender-based impacts or other types of sub-sample analyses. It is worth noting that we were not able to test the parallel trend hypothesis, on which estimates from the difference-in-differences method rely. Future studies may want to consider these limitations. When it comes to the third chapter, the use of cross-section data emerges is a key limitation. Future research should account for and address these limitations.

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