



HAL
open science

Electrification, Environment, and Economic Development in Developing Countries

Alpha Ly

► **To cite this version:**

Alpha Ly. Electrification, Environment, and Economic Development in Developing Countries. Economics and Finance. Université Paris sciences et lettres, 2023. English. NNT: 2023UPSLD022 . tel-04383250

HAL Id: tel-04383250

<https://theses.hal.science/tel-04383250>

Submitted on 9 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



THÈSE DE DOCTORAT
DE L'UNIVERSITÉ PSL

Préparée à l'Université Paris-Dauphine

**Electrification, Environment, and Economic Development
in Developing Countries**

Soutenue par

Alpha LY

Le 20 Octobre 2023

École doctorale n°543

SDOSE

Spécialité

Économie

Composition du jury :

Patrice GEOFFRON

Professeur, Université Paris-Dauphine *Président*

Tooraj JAMASB

Professeur, Copenhagen Business School *Rapporteur*

Katrin MILLOCK

Directrice de Recherche, Paris School of Economics, CNRS *Rapporteuse*

Ahmed TRITAH

Professeur, Université de Poitiers *Examineur*

Anna CRETJ

Professeure, Université Paris-Dauphine *Directrice de thèse*

Raja CHAKIR

Directrice de Recherche, Paris Saclay Applied Economics, INRAE-AgroParisTech *Directrice de thèse*

L'Université Paris-Dauphine n'entend donner aucune approbation ni improbation aux opinions émises dans les thèses; ces opinions doivent être considérées comme propres à leurs auteurs.

Remerciements

Au seuil de la conclusion de ces trois années dédiées à cette recherche, je saisis avec une profonde reconnaissance l'occasion qui m'est offerte de rendre hommage à toutes les personnes qui m'ont prodigué leur soutien inconditionnel et m'ont accompagné tout au long de cette aventure intellectuelle.

Je tiens en tout premier lieu à exprimer ma plus profonde et sincère gratitude envers mes très estimées directrices de thèse, Anna Creti et Raja Chakir. Leur généreuse confiance en ma modeste personne a été le pilier fondateur de cette aventure intellectuelle. Tout au long de ce parcours doctoral, leur bienveillance constante et leur disponibilité exemplaire, malgré leurs responsabilités multiples et leurs emplois du temps chargés, ont été pour moi une source d'inspiration et de soutien inestimable. Les innombrables échanges et les séances de travail collaboratives que nous avons partagés ont été des catalyseurs essentiels, façonnant mon développement personnel et intellectuel de manière profonde et significative.

Ma reconnaissance s'étend également envers Ahmed Tritah et Philippe Delacote, qui ont généreusement accepté de faire partie de mon comité de suivi de thèse. Leurs échanges fructueux, leurs conseils précieux et leur perspective extérieure se sont révélés d'une importance capitale dans mon cheminement.

Je désire adresser mes chaleureux remerciements à Patrice Geoffron, Professeur à l'Université

Paris-Dauphine, à Tooraj Jamasb, Professeur à Copenhagen Business School, à Katrin Millock, Directrice de recherche au CNRS, ainsi qu'à Ahmed Tritah, Professeur à l'Université de Poitiers. Leur consentement à rejoindre mon jury de thèse m'honore grandement.

J'exprime ma gratitude envers la Chaire EIEA (UM6P & CERNA), dont le soutien financier a contribué à la réalisation de cette thèse. Mes remerciements s'étendent également à la Chaire Économie du Climat (Institut Louis Bachelier) et à l'Université Paris-Dauphine (à travers son programme gradué), qui ont généreusement contribué au financement des différentes conférences nationales et internationales et bien d'autres diverses activités de recherche auxquelles j'ai pris part durant cette thèse. Leur engagement à soutenir la vulgarisation de cette recherche est infiniment apprécié.

Je ne saurais omettre de témoigner ma profonde reconnaissance à Megan Elizabeth Lang et à Carolyn Fischer, ainsi qu'à toute l'équipe DECRG de la Banque Mondiale, pour m'avoir ouvert les portes de l'institution et accompagné durant tout le long de mon très enrichissant et bénéfique Fellowship Program au sein de la Banque.

Mes pensées vont également à toute l'équipe de la Chaire EIEA et de la Chaire Économie du Climat, en particulier à mes pairs doctorants et aux chercheurs seniors avec lesquels j'ai eu le privilège d'engager des discussions très enrichissantes.

Ma gratitude envers Abdoulaye, Demba, Estel, Mamadou, et Mansa est immense, pour avoir facilité mon intégration au CERDI, pour leurs conseils avisés et leurs soutiens infaillibles tout au long de ce cheminement.

Comme le veut l'adage africain, "il faut tout un village pour élever un enfant", j'aimerais saisir cette opportunité pour exprimer ma reconnaissance envers toutes les personnes qui ont contribué à ma formation, depuis les années de primaire jusqu'au supérieur. Mes pensées vont notamment à Monsieur Berthé, Monsieur Bamba, Monsieur Loba, Docteur Koivogui, Madame Konan, Professeur Graziosi, Professeur Combes, Monsieur Brun, Professeur Dequiedt, Madame Dury, Monsieur Goujon, Professeur Giraud, et à Professeure Epaulard.

À Mboundor, Quentin, Nacer, Zélie, Arouna, Magloire, Mohamed, Tarek, Farouk, Giulia, Fatou, Mamadou Oury, Ladji, Kelly, et Mahamadou, je reste profondément marqué par l'amitié que vous m'avez témoignée et par votre soutien moral indéfectible tout au long de cette aventure.

Mes remerciements s'étendent également à ma famille :

À toi, père, je suis reconnaissant pour ton encouragement, ton soutien moral et financier, et ta patience durant ces longues années d'absence. J'espère être à la hauteur de tes attentes à travers cette thèse et bien au-delà.

Je tiens également à exprimer une gratitude profonde et empreinte d'émotion envers ma très chère mère qui a quitté ce monde si tôt, mais dont l'influence bienveillante et l'énergie continuent de m'inspirer chaque jour. À titre posthume, je te rends hommage Maman ! Ta bienveillance inestimable et ton engagement sans faille ont été des sources constantes d'inspiration tout au long de cette thèse et continuent de me guider dans mon parcours. Ton esprit demeure présent, ce qui me rappelle constamment l'importance de persévérer et d'honorer ta mémoire par la quête du savoir. Je te porte dans mon cœur avec une profonde gratitude et un respect éternel.

À mes sœurs (Fatim, Awa, Assy), frères (Ibrahim, Mutu, Bocar), tantes, et oncles, je vous remercie chaleureusement pour vos encouragements. A ma belle-soeur Mariam, j'exprime toute ma gratitude pour son soutien constant.

À toi, Samira, je te témoigne ma gratitude pour ta patience et ta présence. Les mots me manquent pour exprimer pleinement ma reconnaissance envers toi.

Ainsi, en achevant ce modeste témoignage de gratitude, je tiens à exprimer mon profond respect et ma reconnaissance envers toutes les personnes qui ont contribué, de près ou de loin, à la réalisation de cette thèse. Votre soutien a été une lumière éclairant mon chemin, et je demeure sincèrement reconnaissant.

Summary

This thesis explores the complex interplay between electrification, deforestation, and economic development in developing countries, with a specific emphasis on Côte d'Ivoire and other African countries. The primary goal is to offer valuable insights into the impacts of electrification on both environmental sustainability and economic growth, identifying policy implications for promoting sustainable development in the context of ongoing electrification efforts. Chapter 1 develops a theoretical framework based on an agricultural household heterogeneous model to explore the potential link between electrification and arable farm expansion. Empirical analysis using household data from multiple waves of the Côte d'Ivoire Living Standards Measurement Surveys reveals that electricity access significantly reduces average arable farm size and biomass fuel consumption. These findings suggest a potential positive impact of electrification on deforestation mitigation. However, an identified electrification threshold of 80% highlights the need for targeted policies to ensure that electrification does not inadvertently lead to further deforestation. Chapter 2 investigates the broader relationship between electrification and deforestation rates in Côte d'Ivoire. Using night light intensity data and official electricity coverage statistics, the study reveals a positive link between electrification and deforestation. As electrification programs expand, deforestation continues to advance, raising environmental conservation concerns and underlining the importance of sustainable electrification planning. Chapter 3 explores the challenges faced by private stakeholders in the power sector in African countries, particularly through independent power producers (IPPs) and public-private partnerships (PPPs). Currency and inflation risks emerge as significant obstacles to private investment in power generation. The chapter identifies measures

such as automatic tariff adjustment and cost reflectivity that can mitigate these risks and encourage private sector involvement, ultimately supporting universal access to electricity. Chapter 4 examines the impact of power constraints on firm-level productivity in developing countries.¹ The empirical analysis based on the World Bank Enterprise Surveys Dataset for 84 countries during the period 2006-2019 shows that power constraints significantly reduce firm-level revenue-based total factor productivity. This finding underlines the importance of ensuring a stable power supply to foster economic growth and competitiveness, particularly for manufacturing firms. The policy implications drawn from these findings cover sustainable electrification planning, close monitoring of deforestation rates, balanced public-private sector involvement in the power sector, investments in power infrastructure to minimize constraints such as outages, and support for productive industries. To sum up, this thesis highlights the complex relationships between electrification, deforestation, and economic development in developing countries. By providing empirical evidence and policy recommendations, this research enhances understanding of the complexities and prospects arising from electrification. It offers valuable insights for policymakers striving to achieve sustainable and inclusive economic growth while safeguarding the environment. As electrification efforts continue to shape the development landscape, the findings presented in this thesis could guide decision-makers in crafting policies that promote a harmonious balance between progress and environmental conservation.

¹Here, the terms "power constraints" and "energy constraints" are used interchangeably. These terms refer to limitations on the total amount of energy (measured in watt-hours or kilowatt-hours) that can be generated, stored, or consumed over a specific period.

Résumé

Cette thèse examine les liens entre électrification, déforestation et développement économique dans les pays en développement, avec un accent particulier sur la Côte d'Ivoire et d'autres pays africains. L'objectif principal est de fournir des éclairages sur les impacts de l'électrification sur la soutenabilité environnementale et la croissance économique, en tirant des implications politiques pour la promotion du développement durable dans le contexte des efforts d'électrification en cours. Dans le Chapitre 1, nous développons un cadre théorique basé sur le modèle hétérogène des ménages agricoles afin d'explorer le lien potentiel entre l'électrification et l'expansion des exploitations agricoles. L'analyse empirique utilisant des données sur les ménages provenant de plusieurs vagues des enquêtes niveaux de vie en Côte d'Ivoire révèle que l'accès à l'électricité réduit de manière significative la taille moyenne des exploitations agricoles et la consommation de combustible provenant de la biomasse. Ces résultats suggèrent un impact positif potentiel de l'électrification sur l'atténuation de la déforestation. Cependant, un seuil d'électrification de 80% met en évidence la nécessité de politiques ciblées pour s'assurer que l'électrification n'entraîne pas par inadvertance une déforestation accrue. Le Chapitre 2 étudie la relation entre l'électrification et les taux de déforestation en Côte d'Ivoire d'une manière plus large. En utilisant des données sur l'intensité de l'éclairage nocturne et des statistiques officielles sur la couverture électrique, l'étude révèle un lien positif entre l'électrification et la déforestation. Alors que les programmes d'électrification se développent, la déforestation continue de progresser, ce qui soulève des préoc-

cupations en matière de conservation de l'environnement et souligne l'importance d'une planification soutenable de l'électrification. Le Chapitre 3 explore les défis auxquels sont confrontés les acteurs privés du secteur de l'électricité dans les pays africains, en particulier les producteurs indépendants d'électricité (PIE) et les partenariats public-privé (PPP). Les risques de change et d'inflation apparaissent comme des obstacles importants à l'investissement privé dans la production d'électricité. Le chapitre identifie des mesures telles que l'ajustement automatique des tarifs et la réfectivité des coûts qui peuvent atténuer ces risques et encourager l'implication du secteur privé, pour finalement soutenir l'accès universel à l'électricité. Le Chapitre 4 examine l'impact des contraintes énergétiques sur la productivité des entreprises dans les pays en développement. L'analyse empirique basée sur l'ensemble des données des enquêtes sur les entreprises de la Banque mondiale pour 84 pays sur la période 2006-2019 démontre que les contraintes électriques réduisent de manière significative la productivité totale des facteurs basée sur les revenus au niveau de l'entreprise. Ce résultat souligne l'importance d'assurer une offre d'électricité stable pour favoriser la croissance économique et la compétitivité, en particulier pour les entreprises manufacturières. Les implications politiques tirées de ces résultats comprennent la planification soutenable de l'électrification, la surveillance étroite des taux de déforestation, l'implication équilibrée des secteurs public et privé dans le secteur de l'électricité, les investissements dans l'infrastructure électrique pour minimiser les contraintes telles que les pannes, et le soutien aux industries productives. En résumé, cette thèse met en évidence les relations complexes entre électrification, déforestation et développement économique dans les pays en développement. En fournissant des preuves empiriques et des recommandations politiques, cette recherche contribue à la compréhension des défis et des opportunités présentés par l'électrification et offre des éclairages quantitatifs aux décideurs politiques qui s'efforcent d'atteindre une croissance économique durable et inclusive tout en sauvegardant l'environnement. Alors que les efforts d'électrification continuent de façonner le paysage du développement, les résultats présentés dans cette thèse peuvent guider les décideurs dans l'élaboration de politiques qui favorisent un équilibre harmonieux entre le développement économique et la préservation de l'environnement.

Contents

Summary	7
General introduction	21
1 Access to electricity and household practices potentially contributing to forest loss in Côte d'Ivoire	41
1.1 Introduction	41
1.2 Related literature	44
1.2.1 Traditional causes of forest loss	44
1.2.2 Effects related to access to electricity	46
1.2.3 Potential links between electrification and forest loss	47
1.3 Theoretical link between electrification and household practices potentially contributing to forest loss	48
1.3.1 Conceptual links between electrification and practices potentially contributing to forest loss (firewood collection and arable farms size)	48
1.3.2 Theoretical framework	49
1.4 Empirical approach	51
1.4.1 Data and variables: socio-economic data	51
1.4.2 Some stylized facts	52
1.4.3 Empirical methodology	53
1.4.4 Results	56
1.4.5 Robustness check	58
1.4.6 Heterogeneity	63
1.5 Conclusion	67
1.6 Acknowledgment	68

Appendices	75
A Theoretical framework (detailed description)	76
A.1 Framework I: Subsistence economy (no labor market)	77
A.2 Framework II: Chayanovian economy (imperfect labor market)	79
A.3 Framework III: Open economy with perfect labor market (static open access)	83
A.4 Framework IV: Open economy with perfect labor market (dynamic open access)	85
A.5 Empirical discussion of each framework	87
B Descriptive statistics	90
C Stylized facts (continuation)	91
D Overlap	92
2 Electrification and Deforestation in Côte d'Ivoire: a spatial econometric analysis	95
2.1 Introduction	95
2.2 Data and variables	98
2.2.1 Variables description and summary statistics	98
2.2.2 Concordance between night lights data and official coverage rate data . . .	103
2.2.3 Exploratory spatial data analysis	105
2.3 Choice of the best spatial specification	107
2.4 Estimation and results interpretation	110
2.4.1 Spatial analysis at departmental level	110
2.4.2 Inclusion of unobservable individual and time specific effects	113
2.5 Discussion	116
2.6 Conclusion	120
2.7 Acknowledgment	120
Appendices	129
E Concordance between night lights data and official data	130
F Moran's I tests using alternatives neighbourhood matrix	131
F.1 Moran I for Regions	131
F.2 Moran I for departments	133
G Bottom-up approach (Florax et al. 2003)	135

H	Top-down approach (LeSage & Pace 2009)	135
I	Two-way comparison approach	135
J	Panel specification tests	136
3	Power Sector Regulation and Private Investment in Power Generation: Evidence from Africa	139
3.1	Introduction	139
3.2	Literature review	142
3.2.1	Private participation and performance	143
3.2.2	Private participation and Regulation	143
3.2.3	Currency and inflation crisis effects on investment	145
3.3	private stakeholders and power sector in Africa	147
3.4	Theoretical framework	149
3.5	Main data and statistics	156
3.5.1	Establishment of Regulators in Africa	156
3.5.2	Electricity Regulatory Index by AfDB	157
3.5.3	Private Participation in the Electricity Sector	157
3.5.4	Data summary and statistics	158
3.6	Empirical methodology	159
3.6.1	Endogeneity concerns when estimating the effect of inflation or currency crisis on private investment	159
3.6.2	Identification strategy: Combining Local Projection and AIPW Estimator	159
3.7	Main Results	163
3.8	Robustness check	167
3.9	Conclusion	168
3.10	Acknowledgment	172
	Appendices	179
K	Private participation in power sector in selected African countries	180
L	Kernel density	181
L.1	Inflation Crisis	181
L.2	Currency Crisis	182

4 Power Constraints and Firm-Level Total Factor Productivity in Developing Countries	185
4.1 Introduction	185
4.2 Related literature	188
4.3 Theoretical framework	190
4.4 Empirical strategy and data	194
4.4.1 Empirical strategy	194
4.4.2 Data and variables	197
4.5 Empirical results: Main results	201
4.5.1 Descriptive statistics	201
4.5.2 Treatment effects	211
4.6 Empirical results: Robustness, heterogeneity and mechanisms	214
4.6.1 Robustness tests	214
4.6.2 Heterogeneity check	218
4.6.3 Transmission channels	219
4.6.4 Mitigating factors	220
4.6.5 Placebo tests	221
4.7 Conclusion	223
4.8 Acknowledgment	224
Appendices	231
M Complementary tables	232
General conclusion	243

List of Figures

1 Changes in forest loss in Côte d’Ivoire between 1990 and 2015	28
2 Percentage of firms identifying each constraint as a top obstacle	29

1.1	Conceptual model of the interrelationship between electrification and households practices potentially contributing to forest loss (biomass fuel consumption and arable farms size)	48
1.2	Connected versus non-Connected households (Full sample)	53
1.3	Relationship between electrification and households practices potentially contributing to forest loss (biomass fuel consumption and arable farms size) at departmental and regional level	53
1.4	Threshold effect of electrification on arable farms size	66
1.5	Electrification rate in Côte d’Ivoire between 1990 and 2018 (WDI)	66
C1	Connected versus non-Connected households (Yearly samples)	91
D1	Connected versus non-Connected households (Overlap)	92
2.2.1	Spatial concentration of high and low values	103
2.2.2	Average growth rates (AGR) for the main variables at the regional and departmental scale	104
2.2.3	Neighbourhood network using Contiguity (queen) matrix	105
2.2.4	Moran plot using Contiguity (queen) matrix at the regional and departmental scale	106
E1	Local Indicators of Spatial Association (LISA)	130
3.3.1	Energy mix and evolution of power generation in Africa	147
3.7.1	AIPW Estimates of the Response of the Output (Capacity), Deviations of Log Output (relative to Year 0, $\times 100$)	166
3.8.1	Robustness check using DID estimates (Currency crisis represents the treatment variable)	168
3.8.2	Robustness check using DID estimates (Inflation crisis represents the treatment variable)	169
L1	Kernel density of the distribution of the propensity scores for the treated and control groups (Inflation Crisis)	181
L2	Kernel density of the distribution of the propensity scores for the treated and control groups (Currency Crisis)	182

4.5.1 Degree of power constraints, declining total factor productivity and capacity utilization in %, and increasing losses in % of total sales	204
4.5.2 Breakdown losses by degree of power constraints and by region	205
4.5.3 The combined effects of outages and other power constraints	205
4.5.4 Kernel densities of the covariates for the treatment and control group (Set 1)	209
4.5.5 Kernel densities of the covariates for the treatment and control group (Set 2)	210
4.5.6 The effect of power constraints on the firm’s revenue-based TFP	213

List of Tables

1.1 Summary of our theoretical findings	50
1.2 The effect of electricity access on firewood collection and arable farms	57
1.3 Robustness check – The effect of electricity access on firewood collection and arable farms	59
1.4 Robustness check – The effect of electricity access on firewood collection and arable farms	62
1.5 Heterogeneity check – The effect of electricity access on firewood collection and arable farms	63
1.6 Heterogeneity check – The effect of electricity access on arable farms, Boserup factor, crop and fallow land	64
1.7 Heterogeneity check – Threshold effect of electricity access on arable farms	65
B1 Descriptive statistics, data from LSMS (ENV) 1998, 2002, 2008 and 2015	90
2.2.1 Main data description	100
2.2.2 Descriptive statistics (33 Regions)	101
2.2.3 Descriptive statistics (108 Departments)	102
2.2.4 Descriptive statistics (Panel of 108 Departments over 2001-2017)	102
2.2.5 Moran test for our main variables using Contiguity (queen) weight matrix - Regions	107

2.2.6 Moran test for our main variables using Contiguity (queen) weight matrix - Departments	107
2.4.1 Regression Results	112
2.4.2 Effect measures, Spatial Autoregressive Model	113
2.4.3 Effect measures, ML panel with spatial lag, random effects, Baltagi spatial error correlation	114
E1 Forest loss AGR 2011-2018 as dependent variable, OLS Regression Results	130
F1 Moran test for our main variables using Contiguity (gabriel) weight matrix	131
F2 Moran test for our main variables using Distance (with k=1) weight matrix	131
F3 Moran test for our main variables using Distance (with k=5) weight matrix	131
F4 Moran test for our main variables using Triangulation weight matrix	132
F5 Moran test for our main variables using 2-nearest neighbours weight matrix	132
F6 Moran test for our main variables using 4-nearest neighbours weight matrix	132
F7 Moran test for our main variables using 6-nearest neighbours weight matrix	132
F8 Moran test for our main variables using Contiguity (gabriel) weight matrix	133
F9 Moran test for our main variables using Distance (with k=1) weight matrix	133
F10 Moran test for our main variables using Distance (with k=5) weight matrix	133
F11 Moran test for our main variables using Triangulation weight matrix	133
F12 Moran test for our main variables using 2-nearest neighbours weight matrix	134
F13 Moran test for our main variables using 4-nearest neighbours weight matrix	134
F14 Moran test for our main variables using 6-nearest neighbours weight matrix	134
G1 Lagrange multiplier diagnostics for spatial dependence	135
H1 Likelihood ratio tests	135
I1 Results of Likelihood ratio tests for spatial models	135
J1 Specification tests under panel models	136
3.5.1 Establishment of Electricity Sector Regulators in Africa	156
3.5.2 Summary Statistics	158
3.7.1 AIPW Estimates	165
K1 Private sector share of installed capacity available in 2016 in 20 African countries	180
4.4.1 Summary statistics on our main variables	200

4.5.1	Summary statistics on the treatment variables	202
4.5.2	Summary statistics on our main categorical variables	203
4.5.3	Descriptive Statistics (T=Power Outages)	206
4.5.4	Covariate balancing (T=Power Outages)	208
4.5.5	The effect of power outages and constraints on the firm’s revenue-based TFP	212
4.5.6	The combined effect of power outages with each level of power constraints on the firm’s revenue-based TFP	214
4.6.1	Robustness tests – The effect of power outages and constraints on the firm’s revenue- based TFP by clustering standards errors at industry level	215
4.6.2	Robustness tests – The effect of power outages and constraints on the firm’s revenue- based TFP by using least squares regressions (without entropy balancing re-weighting scheme)	216
4.6.3	Robustness tests – The effect of power outages on the firm’s revenue-based TFP and factor share based estimates of productivity	217
4.6.4	Heterogeneity check – The effect of power outages on the firm’s revenue-based TFP by countries income group	218
4.6.5	Heterogeneity check – The effect of power outages on the firm’s revenue-based TFP by geographical regions	219
4.6.6	Main channels – The effect of power outages on the firm’s Capacity Utilization (%) and Losses due to Outages (% of annual Sales)	220
4.6.7	Mitigating factors – The effect of power outages on the firm’s revenue-based TFP	221
4.6.8	Placebo tests – The non-significant effects of random treatment variables on the firm’s revenue-based TFP	222
M1	Main variables description	232
M2	Robustness tests – The effect of power outages on the firm’s revenue-based TFP by including additional control variables to the baseline specification	233
M3	Summary statistics on revenue-based TFP by outages and over regions	233
M4	Summary statistics on capacity utilization by outages and over regions	233
M5	Summary statistics on the number of observations by region and over years of survey	234
M6	Summary statistics on the number of observations by region and by income group	234
M7	Summary statistics on the number of observations by industry and by region	235

M8	Summary statistics on the number of observations by industry and over years of survey	236
M9	Sub-Saharan Africa (AFR) 1	236
M10	Sub-Saharan Africa (AFR) 2	237
M11	East Asia and Pacific (EAP) 1	237
M12	East Asia and Pacific (EAP) 2	237
M13	Europe and Central Asia (ECA) 1	238
M14	Europe and Central Asia (ECA) 2	238
M15	Latin America and Caribbean (LAC) 1	238
M16	Latin America and Caribbean (LAC) 2	239
M17	Middle East and North Africa (MNA) 1	239
M18	Middle East and North Africa (MNA) 2	239
M19	South Asia (SAR) 1	239
M20	South Asia (SAR) 2	240

General introduction

Ensuring global availability of affordable, reliable, and modern energy services by 2030 is at the heart of the Millennium Development Goals (under SDG 7.1) set by international development organizations such as the United Nations (UN) and its Development Program (UNDP).¹ Indeed, this goal represents both a fundamental requirement and a potent catalyst for enhancing the living and working conditions of every individual across the globe. This is especially pertinent for the most economically disadvantaged and susceptible communities, who are currently devoid of access to modern energy services. Indeed, access to reliable electricity is crucial for economic growth, poverty reduction, and improving the quality of life for people in developing countries. Electrification is a pivotal factor in the advancement of any society and in enabling various economic activities. Achieving widespread access to electricity is a critical component of developing countries' economic development strategies. Evidence to date suggests that access to energy potentially enhances the level of economic development (Ferguson et al. 2000; Wolde-Rufael 2006). Energy might also accelerate structural transformation, notably by promoting industrial development (Rud 2012). Electricity is the form of energy most closely associated with the vectors of economic development (Lee, Miguel & Wolfram 2020; Stern et al. 2019). Electricity can certainly increase firms' productivity, reduce production costs and increase the producer's surplus and income (Rud 2012; Fisher-Vanden et al. 2015; Allcott et al. 2016). In addition, electricity access is likely to significantly improve the situation of households, especially in rural areas, through agricultural productivity, income growth, education, health and off-farm employment opportuni-

¹Energy Access: Towards the Achievement of SDG 7 and Net-Zero Emissions

ties (Esteban et al. 2018; Kanagawa & Nakata 2008; De Gouvello & Durix 2008; Lipscomb et al. 2013; Dinkelman 2011; Grogan & Sadanand 2013; Lipscomb et al. 2013; Khandker et al. 2009; Khandker et al. 2014). However, the expansion of electrification programs raises concerns about their potential environmental impact. For instance, Villoria et al. (2014) suggest that the promotion of agricultural innovation could improve agricultural profitability and thus encourage forest loss by increasing the area of farmland. On the other hand, in regions with limited access to electricity, communities often resort to using traditional biomass fuels (e.g., firewood, agricultural residues) for cooking and heating. Widespread use of these fuels can lead to deforestation, soil erosion, and loss of biodiversity, contributing to environmental degradation.

Meanwhile, to date there is little evidence pertaining to these complex relationships between electrification, environment, and economic development in developing countries in general and in Africa in particular. In other words, the lack of robust data and research into the specific impacts of electrification on economic development and environment in developing countries, especially in Africa, has been a hindrance to implementing effective policies and strategies.

To close this gap, this thesis aims to explore relationships between electrification, environment, and economic development in developing countries, where there are considerable ongoing electrification efforts, and highlights implications for any country facing similar challenges.² This dissertation has four main objectives. The first is to analyse the impact of electrification on deforestation due to households' activities such as firewood collection and arable land expansion. The second is to provide further evidence on the overall relationship between electrification and forest loss at departmental level (optimal level of aggregation). The third is to document the potential detrimental effect of external shocks on private investment in the power generation sector and the key regulatory measures potentially mitigating those risks and enhancing such private investment. The fourth and final objective of this dissertation is to provide robust evidence on how power supply unreliability might affect firms' performance in developing countries. This dissertation specifically answers the following main questions: What is the effective impact of electrification on deforestation, particularly with respect to households' activities such as firewood collection and

²In fact, many developing countries face unique challenges in their electrification journey, such as limited infrastructure, financial constraints, and political instability. Governments and international organizations often collaborate to expand electrification through various means, including grid extension, off-grid solutions, and renewable energy projects. While these efforts have made significant progress, a considerable proportion of the population still lacks access to reliable and affordable electricity, hindering economic development and social progress.

arable land expansion? How does electrification relate to forest loss at the departmental level (fine level of aggregation)? What are the patterns and relationships observed between electrification and forest degradation? What are the potential detrimental effects of external shocks on private investment in the power generation sector? Additionally, what key regulatory measures can potentially mitigate these risks and enhance private investment in the power generation sector? What is the evidence regarding the impact of power supply unreliability on firms' performance in developing countries? How does the unreliability of the power supply influence business operations and outcomes for manufacturing firms operating in this context?

Previous research has shed light on the importance of energy in general and electricity in particular, power sector supply-side challenges, and the potential link between electrification and environmental conservation. First, the existing body of literature underlines the fact that uncertainties about energy prices, for instance, can result in delayed investment decisions, impacting overall output (Bernanke 1983). Energy price instability has the potential to hamper both short- and long-term output growth (Shi & Sun 2017), while the response of production to oil shocks for instance may be worsened by oil price uncertainty (Elder & Serletis 2009). Changes in oil price volatility can have far-reaching effects on real GDP and investment (Cheng et al. 2019). This aspect of the literature also explores power sector constraints and their implications for firms' performance. Power outages are shown to have adverse effects on firms' sales, profits, and total factor productivity (Cole et al. 2018). Conversely, reduced power outages are linked to increased productivity and overall revenues for firms (Elliott et al. 2021). Power supply alterations are employed as instruments to estimate the impact of power outages on firms' performance (Allcott et al. 2016; Fisher-Vanden et al. 2015). Additionally, this literature examines an array of determinants influencing firms' performance. These factors include international development aid (Chauvet & Ehrhart 2018), financial inclusion (Chauvet & Jacolin 2017; Lee, Wang & Ho 2020), bank concentration (Lee, Wang & Ho 2020), financial innovation (Lee, Wang & Ho 2020), inflation targeting (Bambe et al. 2022), and taxation (Chauvet & Ferry 2021). Foreign aid is found to enhance firms' growth by alleviating infrastructure and financing constraints (Chauvet & Ehrhart 2018), while financial inclusion and competition between banks positively impact firms' growth (Chauvet & Jacolin 2017; Lee, Wang & Ho 2020). The adoption of inflation targeting emerges as a driver of firms' growth and productivity (Bambe et al. 2022), while tax revenues are identified as contrib-

utors to firms' performance, as they support essential business infrastructure (Chauvet & Ferry 2021).

Additionally, the existing literature on energy supply-side issues examines the multifaceted impact of private sector participation in power sector investment. Debates persist about whether private participation negatively affects service efficiency (Koo et al. 2013; Trujillo et al. 2002), with the quality of regulation emerging as a mitigating factor (Koo et al. 2013). Conversely, positive effects of private participation in infrastructure are documented (Wallsten 2001; Hawdon 1996). Regulatory measures combined with private participation are deemed favorable, with independent regulatory bodies attracting private investment and curbing collusion and political interference (Pargal 2003; Wallsten 2002; Bertoméu-Sánchez et al. 2018; Andres et al. 2007). The subsequent discussion in this growing body of literature probes the effects of currency and inflation crises on investment in general. Uncertainty surrounding inflation and exchange rate fluctuations can deter investment (Madsen 2003; Hochman & Palmon 1983). While inflation's impact on investment involves an increase in capital costs, the effects of depreciation on investment are more nuanced due to heightened costs and demand (Harchaoui et al. 2005). Exchange rate volatility is shown to negatively influence investment (Servén 2003).

Finally, some previous analyses document the potential links between electrification and environment (see Tanner & Johnston 2017 for instance). Notably, they show that rural electrification can indirectly reduce forest loss through the introduction of new techniques, improved irrigation, adoption of technology, and agricultural innovation (Tanner & Johnston 2017; Shively & Pagiola 2004; Villoria et al. 2014). Furthermore, the potential of electrification to substitute for firewood and create new energy markets holds promises for the alleviation of pressure on forests (Akpanjar & Kitchens 2017). In addition, there is a growing body of literature documenting the fact that the other traditional causes of forest loss are influenced by factors such as infrastructure expansion, agriculture, and timber extraction (Geist & Lambin 2002). These causes are driven by a complex interplay of demographic, economic, technological, political, and cultural factors (Geist & Lambin 2002). Infrastructure, exemplified by the construction of roads, serves as a facilitator for agricultural expansion but also holds the potential for deforestation (Chomitz & Gray 1999). Other drivers of forest loss include lack of non-agricultural opportunities and armed conflicts (Angelsen 2010; Sangne et al. 2015). The complex dynamics of property rights, fiscal policy, and agricultural

productivity further shape forest ecosystems (Liscow 2013; Foster & Rosenzweig 2002). While the reduction of timber import tariffs is proposed as a measure to decrease forest loss, the potential displacement of this issue remains a concern (Foster & Rosenzweig 2002).

This thesis makes several notable contributions to the field of development economics. First, it provides strong evidence for the impacts of electrification on arable farm expansion, firewood collection and overall deforestation, shedding light on the potential benefits and risks of electrification by focusing on a specific developing country, Côte d'Ivoire. Thus Chapter 1 focuses on the complex relationship between electricity access and deforestation in Côte d'Ivoire. By examining the dynamics of electrification and its potential impacts on household practices contributing to forest loss, the study fills a critical gap in the literature. It offers a nuanced perspective, acknowledging the conflicting results in existing research and shedding light on the complex interplay between electricity access, biomass fuel consumption, and arable farm size. The chapter's empirical findings underline the significant role of electrification in reducing both biomass fuel consumption and arable farm size, thus contributing to forest conservation efforts. Moreover, by identifying an electrification threshold beyond which forest loss could increase, the research offers policymakers a key reference point for sustainable planning. Furthermore, focusing on the specific case of electricity access and its potential effects on overall deforestation, Chapter 2 contributes to the broader discourse on sustainable development. By examining the link between electrification and global deforestation rates, the research provides insights into the balance between expanding access to electricity and conserving natural resources. The chapter's findings offer a nuanced understanding of how electrification might contribute to forest conservation efforts. Policymakers can leverage these insights to design holistic strategies that promote both energy access and environmental sustainability.

Second, the thesis offers valuable insights into the challenges faced by private stakeholders in the power sector in African countries and proposes policy measures to promote private investment and universal access to electricity. Chapter 3 thus provides a comprehensive analysis of the impact of regulatory measures on private investment in power generation across Africa. By considering the effects of currency and inflation crises, the study unveils the challenges faced by private stakeholders and highlights the potential mitigating role of independent regulatory bodies, tariff adjustment mechanisms, and cost reflectivity measures. The empirical evidence presented in this

chapter contributes to a deeper understanding of the complex relationship between regulation and private investment, offering insights for policymakers seeking to attract sustainable investment in the power sector, particularly in the context of financial constraints and crises.

Finally, the examination of how power constraints impact firm-level productivity adds to the understanding of the role of a stable power supply in fostering economic growth and competitiveness in developing countries.³ Indeed, examining the impact of power constraints on firm-level total factor productivity or competitiveness in developing countries, Chapter 4 addresses a critical concern for economic growth and development. Through an innovative matching-based approach, the study explores the nuanced effects of power constraints on manufacturing firms' total factor productivity. By considering the severity of power constraints and identifying potential mechanisms, the research provides a comprehensive understanding of the challenges firms face and the strategies they employ to mitigate productivity losses due to power obstacles. This chapter's insights offer policymakers actionable information to design effective interventions that promote firms' growth and economic development.

In summary, this thesis makes significant contributions to development economics by offering new insights into the complex relationships between electricity access, forest conservation, and firms' productivity in developing countries. The empirical evidence, innovative methodologies, and nuanced perspectives presented in each chapter provide a solid foundation for informed policy decisions and further research in pursuit of sustainable and inclusive development.

This dissertation is organized into four chapters. Each chapter makes contributions to the existing/growing literature by providing strong theoretical and/or empirical evidence. Chapter 1 explores the relationship between electrification and deforestation in Côte d'Ivoire. Specifically, it focuses on how electrification affects household practices, such as arable farm size and biomass fuel consumption, which may contribute to deforestation. The agricultural sector contributes 15% of the country's GDP. The country is the world's largest producer of cocoa beans (40% of global production). However, the Côte d'Ivoire Forestry Development Company (SODEFOR) has identified the fact that the expansion of cocoa plantations has resulted in the destruction of over 200,000 hectares of forest. Another source of forest loss in the country is biomass fuel consumption by

³Here, the terms "power constraints" and "energy constraints" are used interchangeably. These terms refer to limitations on the total amount of energy (measured in watt-hours or kilowatt-hours) that can be generated, stored, or consumed over a specific period.

households. Indeed, like many developing countries, most of the households in the country rely heavily on biomass fuel consumption, including firewood and charcoal, for cooking and heating purposes. Biomass fuel consumption in Côte d'Ivoire is estimated to account for around 80% of the country's total energy consumption, with firewood being the primary source. According to the International Energy Agency (IEA), around 2.4 million tons of firewood are consumed annually for cooking and heating purposes in the country. This high demand for firewood has resulted in the depletion of natural forests, leading to soil erosion and loss of biodiversity. Meanwhile, in 2011, the Ivorian government initiated an extensive electrification program as part of its Social Program. The program aims to improve electricity coverage in the country. To date, there is little evidence relating to the potential impact of electrification on forest loss. Previous studies have produced conflicting results, leaving the direction of the relationship between electrification and forest loss uncertain (Geist & Lambin 2002 Vs Tanner & Johnston 2017). Indeed, on the one hand, the extension of the electricity network or the improvement of agricultural profitability thanks to electrification can be a source of forest loss (Geist & Lambin 2002; Villoria et al. 2014). On the other hand, electrification can also reduce the need to expand arable farms or to collect firewood, and thus help to mitigate forest loss (Tanner & Johnston 2017; An et al. 2002; Mensah & Adu 2015). Using and adapting Angelsen (1999)'s theoretical framework based on agricultural households' heterogeneity and household data from multiple waves of the Living Standards Measurement Surveys, the chapter investigates the link between electricity access and changes in arable farm size and biomass fuel consumption. In other words, the analysis uses household surveys spanning the period 1998-2015, applying fixed effects regression and various alternative econometric models to demonstrate that increased electricity access significantly reduces both average arable farm size and biomass fuel consumption, indicating a potential positive impact on deforestation mitigation in Côte d'Ivoire. The findings underline the role of electrification in curbing deforestation, while also identifying an electrification threshold of 80% beyond which arable farm size might increase.

Chapter 2 examines the link between electrification and deforestation on a broader scale in Côte d'Ivoire. Despite the ongoing vast electrification program, the overall deforestation rates in the country are among the highest in the world. From over 16 million hectares of forest in the 1960s, the country now has only about 2.5 million hectares. Unlike Chapter 1, which focuses on the effect of electrification on deforestation due only to household activities (partial effect), this chapter

focuses on the overall effect of electrification on deforestation including how electrification operates through the key players involved in deforestation. Those players include companies (logging, mining, oil, etc.), the state (extension of road infrastructure, construction of hydroelectric dams, urbanization policy, etc.) and households (agriculture, firewood collection, livestock rearing, gold panning, etc.). By examining night light intensity data alongside official electricity coverage statistics, the chapter explores the relationship between electrification and deforestation rates at a fine spatial resolution. The results demonstrate a positive association between electrification and deforestation, raising concerns about the environmental implications of the country's electrification programs (see [Figure 1](#) for changes in forest loss in the country during the period 1990-2015).

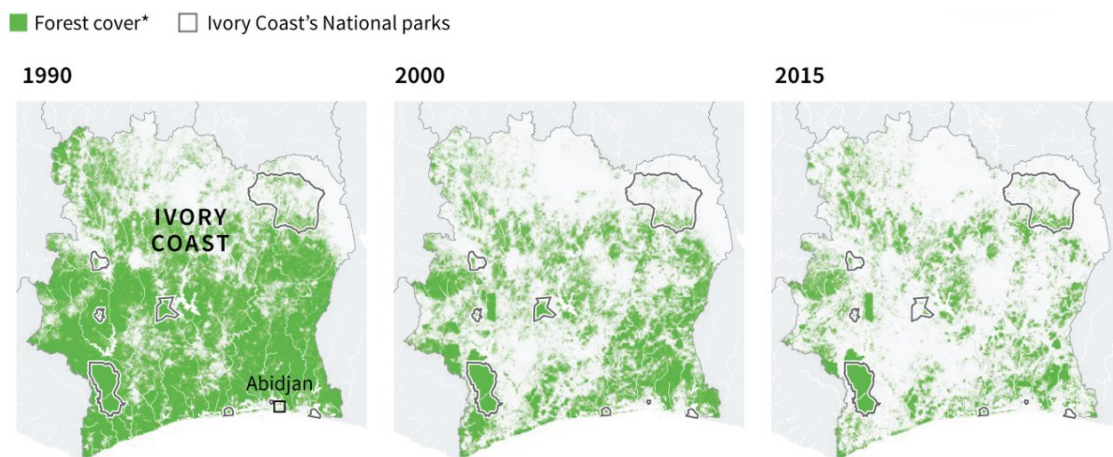


Figure 1: Changes in forest loss in Côte d'Ivoire between 1990 and 2015

Notes: G. Cabrera from Reuters using MapHubs Forest dataset. *Forest cover is defined as any surface sized 1 hectare or more with a tree canopy density of at least 30 percent.

Chapter 3 shifts the focus to the challenges faced by private stakeholders participating in power generation in African countries, particularly through independent power producers (IPPs) and public-private partnerships (PPPs). Access to electricity in Africa is still poor, estimated at less than 54% in 2020 (almost 600 million Africans still do not have access to electricity) due essentially to the lack of adequate investment in the power sector. Governments have not been able to provide the necessary public investment to boost the sector due to fiscal constraints (ERI 2020). These constraints are mainly explained by the recurrent difficulty of mobilising tax revenues (tax optimisation by multinationals, preponderance of the informal sector and the large size of the agricultural sector which is not easy to tax) and by the burden of public debt (debt servicing). On the recommendation of the Bretton Woods institutions (IMF and World Bank) power generation has been opened up to private stakeholders in order to provide the capital needed to meet the chal-

lenges of universal access to electricity on the continent. However, these private stakeholders also face major challenges: local capital markets are weak and limited (debts are essentially denominated in foreign currencies), and inputs are mostly imported. In addition, the cost of local credit remains quite high (exorbitant interest rates). Another difficulty for these stakeholders remains the dependence on foreign markets for the import of fixed inputs (capital) and variable inputs (fuel). With this backdrop of limited capital markets and reliance on imported inputs, private investment in the sector faces currency and inflation risks. The chapter adapts [Nucci & Pozzolo \(2001\)](#)'s theoretical framework and an empirical method combining local projection (LP) à la [Jordà \(2005\)](#) with [Lunceford & Davidian \(2004\)](#)'s impact evaluation methodology (AIPW doubly robust estimator) to demonstrate that measures such as automatic tariff adjustment mechanisms and cost reflectivity can mitigate these risks, positively influencing changes in available total installed capacity across 54 African countries.

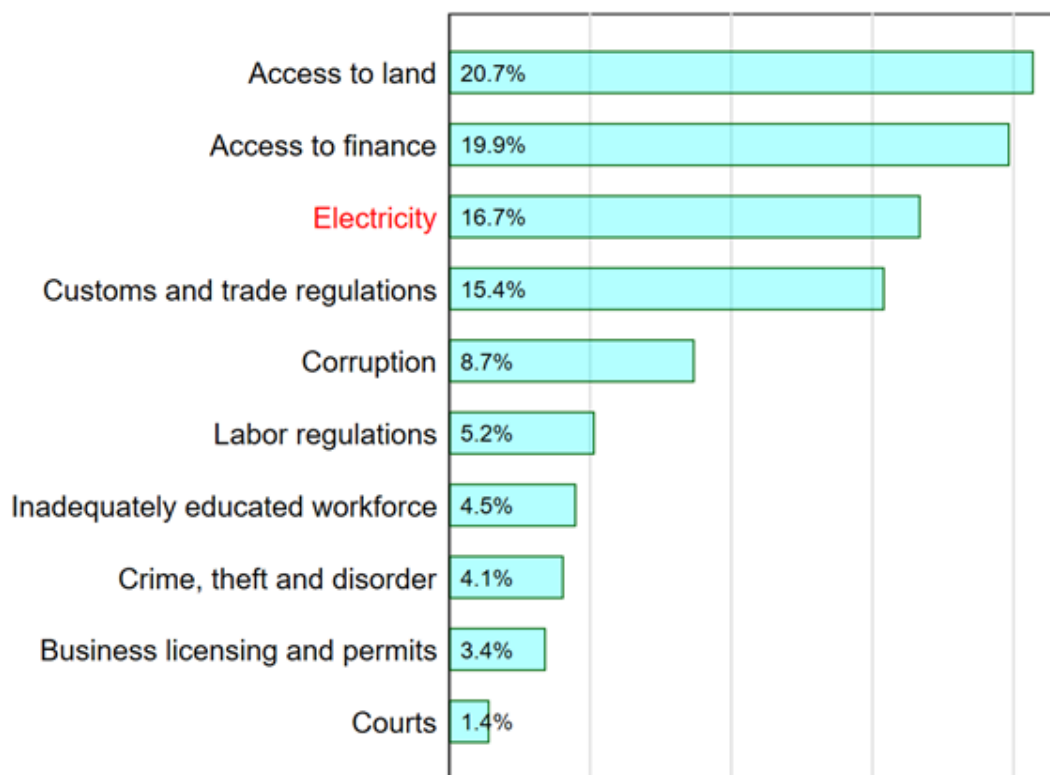


Figure 2: Percentage of firms identifying each constraint as a top obstacle

Notes: Our calculations are based on 34,300 responses from firms in 84 developing countries from 2006 to 2019. Data source: The World Bank Enterprise Surveys (WBES) dataset.

Chapter 4 investigates the impact of power constraints on manufacturing firms' total factor productivity in developing countries using the World Bank Enterprise Surveys data. In these countries,

manufacturing firms face numerous challenges that hinder their productivity and competitiveness. Among these challenges, power outages and other power constraints have emerged as a significant obstacle affecting firms' activities. As drivers of economic growth, a major part of the firms in these countries cite power as the major obstacle or one of the main constraints to their activities (Asiedu et al. 2021). Indeed, power is the third most important constraint after access to land and access to finance (see Figure 2). About 17% of manufacturing firms in our sample report that power is a major or severe constraint on their operations. In most of these developing countries, power thus appears to be of greater concern to these manufacturing firms than many other issues such as corruption and inadequate workforces. However, this literature on power constraints and firms' productivity is still scarce and the results remain rather inconsistent when compared to each other. For example, some studies find a statistically significant negative effect of these constraints on firms' performance (Hardy & McCasland 2021; Abeberese et al. 2021), while other studies find a statistically significant but weak effect (Grainger & Zhang 2017) and yet others do not find a statistically significant relationship between these power obstacles and firms' productivity (Scott et al. 2014). This lack of consistency in previous results could reflect the potential limitations of the different empirical approaches thus far adopted in this literature. For example, Xiao et al. (2022) consider power outages or constraints as a completely exogenous explanatory variable. Meanwhile, authors like Fisher-Vanden et al. (2015), Allcott et al. (2016), Cole et al. (2018) and Elliott et al. (2021) consider this variable as potentially endogenous and propose an instrumental variables technique based on variations in the power supply from hydroelectric generation as an instrument. By proposing a new matching-based approach (Entropy Balancing) and by extending the previous results from the literature to the degree of severity of the power constraints, this analysis reveals a significant negative effect of power constraints on firm-level revenue-based total factor productivity, emphasizing the need for a stable power supply to support economic development and competitiveness. The chapter further highlights the role of the country's stage of economic development and firms' capabilities, such as research and development and backup generator usage, in influencing the magnitude of productivity loss due to power constraints.

To sum up, this thesis aims to contribute to the understanding of electrification's complex relationship with deforestation and economic development, with a substantial focus on Côte d'Ivoire and other African countries. The findings shed light on the importance of sustainable electrifi-

cation strategies and policy interventions to maximize the positive impact of electricity access while mitigating potential environmental and economic challenges. By addressing these issues, policymakers can pave the way for inclusive and sustainable economic growth in these countries.

Bibliography

- Abeberese, A. B., Ackah, C. G. & Asuming, P. O. (2021), 'Productivity losses and firm responses to electricity shortages: Evidence from Ghana', *The World Bank Economic Review* **35**(1), 1–18.
- Akpandjar, G. & Kitchens, C. (2017), 'From darkness to light: The effect of electrification in Ghana, 2000–2010', *Economic Development and Cultural Change* **66**(1), 31–54.
- Allcott, H., Collard-Wexler, A. & O'Connell, S. D. (2016), 'How do electricity shortages affect industry? Evidence from India', *American Economic Review* **106**(3), 587–624.
- An, L., Lupi, F., Liu, J., Linderman, M. A. & Huang, J. (2002), 'Modeling the choice to switch from fuelwood to electricity: implications for giant panda habitat conservation', *Ecological Economics* **42**(3), 445–457.
- Andres, L. A., Guasch, J. L. & Straub, S. (2007), 'Do regulation and institutional design matter for infrastructure sector performance?', *World Bank Policy Research Working Paper* (4378).
- Angelsen, A. (1999), 'Agricultural expansion and deforestation: modelling the impact of population, market forces and property rights', *Journal of development economics* **58**(1), 185–218.
- Angelsen, A. (2010), 'Policies for reduced deforestation and their impact on agricultural production', *Proceedings of the National Academy of Sciences* **107**(46), 19639–19644.

- Asiedu, E., Azomahou, T. T., Gaekwad, N. B. & Ouedraogo, M. (2021), ‘The determinants of electricity constraints by firms in developing countries’, *Energy Economics* **104**, 105605.
- Bambe, B.-W.-W., Combes, J. L., Kaba, K. & Minea, A. (2022), Inflation targeting and developing countries’ performance: Evidence from firm-level data, Technical report, Orleans Economics Laboratory/Laboratoire d’Economie d’Orleans (LEO
- Bernanke, B. S. (1983), ‘Irreversibility, uncertainty, and cyclical investment’, *The quarterly journal of economics* **98**(1), 85–106.
- Bertoméu-Sánchez, S., Camos, D. & Estache, A. (2018), ‘Do economic regulatory agencies matter to private-sector involvement in water utilities in developing countries?’, *Utilities policy* **50**, 153–163.
- Chauvet, L. & Ehrhart, H. (2018), ‘Aid and growth: evidence from firm-level data’, *Journal of Development Economics* **135**, 461–477.
- Chauvet, L. & Ferry, M. (2021), ‘Taxation, infrastructure, and firm performance in developing countries’, *Public Choice* **187**, 455–480.
- Chauvet, L. & Jacolin, L. (2017), ‘Financial inclusion, bank concentration, and firm performance’, *World Development* **97**, 1–13.
- Cheng, D., Shi, X., Yu, J. & Zhang, D. (2019), ‘How does the chinese economy react to uncertainty in international crude oil prices?’, *International Review of Economics & Finance* **64**, 147–164.
- Chomitz, K. & Gray, D. A. (1999), *Roads, lands, markets, and deforestation: a spatial model of land use in Belize*, The World Bank.
- Cole, M. A., Elliott, R. J., Occhiali, G. & Strobl, E. (2018), ‘Power outages and firm performance in sub-saharan africa’, *Journal of Development Economics* **134**, 150–159.
- De Gouvello, C. & Durix, L. (2008), ‘Maximizing the productive uses of electricity to increase the impact of rural electrification programs: An operational methodology’.
- Dinkelman, T. (2011), ‘The effects of rural electrification on employment: New evidence from south africa’, *American Economic Review* **101**(7), 3078–3108.

- Elder, J. & Serletis, A. (2009), 'Oil price uncertainty in canada', *Energy Economics* **31**(6), 852–856.
- Elliott, R. J., Nguyen-Tien, V. & Strobl, E. A. (2021), 'Power outages and firm performance: A hydro-iv approach for a single electricity grid', *Energy economics* **103**, 105571.
- Esteban, A. F. L., Kafarov, V., Guerrero, I., Cortes, A., Ceron, A. M. R. & Duarte, M. M. (2018), 'Assessment of access to electricity and the health, education and agricultural productivity effects in rural areas of colombia', *Chemical Engineering Transactions* **70**, 1219–1224.
- Ferguson, R., Wilkinson, W. & Hill, R. (2000), 'Electricity use and economic development', *Energy policy* **28**(13), 923–934.
- Fisher-Vanden, K., Mansur, E. T. & Wang, Q. J. (2015), 'Electricity shortages and firm productivity: evidence from china's industrial firms', *Journal of Development Economics* **114**, 172–188.
- Foster, A. D. & Rosenzweig, M. R. (2002), 'Economic growth and the rise of forests'.
- Geist, H. J. & Lambin, E. F. (2002), 'Proximate causes and underlying driving forces of tropical deforestation tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations', *BioScience* **52**(2), 143–150.
- Grainger, C. A. & Zhang, F. (2017), 'The impact of electricity shortages on firm productivity: Evidence from pakistan', *World Bank Policy Research Working Paper* (8130).
- Grogan, L. & Sadanand, A. (2013), 'Rural electrification and employment in poor countries: Evidence from nicaragua', *World Development* **43**, 252–265.
- Harchaoui, T., Tarkhani, F. & Yuen, T. (2005), The effects of the exchange rate on investment: Evidence from canadian manufacturing industries, Technical report, Bank of Canada.
- Hardy, M. & McCasland, J. (2021), 'Lights off, lights on: The effects of electricity shortages on small firms', *The World Bank Economic Review* **35**(1), 19–33.
- Hawdon, D. (1996), 'Performance of power sectors in developing countries-a study of efficiency and world bank policy using data development analysis'.

- Hochman, S. & Palmon, O. (1983), 'The irrelevance of capital structure for the impact of inflation on investment', *The Journal of Finance* **38**(3), 785–794.
- Jordà, Ò. (2005), 'Estimation and inference of impulse responses by local projections', *American economic review* **95**(1), 161–182.
- Kanagawa, M. & Nakata, T. (2008), 'Assessment of access to electricity and the socio-economic impacts in rural areas of developing countries', *Energy policy* **36**(6), 2016–2029.
- Khandker, S. R., Barnes, D. F. & Samad, H. A. (2009), *Welfare impacts of rural electrification: a case study from Bangladesh*, The World Bank.
- Khandker, S. R., Samad, H. A., Ali, R. & Barnes, D. F. (2014), 'Who benefits most from rural electrification? evidence in india', *The Energy Journal* **35**(2).
- Koo, J., Yoon, G.-S., Hwang, I. & Barnerjee, S. G. (2013), 'A pitfall of private participation in infrastructure: a case of power service in developing countries', *The American review of public administration* **43**(6), 674–689.
- Lee, C.-C., Wang, C.-W. & Ho, S.-J. (2020), 'Financial inclusion, financial innovation, and firms' sales growth', *International Review of Economics & Finance* **66**, 189–205.
- Lee, K., Miguel, E. & Wolfram, C. (2020), 'Does household electrification supercharge economic development?', *Journal of Economic Perspectives* **34**(1), 122–44.
- Lipscomb, M., Mobarak, A. M. & Barham, T. (2013), 'Development effects of electrification: Evidence from the topographic placement of hydropower plants in brazil', *American Economic Journal: Applied Economics* **5**(2), 200–231.
- Liscow, Z. D. (2013), 'Do property rights promote investment but cause deforestation? quasi-experimental evidence from nicaragua', *Journal of Environmental Economics and Management* **65**(2), 241–261.
- Lunceford, J. K. & Davidian, M. (2004), 'Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study', *Statistics in medicine* **23**(19), 2937–2960.

- Madsen, J. B. (2003), 'Inflation and investment', *Scottish Journal of Political Economy* **50**(4), 375–397.
- Mensah, J. T. & Adu, G. (2015), 'An empirical analysis of household energy choice in Ghana', *Renewable and Sustainable Energy Reviews* **51**, 1402–1411.
- Nucci, F. & Pozzolo, A. F. (2001), 'Investment and the exchange rate: An analysis with firm-level panel data', *European Economic Review* **45**(2), 259–283.
- Pargal, S. (2003), 'Regulation and private sector participation in infrastructure', *The limits of stabilization: infrastructure, public deficits, and growth in Latin America* pp. 171–97.
- Rud, J. P. (2012), 'Electricity provision and industrial development: Evidence from India', *Journal of Development Economics* **97**(2), 352–367.
- Sangne, C., Barima, Y., Bamba, I. & N'Doumé, C.-T. (2015), 'Dynamique forestière post-conflits armés de la forêt classée du haut-sassandra (côte d'ivoire)', *[VertigO] La revue électronique en sciences de l'environnement* **15**(3).
- Scott, A., Darko, E., Lemma, A. & Rud, J.-P. (2014), 'How does electricity insecurity affect businesses in low and middle income countries', *Shaping policy for development* pp. 1–80.
- Servén, L. (2003), 'Real-exchange-rate uncertainty and private investment in LDCs', *Review of Economics and Statistics* **85**(1), 212–218.
- Shi, X. & Sun, S. (2017), 'Energy price, regulatory price distortion and economic growth: a case study of China', *Energy Economics* **63**, 261–271.
- Shively, G. & Pagiola, S. (2004), 'Agricultural intensification, local labor markets, and deforestation in the Philippines', *Environment and Development Economics* **9**(2), 241–266.
- Stern, D. I., Burke, P. J. & Bruns, S. B. (2019), 'The impact of electricity on economic development: A macroeconomic perspective'.
- Tanner, A. M. & Johnston, A. L. (2017), 'The impact of rural electric access on deforestation rates', *World Development* **94**, 174–185.
- Trujillo, L., Martin, N., Estache, A. & Campos, J. (2002), *Macroeconomic effects of private sector participation in Latin America's infrastructure*, Vol. 2906, World Bank Publications.

- Villoria, N. B., Byerlee, D. & Stevenson, J. (2014), 'The effects of agricultural technological progress on deforestation: what do we really know?', *Applied Economic Perspectives and Policy* **36**(2), 211–237.
- Wallsten, S. (2002), 'Does sequencing matter? regulation and privatization in telecommunications reforms', *Regulation and Privatization in Telecommunications Reforms (February 2002)* .
- Wallsten, S. J. (2001), 'An econometric analysis of telecom competition, privatization, and regulation in africa and latin america', *The Journal of industrial economics* **49**(1), 1–19.
- Wolde-Rufael, Y. (2006), 'Electricity consumption and economic growth: a time series experience for 17 african countries', *Energy policy* **34**(10), 1106–1114.
- Xiao, Z., Gao, J., Wang, Z., Yin, Z. & Xiang, L. (2022), 'Power shortage and firm productivity: Evidence from the world bank enterprise survey', *Energy* **247**, 123479.

Access to electricity and household practices potentially contributing to forest loss in Côte d'Ivoire

This chapter is a joint work with Raja Chakir and Anna Creti.

1.1 Introduction

Agriculture, particularly cocoa production, is the backbone of the Ivorian economy, contributing 15% to its Gross domestic product (GDP). The country is the world's largest producer of cocoa beans, accounting for 40% of global production, and cocoa cultivation supports the livelihoods of 20% of the Ivorian population. Additionally, cocoa and its derivatives represent half of the country's total exports, according to the World Bank. However, the Forestry Development Company of Côte d'Ivoire (SODEFOR) has identified that the expansion of cocoa plantations has resulted in the destruction of over 200,000 hectares of forest. A report on the country published in December 2018 by REDD+ confirmed that agriculture was responsible for 62% of the massive deforestation, compared to other factors such as timber exploitation (18%) and infrastructure expansion (10%).¹

¹REDD+ is an international initiative aimed at reducing emissions from deforestation and forest degradation.

Another potential source of forest loss in the country is biomass fuel consumption by households. Indeed, like many developing countries, most of the households in the country heavily rely on biomass fuel consumption, including firewood and charcoal, for cooking and heating purposes. Biomass fuel consumption in Côte d'Ivoire is estimated to account for around 80% of the country's total energy consumption, with firewood being the primary source. According to the International Energy Agency (IEA), around 2.4 million tons of firewood are consumed annually for cooking and heating purposes in the country.² This high demand for firewood has resulted in the depletion of natural forests, leading to soil erosion and loss of biodiversity.

To sum up the situation, the Director of SODEFOR stated that the forest loss observed in the country is one of the highest in the world as the forest cover in the country went from 16 million hectares of forest in the 1960s to approximately 2.5 million hectares nowadays.

In this background, in 2011, the Ivorian government initiated an extensive electrification program as part of Axis III of the Ps-Gouv (Government Social Program). The program is aimed at bolstering electricity coverage in Côte d'Ivoire and comprises of three measures: the National Rural Electrification Program (PRONER), the Electricity for All Program (PEPT), and a recent 20% tariff reduction for low-income households.³

Meanwhile, we have little evidence to date on the link between electrification and forest loss in developing countries. Moreover, we still have conflicting results from this growing body of literature, leaving the direction of the relationship between electrification and forest loss uncertain ([Geist & Lambin 2002](#) Vs [Tanner & Johnston 2017](#)). Indeed, on the one hand, the extension of the electricity network or the improvement of agricultural profitability thanks to electrification might be a source of forest loss ([Geist & Lambin 2002](#); [Villoria et al. 2014](#)). On the other hand, electrification could also reduce the need to expand arable farms or to collect firewood, and thus help to mitigate forest loss ([Tanner & Johnston 2017](#); [An et al. 2002](#); [Mensah & Adu 2015](#)).

The aim of this paper is to provide insights into the connections between electricity access and forest loss in Côte d'Ivoire. More precisely, the primary objectives of the paper is to provide new evidence on the links between electrification and the household practices that may contribute to forest loss, such as biomass fuel consumption and arable farms size, in the country. In other words,

²IEA Energy Access Outlook 2021.

³The investment in PRONER is estimated to be up to 6,800bn FCFA (10.4bn euros) over the period of 2014-2030.

what is the relationship between electricity access and biomass fuel consumption in households in Côte d'Ivoire? How does electricity access influence the size and expansion of arable farms in Côte d'Ivoire? Finally, to what extent does the provision of electricity in rural areas of Côte d'Ivoire lead to changes in household practices that may contribute to forest loss? Answers to these questions could help policymakers understanding the underlying mechanism and allow them to prescribe meaningful complementary policies in their efforts to enhance electricity access while minimizing forest loss in the country.

We contribute to this growing body of literature in three different ways. First, we document how electrification could affect households practices potentially contributing to forest loss (biomass fuel consumption and arable farms size) by focusing specifically on the case of households in Côte d'Ivoire. This is a contribution to [Tanner & Johnston \(2017\)](#)'s macro (country-level) approach. Second, we adapt [Angelsen \(1999\)](#)'s theoretical framework and explore a potential link between electrification and households practices potentially contributing to forest loss (biomass fuel consumption and arable farms size) from a theoretical point of view. Finally, using the last four waves of the nationally representative households' Living Standards Measurement Surveys (1998, 2002, 2008 and 2015) and a pseudo-panel fixed effects regression model with robust standard errors, we document that the electricity access rate significantly reduces both arable farms size and biomass fuel consumption (firewood collection from the forest), providing further empirical evidence in this growing body of literature. Our findings are robust to various alternative relevant specifications (time FE inclusion; time trends inclusion; cocoa price trends inclusion; probit model; entropy balancing; IPW regression adjustment; nearest-neighbor matching; and propensity-score matching). We also document that there is an electrification threshold of 80% beyond which the effect of the electrification would be to increase arable farms size. So increasing electrification without some supportive policies would potentially increase forest loss within the most urbanized localities in the country.

The rest of the paper is divided into four main sections: section [1.2](#) presents the literature review, section [1.3](#) presents the theoretical link between electrification and household practices potentially contributing to forest loss. Section [1.4](#) presents our empirical analysis which includes the main data and variables, some stylized facts, the empirical modeling and the empirical results. Section [1.5](#) presents our concluding remarks.

1.2 Related literature

We have divided this literature review into three sub-sections: (i) traditional causes of forest loss, (ii) effects related to access to electricity, and (iii) potential links between electrification and forest loss. The literature on the traditional causes of forest loss and on the effects resulting from electrification is fairly substantial, unlike that in the third sub-section, devoted to the relationship between electrification and forest loss. We found very few studies documenting this relationship, and no studies dealing with Côte d'Ivoire or even with the West African zone as a whole.

1.2.1 Traditional causes of forest loss

As mentioned above, the literature on the direct and indirect causes of forest loss is quite abundant. Among the most influential studies is that by [Geist & Lambin \(2002\)](#) which documents the direct and indirect causes of forest loss. For these two authors, factors such as the extension of infrastructure (roads, electricity supply networks, etc.), the expansion of agriculture, wood extraction (wood exploitation, firewood, charcoal, etc.) directly impact forest cover. They also point out that demographic (density, migration and population distribution), economic (market size, urbanization, price changes, etc.), technological (changes in agricultural techniques), political and institutional (corruption, property rights) and cultural factors can indirectly affect forest loss.

Several other studies particularly single out infrastructure expansion. Based on a land use model, [Chomitz & Gray \(1999\)](#) document that infrastructure (e.g. roads) increases agricultural expansion (especially commercial agriculture) because it facilitates access to markets. Therefore, while such infrastructure can reduce poverty, it also increases forest loss and induces environmental degradation. Similarly, in a meta-analysis of the causes of tropical forest loss, [Angelsen & Kaimowitz \(1999\)](#) document that a fairly large transport network –and therefore higher prices for agricultural products– generally leads to more forest loss. The other major source of forest loss is lack of opportunity in the non-agricultural sector, which keeps much of the labor force in plantations. Indeed, [Angelsen \(2010\)](#) argues, on the basis of a meta-analysis of 140 economic models of forest loss, that lack of non-agricultural employment is one of the main causes of forest loss. [Angelsen & Kaimowitz \(1999\)](#) document from a meta-analysis of the causes of tropical forest loss that low wages and a shortage of non-agricultural employment generally lead to more forest

loss. The creation of employment opportunities in non-agricultural sectors would therefore help to safeguard much of the forest.

Armed conflicts are also detrimental to the preservation of forests. For example, in their analysis of the dynamics of the designated forest of Haut-Sassandra (Côte d'Ivoire) in a post-armed conflict situation, [Sangne et al. \(2015\)](#) found that the area, once considered one of the country's best protected designated forests, was experiencing several intrusions into its historical boundaries as a result of the country's military-political crisis that lasted from 2002 to 2011. Numerous pioneering fronts were opened, leading to the clearance of several thousand hectares of natural forest (formerly controlled by rebel armed groups from the north) followed by the plantation of cash crops (mainly cocoa).

Other variables such as property rights, fiscal policy, the real exchange rate or agricultural productivity could have an impact on the dynamics of forest loss. According to [Liscow \(2013\)](#), the effects of property rights would be to increase forest loss. Using the example of Nicaragua, he found that property rights encourage investment, which leads to improved agricultural productivity and thus to forest loss. Indeed, improving productivity increases agricultural profit and thus the incentive to expand arable farms at the expense of forests .

[Foster & Rosenzweig \(2002\)](#) point out that fiscal measures such as lowering timber import tariffs can decrease forest loss at the national level. However, this only shifts the source of wood supply, thus increasing forest loss elsewhere in the world. [Arcand et al. \(2008\)](#), using a sample of 101 countries covering the period 1961-1988, point out that: (i) lower discount rates and stronger institutions reduce forest loss, (ii) a depreciation of the real exchange rate increases forest loss in developing countries and reduces it in developed countries, and (iii) paradoxically, better institutions can exacerbate the deleterious effect of real depreciation in developing countries. Finally, it is important to focus on the role of agricultural productivity on the phenomenon of agricultural land expansion, which is the main source of tropical forest loss. According to [Gibbs et al. \(2010\)](#), agricultural expansion (especially commercial agriculture) is one of the major causes of tropical forest loss. Similarly, [Hertel \(2012\)](#) resurrects the Borlaug Vs Jevons debate on the effects of agricultural productivity on land use. According to [Borlaug \(2002\)](#), agricultural innovation leads to parcels of land being saved when demand for agricultural products remains inelastic (fixed). He supports the idea that improved farming techniques lead to increased agricultural production

and an improved environment. In the same vein, [Abman & Carney \(2020\)](#) provide evidence that subsidized fertilizer increased agricultural productivity and reduced pressure to expand agriculture into forest margins in Malawi. Their results suggest that policies aimed at increasing small-scale agricultural productivity may have positive environmental spillovers. Contrary to Borlaug's idea, based on the Jevons paradox, an improvement in agricultural productivity is accompanied by an expansion of the cultivated area.⁴ [Rudel et al. \(2009\)](#) have also been critical of Borlaug's idea. Looking at FAO (Food and Agriculture Organization) data for 961 agricultural sectors in 161 countries over a 15-year period, they find no significant decline in agricultural area as a result of increased crop yields.

1.2.2 Effects related to access to electricity

In addition to its contribution to development and the improvement of people's well-being, access to electricity is placed at the heart of the Millennium Development Goals, particularly by international development organizations such as the United Nations (UN) and its Development Programme (UNDP). A large number of studies have established a positive relationship between access to energy and the level of economic development ([Ferguson et al. 2000](#); [Wolde-Rufael 2006](#)). Energy also accelerates structural transformation, notably by promoting industrial development ([Rud 2012](#)). Electricity is the form of energy most closely associated with the vectors of economic development ([Lee et al. 2020](#); [Stern et al. 2019](#)).

Indeed, electricity increases firms' productivity, reduces production costs and increases the producer's surplus and income ([Rud 2012](#); [Fisher-Vanden et al. 2015](#); [Allcott et al. 2016](#)). In addition, it significantly improves the situation of households, especially in rural areas, through agricultural productivity, income growth, education, health and off-farm employment opportunities ([Esteban et al. 2018](#); [Kanagawa & Nakata 2008](#); [De Gouvello & Durix 2008](#) [Lipscomb et al. 2013](#); [Dinkelman 2011](#); [Grogan & Sadanand 2013](#); [Lipscomb et al. 2013](#); [Khandker et al. 2009](#); [Khandker et al. 2014](#)). Access to electricity also has a fairly significant impact on the demographic dynamics of rural areas. Thus [Peters & Vance \(2011\)](#) suggest, based on ENV (Living Standards Surveys in Côte d'Ivoire) data, that electrification increases the fertility rate for urban households and reduces it for rural households.

⁴The Jevons paradox implies that since technical progress improves the efficiency of the use of a resource, the total consumption of that resource may increase rather than decrease.

1.2.3 Potential links between electrification and forest loss

Although relatively few previous studies have provided evidence on the impact of electrification on forest loss, one of the most influential is that by [Tanner & Johnston \(2017\)](#). Using a panel of 158 countries for the years 1990, 2000 and 2010, the authors find that rural electrification reduces forest loss and better explains this phenomenon compared to factors such as population growth or development. Moreover, electrification often acts indirectly on forest loss, notably through the adoption of new techniques requiring electricity. This is illustrated by [Shively & Pagiola \(2004\)](#) who find that improvement of irrigation systems in the Philippines would have made it possible to reduce forest loss by half. They explain this by the fact that extensive farmers, who are not very competitive with the intensive farmers who have benefited from this improvement, are being squeezed out of the market. Also, [Angelsen et al. \(2001\)](#) argue that the adoption of new technologies could reduce the need to expand farms. On the other hand, [Villoria et al. \(2014\)](#) suggest that the promotion of agricultural innovation could improve agricultural profitability and thus encourage forest loss through the expansion of agricultural land.

Finally, many studies have documented that electricity is a substitute for firewood outside Africa. Apart from [Akpanjar & Kitchens \(2017\)](#) which found that electrification led to a shift away from the use of firewood for cooking by Ghanaian households over the period 2000 to 2010, this is not necessarily the case in Africa because cooking with electricity requires stoves, which are still relatively expensive for the majority of poor households, especially in sub-Saharan Africa. However, it is conceivable that this substitution could take place, indirectly, through other channels such as household appliances. It is known, for example, that a large proportion of households in rural Africa have recently acquired refrigerators, which could optimize food preservation and thus reduce the demand for firewood and charcoal for cooking. Furthermore, electrification of a rural locality could help to develop a market for butane gas, for example, or even alternative energy sources, which could possibly reduce the pressure on forest resources for cooking.⁵ Electrification could also reduce the amount of firewood used for cooking without necessarily replacing firewood with other types of fuel such as electric stoves or butane gas. The reason is that with electric light, women can prepare the main meal just before it is eaten rather than preparing it during the day and then reheating it in the evening.

⁵Butane gas is one of the main energy sources for cooking in Côte d'Ivoire.

1.3 Theoretical link between electrification and household practices potentially contributing to forest loss

This section aims to theoretically document the link between electrification and households practices potentially contributing to forest loss (biomass fuel consumption and arable farms size).

1.3.1 Conceptual links between electrification and practices potentially contributing to forest loss (firewood collection and arable farms size)

In this analysis, our intuition (Figure 1.1) is that electricity could affect households practices potentially contributing to forest loss (biomass fuel consumption and arable farms size) in Côte d’Ivoire. Indeed, electrification, notably via irrigation techniques and/or borehole drilling systems, might have a positive effect on agricultural yield.

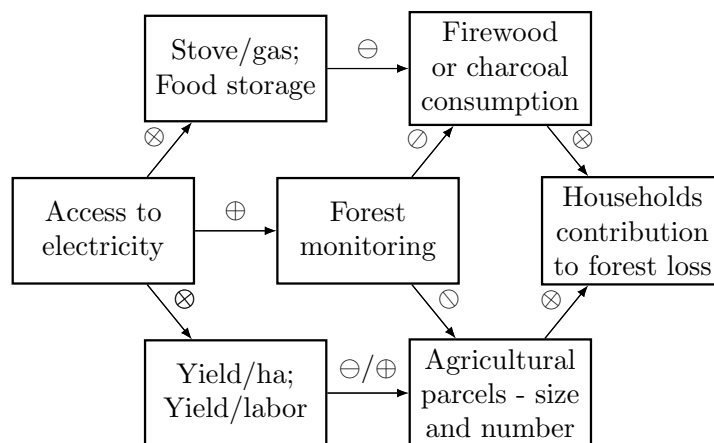


Figure 1.1: Conceptual model of the interrelationship between electrification and households practices potentially contributing to forest loss (biomass fuel consumption and arable farms size)

Notes: ⊕ indicates expected positive relationship, ⊖ indicates expected negatives relationship and ⊕/⊖ indicates an ambiguous relationship (positive relationship or negative relationship, depending on the prevailing market structure).

However, the impact of agricultural productivity on the size of arable farms remains rather ambiguous, especially in view of the Borlaug vs Jevons debate. According to Borlaug (2002)’s hypothesis, improved agricultural productivity leads to an economy of land when the demand for agricultural products remains inelastic (fixed). However, according to Jevons’ paradox, an improvement in agricultural productivity is accompanied by an expansion in the area of cultivated land. We also

believe that electrification of a locality could accelerate its structural transformation by creating new off-farm employment opportunities (Chhay et al. 2020; Dinkelman 2011). This would free up agricultural labor for these new sectors. Thanks to the complementarity of factors, this would tend to broadly reduce arable farms size. This labor transfer is also valid for the labor force collecting firewood. Moreover, access to electricity encourages the adoption of electric cookers, which would be an alternative to firewood. We could also consider the establishment of a butane gas supply market following the electrification of a locality. Another important element is the acquisition of refrigerators, which generally allows households to optimize food conservation, and therefore to reduce the frequency of cooking (reduction in energy demand for cooking). Finally, the role of forest monitoring in the country should also be highlighted. Forest monitoring in Côte d'Ivoire is carried out by "water and forest" agents, who are government officials. The assignment of these agents to a locality takes into account the basic amenities within that locality, of which electricity is a part. Thus, these agents are present in greater numbers in localities that are electrified than in those that are not.

1.3.2 Theoretical framework

Our theoretical contribution has been to start from the heterogeneous frameworks approach proposed by Angelsen (1999) and to introduce the electrification variable in order to open a new debate on its potential theoretical links with household activities that can lead to forest loss or degradation in tropical countries like Côte d'Ivoire. Our choice of this heterogeneous framework approach is also justified by Côte d'Ivoire's large geographical disparities. Indeed, major geographical disparities remain between Abidjan (economic capital) and the rest of the country. This polarization and the great differences in terms of development between the country's major zones prevent us from adopting a single economic framework adapted to the case of Côte d'Ivoire (for example the most common agricultural household framework).

The main idea of this type of framework is to progressively include hypotheses, starting from the most basic framework (subsistence economy without market) to arrive at the most comprehensive framework (with markets, property regime, etc.). In appendix A, we present in details and discuss theoretically the most important channels through which we think electricity could affect households practices potentially contributing to forest loss (arable farms size expansion).

We summarize our main theoretical findings in [Table 1.1](#) below by framework and by channel. We broadly documented that the effect of electrification through demography would accentuate the forest loss of a locality in frameworks I and II (when the migration effect outweighs the natality effect). However, the channel of demography becomes irrelevant as soon as freedom of movement (migration of the labor force) is introduced in frameworks III and IV. Electrification through agricultural productivity is a means of mitigating forest loss in framework I and in framework II (only when the subsistence effect outweighs the farm-firm effect). On the other hand, it becomes a source of forest loss when the subsistence effect disappears (introduction of perfect markets) in framework III and IV. The productivity channel is relevant in all the frameworks we considered. Moreover, the more electrification reduces fallow time (increase in agricultural intensification), the more it reduces forest loss in frameworks I and II. This agricultural intensification channel becomes irrelevant once perfect markets are introduced in frameworks III and IV. Finally, the effect of electrification through both the intensification of forest monitoring and the creation of new employment opportunities would help to fight forest loss in framework II, III and IV (none relevant channels in framework I).

Table 1.1: Summary of our theoretical findings

Framework	Main transmission channel					
	Demography	Agricultural productivity	Agricultural intensification	Forest monitoring	Off-farm wages	Wages in economy
I	\nearrow (if $\frac{dN}{de} > 0$)	\searrow	\searrow	n.a	n.a	n.a
II	\nearrow (if $\frac{dN}{de} > 0$)	\searrow (if $X < \frac{C^{min} - wL^{out}}{\alpha}$)	\searrow	\searrow	\searrow	n.a
III	n.a	\nearrow	n.a	\searrow	n.a	\searrow
IV	n.a	\nearrow (if $g > 0; \delta + \lambda > g$)	n.a	\searrow (if $g > 0; \delta + \lambda > g$)	n.a	\searrow (if $g > 0; \delta + \lambda > g$)

Notes: Framework I: Subsistence economy (no labor market) ; Framework II: Chayanovian economy (imperfect labor market) ; Framework III: Open economy with perfect labor market (static open access) ; Framework IV: Open economy with perfect labor market (dynamic open access). \searrow means that electrification reduces forest loss and \nearrow means that electrification increases forest loss given a specific framework and transmission channel. n.a means not applicable.

In other words, framework I indicates that if the migratory effect of electrification on demography does not outweigh the fertility (or natality) effect, then electrification would globally reduce the expansion of arable farms size in rural areas of Côte d'Ivoire. Framework II, through the agricultural productivity channel, highlights the fact that the environmental effect of electrification would decrease following the urbanisation rate (demography) of localities in Côte d'Ivoire. More precisely, electrification would reduce forest loss in rural areas more effectively than in urban areas. Finally, through frameworks III and IV, the favourable effects of electrification on forest

loss through other channels (forest monitoring and off-farm employment) would be somewhat mitigated by the unfavourable effect through the agricultural productivity channel.

Although our theoretical section opens a fascinating debate on the potential links between electrification and the arable farms size –potentially leading to forest loss– it does not necessarily allow us to conclude on the overall effect of electrification on arable farms size. Our next empirical section 1.4 provides a clear answer to this question about the effect of electrification on households practices potentially contributing to forest loss (arable farms size and biomass fuel consumption).

1.4 Empirical approach

Our empirical analysis includes the main data and variables subsection, some stylized facts, the empirical approach and the empirical results.

1.4.1 Data and variables: socio-economic data

In this study, we use data from the last four waves of the Côte d'Ivoire nationally representative households' Living Standards Measurement Survey (LSMS or ENV) for the years 1998, 2002, 2008 and 2015.⁶ ENV data are provided by the National Institute of Statistics of Côte d'Ivoire. The main objective of an ENV is to collect information to improve the planning and evaluation of economic and social policies in the country. The main variables used in our empirical models are: Access to electricity, Firewood collection, and Arable farms size.

To find out whether a household has access to electricity or not, we refer to the question "what is your main source of lighting?". To find out how households cook, we refer to the question: "what is your main source of fuel?". Finally, to find out how much land households farm, interviewers asked households to estimate the size of each arable farms in hectare, hundredths of a hectare or m^2 . We converted all the arable farms size into hectares and added up the total per household.

Our analysis also included several relevant control variables such as Household size, Household expenditure, Household head gender, Male/female ratio in households, Possession of a refrigerator and stove, Location, and Development hub.

⁶ENV: Enquête Niveau de Vie

The average household size was calculated by adding up all household members. The average size of Ivorian households is around 5 people. The per capita average expenditure is around 500 euros per year in the country over the study period. Regarding the household head gender, in Côte d'Ivoire, decisions in households are very often made by men. Our calculations document that the proportion of households headed by men remains high and almost constant despite the recent waves of emigration. In fact, around 4/5 of Ivorian households remained male-headed over the period 1998-2015. Regarding the possession of a refrigerator and stove, on average, over the study period, around 15% of households had a stove and around 20% had a refrigerator, according to our calculations from the ENV data. We also define three main development hubs. The first consists of all households living in and around the economic capital (District of Abidjan). The second consists of all urban households that are not around the city of Abidjan (intermediate cities), and the third consists of all rural households in the country. Finally, we also considered the male/female ratio in households, and the living area binary variable which tells us whether the household lives in a rural or urban area.

1.4.2 Some stylized facts

[Figure 1.2](#) below and [Figure C1](#) (see appendix C) compare households connected to electricity with households not connected to electricity. For all surveys and for yearly observations, having access to electricity is negatively correlated with firewood collection and agricultural activities. Specifically, while the share of households collecting firewood exceeds 75% in the unconnected group, it remains just below 30% in the connected group. This difference can also be seen when observing the average size of arable farms. Indeed, the average size exceeds 3 hectares in the group of non-connected households. The average size of arable farms is twice as small in the connected group. The difference between connected and unconnected households in terms of firewood collection and agricultural activities remains verified for all survey years (1998, 2002, 2008, and 2015), see appendix C.

[Figure 1.3](#) documents some interesting trends at the departmental (county) and regional levels. The first graph in the first row documents that the proportion of households collecting firewood within a department decreases with that department's electrification rate. Similarly, the second graph on the first row documents that the proportion of households owning at least one arable

farm decreases with the electrification rate. The third graph on the top row documents that the average size of arable farms also decreases with the electrification rate of the departments. These results are also verified at the regional level (second row).⁷

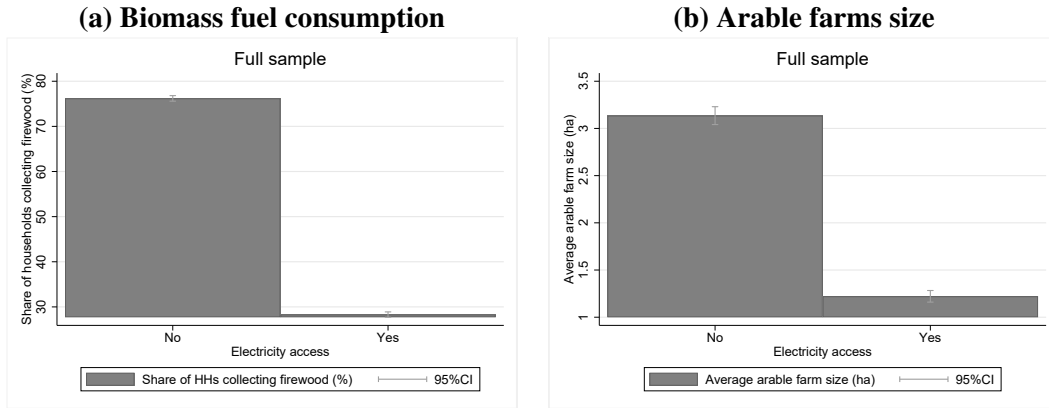


Figure 1.2: Connected versus non-Connected households (Full sample)

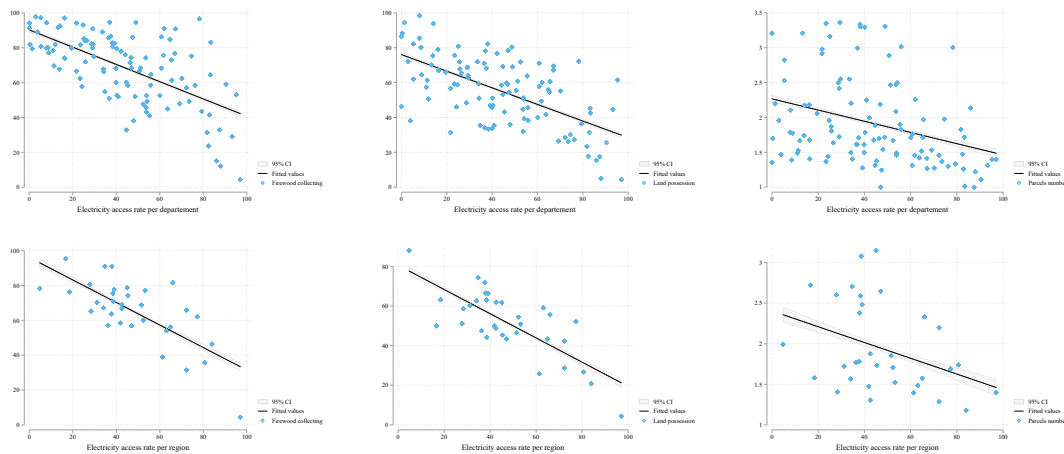


Figure 1.3: Relationship between electrification and households practices potentially contributing to forest loss (biomass fuel consumption and arable farms size) at departmental and regional level

1.4.3 Empirical methodology

To confirm the previous stylized facts, we need to consider any potential endogeneity issue of the electrification variable. Indeed, electrification depends on household group-specific factors that may also affect firewood collection and arable farms size. Although we control for observable factors (household size, male/female ratio, expenditure, etc.), there might remain some unobservable

⁷Côte d'Ivoire has 108 departments and 33 regions.

factors (household preference, cultural practices, etc.) that could potentially affect the choice of electrification and our two outcome variables, leading to potential endogeneity of the electrification variable. Therefore, the primary objective of the cohort fixed effects in our specification is to capture these unobservables as long as they are fixed over time.

We address this potential endogeneity issue by adopting a pseudo-panel fixed effects regression model analysis. The main purpose for building pseudo-panel is to control for unobserved heterogeneity or group-specific characteristics as in a usual panel data analysis. The role of fixed effects is to account for the impact of group-specific unobservable characteristics on the cohorts of households activities (firewood collection and arable farms size). In other words, fixed effects allow us to isolate the causal effect of electrification on household activities (firewood collection and arable farms size) by removing the potential bias that arises from unobserved heterogeneity.

The pseudo-panel approach is used when formal panel data are not available and when only independent, repeated cross-sectional data are available. A pseudo-panel can be constructed using subgroups of the cross-sectional data (called cohorts). Cohort averages are used as point observations in the pseudo-panel (Deaton 1985). Each cohort consists of a homogeneous group of individuals that are assumed to share the same time invariant characteristics from one cross-sectional survey to the next, (year of birth, gender, location, degree or level of education, etc.). However, since cohort averages are based on a set of individuals, they are subject to possible measurement errors that can be ignored if the number of individuals in each cohort is sufficiently large. Generally, there is a trade-off between the number of cohorts and their size. A large number of cohorts increases the heterogeneity of the pseudo-panel but decreases the average number of individuals per cohort leading to less precise estimates of cohort averages and vice-versa. As the available data consist of repeated cross-sections of household surveys, we aggregate households into cohorts, by taking the cross-sectional average for each cohort to construct the model variables. In particular, each quantitative model variable z_{it} , is given by the average of observed values of all \bar{z}_{ct} in each cohort c for period t .

The criteria for forming cohorts cannot be chosen at random. It should be remembered that the principle of pseudo-panels is to form cohorts, in other words profiles, grouping together individuals whose behaviour is considered to be similar. A good grouping criterion should: (1) be a characteristic that does not change over time at the individual level, defines a stable sub-population

and results from a trade-off that (2) forms sufficiently large cohorts while (3) not losing too much variability. In our case, we established cohorts on the basis of the following time-invariant criteria: the area or location (rural household or urban household), the strata (District of Abidjan, Intermediate Cities, Eastern Rural Forest, Western Rural Forest, Rural Savannah), and the year of birth of the household head (or generation of households). Once the cohorts had been established, the following model is estimated:

$$\overline{\text{Outcome}}_{ct} = \beta_1 \overline{\text{Electricity}}_{ct} + \beta_2 \overline{X}_{ct} + \overline{\alpha}_c + \overline{\varepsilon}_{ct} \quad (1.1)$$

$\overline{\text{Outcome}}_{ct}$ represents the share of households collecting firewood ($\overline{\text{Firewood}}_{ct}$) or the average arable farms size ($\overline{\text{Farm}}_{ct}$) within a cohort c at year t . $\overline{\text{Electricity}}_{ct}$ represents the electricity access rate per cohort c at year t . \overline{X}_{ct} represents the control variables per cohort c at year t . $\overline{\alpha}_c$ represents cohorts fixed effects and $\overline{\varepsilon}_{ct}$ is the error term. As control variables, we include household characteristics that are likely to impact on electricity adoption, firewood collection and household agricultural decisions. The choice of control variables included in the model is based on previous empirical works on the subject as well as on our theoretical framework. These characteristics include male/female ratio, average household size, migration (approximated by the gender of the household head, female head in this country probably means that the male head has migrated), expenditure levels (a proxy of household wealth), and ownership of equipment such as refrigerators and stoves (access to energy services). We control for household male/female ratio as this may be relevant in explaining both firewood collection and agricultural activities. Indeed, in sub-Saharan Africa, firewood collection is mainly carried out by women. Thus a household composed mainly of men would have a low tendency to collect firewood. In addition, the agricultural labor force in this part of Africa is predominantly male. So a high household male/female ratio could be a key factor in expanding agricultural land. Household size is also relevant in explaining both energy and agricultural choices. Another fairly relevant variable that we control for is the gender of the household head. In this region, households are largely headed by men. Studies have documented that female-headed households are generally households where the male (head of household) has migrated. In addition to the fact that these households benefit from more optimal management by these women, they tend to be the richest (receiving remittances from migrants). This can therefore condition both the energy and activity choices of these households. Finally, we also control

for the level of expenditure (a proxy of wealth) and ownership of equipment (energy services) at household level.

1.4.4 Results

[Table 1.2](#) presents the effect of electrification rate on the percentage of households collecting firewood and on average arable farms size within cohorts. The results document that the effect of electrification on the percentage of households collecting firewood and on average arable farms size is negative and statistically significant. These main results are obtained by controlling for specific fixed effects, and by considering robust and replications-based standard deviations.⁸ The coefficients are obtained using Within estimation taking into account cohort fixed effects (FE), which capture any time-invariant heterogeneity across cohorts.

To our main specification ([Equation 1.1](#)), we also add year fixed effects to control for factors changing over time that are common to all cohorts for a given time period (electoral crisis, coups, etc.). We also add time trend to control for trend variable that affects the dependent variable and is not directly observable but is highly correlated with time (for instance, government ongoing national rural electrification program, other infrastructure expansion programs, land property rights reinforcement in the country, etc.). Finally, as cocoa farming represents the main source of revenue in the country, we add cocoa price index to control for arable farming dynamics in the country as in [Berman et al. \(2023\)](#).

The first side of [Table 1.2](#) documents that a high electrification rate is associated with a low proportion of households collecting firewood within a given cohort, as the coefficient is negative and significant. More precisely, each increase in the electrification rate per cohort by one unit above the average leads to a decrease of 0.147% in the proportion of households collecting firewood within the cohort. This result is in line with [Akpandjar & Kitchens \(2017\)](#) who found that electrification led to a shift away from the use of firewood by Ghanaian households over the period 2000 to 2010, and [Dendup \(2022\)](#) who found that electrification reduces firewood consumption by about 0.83–2.09 cubic meters per month in rural Bhutan. This negative relationship persists after controlling for time FE, time trend and cocoa price index.

⁸The Robust standards errors permit for the errors to be heteroskedastic and also be correlated with each other within clusters. The Bootstrap standards errors based on 200 replications and the Jakknife standards errors based on 138 replications allow us to rule out any suspicion of over-rejection of the hypothesis that the effect is not significant.

Table 1.2: The effect of electricity access on firewood collection and arable farms

	Firewood collection						Arable farms size					
	Robust std. err.	Bootstrap std. err.	jackknife std. err.	Time FE	Time trend	Cocoa price Index	Robust std. err.	Bootstrap std. err.	jackknife std. err.	Time FE	Time trend	Cocoa price Index
Electricity access rate	-0.147** [0.060]	-0.147** [0.069]	-0.147** [0.063]	-0.185*** [0.069]	-0.202*** [0.069]	-0.200*** [0.069]	-0.265** [0.106]	-0.265*** [0.093]	-0.265** [0.112]	-0.128* [0.068]	-0.152** [0.070]	-0.134** [0.063]
Male/female ratio	-0.187** [0.075]	-0.187*** [0.068]	-0.187** [0.083]	-0.139 [0.091]	-0.106 [0.087]	-0.108 [0.084]	-0.149 [0.175]	-0.149 [0.217]	-0.149 [0.174]	-0.177 [0.189]	-0.247 [0.196]	-0.249 [0.197]
Households size	-0.011** [0.005]	-0.011** [0.006]	-0.011** [0.005]	0.001 [0.006]	-0.000 [0.006]	0.000 [0.005]	0.005 [0.009]	0.005 [0.007]	0.005 [0.009]	-0.002 [0.009]	-0.008 [0.009]	-0.010 [0.010]
Male-headed households	-0.076 [0.076]	-0.076 [0.092]	-0.076 [0.082]	-0.046 [0.073]	-0.054 [0.080]	-0.047 [0.079]	0.093 [0.067]	0.093 [0.073]	0.093 [0.070]	0.037 [0.070]	0.062 [0.062]	0.048 [0.062]
Refrigerator owners	0.017 [0.035]	0.017 [0.042]	0.017 [0.038]	-0.005 [0.032]	0.011 [0.037]	0.004 [0.038]	-0.040 [0.037]	-0.040 [0.038]	-0.040 [0.039]	-0.014 [0.041]	-0.034 [0.034]	-0.022 [0.033]
Log expenditure	0.012** [0.005]	0.012** [0.005]	0.012** [0.005]	-0.052*** [0.014]	0.001 [0.004]	-0.005 [0.004]	-0.141 [0.093]	-0.141 [0.104]	-0.141 [0.095]	0.069 [0.073]	-0.009 [0.073]	0.029 [0.072]
Stove owners	-0.071** [0.034]	-0.071* [0.037]	-0.071* [0.037]	-0.065* [0.036]	-0.070* [0.036]	-0.073** [0.035]	-0.012 [0.049]	-0.012 [0.061]	-0.012 [0.051]	0.048 [0.049]	0.006 [0.046]	0.019 [0.044]
Observations	552	552	552	552	552	552	552	552	552	552	552	552
R^2	0.131	0.131	0.131	0.252	0.203	0.215	0.016	0.016	0.016	0.063	0.033	0.040
ρ	0.897	0.897	0.897	0.886	0.893	0.892	0.284	0.284	0.284	0.284	0.282	0.282

Notes: The table presents our main results by controlling for specific fixed and variable effects, and by considering standard deviations based on replications. The coefficients are obtained using Within estimation taking into account cohort fixed effects (FE), which capture any time-invariant differences across cohorts. Year fixed effects control for factors changing over time that are common to all cohorts for a given time period (electoral crisis, coups, etc.). Time trend control for trend variable that affects the dependent variable and is not directly observable but is highly correlated with time (for instance, government ongoing national rural electrification program). Cocoa price index control for arable farming dynamics in the country. Unreported constant is included. Bootstrap standards errors are based on 200 replications. Jackknife standards errors are based on 138 replications. Robust standards errors permit for the errors to be heteroskedastic and also be correlated with each other within clusters. Robust, Bootstrapped and Jackknife Standard errors in brackets. The intraclass correlation (ρ), documents how much of the variance in the output (firewood collection, arable farms size) is explained by the difference across cohorts. In our case, around 90% for firewood collection and 28% for arable farms size (this difference is essentially explained by the relative higher "Between" variability of 35% for firewood collection compared to 22% for arable farm variable in our sample). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

It can also be seen that household firewood collection is neither explained by the gender of household heads nor by refrigerator ownership. Ownership of a refrigerator is not a key element in reducing the proportion of households collecting firewood. But, one might think that households with a refrigerator can easily conserve their food, thus helping to reduce the frequency of cooking (reduction in the amount of firewood collected). Electrification could also reduce the amount of firewood used for cooking without necessarily replacing firewood with other types of fuel such as electric stoves or butane gas. The reason is that with lighting, households can prepare the main meal just before it is eaten rather than preparing it during the day and then reheating it in the evening. However, firewood collection decreases with the proportion of men, household size and stove ownership. Indeed, in most countries in Africa, firewood collection is mainly carried out by women. Finally, firewood collection increases paradoxically with the level of household expenditure. Our intuition is that, as collected firewood is free of charge, high-spending households, which are in general large households, would collect as much firewood as possible to reduce their energy expenditure, thus their total expenditure.

The second side of Table 1.2 presents our estimates of the effect of electrification on the average arable farms size within a given cohort as dependent variable. For all our estimates, electrification has a negative and significant effect on arable farms size. Each increase in the electrification rate per cohort by one unit above the average leads to a decrease of 0.265% in the amount of agricul-

tural land within the cohort. It can also be seen that arable farms size is not significantly explained by household size, the gender of the household head, the male/female ratio in the household, the possession of a refrigerator and electric cooker or household expenditure. Our results are in line with those obtained by [Tanner & Johnston \(2017\)](#), [Shively & Pagiola \(2004\)](#) and [Angelsen et al. \(2001\)](#). But they are in contrast to those obtained by [Villoria et al. \(2014\)](#), who raised the idea that the promotion of agricultural innovation could improve agricultural profitability, leading to the expansion of arable farms and thus to increased forest loss.

1.4.5 Robustness check

Individual cross-sectional analysis

To support the robustness of our pseudo-panel fixed effects regression approach, we first opt for an independent cross-sectional analysis over the full sample and covering each survey wave in the country (1998, 2002, 2008 and 2015). Although this approach leads to the loss of the panel dimension of the first part (pseudo-panel approach), it nevertheless makes it possible to exploit the large number of observations per household (potential gain on the precision of the estimators) and to verify if the grouping of households for the formation of the pseudo-panel in the first part gives coherent results at least in terms of sign of the effects. To predict the probability of a household collecting firewood, we adopt the probit cross-sectional model. According to our results (first side of [Table 1.3](#)), for an average household with access to electricity, the probability of collecting firewood decreases by 28 percentage points for the full sample or over the period 1998-2015 (33.5 percentage points in 1998, 21.6 percentage points in 2002, 31.6 percentage points in 2008 and 19.3 percentage points in 2015). In the second side of [Table 1.3](#), for an average household with access to electricity, the probability of having at least one arable farm decreases by 23.7 percentage points for the full sample (32.9 percentage points in 1998, 26.9 percentage points in 2002, 17.9 percentage points in 2008 and 19.3 percentage points in 2015). To sum up, although it is difficult to compare the magnitude of these results with our pseudo-panel results because of different econometric specifications, we can nevertheless confirm the negative and significant effect of electrification on our two outcome variables (for the full sample and for each year of survey). Moreover, we also observe a gain in the precision of our estimators (smaller standard deviations).

Table 1.3: Robustness check – The effect of electricity access on firewood collection and arable farms

	Firewood collection					Arable farms				
	Full sample	1998	2002	2008	2015	Full sample	1998	2002	2008	2015
Electricity access (No=0, Yes=1)	-0.280*** [0.003]	-0.335*** [0.009]	-0.216*** [0.005]	-0.316*** [0.005]	-0.193*** [0.008]	-0.237*** [0.004]	-0.329*** [0.011]	-0.269*** [0.007]	-0.179*** [0.007]	-0.193*** [0.008]
Number of women	0.101*** [0.006]	0.116*** [0.015]	0.045*** [0.007]	0.088*** [0.010]	0.203*** [0.016]	0.067*** [0.006]	0.073*** [0.017]	0.047*** [0.009]	0.029** [0.010]	0.143*** [0.017]
Households size	0.026*** [0.001]	0.013*** [0.001]	0.043*** [0.001]	0.031*** [0.001]	0.028*** [0.002]	0.029*** [0.001]	0.019*** [0.002]	0.037*** [0.001]	0.021*** [0.001]	0.030*** [0.002]
Male-headed households	0.054*** [0.006]	0.046** [0.017]	-0.019* [0.009]	0.071*** [0.010]	0.112*** [0.012]	0.111*** [0.006]	0.079*** [0.018]	0.054*** [0.011]	0.083*** [0.011]	0.188*** [0.012]
Fridge ownership	-0.216*** [0.010]	-0.102*** [0.022]	-0.085*** [0.015]	-0.224*** [0.019]	-0.245*** [0.023]	-0.124*** [0.010]	-0.052* [0.022]	-0.065*** [0.015]	-0.118*** [0.018]	-0.191*** [0.023]
Log expenditure	-0.088*** [0.002]	-0.106*** [0.006]	-0.649*** [0.034]	-0.075*** [0.003]	-0.095*** [0.004]	-0.065*** [0.002]	-0.078*** [0.007]	-0.160*** [0.006]	-0.011** [0.003]	-0.034*** [0.005]
Stove ownership	-0.342*** [0.012]	-0.118*** [0.027]	-0.223*** [0.020]	-0.405*** [0.024]	-0.384*** [0.025]	-0.215*** [0.011]	-0.100*** [0.026]	-0.187*** [0.018]	-0.217*** [0.018]	-0.230*** [0.023]
Observations	40498	4200	10799	12600	12899	40498	4200	10799	12600	12899
Pseudo R ²	0.280	0.386	0.522	0.321	0.167	0.182	0.268	0.322	0.128	0.113
Wald chi2	15725.5	2245.2	7817.0	5553.4	2971.7	9894.6	1556.8	4825.4	1793.1	1975.2
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Year FE	Yes	No	No	No	No	Yes	No	No	No	No

Notes: The table highlights the negative and statistically significant effect of access to electricity on the probability of firewood collection and arable farms ownership at the household level. The result is robust for each survey year and when all survey years are combined. The coefficients represent the average marginal effects based on probit estimates. Unreported constant is included. Standard errors in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Other potential endogeneity concerns and attempted solutions using Entropy

Balancing and treatment-effect approaches

Another potential limitation of our pseudo-panel fixed effects regression approach would be that it may not control for a possible selection bias related to the non-random nature of electrification. For instance, a household's probability to connect to electricity could be not independent of factors such as the area of residence (Urban versus Rural), the characteristics of the household and the head of the household, and the level of revenue of the household (proxied here by household expenditures). This leads us to test the robustness of our results using the most robust impact assessment approaches: entropy balancing and the treatment-effects methodologies (IPW regression adjustment, nearest-neighbor matching, and propensity-score matching).

Entropy Balancing approach:

The first approach, Entropy Balancing, is based on the idea that connection to electricity represents a treatment. Connected households constitute the treatment group, while none-connected households constitute a potential control group. The average treatment effect on treated households (ATT) is defined as follows:

$$\tau_{\text{ATT}} = E[y(1) | T = 1] - E[y(0) | T = 1] \quad (1.2)$$

$y(\cdot)$ is the outcome variable (biomass fuel consumption or arable farms size). T indicates whether the household is connected to electricity ($T = 1$) or not ($T = 0$). Therefore, $E[y(1) | T = 1]$ is the expected outcome for the connected households and $E[y(0) | T = 1]$ is the counterfactual outcome, i.e. the outcome that a connected household would have obtained if it had not connected to electricity. As the counterfactual outcome is not observable, we need an appropriate proxy to identify the ATT. If the treatment is randomly assigned, then the average outcome of the non-connected households, $E[y(0) | T = 0]$, is an appropriate proxy. However, connection to electricity could be non-random.

The idea of matching estimators is to mimic randomisation with respect to treatment assignment. The unobserved counterfactual outcome is imputed by matching treated units with untreated units that are as similar as possible with respect to all pre-treatment characteristics that: (i) are associated with selection into treatment (i.e. the probability to have access to electricity), and (ii) influence the outcome of interest. The realisations of the outcome gap measure for these matches are then used as an empirical proxy for the unobserved counterfactual. Formally, the matching-based ATT estimate is defined as follows:

$$\tau_{\text{ATT}}(x) = E[y(1) | T = 1, X = x] - E[y(0) | T = 0, X = x] \quad (1.3)$$

where x is a vector of relevant pre-treatment characteristics (our control variables), $E[y(1) | T = 1, X = x]$ is the expected outcome for the units that received the treatment, and $E[y(0) | T = 0, X = x]$ is the expected outcome for the best matches of the treated units.

Here, as [Neuenkirch & Neumeier \(2016\)](#) in the analysis of the effect of US sanctions on poverty gap in the target countries, we use Entropy Balancing to select matches for units exposed to the treatment and to estimate the ATT. Entropy Balancing is a method proposed by [Hainmueller \(2012\)](#). This method is implemented in two steps. First, weights are calculated and assigned to the units not subject to treatment. These weights are chosen to satisfy prespecified equilibrium constraints involving sample moments of the pre-treatment features while at the same time remaining as close as possible to the uniform base weights. In our analysis, the equilibrium con-

straints require equal covariate means between the treatment and control groups, which ensures that the control group contains, on average, non-treatment units that are as similar as possible to the treatment units. Second, the weights obtained in the first step are used in a regression analysis with the treatment indicator as an explanatory variable. This yields an estimate of the ATT, i.e. the conditional difference in the means of the outcome variable between the treatment group and the control group.⁹ Broadly, the idea of Entropy Balancing here is to compare the outcome gap of connected households with that of none-connected households that are as similar as possible to the connected one. The average difference in biomass fuel consumption and arable farms size between the connected households and the "closest" none-connected households must then be due to the treatment, i.e. connection to electricity. In this sense, the empirical approach mimics a randomised experiment by balancing the treatment and control groups on the basis of observable characteristics.

By combining matching and regression analysis, Entropy Balancing has some advantages over other treatment effect estimators. A particularly important advantage over regression-based approaches (including DiD estimation) as well as propensity score-based matching methods is that Entropy Balancing is non-parametric in the sense that no empirical model for the outcome variable or selection into treatment needs to be specified. Furthermore, unlike regression-based analyses, there is no multicollinearity, as the reweighting scheme orthogonalizes the covariates to the treatment variable. Finally, unlike other matching methods, Entropy Balancing ensures a high balance of covariates between treatment and control groups, even in small samples.

Treatment-effects estimators ("teffect"):

We also tested the robustness of our findings by using the treatment-effects estimators (IPW regression adjustment, nearest-neighbor matching, and propensity-score matching). These estimators measure the average difference in the outcome between the connected group and the none-connected group (comparison of the outcome of the treated group with the outcome of the untreated group). These methods allow transforming electricity adoption into a quasi-experimental event, and as such estimate the treatment effect of electricity adoption on the biomass fuel con-

⁹In the regression step, we additionally control for the covariates used in the first step. This is equivalent to including control variables in a randomised experiment to increase the efficiency of the estimation.

sumption and the arable farms size.

The inverse-probability-weighted regression adjustment (IPWRA), the nearest-neighbor matching, and the propensity-score matching estimate the average treatment effect on the treated (connected households) from observational data.

IPWRA estimators use weighted regression coefficients to compute averages of treatment-level predicted outcomes, where the weights are the estimated inverse probabilities of treatment. The contrasts of these averages estimate the treatment effects. IPWRA estimators have the double-robust property.

Both the nearest-neighbor matching and the propensity-score matching estimate the average treatment effect on the treated from observational data and impute the missing potential outcome for each household by using an average of the outcomes of similar households that receive the other treatment level. Meanwhile, in the nearest-neighbor matching similarity between households is based on a weighted function of the covariates for each observation. In the propensity-score matching, similarity between households is based on estimated treatment probabilities, known as propensity scores. Finally, the treatment effect is computed by taking the average of the difference between the observed and imputed potential outcomes for each household in both methods.

Table 1.4 highlights the negative and statistically significant effect of access to electricity on firewood collection and arable farms at the household level for all our estimators, confirming our main findings.

Table 1.4: Robustness check – The effect of electricity access on firewood collection and arable farms

	Firewood collection				Arable farms			
	Entropy balancing	IPW regression adjustment	Nearest-neighbor matching	Propensity-score matching	Entropy balancing	IPW regression adjustment	Nearest-neighbor matching	Propensity-score matching
ATT	-0.659*** [0.076]	-0.312*** [0.005]	-0.276*** [0.008]	-0.284*** [0.008]	-0.417*** [0.094]	-0.235*** [0.008]	-0.201*** [0.009]	-0.211*** [0.009]
Observations	40498	40498	40498	40498	40498	40498	40498	40498
Pseudo R ²	0.292	n.a	n.a	n.a	0.163	n.a	n.a	n.a

Notes: The table highlights the negative and statistically significant effect of access to electricity on firewood collection and arable farms. The Entropy balancing coefficients represent the average treatment effects on the treated (ATT) obtained by weighted probit regressions. Our control variables are included in the first stage and second stage and the standard errors are clustered at strates level. The treatment-effects estimation coefficients represent the average treatment effects on the treated (ATT) obtained by IPW regression adjustment, nearest-neighbor matching, and propensity-score matching. Unreported constant is included. Standard errors in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.4.6 Heterogeneity

In the first side of [Table 1.5](#), we can see that the overall effect of electrification on biomass fuel consumption is mainly driven by the effect in rural areas (Rural). Indeed, the beneficial overall effect of electrification on firewood collection disappears when looking at urban areas (Urban, Intermediate cities, District of Abidjan). The non-significance of the effect in urban areas could nevertheless be explained by several factors, including an already high electricity access rate in these areas, the availability of other alternative sources (e.g. butane gas), or the considerable distance to forests. As in the first side, the second side of the table also documents that the overall effect of electrification on arable farms size is mainly driven by the effect in rural areas. The electrification significantly reduce forest loss for the sub-sample of rural households as predicted by our theoretical Framework I based on the subsistence economy. It is also the largest effect we found.

Table 1.5: Heterogeneity check – The effect of electricity access on firewood collection and arable farms

	Firewood collection					Arable farms				
	Full sample	Rural	Urban	Intermediate cities	District of Abidjan	Full sample	Rural	Urban	Intermediate cities	District of Abidjan
Electricity access rate	-0.147** [0.060]	-0.181*** [0.058]	-0.083 [0.074]	0.051 [0.169]	-0.037 [0.061]	-0.265** [0.106]	-0.788** [0.302]	0.024 [0.035]	-0.144 [0.210]	0.006 [0.008]
Male/female ratio	-0.187** [0.075]	-0.352** [0.139]	-0.190** [0.078]	-0.552*** [0.149]	-0.067 [0.087]	-0.149 [0.175]	0.175 [0.657]	-0.197 [0.194]	-0.687 [0.730]	-0.007 [0.008]
Households size	-0.011** [0.005]	0.015*** [0.005]	-0.022*** [0.006]	-0.020** [0.008]	-0.015** [0.006]	0.005 [0.009]	0.024 [0.033]	-0.001 [0.004]	-0.016 [0.014]	0.001 [0.001]
Male-headed households	-0.076 [0.076]	-0.086 [0.079]	-0.058 [0.075]	0.020 [0.157]	-0.119 [0.075]	0.093 [0.067]	-0.315 [0.497]	0.094 [0.066]	0.536 [0.407]	0.011** [0.004]
Refrigerator owners	0.017 [0.035]	-0.002 [0.019]	0.023 [0.048]	-0.492*** [0.148]	0.126** [0.048]	-0.040 [0.037]	-0.016 [0.069]	-0.015 [0.023]	-0.177 [0.213]	0.007 [0.005]
Log expenditure	0.012** [0.005]	0.005 [0.005]	0.015** [0.007]	0.049*** [0.011]	-0.013** [0.005]	-0.141 [0.093]	-0.141*** [0.041]	-0.050 [0.041]	-0.123 [0.099]	-0.000 [0.001]
Stove owners	-0.071** [0.034]	-0.023 [0.019]	-0.101** [0.046]	0.252* [0.137]	-0.004 [0.046]	-0.012 [0.049]	0.097 [0.087]	-0.011 [0.014]	0.225 [0.235]	-0.009** [0.004]
Observations	552	184	368	184	184	552	184	368	184	184
R ²	0.131	0.264	0.173	0.446	0.269	0.016	0.207	0.024	0.056	0.097
ρ	0.897	0.229	0.445	0.287	0.221	0.284	0.173	0.332	0.333	0.234

Notes: The Table estimates the effect of electrification rate on the percentage of households collecting firewood and on average arable farms size within cohorts. The results document that the effect of electrification on the percentage of households collecting firewood and on average arable farms size is negative and statistically significant when considering the entire sample. This effect is driven primarily by rural areas. The effect is not statistically significant in urban areas. The coefficients are obtained using Within estimation taking into account cohort fixed effects (FE), which capture any time-invariant differences across cohorts. Unreported constant is included. Robust Standard errors in brackets, which permit for the errors to be heteroskedastic and also be correlated with each other within clusters. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[Table 1.6](#) highlights further important heterogeneity. It documents that electrification reduces the average arable farms size by improving the Boserup land use intensity factor (Fallow land/(Fallow land+Crop land)). This is more noticeable in the decrease in fallow land than in cultivated land.

Finally, we empirically test for the existence of a possible threshold effect of electrification. We therefore test the quadratic model ([Table 1.7](#)). The resolution gives us a threshold of $S = 0.795632$,

Table 1.6: Heterogeneity check – The effect of electricity access on arable farms, Boserup factor, crop and fallow land

	Total land	Boserup factor	Crop land	Fallow land
Electricity access rate	-0.265** [0.106]	-0.382*** [0.114]	-0.314 [0.380]	-0.858* [0.497]
Male/female ratio	-0.149 [0.175]	0.386** [0.193]	-0.184 [0.158]	-0.501 [1.145]
Households size	0.005 [0.009]	0.024*** [0.007]	-0.028 [0.032]	0.009 [0.043]
Male-headed households	0.093 [0.067]	0.284** [0.128]	0.486 [0.339]	0.001 [0.477]
Refrigerator owners	-0.040 [0.037]	0.292*** [0.056]	-0.078 [0.088]	0.099 [0.070]
Log expenditure	-0.141 [0.093]	-0.151* [0.078]	-0.849** [0.330]	-0.726 [0.578]
Stove owners	-0.012 [0.049]	0.123** [0.058]	0.049 [0.090]	0.075 [0.133]
Observations	552	486	361	348
R^2	0.016	0.541	0.046	0.011
ρ	0.284	0.260	0.442	0.234

Notes: The table highlights some important heterogeneity. Electrification reduces the average arable farms size by improving the Boserup land use intensity factor (Fallow land/(Fallow land+Crop land)). This is more noticeable in the decrease in fallow land than in cultivated land. The coefficients are obtained using Within estimation taking into account cohort fixed effects (FE), which capture any time-invariant differences across cohorts. Unreported constant is included. Robust standards errors permit for the errors to be heteroskedastic and also be correlated with each other within clusters.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

i.e. an electrification rate of 80% (Figure 1.4). For an electrification rate below 80%, the effect of electrification would be to reduce arable farms size in Côte d’Ivoire. On the contrary, above an access rate of 80%, electrification contributes to rapid clearance of Ivorian forests for agricultural purposes. According to Figure 1.5, at the national level and in rural areas, the overall effect of electrification would be to reduce forest loss because electrification access rates are still well below the 80% threshold. In urban areas, the overall effect of electrification would be to increase forest loss from the 2000s onwards (urban electrification rate exceeding 80%).

Table 1.7: Heterogeneity check – Threshold effect of electricity access on arable farms

	FE
Electricity access rate	-1.079** [0.428]
Electricity access rate × Electricity access rate	0.678** [0.335]
Male/female ratio	-0.129 [0.203]
Households size	0.002 [0.014]
Male-headed households	0.088 [0.168]
Refrigerator owners	-0.026 [0.077]
Log expenditure	-0.128 [0.159]
Stove owners	-0.027 [0.078]
Observations	552
R^2	0.026
ρ	0.292

Notes: The Table documents the significance of the quadratic model. This characterizes a threshold effect of electrification on the average size of arable farms. Our calculations allow us to find a threshold of 80%, a situation that characterizes the most urbanized areas of the country. In these urban areas, there is more commercial agriculture –as opposed to food crops in remote rural areas– because households have access to national and international markets. The coefficients are obtained using Within estimation taking into account cohort fixed effects (FE), which capture any time-invariant differences across cohorts. Unreported constant is included. Robust Standard errors in brackets, which permit for the errors to be heteroskedastic and also be correlated with each other within clusters. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

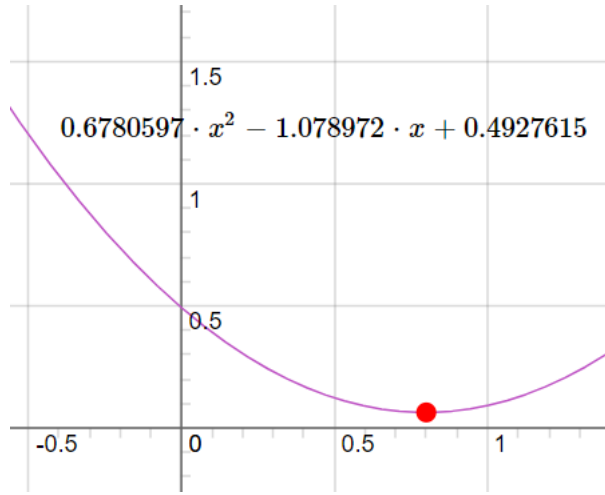


Figure 1.4: Threshold effect of electrification on arable farms size

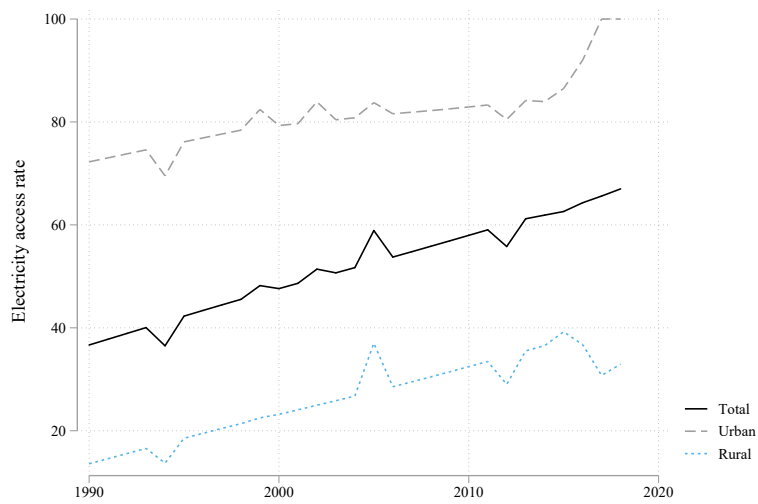


Figure 1.5: Electrification rate in Côte d'Ivoire between 1990 and 2018 (WDI)

1.5 Conclusion

The primary aim of this study was to assess the impact of electrification on forest loss caused by the activities of Ivorian households, such as firewood collection and expansion of arable farms, which are harmful to forests. We examined forest loss at the household level by looking at the percentage of households involved in firewood collection and the size of their arable farms. To address any possible endogeneity issues, we used a pseudo-panel fixed effects regression model and various alternative specifications (time FE inclusion; time trends inclusion; cocoa price trends inclusion; probit model; entropy balancing; IPW regression adjustment; nearest-neighbor matching; and propensity-score matching).

Our sample includes 138 cohorts of households over the years 1998, 2002, 2008 and 2015 in our pseudo-panel fixed effects approach, and an important number of 40,498 observations in our impact assessment analysis. Our empirical findings indicate that electrification would have a significant impact on reducing forest loss caused by the activities of Ivorian households. Specifically, a 1% increase in the electrification rate within a cohort, on average, lowers the percentage of households collecting firewood by 0.147%, and reduces the average arable farms size by 0.265%. Our results suggest that electrification could be one the solutions for reducing the part of the forest loss due households practices in Côte d'Ivoire. In other words, in addition to the positive effects on job creation and poverty reduction, Côte d'Ivoire's ongoing national electrification programs could also contribute to the preservation of the country's forests.

It is also important to point out that the decrease in firewood collection linked to electrification is more likely to result from the acquisition of equipment such as refrigerators than from the substitution of electricity for firewood as a source of energy for cooking (stove). Indeed, by acquiring refrigerators, households are better able to preserve their food, thus leading to a reduction in cooking frequency (optimization). Moreover, the electrification of rural or remote localities would have a greater environmental impact than the electrification of localities integrated into the national market (see subsistence effect vs firm effect in the theoretical framework).

As part of the main limitation of this study, we could –to a lesser extent– attribute the effects resulting from the decrease in arable farms size to those that specifically pass through the channel of agricultural productivity (or profitability). Indeed, due to a lack of information on household

agricultural inputs, we have made the assumption that households with access to electricity in their living home are more likely to have access to electricity in their agricultural production process compared to non-connected households. This assumption could be "strong" in some circumstance as having electricity at home does not necessary imply having electricity on one's arable farm. Meanwhile, it should be remembered that productivity (or profitability) can also be seen as the increase in agricultural product prices in a locality following electrification. This could increase the expected future rent from the land, and thus accelerate the race for arable farms (which would result in a decrease in arable farms size or agricultural intensification).

In terms of avenues for research, we would consider possible assessments of the effects of electrification passing through the agricultural productivity channel if more accurate data are available. This would make it possible to confirm or reject Jevons' paradox and Borlaug's hypothesis we mentioned for instance. We would also consider, subject to the availability of locality variables, an analysis based on a panel of localities (districts, regions, departments, villages etc.). Finally, similar analyses focusing on other types of stakeholders such as companies (logging, mining, oil, etc.), the public stakeholders (road infrastructure expansion, hydroelectric dam construction, urbanization policy, etc.), or on other types of household activities (livestock rearing, gold panning, etc.) would be a considerable addition to this growing body of literature.

1.6 Acknowledgment

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. It has been presented at the Africa Meeting of The Econometric Society (AFES) in June 2021 (Abidjan, Côte d'Ivoire); at the "Journées de Microéconomie Appliquée" (JMA) in June 2021 (Annecy, France); and at the 27th Annual Conference of the European Association of Environmental and Resource Economists (EAERE) in June 2022 (Rimini, Italy). We thank the participants for their valuable comments.

Bibliography

- Abman, R. & Carney, C. (2020), 'Agricultural productivity and deforestation: Evidence from input subsidies and ethnic favoritism in malawi', *Journal of Environmental Economics and Management* **103**, 102342.
- Akpandjar, G. & Kitchens, C. (2017), 'From darkness to light: The effect of electrification in ghana, 2000–2010', *Economic Development and Cultural Change* **66**(1), 31–54.
- Allcott, H., Collard-Wexler, A. & O'Connell, S. D. (2016), 'How do electricity shortages affect industry? evidence from india', *American Economic Review* **106**(3), 587–624.
- Amuakwa-Mensah, S. (2019), 'The impact of rural electrification and institutional quality on agricultural output'.
- An, L., Lupi, F., Liu, J., Linderman, M. A. & Huang, J. (2002), 'Modeling the choice to switch from fuelwood to electricity: implications for giant panda habitat conservation', *Ecological Economics* **42**(3), 445–457.
- Angelsen, A. (1999), 'Agricultural expansion and deforestation: modelling the impact of population, market forces and property rights', *Journal of development economics* **58**(1), 185–218.
- Angelsen, A. (2010), 'Policies for reduced deforestation and their impact on agricultural production', *Proceedings of the National Academy of Sciences* **107**(46), 19639–19644.

- Angelsen, A. & Kaimowitz, D. (1999), 'Rethinking the causes of deforestation: lessons from economic models', *The world bank research observer* **14**(1), 73–98.
- Angelsen, A., Kaimowitz, D. et al. (2001), 'Agricultural technology and forests: a recapitulation', *Agricultural technologies and tropical deforestation* pp. 383–402.
- Arcand, J.-L., Guillaumont, P. & Jeanneney, S. G. (2008), 'Deforestation and the real exchange rate', *Journal of Development Economics* **86**(2), 242–262.
- Assunção, J., Lipscomb, M., Mobarak, A. M. & Szerman, D. (2014), 'Electrification, agricultural productivity and deforestation in brazil', *Pontifical Catholic University of Rio de Janeiro (PUC-Rio) Working Paper* .
- Barnes, D. F. & Binswanger, H. P. (1986), 'Impact of rural electrification and infrastructure on agricultural changes, 1966-1980', *Economic and Political Weekly* pp. 26–34.
- Berman, N., Couttenier, M., Leblois, A. & Soubeyran, R. (2023), 'Crop prices and deforestation in the tropics', *Journal of Environmental Economics and Management* **119**, 102819.
- Borlaug, N. E. (2002), 'Feeding a world of 10 billion people: the miracle ahead', *In Vitro Cellular & Developmental Biology. Plant* **38**(2), 221–228.
- Chhay, P., Yamazaki, K. et al. (2020), Rural electrification and changes in employment structure in cambodia, Technical report, Graduate School of International Cooperation Studies, Kobe University.
- Chomitz, K. & Gray, D. A. (1999), *Roads, lands, markets, and deforestation: a spatial model of land use in Belize*, The World Bank.
- De Gouvello, C. & Durix, L. (2008), 'Maximizing the productive uses of electricity to increase the impact of rural electrification programs: An operational methodology'.
- Deaton, A. (1985), 'Panel data from time series of cross-sections', *Journal of econometrics* **30**(1-2), 109–126.
- Dendup, N. (2022), 'Returns to grid electricity on firewood and kerosene: Mechanism', *Journal of Environmental Economics and Management* **111**, 102606.

- Dinkelman, T. (2011), 'The effects of rural electrification on employment: New evidence from south africa', *American Economic Review* **101**(7), 3078–3108.
- Esteban, A. F. L., Kafarov, V., Guerrero, I., Cortes, A., Ceron, A. M. R. & Duarte, M. M. (2018), 'Assessment of access to electricity and the health, education and agricultural productivity effects in rural areas of colombia', *Chemical Engineering Transactions* **70**, 1219–1224.
- Ferguson, R., Wilkinson, W. & Hill, R. (2000), 'Electricity use and economic development', *Energy policy* **28**(13), 923–934.
- Fisher-Vanden, K., Mansur, E. T. & Wang, Q. J. (2015), 'Electricity shortages and firm productivity: evidence from china's industrial firms', *Journal of Development Economics* **114**, 172–188.
- Foster, A. D. & Rosenzweig, M. R. (2002), 'Economic growth and the rise of forests'.
- Geist, H. J. & Lambin, E. F. (2002), 'Proximate causes and underlying driving forces of tropical deforestation tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations', *BioScience* **52**(2), 143–150.
- Gibbs, H. K., Ruesch, A. S., Achard, F., Clayton, M. K., Holmgren, P., Ramankutty, N. & Foley, J. A. (2010), 'Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s', *Proceedings of the National Academy of Sciences* **107**(38), 16732–16737.
- Grogan, L. & Sadanand, A. (2013), 'Rural electrification and employment in poor countries: Evidence from nicaragua', *World Development* **43**, 252–265.
- Hainmueller, J. (2012), 'Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies', *Political analysis* **20**(1), 25–46.
- Harbison, S. F. & Robinson, W. C. (1985), 'Rural electrification and fertility change', *Population Research and Policy Review* **4**(2), 149–171.
- Harding, T., Herzberg, J. & Kuralbayeva, K. (2021), 'Commodity prices and robust environmental regulation: Evidence from deforestation in brazil', *Journal of Environmental Economics and Management* **108**, 102452.

- Hertel, T. (2012), 'Implications of agricultural productivity for global cropland use and ghg emissions: Borlaug vs. jevons'.
- Kanagawa, M. & Nakata, T. (2008), 'Assessment of access to electricity and the socio-economic impacts in rural areas of developing countries', *Energy policy* **36**(6), 2016–2029.
- Khandker, S. R., Barnes, D. F. & Samad, H. A. (2009), *Welfare impacts of rural electrification: a case study from Bangladesh*, The World Bank.
- Khandker, S. R., Samad, H. A., Ali, R. & Barnes, D. F. (2014), 'Who benefits most from rural electrification? evidence in india', *The Energy Journal* **35**(2).
- Lee, K., Miguel, E. & Wolfram, C. (2020), 'Does household electrification supercharge economic development?', *Journal of Economic Perspectives* **34**(1), 122–44.
- Lipscomb, M., Mobarak, A. M. & Barham, T. (2013), 'Development effects of electrification: Evidence from the topographic placement of hydropower plants in brazil', *American Economic Journal: Applied Economics* **5**(2), 200–231.
- Liscow, Z. D. (2013), 'Do property rights promote investment but cause deforestation? quasi-experimental evidence from nicaragua', *Journal of Environmental Economics and Management* **65**(2), 241–261.
- Mensah, J. T. & Adu, G. (2015), 'An empirical analysis of household energy choice in ghana', *Renewable and Sustainable Energy Reviews* **51**, 1402–1411.
- Neuenkirch, M. & Neumeier, F. (2016), 'The impact of us sanctions on poverty', *Journal of Development Economics* **121**, 110–119.
- Peters, J. & Vance, C. (2011), 'Rural electrification and fertility—evidence from côte d'ivoire', *The Journal of Development Studies* **47**(5), 753–766.
- Rud, J. P. (2012), 'Electricity provision and industrial development: Evidence from india', *Journal of development Economics* **97**(2), 352–367.
- Rudel, T. K., Schneider, L., Uriarte, M., Turner, B. L., DeFries, R., Lawrence, D., Geoghegan, J., Hecht, S., Ickowitz, A., Lambin, E. F. et al. (2009), 'Agricultural intensification and

- changes in cultivated areas, 1970–2005’, *Proceedings of the National Academy of Sciences* **106**(49), 20675–20680.
- Sangne, C., Barima, Y., Bamba, I. & N’Doumé, C.-T. (2015), ‘Dynamique forestière post-conflits armés de la forêt classée du haut-sassandra (côte d’ivoire)’, [*VertigO*] *La revue électronique en sciences de l’environnement* **15**(3).
- Shively, G. & Pagiola, S. (2004), ‘Agricultural intensification, local labor markets, and deforestation in the philippines’, *Environment and Development Economics* **9**(2), 241–266.
- Stern, D. I., Burke, P. J. & Bruns, S. B. (2019), ‘The impact of electricity on economic development: A macroeconomic perspective’.
- Tagliapietra, S., Occhiali, G., Nano, E. & Kalcik, R. (2020), ‘The impact of electrification on labour market outcomes in nigeria’, *Economia Politica* **37**(3), 737–779.
- Tanner, A. M. & Johnston, A. L. (2017), ‘The impact of rural electric access on deforestation rates’, *World Development* **94**, 174–185.
- Villoria, N. B., Byerlee, D. & Stevenson, J. (2014), ‘The effects of agricultural technological progress on deforestation: what do we really know?’, *Applied Economic Perspectives and Policy* **36**(2), 211–237.
- Wolde-Rufael, Y. (2006), ‘Electricity consumption and economic growth: a time series experience for 17 african countries’, *Energy policy* **34**(10), 1106–1114.

Appendices

A Theoretical framework (detailed description)

We start by recalling some key assumptions about the impact that electrification (e) could have on a number of key parameters or intermediate variables from the framework such as agricultural productivity (A), Boserup's land use intensity factor (m), off-farm employment (L^{out} or w^{out}) and demography (N). In the rest of this section, we assume that $\frac{dA}{de} > 0$. Indeed, according to [Amuakwa-Mensah \(2019\)](#), electrification has a positive and significant effect on productivity. Similarly, [Barnes & Binswanger \(1986\)](#) argue that electrification improves agricultural productivity through local communities' acquisition of electric pumps. [Assunção et al. \(2014\)](#) also document that rural electrification has a positive effect on productivity in Brazil. We also assume that $\frac{dm}{de} > 0$. In fact, access to electricity helps to considerably reduce the length of time land is left fallow, notably thanks to irrigation ([Assunção et al. 2014](#)). [Shively & Pagiola \(2004\)](#) also find that improving the irrigation system in the Philippines would have reduced forest loss by half.

We then assume that electrification is a source of new employment opportunities outside the agricultural sector or the off-farm sector ($\frac{dL^{out}}{de} > 0$ and $\frac{dw^{out}}{de} > 0$). Indeed, according to [Chhay et al. \(2020\)](#), access to electricity has increased non-agricultural self-employment in Cambodia. For [Akpandjar & Kitchens \(2017\)](#), access to electricity in Ghana led to a shift away from agriculture to higher-skilled wage-earning employment. In the same vein, [Dinkelman \(2011\)](#) points out that rural electrification promotes off-farm employment and accelerates the creation of off-farm micro-enterprises. [Tagliapietra et al. \(2020\)](#) conclude that access to electricity would induce the migration of agricultural labor to non-agricultural sectors and increase the proportion of workers in households. Finally, it can be assumed that electrification has an ambiguous effect on demography ($\frac{dN}{de} < > 0$). In fact, as electrification is one of the factors in the development of a locality, an electrified locality should attract more people than a similar, non-electrified locality. Thanks to migration, electrification would increase demography. However, this positive effect of electricity on demography becomes questionable if one focuses on fertility. Indeed, [Harbison & Robinson \(1985\)](#) document that, based on a comparison of nine studies conducted in six countries, rural electrification reduces fertility rates. However, [Peters & Vance \(2011\)](#) find that the effect of electrification would be to increase fertility in urban areas and to reduce it in rural areas.

A.1 Framework I: Subsistence economy (no labor market)

In this kind of economy, found in rural areas of Côte d'Ivoire, households are assumed to have no access to markets (or are very distant from international and national markets). Households produce essentially for their own consumption (self-sufficiency). Households maximize their leisure time under the constraint of reaching a certain level of production ($\bar{Q}^{ag} = C^{min}$) necessary for their subsistence. They therefore extend their cultivated area H until they reach the required production level \bar{Q}^{ag} . On the basis of Von Thünen (1966)'s centre-periphery framework, we assume that land is abundant and homogeneous. We also assume that the village population is concentrated in the centre of the village. Assuming that the number of households is N , the total agricultural land area would be a circle around the village:

$$N \cdot H = \pi(r^{max})^2 = \int_0^{r^{max}} (2\pi r) dr \quad (\text{A.1})$$

where r represents the village-field distance and r^{max} represents the agricultural frontier.

We can also introduce Boserup (1965)'s land-use intensity factor (m) to take account of the length of cropping (C) and fallow (F) periods. Boserup defined this land-use intensity as $m = \frac{C}{C+F}$. The land under cultivation by the representative household is thus given by:

$$H = \frac{m\pi}{N} (r^{max})^2 = \int_0^{r^{max}} \frac{2m\pi r}{N} dr \quad (\text{A.2})$$

Let us now express the agricultural frontier in terms of the subsistence threshold (or requirement):

$$\bar{Q}^{ag} = A \cdot H = A \frac{m\pi}{N} (r^{max})^2 \quad (\text{A.3})$$

$$r^{max} = \sqrt{\frac{N\bar{Q}^{ag}}{\pi mA}} \quad (\text{A.4})$$

From [Equation A.4](#) it can be deduced that in a subsistence economy, the frontier of agriculture (or forest loss) is determined by the following factors: demography (N), subsistence level (C^{min}), land-use intensity (m) and, mainly, agricultural productivity (A).

Now, let $r^{max} = f(N, m, A)$ be a multivariate function and $N(e)$, $m(e)$, $A(e)$ be functions of e . If it exists, the total derivative with respect to e of the composite function $f(N(e), m(e), A(e))$ is derived from the differential expression:

$$\frac{df}{de} = \frac{dr^{max}}{de} = \underbrace{\frac{\partial r^{max}}{\partial N} \times \frac{dN}{de}}_{\left. \frac{dr^{max}}{de} \right|_N} + \underbrace{\frac{\partial r^{max}}{\partial m} \times \frac{dm}{de}}_{\left. \frac{dr^{max}}{de} \right|_m} + \underbrace{\frac{\partial r^{max}}{\partial A} \times \frac{dA}{de}}_{\left. \frac{dr^{max}}{de} \right|_A} \quad (\text{A.5})$$

with, for the rest of this paper, $\left. \frac{dr^{max}}{de} \right|_X$ meaning the effect of electrification (e) on forest loss (r^{max}) via a given channel X (N , m , A , etc.). [Equation A.4](#) gives us:

$$\frac{\partial r^{max}}{\partial N} = \frac{r^{max}}{2N} > 0 \Leftrightarrow \boxed{\left. \frac{dr^{max}}{de} \right|_N = \frac{r^{max}}{2N} \times \frac{dN}{de} > 0} \text{ if } \frac{dN}{de} > 0 \quad (\text{A.6})$$

If the migratory effect resulting from electrification outweighs the natality effect, then the effect of electrification would be to increase forest loss through demography ([Equation A.6](#)). On the other hand, if the natality or fertility effect is much greater than the migratory effect, then in this case, electrification of a locality would have a mitigating effect on the agricultural frontier, and thus on forest loss.

$$\frac{\partial r^{max}}{\partial A} = -\frac{r^{max}}{2A} < 0 \Leftrightarrow \boxed{\left. \frac{dr^{max}}{de} \right|_A = -\frac{r^{max}}{2A} \times \frac{dA}{de} < 0} \quad (\text{A.7})$$

Based on the hypothesis (already justified at the beginning of the theoretical framework) that access to electricity promotes agricultural productivity or agricultural yield per unit area ($\frac{dA}{de} > 0$) via, for example, drilling of boreholes or the adoption of irrigation techniques, then electricity would act as a mitigating factor on the agricultural frontier (or forest loss) through agricultural productivity ([Equation A.7](#)).

$$\frac{\partial r^{max}}{\partial m} = -\frac{r^{max}}{2m} < 0 \Leftrightarrow \boxed{\left. \frac{dr^{max}}{de} \right|_m = -\frac{r^{max}}{2m} \times \frac{dm}{de} < 0} \quad (\text{A.8})$$

Assuming also that electricity, notably through the implementation of irrigation, drilling of boreholes and electric pumping techniques, reduces fallow time (the value of m increases), we can state that electrification reduces the agricultural frontier, and therefore its effect would be to reduce for-

est loss (Equation A.8).

Finally, it can also be imagined that a high subsistence threshold (\bar{Q}^{ag}) would require the collection of more firewood, and therefore more forest loss. The greater households' food requirements, the more they clear forest for agricultural purposes and the more firewood they collect, the higher the forest loss rate would be.

A.2 Framework II: Chayanovian economy (imperfect labor market)

This type of economy refers to intermediate cities in terms of development in the case of Côte d'Ivoire, or urban areas distant from Abidjan (the economic capital). Within these cities, we find both a subsistence economy and a market economy (farm firm economy).¹⁰ In this kind of economy, a representative household maximizes its utility (U) by finding a trade-off between consumption (C) and leisure time (T). It is generally assumed that there is no perfect labor market. That is, a household may sell some of its labor on the labor market (off-farm), but only family labor is allowed on agricultural plantations. The household maximization program is written:

$$\max_{r^{max}} U(C, T) \equiv \max_{r^{max}} U \left(A \cdot \int_0^{r^{max}} \frac{2m\pi r}{N} dr + w^{out} L^{out}, \int_0^{r^{max}} (1 + c \cdot r) \frac{2m\pi r}{N} dr + L^{out} \right) \quad (A.9)$$

with the on-field labor (clearing, weeding, harvesting, etc.) cost set to 1 and $c \cdot r$ representing the cost due to both the forest monitoring intensity (c) and the agricultural land expansion to the detriment of forest around a given locality (r). This cost include above all the risk of being caught for illegal occupation of a forest and increases with the level of electrification in the locality and with the farm's distance from the center the locality. The idea is that electrification as a convenience would increase the presence of "water and forestry" agents. The task of these agents is to limit the advance of the agricultural frontier to the detriment of the forest. At the optimum, we have:

$$\frac{\partial U}{\partial r^{max}} = \frac{\partial U}{\partial C} \times \frac{\partial C}{\partial r^{max}} + \frac{\partial U}{\partial T} \times \frac{\partial T}{\partial r^{max}} = 0 \quad (A.10)$$

¹⁰See [Angelsen \(1999\)](#) for more details on the Chayanovian economy.

$$U_C \times \left(A \cdot \frac{2m\pi}{N} r^{max} \right) + U_T \times \left((1 + c \cdot r^{max}) \frac{2m\pi}{N} r^{max} \right) = 0 \quad (\text{A.11})$$

$$A = -\frac{U_T}{U_C} \times (1 + c \cdot r^{max}) \quad (\text{A.12})$$

At the optimum, the productivity resulting from clearing an additional unit of land for agricultural purposes (A) is equal to the cost required at the agricultural frontier ($1 + c \cdot r^{max}$), multiplied by the opportunity cost of labor ($-\frac{U_T}{U_C}$).

$$r^{max} = \frac{1}{c} \times \left(\frac{A}{-\frac{U_T}{U_C}} - 1 \right) \quad (\text{A.13})$$

The agricultural frontier depends on agricultural productivity A (or crop unit value per hectare, since the price of agricultural output is taken as cash and is therefore worth one), cost c and the opportunity cost of labor ($-\frac{U_T}{U_C}$). $-\frac{U_T}{U_C}$ represents the Marginal Rate of Substitution (MRS) between consumption and leisure, i.e. the amount of consumption that a household is willing to renounce for one unit of extra leisure time. It should be noted that this figure becomes very small when consumption is fairly close to the subsistence level and very large when leisure time is close to zero.

However, $-\frac{U_T}{U_C}$ is endogenous because it also depends on r^{max} , so the effect of other quantities on r^{max} cannot be interpreted very well. To provide more relevant comparative analyses, [Angelsen \(1999\)](#) introduces a function which is a combination of the standard multiplicative Stone-Geary utility function and the Houthakker additive function:

$$U(C, T) = (C - C^{min})^\alpha + v(T^{max} - T)^\beta \text{ with } v > 0; \alpha, \beta \in (0, 1); (C - C^{min}) > 0; (T^{max} - T) > 0 \quad (\text{A.14})$$

Moreover, when we set $\alpha = \beta$, we find ourselves with the CES (Constant Elasticity of Substitution) production function. This function makes it possible, above all, to distinguish the case where the household behaves as a producer, maximising its agricultural profit, from the case where the household behaves as a consumption unit maximising its utility. For more details on this function, refer to [Angelsen \(1999\)](#). Consequently, the partial derivatives of the new function are:

$$U_C = \alpha(C - C^{min})^{\alpha-1} \quad \text{and} \quad U_T = -\beta v(T^{max} - T)^{\beta-1} \quad (\text{A.15})$$

From this, we can deduce the expression for the MRS between consumption and leisure:

$$z \equiv -\frac{U_T}{U_C} = \frac{v\beta(C - C^{min})^{1-\alpha}}{\alpha(T^{max} - T)^{1-\beta}} \quad (\text{A.16})$$

The impact of electrification on forest loss through productivity is derived from this:

$$\left. \frac{dr^{max}}{de} \right|_A = \frac{1}{\mu} \times \left[1 - \frac{\partial z}{\partial A} \times \frac{A}{z} \right] \times \frac{dA}{de} \Rightarrow \boxed{\left. \frac{dr^{max}}{de} \right|_A < 0} \Leftrightarrow Y < \frac{C^{min} - w^{out}L^{out}}{\alpha} \quad (\text{A.17})$$

When the production value Y is below $(C^{min} - w^{out}L^{out})/\alpha$, then the subsistence effect would predominate over the farm-firm effect (Equation A.17). In this case, electrification would have a mitigating effect on the agricultural frontier, and thus on forest loss, through productivity. It should be remembered, however, that in the richer localities of the country, households behave more like firms that maximize their profit, since the question of subsistence is rarely raised in these cases. This result therefore remains more relevant in the case of the country's poor localities. The increase in agricultural productivity due to electrification would therefore not have the same effects on the agricultural frontier in poor and rich localities in Côte d'Ivoire. Rural electrification programs would therefore help to reduce forest loss and therefore they can be environmentally sustainable. Finally, it is important to note that the farm-firm effect would always dominate when the off-farm income is higher than the subsistence requirement ($C^{min} < w^{out}L^{out}$). Then a low value of α means that the valuation of consumption above subsistence declines rapidly. This is especially the case in societies with low materialism where an increase in agricultural productivity due to electrification would have the effect of reducing the amount of cultivated land because more importance is given to leisure.

The other interesting result remains the analysis of the impact of electrification on the agricultural frontier through costs (Equation A.18 below). Costs c include above all the risk of being caught for illegal occupation of a forest area. Our intuition is that the risk of being caught increases with greater presence of "water & forest" agents in a locality. As these agents are Ivoirian

government officials, they are essentially posted to localities with a certain number of amenities, including access to electricity. Forests in electrified localities therefore benefit from more surveillance due to the increased presence of these agents, and therefore more risk for operators who extend their cultivated area. We therefore assume that $\frac{dc}{de} > 0$.

$$\left. \frac{dr^{max}}{de} \right|_c = -\frac{1}{\mu} \times \left[z \cdot r^{max} + \frac{\partial z}{\partial c} \times (1 + c \cdot r^{max}) \right] \times \frac{dc}{de} < 0 \Rightarrow \boxed{\left. \frac{dr^{max}}{de} \right|_c < 0} \quad (\text{A.18})$$

Regardless of the effect that prevails (subsistence effect vs farm-firm effect), electrification has a mitigating effect on forest loss through, among other things, increased monitoring frequency. Indeed, in localities benefiting from electricity, there is genuine control over forests, so it is more expensive to expand arable farms size to the detriment of the forest than in other localities.

$$\text{Since } \frac{\partial z}{\partial h} = z_C \cdot \int_0^{r^{max}} A \cdot r dr + z_T \cdot \int_0^{r^{max}} (1 + c \cdot r) r dr > 0 \text{ and } h = \frac{2\pi m}{N}$$

[Equation A.19](#) and [Equation A.20](#) then tell us that the impact of electrification on the agricultural frontier, whether through demography or the adoption of intensive agriculture, does not depend on the dominance of any one effect (subsistence or farm-firm). The effects are also the same as those found in Framework I.

$$\left. \frac{dr^{max}}{de} \right|_m = -\frac{1}{\mu} \left[\frac{\partial z}{\partial h} \times (1 + c \cdot r^{max}) \right] \times \frac{dm}{de} \Rightarrow \boxed{\left. \frac{dr^{max}}{de} \right|_m < 0} \quad (\text{A.19})$$

Indeed, electrification has a mitigating effect on forest loss when it reduces the fallow period on arable farms ([Equation A.19](#)).

$$\left. \frac{dr^{max}}{de} \right|_N = -\frac{1}{\mu} \left[\frac{\partial z}{\partial h} \times (1 + c \cdot r^{max}) \right] \times \frac{dN}{de} \Rightarrow \boxed{\left. \frac{dr^{max}}{de} \right|_N > 0} \text{ if } \frac{\partial N}{\partial e} > 0 \quad (\text{A.20})$$

The effect involving demography, on the other hand, remains ambiguous because it depends on two further, opposing effects, namely migration and natality ([Equation A.20](#)).

Finally, we mention the effect of electrification on the agricultural frontier through the channel

of employment opportunities outside the agricultural sector (off-farm sector).

$$\frac{dr^{max}}{de} \Big|_{L^{out}} = -\frac{1}{\mu} \times \left[\frac{\partial z}{\partial L^{out}} \times (1 + c \cdot r^{max}) \right] \times \frac{dL^{out}}{de} \Rightarrow \boxed{\frac{dr^{max}}{de} \Big|_{L^{out}} < 0} \text{ since } \frac{\partial z}{\partial L^{out}} = w \cdot z_C + z_T > 0 \quad (\text{A.21})$$

One of the major objectives of electrification programs remains the creation of employment opportunities in order to eradicate extreme poverty in rural areas. Electrification at the locality level offers huge employment opportunities outside the agricultural sector. It would therefore make agricultural labor available to the new sectors that have emerged thanks to the arrival of electricity. Through the complementarity of factors, this can slow forest clearance at the expense of agriculture (Equation A.21).

$$\frac{dr^{max}}{de} \Big|_{w^{out}} = -\frac{1}{\mu} \times \left[\frac{\partial z}{\partial w^{out}} \times (1 + c \cdot r^{max}) \right] \times \frac{dw^{out}}{de} \Rightarrow \boxed{\frac{dr^{max}}{de} \Big|_{w^{out}} < 0} \text{ since } \frac{\partial z}{\partial w^{out}} = E \cdot z_C > 0 \quad (\text{A.22})$$

This is all the more true if w^{out} (off-farm) wages are more attractive (Equation A.22). Remember that in this framework, a household cannot hire outside labor for farms work. In a country like Côte d'Ivoire, the most important channel would be self-employment (hairdressing salon, sewing, night activity, games room, video club, etc.).

A.3 Framework III: Open economy with perfect labor market (static open access)

This type of economy refers to the main cities of Côte d'Ivoire, District of Abidjan and urban areas around this District. In these areas, we assume that households have access to both national and international markets, and that the markets are fairly well integrated. In this context, increasing international agricultural commodity prices for instance could create pressure on forests (Harding et al. 2021). The market economy therefore largely prevails over the subsistence economy (disappearance of the subsistence effect in favor of the farm-firm effect). Next, the notion of static open access, as opposed to the notion of dynamic open access (following framework), refers to the fact that the clearing of forest for agricultural purposes does not give rise to a permanent property rights over the cleared area. Thus, households' rent calculation does not take into account future land yields. Moreover, unlike the previous framework, this time we introduce a perfect labor market. The wage rate for the whole economy is therefore w , thanks to the free movement of the labor

force between all sectors of the economy, or at least regionally. At this rate, any household can sell or hire a labor force. The agricultural production problem can be formulated as:

$$\max_{r^{max}} R = Y - wL = A \cdot \int_0^{r^{max}} \frac{2m\pi r}{N} dr - w \int_0^{r^{max}} (1 + c \cdot r) \frac{2m\pi r}{N} dr \quad (\text{A.23})$$

R and Y represent the farms rent and the value of agricultural production, respectively. At the optimum:

$$A = w(1 + c \cdot r^{max}) \quad (\text{A.24})$$

$$r^{max} = \frac{1}{c} \times \left(\frac{A}{w} - 1 \right) \quad (\text{A.25})$$

We deduce that demography (N) is no longer a key channel through which electrification could influence the agricultural frontier, and thus forest loss, precisely because of the labor force migration that is allowed in this type of economy. The key channels therefore include agricultural productivity, the rate of labor remuneration and the costs of access to the forest.

$$\frac{\partial r^{max}}{\partial A} = \frac{1}{w \cdot c} = \frac{r^{max}}{A - w} > 0 \Leftrightarrow \boxed{\frac{dr^{max}}{de} \Big|_A = \frac{r^{max}}{A - w} \times \frac{dA}{de} > 0} \quad (\text{A.26})$$

Contrary to the first two frameworks, in this type of economy, the farm-firm effect always prevails. Therefore, households would globally behave like firms that maximize their agricultural profits. Electrification, by improving agricultural productivity, would lead to the expansion of the agricultural frontier, and thus to forest loss (Equation A.26). For economies that are already integrated, any policy that aims to improve agricultural productivity would lead to increased forest loss since the agricultural frontier, which was not profitable before the policy, becomes profitable after the policy is implemented.

$$\frac{\partial r^{max}}{\partial w} = -\frac{A}{c \cdot w^2} = -\frac{1 + c \cdot r^{max}}{c \cdot w} < 0 \Leftrightarrow \boxed{\frac{dr^{max}}{de} \Big|_w = -\frac{1 + c \cdot r^{max}}{c \cdot w} \times \frac{dw}{de} < 0} \quad (\text{A.27})$$

In this framework, it is assumed that there is free movement of labor between different sectors, giving $w^{ag} = w^{out} = w$. By creating new opportunities, electrification would boost the demand for labor, thus pushing up wage rates. As rates equalize due to the free movement of labor, this would result in higher agricultural sector wages, thus a decrease in the agricultural labor force and less agricultural pressure on forests. Broadly speaking, therefore, in this case electrification would be a means of fighting forest loss, in particular by creating off-farm employment (Equation A.27).

$$\frac{\partial r^{max}}{\partial c} = -\frac{A-w}{w \cdot c^2} = -\frac{r^{max}}{c} < 0 \Leftrightarrow \boxed{\frac{dr^{max}}{dc} \Big|_c = -\frac{r^{max}}{c} \times \frac{dc}{de} < 0} \quad (\text{A.28})$$

Finally, in this kind of economy, as in the two previous frameworks, the intensity of the presence of "water & forest" agents following electrification has a mitigating effect on forest clearance (Equation A.28).

A.4 Framework IV: Open economy with perfect labor market (dynamic open access)

This framework is just an extension of the previous one where households incorporate the dynamic nature of the agricultural rent. Households push the frontier of agriculture to the point where the discounted rent cancels out. The dynamic problem is written as follows:

$$\int_0^{\infty} e^{-\lambda t} e^{-\delta t} \left[e^{gt} A - w(1 + c \cdot r^{max}) \right] dt = \int_0^{\infty} \left(\frac{A}{e^{(\delta+\lambda-g)t}} - \frac{w(1 + c \cdot r^{max})}{e^{(\delta+\lambda)t}} \right) dt = 0 \quad (\text{A.29})$$

with λ being the probability of losing the area cleared in each period, δ is the discount rate or rate of preference for the present and g is the rate of growth in agricultural commodity prices or agricultural output that households expect.

$$\int_0^{\infty} e^{-\lambda t} e^{-\delta t} \left[e^{gt} A - w(1 + c \cdot r^{max}) \right] dt = \frac{A}{\delta + \lambda - g} - \frac{w(1 + c \cdot r^{max})}{\delta + \lambda} = 0 \quad (\text{A.30})$$

$$r^{max} = \frac{1}{c} \times \left(\frac{\theta A}{w} - 1 \right) \text{ with } \theta \equiv \frac{\delta + \lambda}{\delta + \lambda - g} > 1 \text{ for } (g > 0) \text{ and } (\delta + \lambda > g) \quad (\text{A.31})$$

Since the factor θ is greater than 1 for $g > 0$, the effect of electrification on the forest, through agricultural productivity, would be greater than the effect found in the previous static framework (Equation A.31 and Equation A.32). This is certainly due to the fact that households clear the forest even when the present rent is below zero, as they hope for a future rent. They therefore engage in forest clearance in order to establish property rights and to avoid land being taken by others.

$$\frac{\partial r^{max}}{\partial A} = \frac{\theta}{w \cdot c} = \frac{\theta r^{max}}{\theta A - w} > 0 \Leftrightarrow \boxed{\frac{dr^{max}}{de} \Big|_A = \frac{\theta r^{max}}{\theta A - w} \times \frac{dA}{de} > 0} \quad (\text{A.32})$$

If it is assumed that electrification increases the expectation of a future land rent, then it would be a vector for forest loss, particularly through the g factor. So the implementation of rural electrification programs would accelerate forest loss when we have this type of property regime. Similarly, electrification programs may increase the value given to future rent (decrease in the δ parameter), which would be to increase forest loss. Finally, it should be remembered that changes in the λ parameter depend purely on institutional factors, and therefore on the property regime. If this parameter is low, it reflects secure property rights to the land, which would be paradoxically to increase forest loss (Equation A.33). Liscow (2013) has also found this similar paradoxical result in the case of Nicaragua. He found that property rights significantly increase forest loss in the country as they increase investment, increasing agricultural productivity and therefore the returns to forest loss. For instance, titling land may exacerbate forest loss. Property rights is not a complete panacea for the environmental conservation.

$$\frac{\partial r^{max}}{\partial(\delta + \lambda)} = -\frac{\theta A}{c \cdot w} \times \frac{g}{(\delta + \lambda - g)} < 0 \quad \text{and} \quad \frac{\partial r^{max}}{\partial g} = \frac{A}{c \cdot w} \times \frac{\delta + \lambda}{(\delta + \lambda - g)^2} > 0 \quad (\text{A.33})$$

On the other hand, the effects of electrification on the agricultural frontier through access costs and opportunities remain the same as those found in the previous static framework (Equation A.34 and Equation A.35).

$$\frac{\partial r^{max}}{\partial c} = -\frac{\theta A - w}{w \cdot c^2} = -\frac{r^{max}}{c} < 0 \Leftrightarrow \boxed{\frac{dr^{max}}{de} \Big|_c = -\frac{r^{max}}{c} \times \frac{dc}{de} < 0} \quad (\text{A.34})$$

Indeed, electrification would reduce forest loss through the employment opportunities or access costs channels.

$$\frac{\partial r^{max}}{\partial w} = -\frac{\theta A}{c \cdot w^2} = -\frac{1 + c \cdot r^{max}}{w \cdot c} < 0 \Leftrightarrow \boxed{\frac{dr^{max}}{de} \Big|_w = -\frac{1 + c \cdot r^{max}}{w \cdot c} \times \frac{dw}{de} < 0} \quad (A.35)$$

A.5 Empirical discussion of each framework

This empirical discussion of our theoretical frameworks is essentially based on the heterogeneity found in the second side of our [Table 1.5](#) in the paper.

- In order to check the results for Framework I (subsistence economy), we considered the sub-sample of rural households alone, on the assumption that this type of household is on average very far from markets and would therefore be more likely to fit in with the reality of a subsistence economy. Framework I tells us that if the migratory effect does not outweigh the fertility or natality effect ($\frac{dN}{de} < 0$ or $\frac{dN}{de} = 0$), then the overall effect of electrification would be to reduce forest loss ($\frac{dr^{max}}{de} < 0$). This means that the effect of electricity on forest loss (approximated here by arable farms size) would be larger for the sub-sample of rural households compared to the full sample or to the other samples in urban areas. This effect of electrification would be to significantly reduce forest loss for the sub-sample of rural households as predicted by our theoretical Framework I based on the subsistence economy. It is also the largest effect.

- Framework II can be empirically verified at two levels. First, we consider the sub-sample of intermediate cities (far from the economic capital, Abidjan) as being that which best groups together households living in a subsistence economy and those behaving as agricultural firms. The effect of electrification would be to reduce forest loss, but not statistically significant enough for this sub-sample. This is certainly linked to the fact that two effects working in opposite directions (subsistence and farm-firm effects) counterbalance one another. The second level of verification of Framework II consists of classifying the sub-samples according to their degree of market integration and comparing the effects obtained. Using the hypothesis that the effect of electrification would be to reduce forest loss and that this effect is greater for subsistence economies (result from Framework II), this effect of electrification on forest loss should increase as one moves from the most urbanized areas to the most rural areas (the effect should decrease in parallel with the rate of urbanization). Considering the Rural sample to the District of Abidjan sample, the highest neg-

ative effect is indeed found for rural areas (-0.788), followed by the intermediate cities (-0.144). For the Urban sample and the District of Abidjan, the negative effect has disappeared.¹¹ Thus, in a market economy, electrification programs would have smaller environmental effects compared to the effects obtained in a rural or subsistence economy.

· In Frameworks III and IV, the subsistence effect disappears with the introduction of perfect markets. The sub-sample of households living in the District of Abidjan is therefore most likely to fit this reality. In these two Frameworks, the effect of electrification would be to increase forest loss through the channel of agricultural productivity. If the global effect of electrification on forest loss is to increase forest loss in this case, then we conclude that the effect through the agricultural productivity channel outweighs, in absolute value, the combined effect through both the intensification of forest monitoring and the creation of new employment sectors that are less forest loss-intensive compared to the agricultural sector.¹² According to the results of the estimation on the District of Abidjan sample, these two opposing effects would tend to cancel each other out, although it should be noted that the effect passing through the channel of agricultural productivity (resulting from the dominance of the farm-firm effect in these types of economy) barely outweighs the mitigating effects through both the intensification of forest monitoring and the creation of new employment sectors that are less forest loss-intensive compared to the agricultural sector. So in a market economy, agricultural households behave like firms. The pro-environmental effects of electrification (strong presence of forestry authorities, creation of new opportunities outside the agricultural sector etc.) are generally outweighed by the farm-firm effect. In fact, electrification, by making it possible to improve agricultural rent, would encourage increasingly rapid forest clearance for agricultural purposes. This dynamic is even more harmful if households acquire ownership of cleared forest arable farms (open access dynamics). Indeed, we emphasize that in open access dynamics households clear the forest even when the present rent is below zero, because they hope for a future rent. They therefore clear the forest in order to establish property rights and to avoid having all the land taken. If it is assumed that electrification increases the expectation of a future land rent (increase in prices and/or in yields), then it would be a vector for forest loss, notably thanks to the future profitability anticipated by the agents. So the implementation of rural electrification programs when we have this type of property regime would reduce the

¹¹As noted earlier, rural households would be more likely to be subsistence households as they are further from markets.

¹²Mining and livestock farming, for instance, are more forest loss-intensive than the agricultural sector.

intensity of land use. Basically, farmers would start clearing more land than they need at present.

To sum up, the theoretical analysis of the effect of electrification on forest loss through the agricultural productivity channel using the four frameworks gives rise to differences in terms of the amplitude or sign of the expected effects. Indeed, all other things being equal, the effect of electrification would be to reduce forest loss through the agricultural productivity channel in the absence of markets (Framework I, subsistence economy). Using the hypothesis of imperfect markets (Framework II), the effect of electrification would be to reduce forest loss when the subsistence effect prevails over the farm-firm effect, and to increase it otherwise. As soon as perfect markets are introduced (Frameworks III and IV), the effect of electrification would be to increase forest loss through the agricultural productivity channel.

B Descriptive statistics

Table B1: Descriptive statistics, data from LSMS (ENV) 1998, 2002, 2008 and 2015

Variable	Year	Sample size	Mean	Std. Dev.	Min. Value	Max. Value
Access to electricity (1=yes, 0=no)	1998	4,200	0.47	0.45	0.00	1.00
	2002	10,799	0.51	0.50	0.00	1.00
	2008	12,600	0.60	0.53	0.00	1.00
	2015	12,899	0.65	0.58	0.00	1.00
Household size	1998	4,200	5.77	4.01	1.00	34.00
	2002	10,799	5.32	3.77	1.00	40.00
	2008	12,600	4.84	3.46	1.00	37.00
	2015	12,899	3.55	2.37	1.00	36.00
Firewood collection (1=yes, 0=no)	1998	4,200	0.53	0.50	0.00	1.00
	2002	10,799	0.51	0.50	0.00	1.00
	2008	12,600	0.50	0.50	0.00	1.00
	2015	12,899	0.48	0.50	0.00	1.00
Arable farm size (ha)	1998	4,200	5.64	9.26	0.00	95.00
	2002	10,799	4.53	1.85	0.00	95.00
	2008	12,600	4.10	2.29	0.00	95.00
	2015	12,899	3.42	7.55	0.00	95.00
Male/Female ratio	1998	4,200	0.52	0.50	0.00	1.00
	2002	10,799	0.54	0.50	0.00	1.00
	2008	12,600	0.55	0.50	0.00	1.00
	2015	12,899	0.56	0.31	0.00	1.00
Refrigerator ownership (1=yes, 0=no)	1998	4,200	0.16	0.37	0.00	1.00
	2002	10,799	0.12	0.33	0.00	1.00
	2008	12,600	0.25	0.16	0.00	1.00
	2015	12,899	0.28	0.26	0.00	1.00
Stove ownership (1=yes, 0=no)	1998	4,200	0.12	0.33	0.00	1.00
	2002	10,799	0.14	0.35	0.00	1.00
	2008	12,600	0.13	0.11	0.00	1.00
	2015	12,899	0.19	0.28	0.00	1.00
Per capita household consumption (euros)	1998	4,200	411.75	342.18	17.71	6,074.73
	2002	10,799	548.74	1,690.23	16.84	27,370.39
	2008	12,600	522.49	614.25	19.36	20,675.48
	2015	12,899	588.78	659.90	6.15	16,333.17
Gender of household head (1=male, 0=female)	1998	4,200	0.80	0.39	0.00	1.00
	2002	10,799	0.81	0.39	0.00	1.00
	2008	12,600	0.80	0.40	0.00	1.00
	2015	12,899	0.80	0.40	0.00	1.00
Age of household head	1998	4,200	45.94	16.89	16.00	99.00
	2002	10,799	46.33	22.81	11.00	99.00
	2008	12,600	45.51	18.80	14.00	99.00
	2015	12,899	42.84	18.93	12.00	99.00
Household living in rural area (1=yes, 0=no)	1998	4,200	0.55	0.50	0.00	1.00
	2002	10,799	0.57	0.50	0.00	1.00
	2008	12,600	0.59	0.49	0.00	1.00
	2015	12,899	0.50	0.50	0.00	1.00

C Stylized facts (continuation)

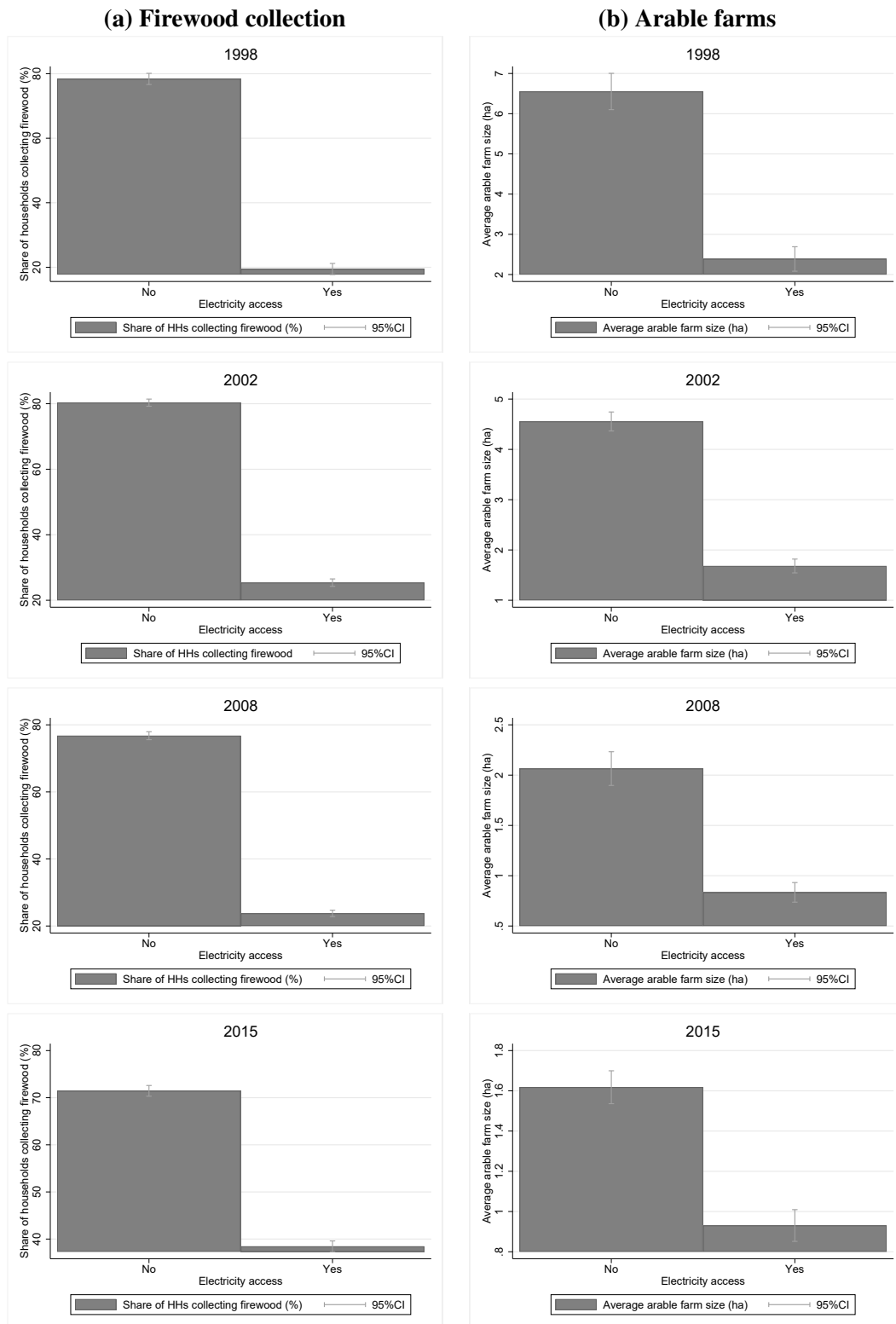


Figure C1: Connected versus non-Connected households (Yearly samples)

D Overlap

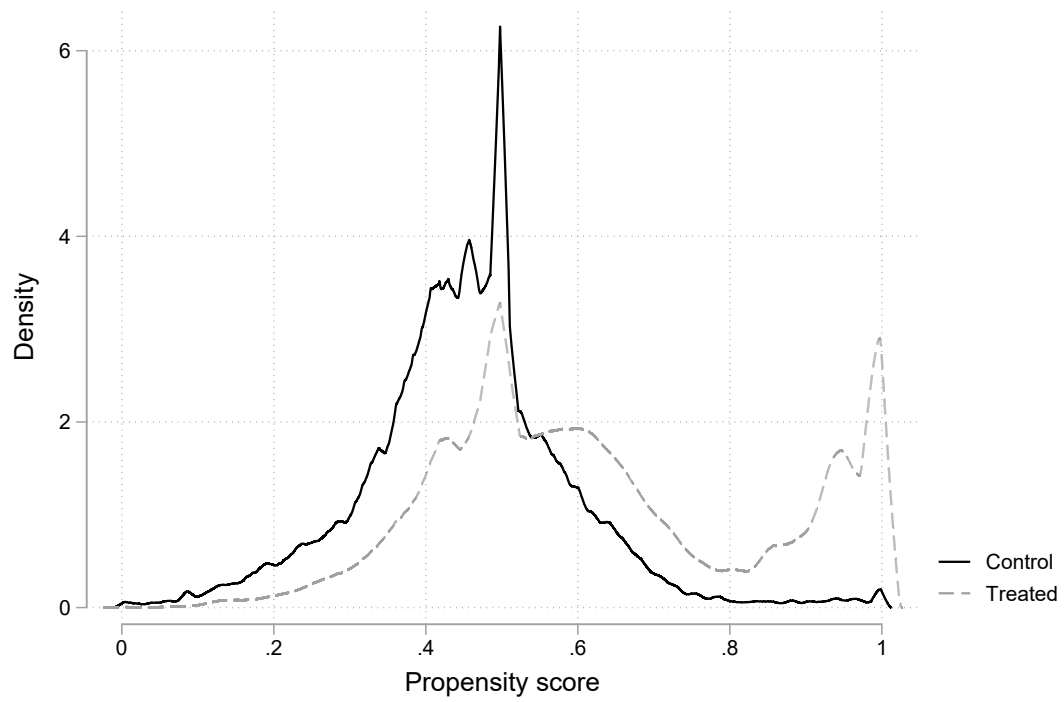


Figure D1: Connected versus non-Connected households (Overlap)

Electrification and Deforestation in Côte d'Ivoire: a spatial econometric analysis

This chapter is a joint work with Raja Chakir and Anna Creti. A version of this paper is under review in *Journal of Spatial Econometrics*.

2.1 Introduction

In 2011, Côte d'Ivoire experienced a post-electoral crisis, and in its aftermath, the government launched a comprehensive rural electrification program as part of the Social Program (PsGouv). The primary objective of this program was to enhance electricity coverage in the country, combat rapid deforestation, expedite structural transformation, and create new employment opportunities. The total installed capacity in the country significantly increased from 1,391 MW in 2011 to 2,215 MW by the end of 2018, which, when combined with improved electricity transmission and sector management, resulted in improved access to electricity. As a result, between 2011 and 2018, the program successfully electrified 2,122 localities, raising the coverage rate from 33% to 58%.

However, despite these efforts, Côte d'Ivoire continues to face alarming deforestation rates,

with the country losing a substantial portion of its forest cover over the years. In the 1960s, the nation possessed over 16 million hectares of forest, but this area has shrunk to merely about 2.5 million hectares, reflecting an annual deforestation rate of approximately 150,000 to 200,000 hectares. Satellite imagery-based assessments by the Côte d'Ivoire Ministry of Water and Forests have clearly illustrated the persistent trend of forest loss, with the Ivorian forest shrinking from 7.8 million hectares in 1990 to only 3.4 million hectares in 2015.

Meanwhile, little evidence is available to date on the potential impacts of electrification on deforestation or forest loss. Indeed, some studies in the existing literature suggest that electrification might reduce the demand for expanding arable farms due to improved agricultural productivity and also decrease the reliance on firewood, thereby potentially serving as an effective measure to mitigate deforestation ([An et al. 2002](#); [Dube et al. 2014](#); [Mensah & Adu 2015](#); [Tanner & Johnston 2017](#); [Bakehe & Hassan 2022](#)). On the other hand, other authors acknowledge that the expansion of the electricity network or enhanced agricultural profitability resulting from electrification could potentially contribute to deforestation ([Geist & Lambin 2002](#); [Villoria et al. 2014](#)).

The present study aims to shed light on the potential effects of electrification on deforestation in Côte d'Ivoire. Its primary objective is to empirically assess the impact of increased access to electricity on overall deforestation rates in the country. The central research question is: To what extent does improved electricity access influence overall deforestation in Côte d'Ivoire? By addressing this crucial research question, the paper intends to offer valuable insights for policy-makers and stakeholders. These insights can help in the design and implementation of effective strategies that strike a balance between the important goals of expanding electricity access and fighting deforestation in Côte d'Ivoire.

Our research provides insights that address various gaps in the existing literature regarding the relationship between electrification and deforestation. First, many previous studies have not conducted an overall impact analysis of electrification on deforestation, focusing instead on specific aspects (e.g. [Mensah & Adu 2015](#) focused only on the decrease in the use of firewood for cooking due to electrification in Ghana). This research seeks to fill this gap by providing a comprehensive assessment of the global effect of electrification, considering the involvement of various key stakeholders in deforestation, including companies, the state, and households. Second, there is an ongoing debate about the appropriate level of aggregation for such studies. While some studies

have used country-level data (see [Tanner & Johnston 2017](#) for instance), this research recognizes the importance of intra-country heterogeneity and conducts its analysis at the regional and departmental level. By using disaggregated data, the study aims to shed light on relevant dynamics within specific areas of interest. Third, this study contributes to the growing body of literature that considers the spatial dimension when analyzing deforestation (see [Baggio & de Barros 2021](#) for an illustration). It emphasizes the significance of accounting for spatial interactions in understanding forest conversion and land use change. By controlling for spatial interactions, we aim to improve the predictive power of our model (as suggested by [Maddison 2006](#); [Robalino & Pfaff 2012](#); [Choumert et al. 2013](#); [Chakir & Lungarska 2017](#)) and gain insights into the effects of neighboring localities on deforestation. Finally, our research takes into account geographical and climatic conditions (as in [Alves 2002](#); [Hargrave & Kis-Katos 2013](#); [Barber et al. 2014](#); [Newman et al. 2014](#); [Ferreira & Coelho 2015](#); [Kleinschroth et al. 2019](#); [Asher et al. 2020](#); [Baggio & de Barros 2021](#)), as they influence the costs of building and maintaining transport infrastructure, which, in turn, affects deforestation. By considering these factors, the study aims to enhance our model's accuracy and avoid the problem of omitted variables. Overall, this research seeks to provide a comprehensive and spatially aware analysis of the impact of electrification on deforestation, taking into account various key factors and shedding light on the dynamics at different levels of aggregation.

The article makes contributions in four key areas. First, it examines the concordance between night lights intensity data (derived from satellite data) and official data on electrification progress in Côte d'Ivoire at the regional level. This is crucial as satellite data is commonly used to estimate economic activity, population density, and electrification in developing countries due to the lack of official data at sub-national scales (e.g. [Sutton et al. 2001](#); [Sutton et al. 2007](#); [Dai et al. 2017](#); [Kumar et al. 2019](#); [Beyer et al. 2021](#)). The study reveals that the electricity coverage rate data provided by Ivorian authorities and night lights intensity data yield consistent results at the regional level. Second, the article documents how the extent of spatial interaction is influenced by the selected level of aggregation. Through rigorous statistical tests, it demonstrates that aggregated data at the regional level (N=33) show no spatial autocorrelation, while at the departmental level (N=108), a spatial lag model is found to be the most suitable. This sheds light on the importance of considering different levels of aggregation when analyzing deforestation phenomenon. Third, the article investigates whether conducting the analysis at a finer level of aggregation (108

departments) while accounting for both spatial effects and unobservable individual and temporal specific effects can lead to improved model specification. This approach provides valuable insights into enhancing the accuracy and robustness of the model. Finally, the article contributes to the understanding of the global impact of electrification on deforestation, both at the regional and departmental levels in Côte d'Ivoire. By drawing parallels with a previous study on a panel of developing countries (see [Tanner & Johnston 2017](#)), the research uncovers a noteworthy finding: contrary to previous results, electrification appears to increase deforestation in Côte d'Ivoire. This empirical evidence aligns with the situation on the ground in the country and provides important implications for environmental policy and sustainable development efforts.

The rest of the paper is as follows: data and variables are presented in section [2.2](#), section [2.3](#) presents the choice for the best spatial specification, section [2.4](#) presents our estimations and results, section [2.5](#) engages further discussions, and section [2.6](#) concludes.

2.2 Data and variables

This section includes respectively the variables description and summary statistics, the concordance between night lights data and official electrification coverage rate data, and our exploratory spatial data analysis.

2.2.1 Variables description and summary statistics

In [Table 2.2.1](#), we provide a description of the data sources and variables utilized in our analysis to assess the impact of electrification on deforestation. Specifically, we focus on two key variables: forest loss and night lights. These variables are crucial in understanding the relationship between electrification and its effect on deforestation.

We mainly exploit data on forest cover in 2000 (>20% trees) and deforestation or forest loss over 2001-2018 provided by [Hansen et al. \(2013\)](#). The forest loss variable is derived from pixel-level data and offers detailed information about changes in forest cover over time. Each pixel in the dataset represents a specific geographic area, and the forest loss variable quantifies the extent of deforestation that has occurred in these individual pixels. These pixel-level values provide a comprehensive view of the spatial distribution and magnitude of forest loss, allowing us to analyze

the impact of electrification on deforestation at regional and departmental levels in Cote d'Ivoire.

In order to estimate the electrification rate by region and department, we exploit high resolution satellite data on night lights intensity provided by the Earth Observation Group, NOAA National Centers for Environmental Information (NCEI). The night lights variable is based on radiance data sourced and captures the amount of light emitted from various sources during nighttime. This variable provides insight into the level electrification in different areas in Cote d'Ivoire. By examining changes in radiance before and after electrification, we can gauge shifts in nighttime activity patterns, potentially indicating changes in electricity access that could influence deforestation rates.

In our analysis, we leverage these two distinct variables —forest loss and night lights— to investigate the complex interplay between electrification efforts and deforestation trends in Cote d'Ivoire. While the forest loss variable allows us to directly quantify changes in forest cover, the night lights variable offers a measure of electrification evolution in the country.

We also retain the control variables that are commonly used in studies undertaken on the evolution of the deforestation rate. To measure the effect of economic factors, we use GDP (by region, by department). As a reminder, in the economic literature, the debate on the relationship between deforestation and economic growth is summarised by the existence of an inverted U-shaped relationship called the "environmental Kuznets curve".¹

Also, several authors have identified large and/or growing populations as a causal factor of deforestation ([Celentano et al. 2012](#); [Tacconi 2011](#)). This is why demography also requires special attention in this analysis, since population is considered to be one of the main causes of environmental degradation, and therefore of deforestation. In developing countries with forest resources, the population migrates when access to land is improved and converts forests into arable land ([Bakehe & Hassan 2022](#)). Since the pioneering work of [Cropper & Griffiths \(1994\)](#), several econometric analyses have documented that population density increases deforestation in developing countries. In this study, the potential role of demographic factors on deforestation is taken into account through the population density per locality (region or department). Demographic data on population density by locality are available from NASA's Socioeconomic Data and Applications Center (SEDAC).²

¹Here we do not test for the existence of an environmental Kuznets curve.

²NOAA (National Oceanic and Atmospheric Administration)

Table 2.2.1: Main data description

Data	Description	Source/Authors
VIIRS Nighttime Lights (Radiance)	Yearly VIIRS day night band nighttime lights data (without stray light correction).	Christopher et al. (2017)
DMSP-OLS Nighttime Lights (digital number 0-63)	The lights from cities, towns, and other sites with persistent lighting, including gas flares. Ephemeral events, such as fires have been discarded.	NOAA National Geophysical Data Center
Evolution of the coverage rate 2011 - 2018	Evolution of the number of electrified localities and the coverage rate by region from 2011 to 2018.	Ministry of Petroleum, Energy and Renewable Energies (MPEER)
Precipitation (Yearly Average)	Average monthly precipitation per year in millimeters. Created using UDel Precipitation dataset (v5.01)	University of Delaware
Air Temperature (Yearly Average)	Average monthly air temperature per year in degrees Celsius. Created using UDel Air Temperature dataset (v5.01)	University of Delaware
Tree canopy cover for year 2000 (percent forest cover)	Tree cover in the year 2000, defined as canopy closure for all vegetation taller than 5m in height. In the range 0-100.	Hansen et al. (2013)
Year of gross forest cover loss event (pixels of forest loss)	Forest loss during the period 2000-2018, defined as a stand-replacement disturbance, or a change from a forest to non-forest state.	Hansen et al. (2013)
Population Density (persons per square kilometer)	Population density (UN Adjusted values) from Gridded Population of the World v4. GPWv4 depicts the density of human population across the globe.	Warszawski et al. (2017)
Gross Domestic Product (millions of dollars)	Map of total economic activity, including both formal and informal economic activity for 2006; created from nighttime lights and LandScan population grid.	Ghosh et al. (2010)
ACLED Conflict Events (Africa)	Number of conflict event counts per 0.1 decimal degree grid cell using ACLED (Armed Conflict Location & Event Data Project) v3.	Raleigh et al. (2010)
Travel time to major cities (time in minutes)	Estimated travel time (in minutes) to the nearest city of 50,000 or more people in year 2000.	Nelson (2008)

Our control variables also include weather (temperature and precipitation), forest cover, conflict and market access (distance to a major city). The weather and market access variables are mainly used to control agricultural activity. The forest cover variable is used to capture the role of forest abundance. Finally, the conflict variable also remains very important because in case of conflict in a locality, two effects may emerge: a decrease in deforestation due to emigration or an increase in deforestation due to the violation of certain protected areas (parks, reserves, etc.).

In [Table 2.2.2](#), on average and at the regional scale, the AGR analysis suggests that deforestation as well as electrification have steadily increased over the period 2011-2018 (19% forest loss on average and 36% increase in lights intensity which is a proxy for electrification).³ Similarly, we have an increase in average temperature over the same period, while rainfall has continued to decline. The forest cover is about 34% on average per region. However, when we observe the minimum and maximum values for all of these quantities, there is strong heterogeneity between the regions, as [Tanner & Johnston \(2017\)](#) pointed out in the context of the limit of an analysis by country that would ignore this phenomenon of intra-country heterogeneity. Also, we can see that electrification continues to grow by looking at either the official data (row 3) or the lights intensity data (row 2). However, the difference in the magnitude of AGR is due to changes in the measurement of night lights intensity data over the period, which makes the rate larger for this data source.

Table 2.2.2: Descriptive statistics (33 Regions)

Statistics	N	Mean	St. Dev.	Min	Max
Forest loss AGR 2011-2018	33	18.817	12.148	-3.199	41.209
Night lights AGR 2011-2018	33	35.568	29.398	0.693	131.205
Elec. coverage AGR 2011-2018	33	9.880	9.682	0.148	36.138
Average temperature AGR 2011-2017	33	0.212	0.304	0	1
Average precipitation AGR 2011-2017	33	-1.329	2.000	-7.597	3.521
Population density AGR 2010-2020	33	2.768	0.864	1.372	4.741
Percent forest cover	33	33.848	12.947	13	60
Gross Domestic Product	33	1,196	1,637	44	9,329
ACLED Conflict Events	33	82.788	38.654	18	186
Travel time to major cities	33	260.364	126.197	93	637

The trend in [Table 2.2.3](#) (departmental scale) is almost the same as described in [Table 2.2.2](#) (regional scale). The fundamental difference is that we do not have official data on forest cover

³AGR = (Annual) Average Growth Rate

Table 2.2.3: Descriptive statistics (108 Departments)

Statistics	N	Mean	St. Dev.	Min	Max
Forest loss AGR 2011-2018	108	22.367	19.045	-12.446	104.179
Night lights AGR 2011-2018	108	46.138	49.453	-5.579	262.188
Average temperature AGR 2011-2017	108	0.254	0.308	0	1
Average precipitation AGR 2011-2017	108	-1.401	2.180	-9.059	3.789
Population density AGR 2010-2020	108	2.803	1.817	0.000	11.514
Percent forest cover	108	34.546	13.777	8	67
Gross Domestic Product	108	365.750	945.970	10	9,330
ACLED Conflict Events	108	26.111	18.043	4	123
Travel time to major cities	108	258.648	131.132	85	858

at the departmental level and that we have more heterogeneity at this departmental level as documented by the St. Dev. values and the differences between the minimum and maximum values. Keeping only the regional level of disaggregation therefore runs the risk of ignoring these huge intra-regional heterogeneities. Therefore it is important for us to check more or less the concordance between the official data and the regional night lights intensity data in order to be able to use the departmental night lights intensity data as a proxy for electrification in Côte d'Ivoire.

Table 2.2.4: Descriptive statistics (Panel of 108 Departments over 2001-2017)

Statistics	N × T	Mean	St. Dev.	Min	Max
Forest loss	1,836	23,496	31,444	0	307,665
Night lights	1,836	3,237	5,957	0	81,497
Average temperature	1,836	26.687	0.786	24	28
Average precipitation	1,836	111.377	24.952	56	210
Population density	1,836	80.366	219.565	7	2,312
Percent forest cover	1,836	34.546	13.717	8	67
Gross Domestic Product	1,836	365.750	941.837	10	9,330
ACLED Conflict Events	1,836	26.111	17.964	4	123
Travel time to major cities	1,836	258.648	130.559	85	858

Table 2.2.4 summarises our variables for the panel analysis at department level over the period 2001-2017. The Forest loss variable is in pixels and the Night lights variable is in radiance as described in details earlier. The average temperature per department over this period is 27 degrees Celsius on average with a minimum temperature of 24 degrees Celsius and a maximum temperature of 28 degrees Celsius. The average rainfall is 111 millimetres per year. The average density is 80 people per km². The departments have an average GDP of 366 million USD and there is an

average of 26 conflicts per department, this characterises the fact that the period has been particularly turbulent in the country (post-election crisis, conflicts between rebel forces from the north and pro-governmental forces, etc.).

2.2.2 Concordance between night lights data and official coverage rate data

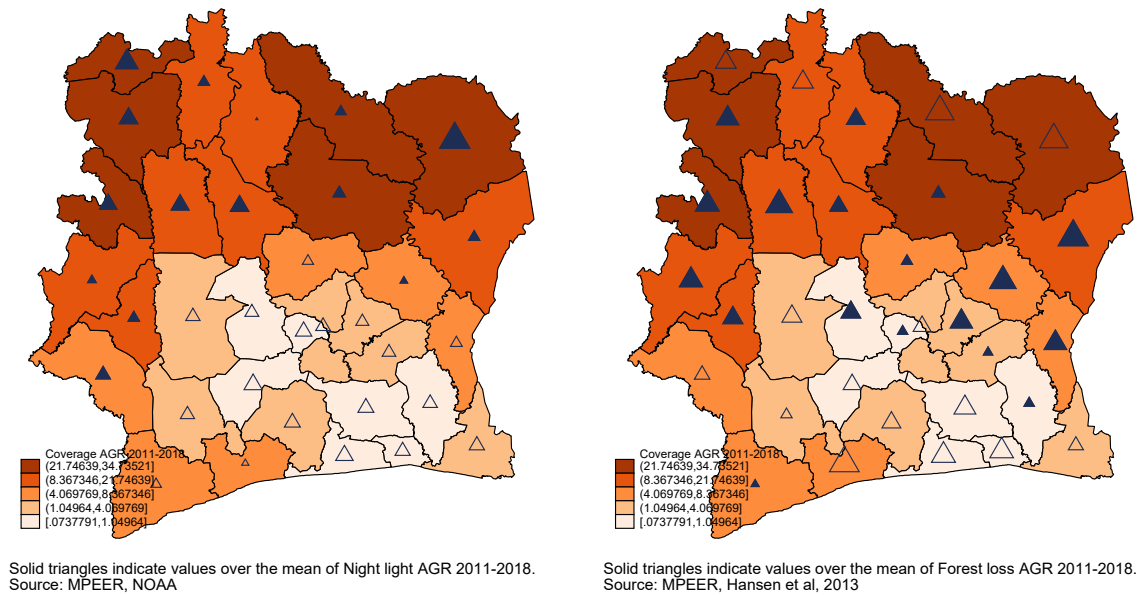


Figure 2.2.1: Spatial concentration of high and low values

The first map in Figure 2.2.1 indicates that there is a strong spatial concentration between night lights intensity data and electricity coverage (official data).⁴ The regions that have experienced rapid increases in coverage are those that predominantly have above-average increases in lights intensity (solid triangles). This proves, in somewhat, the concordance between these two data sources. With the exception of some northern regions on the border with Mali and Burkina Faso (area under threat from extremist groups, thus decreasing population due to emigration and thus less pressure on forests) and some central regions where a kind of negative spatial correlation can be noticed, the second map in Figure 2.2.1 also seems to document a trend of positive spatial correlation between electrification and the highest deforestation rates.

Moreover, Table E1 (appendix E) presents the results of the a-spatial model by comparing the coefficients (sign and significance) of the night lights intensity data and the official coverage rate data. As already documented in Table 2.2.2, at the regional scale, the average annual growth rates

⁴Our Local Indicators of Spatial Association (LISA) clustering maps also highlight the similar trends (see Figure E1 in appendix E)

are increasing for both variables over the period 2011 to 2018. The two rates do not evolve with the same magnitude because there has been a change in the scale of measurement over the period for the night lights intensity variable. This is also reflected in the difference in magnitudes of the two coefficients expressed in this table. However, both coefficients remain insignificant in this model and keep the same positive sign.

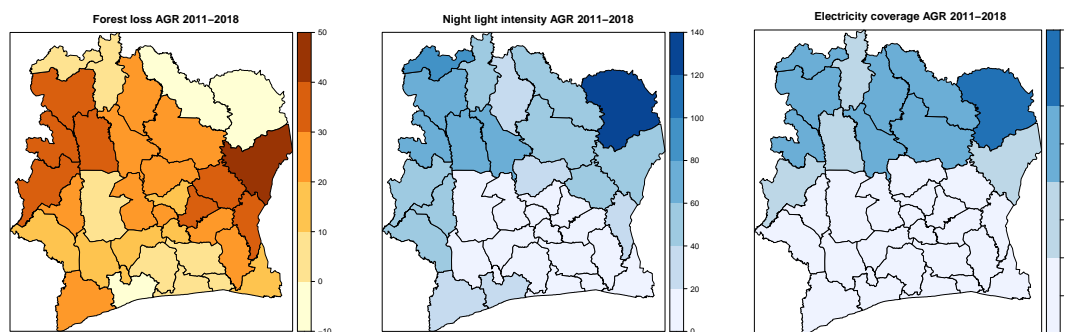


Figure 2.2.2: Average growth rates (AGR) for the main variables at the regional and departmental scale

Finally, [Figure 2.2.2](#) represents the administrative division of the national territory into 33 regions. This figure also represents the average annual growth rates (2011-2018) of our main variables at the regional level. By observing the last two maps, we can see that the variables night lights intensity and coverage rate reflect the same phenomenon of spatial polarisation (or spatial heterogeneity) in favour of localities in the north of the country. Indeed, these localities have long remained on the sidelines of the country's development process, but as soon as the current president (originating from the north of the country) took the country's presidency, massive investments were undertaken in these localities. This once again demonstrates the reliability of the night lights intensity data. The first map documents a strong concentration of high deforestation rates in the east and west of the country (spatial autocorrelation).

Even if the reliability of night lights intensity data is sometimes questioned, at least in the case of Côte d'Ivoire, our results document that it seems to be suitable as a proxy of electrification in the country at the regional level. Given the unavailability of official data on the evolution of electrification at disaggregated levels (notably at the departmental level) in developing countries, and more particularly in Côte d'Ivoire, we use these data as a proxy for electrification at a lower

aggregation level (departmental level) in the rest of this analysis.

2.2.3 Exploratory spatial data analysis

Let us now define the spatial interaction matrix. It is obvious that in order to implement a spatial econometric model, the construction of a weight matrix W that best describes the spatial interactions between observations (localities, regions and departments in our case) is essential. A neighbourhood matrix W must indeed respect several technical constraints to ensure in particular the invertible character of the matrix, and the identification of the models (Lee 2004; Elhorst 2010). According to Insee (2018), the usual contiguity matrix respects these two different constraints. Only one shared border point fulfils the condition of contiguity (queen=TRUE). Otherwise, more than one shared point would be required or simply a shared boundary line. Figure 2.2.3 summarises the neighbourhood networks of the country's regions and departments.

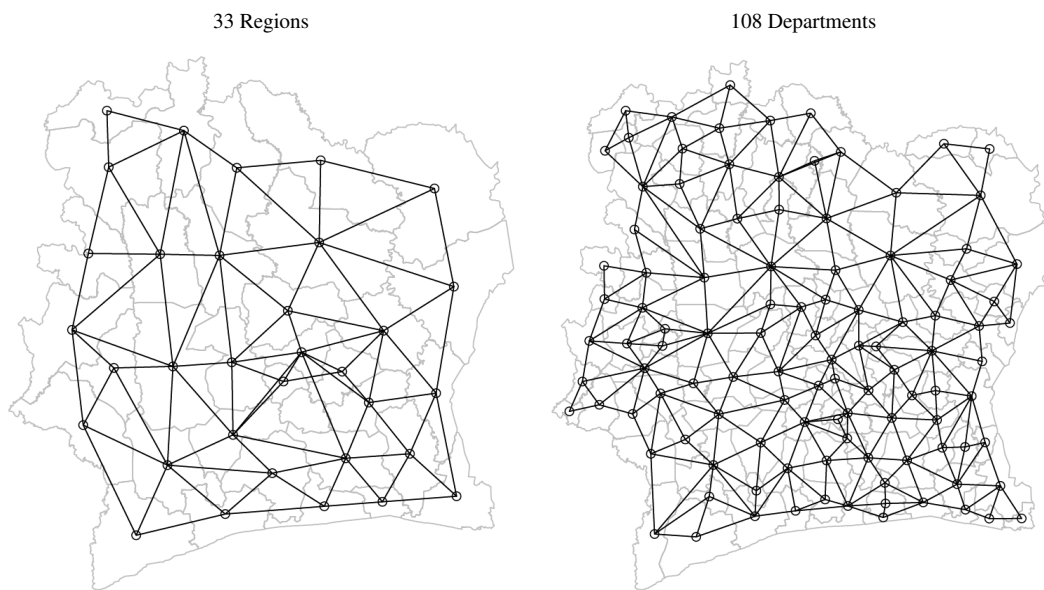


Figure 2.2.3: Neighbourhood network using Contiguity (queen) matrix

Then, before opting for a potential spatial model, it is essential to ensure the existence of spatial interaction between the observations, in particular by means of graphic maps and statistical tests (the main one being Moran's I). For the quantitative variables, Moran's index (I_W) is often preferred to Geary's because of its greater general stability (Upton & Fingleton 1985):

$$I_W = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (2.2.1)$$

$H_0 : I_W = 0 \rightarrow$ No spatial autocorrelation.

$H_1 : I_W \neq 0 \rightarrow$ Spatial autocorrelation (positive or negative depending on the sign of I_W).

In order to carry out the Moran test, it is necessary to specify the distribution for each of our main variables in the absence of spatial autocorrelation (Insee 2018). In this context, statistical inference is generally carried out by considering either the Normality Hypothesis (each of the values of the variable is the result of an independent draw from the normal distribution specific to each geographical area on which this variable is measured), or the Randomisation Hypothesis (the estimate of the statistic obtained from the data is compared with the distribution of that obtained by randomly reordering the data).

The Moran diagrams (Figure 2.2.4) allow a quick reading of the spatial interaction at both the regional and departmental levels for each of our main variables.

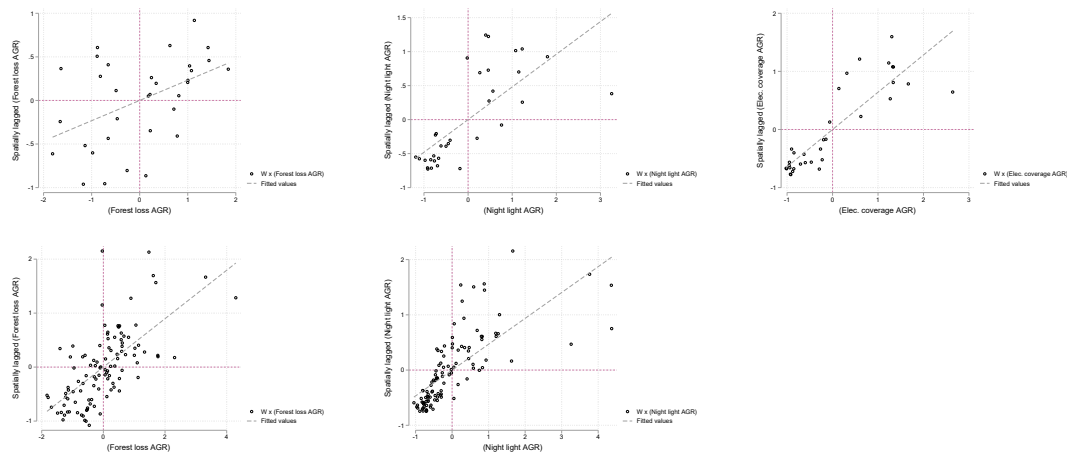


Figure 2.2.4: Moran plot using Contiguity (queen) matrix at the regional and departmental scale

Through Table 2.2.5 and Table 2.2.6 (but also the tables in appendix F), we document that whatever the definition of the neighbourhood or the scale of aggregation chosen, the spatial autocorrelation of electrification and deforestation is positive and significant. The strength of the spatial autocorrelation does not change enough following the type of neighbourhood chosen, but varies drastically for the Forest loss variable following the aggregation level. Indeed, the significance of the test remains weak at the level of the 33 regions for this variable. Nevertheless, it does not present any ambiguity when a lower level of aggregation is adopted (108 departments).

Table 2.2.5: Moran test for our main variables using Contiguity (queen) weight matrix - Regions

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.243	-0.031	0.011	2.59	0.0048
Forest loss (randomisation)	0.243	-0.031	0.012	2.55	0.0054
Night lights (normality)	0.498	-0.031	0.011	5	2.9e-07
Night lights (randomisation)	0.498	-0.031	0.011	5.15	1.3e-07
Elec. coverage (normality)	0.680	-0.031	0.011	6.72	<1e-08
Elec. coverage (randomisation)	0.680	-0.031	0.011	6.72	<1e-08

Table 2.2.6: Moran test for our main variables using Contiguity (queen) weight matrix - Departments

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4583	-0.0093	0.0036	7.78	<1e-08
Forest loss (randomisation)	0.4583	-0.0093	0.0035	7.89	<1e-08
Night lights (normality)	0.5654	-0.0093	0.0036	9.56	<1e-08
Night lights (randomisation)	0.5654	-0.0093	0.0034	9.91	<1e-08

2.3 Choice of the best spatial specification

From a statistical point of view, many analyses (linear regressions in particular) are based on the hypothesis of independence of the observations of a variable. When a variable is spatially autocorrelated, the independence assumption is no longer respected, thus calling into question the validity of the assumptions on which these analyses are based. Thus, as highlighted in the introduction section, the analysis of the deforestation phenomenon requires the consideration of spatial interactions between different localities (regions and departments in Côte d'Ivoire in our case). In order to take into account the relative location and interactions of localities in Côte d'Ivoire, we opt for spatial econometric models. Spatial econometrics is certainly a recent discipline, but it is already the subject of interesting applications, particularly in the field of environmental economics. To illustrate this, we can, for example, recall its application in land use models by [Chakir & Lungarska \(2017\)](#). Indeed, in their comparison of different econometric models of land use, the two authors manage to document that taking into account spatial effects significantly improves the quality of the predictions of the different models studied.

Spatial econometric models extend linear regressions by taking into account the non indepen-

dence of observations across space.⁵ In other words, these models may contain spatial lags of the outcome variable and/or spatial lags of the covariates, and/or spatial lags of error terms. Formally, the model which groups together all these interactions is the model of [Manski \(1993\)](#) or GNS:

$$\begin{aligned} D &= \rho WD + X\beta + WX\theta + u \\ u &= \lambda Wu + \varepsilon \end{aligned} \tag{2.3.1}$$

where, D represents deforestation (or forest loss), X represents a set of explanatory variables (electrification, population density, precipitation, temperature, forest cover, gross domestic product, conflicts, travel time to major cities or access to markets). The model of [Manski \(1993\)](#) is not identifiable ([Insee 2018](#)). To make the model identifiable, the literature proposes to impose restrictions on the different parameters of the model such as:

$$\theta = 0, \lambda = 0, \rho \neq 0 \rightarrow \text{SAR}$$

$$\theta = 0, \lambda \neq 0, \rho = 0 \rightarrow \text{SEM}$$

$$\theta \neq 0, \lambda = 0, \rho = 0 \rightarrow \text{SLX}$$

$$\theta \neq 0, \lambda = 0, \rho \neq 0 \rightarrow \text{SDM (SAR+SLX)}$$

$$\theta \neq 0, \lambda \neq 0, \rho = 0 \rightarrow \text{SDEM (SLX+SEM)}$$

$$\theta = 0, \lambda \neq 0, \rho \neq 0 \rightarrow \text{SAC (SAR+SEM)}$$

After having established the existence of spatial interactions between our localities in [subsection 2.2.3](#), we proceed now to the choice of the best spatial specification. To do this, first, we opt for the bottom-up approach proposed by [Florax et al. \(2003\)](#) which consists in starting with the a-spatial model using the Lagrange multiplier (LM) tests proposed by [Anselin et al. \(1996\)](#) to decide between the different spatial specifications and the a-spatial model. These tests are also robust to the presence of other types of spatial interactions (beyond the specifications of the SAR or SEM models). This approach is based on the residuals of the a-spatial model and has the advantage of being computationally inexpensive. [Florax et al. \(2003\)](#) have also documented, using simulations, that this procedure is the most efficient in the case the true model is a SAR or a SEM.

From the constrained or a-spatial model (OLS in our case), we use the statistics of the LM test

⁵Spatial Autoregressive Models Reference Manual (Stata, Release 17)

to guide the selection of the correct specification. According to [Anselin \(2013\)](#), if neither of the two tests (LMerr and LMlag) is significant, then the model to adopt is the a-spatial model (OLS). On the other hand, if LMerr is the only one of the two tests to be significant, then we opt for a SEM. Otherwise, if LMlag is the only one of the two tests to be significant, then the SAR is chosen. However, if both are significant, the robust versions (RLMerr and RLMLag) are used to discriminate between them.

Through [Table G1](#) (appendix [G](#)), we conclude that the best spatial specification remains the a-spatial model (OLS) when considering the administrative division of the 33 regions. This is the case regardless of whether the night lights intensity data or the official electricity coverage data provided by the country's authorities are used as the variable of interest. However, when considering the administrative division of the 108 departments, it appears that the best spatial specification to use is the SAR or Spatial Lag Model (SLM) specification.⁶

Indeed, the administrative division of a territory as vast as Côte d'Ivoire (with its 322,462 km²) into only 33 regions did not allow the identification of spatial interaction phenomena (as some deforestation mechanisms are more local so less strong across the 33 regions). On the other hand, when we move to a much lower level of aggregation (108 departments), we realise the need to opt for a spatial model that takes into account the strong heterogeneity between the different entities. Spatial division therefore has an influence on the results of statistical processing or modelling, as emphasised by [Openshaw \(1984\)](#) through the concept of MAUP (Modifiable Areal Unit Problem). More precisely, the irregular shapes and limits of administrative grids which do not necessarily reflect the reality of the spatial distributions studied are an obstacle to the comparability of unequally subdivided spatial units. According to [Openshaw \(1984\)](#), the MAUP is a combination of two distinct but related problems. The first is the problem of scale, which is related to a variation in information generated when a set of spatial features is aggregated to form fewer and larger units for the purposes of analysis or for data availability issues. The second is the problem of aggregation (or zoning), which is related to a change in the diversity of information generated by different

⁶The Top-down approach (starting with the Spatial Durbin Model or SDM) due to [LeSage & Pace \(2009\)](#) also gives the SAR as the best spatial specification in this application (see appendix [H](#)). [Elhorst \(2010\)](#)'s "mixed" approach, which is a combination of the top-down and bottom-up approaches, is usually conducted in case of different results. In our case, the result is the same. Thus, this approach also would lead us to a SAR specification. Finally, we also used the two-way comparison approach (see appendix [I](#)). In this last approach, we could see that SAC prevails over GNS. Then, SDM and SDEM also outperform GNS, and SLX. OLS also prevails over SLX. However, SEM is preferred to SDM, SDEM and OLS. However, SAC prevails over SEM. Finally, SAR prevails over SAC, SDM and OLS. We conclude for all these approaches that the SAR is the best model adapted to our data.

possible aggregation schemes at the same scale. This effect is characteristic of administrative (particularly electoral) boundaries and is in addition to the scale effect.

The fact that we have the SAR model as our best spatial model means that deforestation in a given locality is determined jointly with that of neighbouring localities. This implies that: (i) the global spillover effects: on average, the value of deforestation for a locality is not only explained by the values of the explanatory variables for that locality, but also by those associated with all localities (spatial multiplier effect); and (ii) a global spatial diffusion effect: a random shock in a locality affects the value of deforestation of this locality as well as those of other localities. In our case this means that deforestation in a particular locality depends on the electrification rate of other localities. The interaction effects among the error terms do not require a theoretical model but instead, are consistent with a situation where determinants of deforestation omitted from the model are spatially autocorrelated, or with a situation where unobserved shocks follow a spatial pattern.

2.4 Estimation and results interpretation

In this section, we document the overall effect of electrification on deforestation at the departmental level taking into account only spatial specificities, and then consider spatial effects and unobservable individual and temporal specific effects in order to correctly identify the overall effect of electrification on deforestation

2.4.1 Spatial analysis at departmental level

Table 2.4.1 presents the results of the a-spatial model (OLS) and all the possible spatial specifications (SEM, SAR, SDM, SAC, SLX, SDEM and GNS) at the scale of the country's departments. The analysis of the AIC confirms our choice of the SAR model (AIC=899.681 being the lowest). However, the AIC of the SAR model is very close to that of the SAC model (AIC=901.679). Moreover, when we focus on the coefficients for these two models, we notice that they are almost identical. Also, these two coefficients have the highest electrification effects on deforestation (0.036) except for the linear model (which has to be compared to the marginal effects that we calculate). On closer inspection, we notice that $\hat{\lambda} = 0$ for the SAC model, which simply reduces

it to the SAR model. Finally, we also notice that LM test for residual autocorrelation is not significant for the SAR model. Thus, the possible risk of an omitted relevant variable is eliminated. As we defined also the SAR as the composition of SEM and SLX, this absence of spatial interaction effects in error terms lead to the fact that our SAR model implies finally that: (i) deforestation in a given locality depends on the electrification rate of other localities; (ii) there are the global spillover effects (on average, the value of the deforestation for a locality is not only explained by the level of the electrification for that locality, but also by those associated with all localities, spatial multiplier effect); and (iii) there is a global spatial diffusion effect (a random shock in a locality affects not only the value of the deforestation of this locality but also has an effect on the values of the deforestation of other localities).

Following [LeSage & Pace \(2009\)](#), the effect of the explanatory variables on the dependent variable is decomposed into direct and indirect effects. The direct effect of electrification on deforestation measures the effect of a change in the rate of electrification (improvement of electrification for example) of a given department on deforestation in this same department. The indirect effect measures the effect of a change in electrification in one department on deforestation in all other departments. In other words, indirect effects are global spillovers because they occur in all departments and are not necessarily limited to neighbourhood departments. However, these indirect effects relate more to the neighbourhood of a given department because they decrease with distance.

[Table 2.4.2](#) presents the direct and indirect effects of electrification on deforestation from the SAR specification at departmental level in Côte d'Ivoire. The empirical confidence intervals are obtained using 200 simulations from the empirical distribution ([Table 2.4.1](#), column 4). Only the direct effects of conflict and rainfall are significant and negative. Indeed, areas that experienced conflict, notably during the post-election crisis or during armed attacks in the north of the country (border with Burkina Faso and Mali) experienced population displacement to other areas. This would have reduced the demographic pressure on the forests in these areas. With regard to rainfall, [Hargrave & Kis-Katos \(2013\)](#) recall that a high level of rainfall can make runoff difficult and reduce the potential for agricultural production, thus reducing the profitability margin, and acting as a barrier to deforestation. Thus, only the precipitation variable would have a significant indirect effect. We get the same sign with the direct effect of this variable because neighbouring

Table 2.4.1: Regression Results

	OLS	SEM	SAR	SDM	SAC	SLX	SDEM	GNS
Night lights intensity AGR 2011-2018	0.059 (0.045)	0.025 (0.045)	0.036 (0.036)	-0.010 (0.050)	0.036 (0.037)	-0.011 (0.062)	0.004 (0.048)	-0.000 (0.049)
Average temperature AGR 2011-2017	2.261 (5.643)	2.491 (4.719)	2.167 (4.535)	1.750 (4.635)	2.172 (4.544)	1.475 (5.819)	0.210 (4.989)	0.962 (4.943)
Average precipitation AGR 2011-2017	-4.050*** (0.813)	-3.136*** (1.163)	-2.032*** (0.720)	1.176 (2.089)	-2.036** (1.000)	0.341 (2.622)	1.459 (2.051)	1.429 (2.095)
Percent forest cover in 2000	0.360** (0.147)	0.270 (0.189)	0.187 (0.121)	0.123 (0.274)	0.178 (0.134)	0.256 (0.344)	0.093 (0.254)	0.085 (0.261)
Population density AGR 2010-2020	0.306 (1.025)	0.718 (0.808)	0.694 (0.824)	0.589 (0.867)	0.694 (0.825)	0.190 (1.088)	0.558 (0.960)	0.592 (0.964)
Gross Domestic Product	-0.002 (0.002)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.002)	-0.001 (0.002)	-0.001 (0.002)
ACLED Conflict Events	-0.166 (0.102)	-0.167** (0.085)	-0.153* (0.082)	-0.139 (0.087)	-0.153* (0.083)	-0.159 (0.109)	-0.132 (0.095)	-0.133 (0.093)
Travel time to major cities	-0.017 (0.017)	-0.012 (0.018)	-0.010 (0.014)	-0.008 (0.020)	-0.010 (0.014)	-0.017 (0.024)	-0.003 (0.019)	-0.003 (0.019)
$\hat{\rho}$			0.613*** (0.089)	0.577*** (0.097)	0.612*** (0.223)			0.134 (0.569)
$\hat{\lambda}$		0.608*** (0.094)			0.003 (0.374)		0.626*** (0.091)	0.530 (0.421)
lag.Night lights intensity AGR 2011-2018				0.050 (0.074)		0.096 (0.093)	0.115 (0.093)	0.102 (0.100)
lag.Average temperature AGR 2011-2017				-3.254 (9.268)		-1.629 (11.636)	-9.027 (12.158)	-7.316 (11.590)
lag.Average precipitation AGR 2011-2017				-3.959 (2.661)		-4.950 (3.283)	-7.598*** (2.921)	-6.749* (3.775)
lag.Percent forest cover in 2000				0.102 (0.351)		0.145 (0.436)	0.536 (0.394)	0.440 (0.454)
lag.Population density AGR 2010-2020				-2.289 (2.004)		-2.531 (2.516)	-2.309 (2.385)	-2.237 (2.330)
lag.Gross Domestic Product				-0.003 (0.003)		-0.007* (0.004)	-0.001 (0.004)	-0.001 (0.004)
lag.ACLED Conflict Events				-0.041 (0.164)		-0.146 (0.204)	-0.128 (0.228)	-0.103 (0.239)
lag.Travel time to major cities				0.011 (0.031)		0.011 (0.038)	-0.020 (0.038)	-0.014 (0.039)
Constant	9.548 (7.116)	12.474 (8.222)	2.596 (5.809)	7.060 (12.057)	2.613 (6.273)	18.413 (15.093)	7.510 (18.614)	7.321 (17.993)
Observations	108	108	108	108	108	108	108	108
Adjusted R ²	0.229					0.239		
Akaike Inf. Crit.		903.858	899.681	910.975	901.679		910.67	912.618
Moran's Test	0.000					0.000		
LM-Error Test	0.000					0.000		
LM-Lag Test	0.000					0.000		
Robust LM-Error Test	0.509					0.019		
Robust LM-Lag Test	0.021					0.002		
Common Factor Test				0.352				
LM test for residual auto.			0.991	0.627				

*p<0.1; **p<0.05; ***p<0.01

Table 2.4.2: Effect measures, Spatial Autoregressive Model

	Direct	Indirect	Total
Night lights intensity AGR 2011-2018	0.0396	0.053	0.092
Average temperature AGR 2011-2017	2.409	3.198	5.607
Average precipitation AGR 2011-2017	-2.259***	-2.998**	-5.258***
Percent forest cover in 2000	0.208	0.276	0.483
Population density AGR 2010-2020	0.771	1.023	1.795
Gross Domestic Product	-0.001	-0.002	-0.003
ACLED Conflict Events	-0.171*	-0.226	-0.397
Travel time to major cities	-0.011	-0.015	-0.026

*p<0.1; **p<0.05; ***p<0.01

departments would certainly have similar levels of precipitation.

In spite of taking into account spatial effects through the SAR model, we notice that the overall effect of electrification on deforestation at the department level remains positive but not significant, contrary to what we had expected through the statistical analysis of the data. This leads us to include specific unobservable effects (individual and temporal) using the panel dimension.

2.4.2 Inclusion of unobservable individual and time specific effects

For [Amin et al. \(2019\)](#), taking into account individual and temporal dimensions allows a considerable gain of information linked to the exploitation of the double dimension of the data (control of the presence of unobservable heterogeneity), gives rise to a size of the samples generally higher (improvement of the precision of the estimates) and allows the modelling of dynamic relations. Indeed, even if spatial cross-sectional models allow spatial dependence effects to be captured, panel data also allow some form of unobservable heterogeneity to be controlled for (individual and time specific effects).

As in the case of cross-sectional data, taking into account spatial effects in panel data also requires specification tests. The first specification test is the Hausman test for spatial models. This test makes it possible to arbitrate between a fixed effects (FE) model and a random effects (RE) model. If the null hypothesis of this test is not rejected, the two estimators GLS (random effects model) and Within (fixed effects model) would converge, but only the GLS would be consistent.⁷ Otherwise, the GLS estimator would not be convergent, while the Within estimator would remain

⁷GLS = Generalized Least Squares

convergent. The result of the Hausman test for spatial models (appendix J) leads to the non-rejection of the null hypothesis of the absence of correlation between the individual effects and the explanatory variables. We therefore opt for a random effects model in the rest of this empirical analysis.

The specification tests for the spatial effects are then carried out in order to select the most appropriate specification for taking account of spatial dependence. The most commonly used spatial autocorrelation specification tests for panel data are based on the Lagrange multiplier test. They make it possible to test for the absence of each of the spatial terms without having to estimate the unconstrained model (Insee 2018). These two tests are very often completed by their robust version to the alternative form of taking into account the spatial autocorrelation (RLMlag or RLM-lag). In addition, Pesaran (2004)'s CD test for cross-sectional dependence in panels and CD test for local cross-sectional dependence in panels, plus Millo (2017)'s Randomized W test for spatial correlation of order 1 support the cross-sectional dependence in our data. Finally, Baltagi et al. (2003)'s LM*-mu conditional LM test confirms the existence of the Random regional effects, and Baltagi et al. (2003)'s LM*-lambda conditional LM test confirms the existence of Spatial autocorrelation. The results of all the tests (appendix J) guide us to estimate a random effects model with a SAR process.

Table 2.4.3: Effect measures, ML panel with spatial lag, random effects, Baltagi spatial error correlation

	Direct	Indirect	Total
Night lights intensity	0.425***	-0.095**	0.331***
Average temperature	372.124	-82.794	289.330
Average precipitation	93.766	-20.862	72.904
Percent forest cover	769.228***	-171.146***	598.082***
Population density	-27.525	6.124	-21.401
Gross Domestic Product	5.452	-1.213	4.239
ACLED Conflict Events	605.629***	-134.747***	470.882***
Travel time to major cities	-7.398	1.646	-5.752

*p<0.1; **p<0.05; ***p<0.01

Table 2.4.3 summarises the results of the model estimation with spatial autocorrelation taken into account using a SAR model (Baltagi error term specification). The calculation of direct, indirect and total effects followed the approach of Piras (2014). Electrification (night lights intensity), percentage of forest cover and conflicts appear to have significant effects on deforestation. Con-

trary to the results of [Tanner & Johnston \(2017\)](#) which documented, using data from 158 countries, that improving access to electricity in rural areas reduces the rate of deforestation, our main results suggest that electrification broadly increases deforestation. In other words, the improvement of the electrification rate reduces the forest cover at the scale of the departments of Côte d'Ivoire. This result appears after successively taking into account spatial effects and specific individual and temporal unobservable effects.

The direct positive effect of electrification on deforestation could be explained by several mechanisms. First, when a locality is connected to the national electricity grid, this creates new employment opportunities and could contribute to the well-being of that locality. This would therefore lead to an inflow of migrants to that locality and the installation of new industrial stakeholders for example (thus more pressure on the forests in terms of habitats, firewood collection, timber exploitation or mining, etc.). Furthermore, as mentioned in the introduction, there is the case of the very important weight of cash crops (notably cocoa and rubber) in Côte d'Ivoire. Therefore, any improvement in the productivity of these cash crops (notably via irrigation techniques made possible by access to electricity) would not necessarily have an effect on the slowing down of farming to the detriment of forests, and could even increase the expansion of agricultural land to the detriment of forests. This is known as Jevons' paradox.⁸

The indirect effect of electrification on deforestation is rather negative and strongly significant even if its magnitude is much smaller than that found with the direct effect. This could be explained by the fact that an increase in deforestation resulting from electrification that is significant enough in the surrounding localities could reduce the internal pressure on the forests (less migrants and more immigrants). Moreover, deforestation increases with the abundance of the forest resource. Also, the fact of surrounding oneself with territories rich in forest resources relatively reduces the pressure on the forest of a given locality. Finally, conflicts increase deforestation because during conflicts even protected areas are affected. For example, in their analysis of the dynamics of the designated forest of Haut-Sassandra (Côte d'Ivoire) in a post-armed conflict situation, [Sangne et al. \(2015\)](#) found that the area, once considered one of the country's best protected designated forests, was experiencing several intrusions into its historical boundaries as a result of the country's military-political crisis that lasted from 2002 to 2011. Numerous pioneering fronts were opened,

⁸The Jevons paradox implies that since technical progress improves the efficiency of the use of a resource, the total consumption of that resource may increase rather than decrease.

leading to the clearance of several thousand hectares of natural forest (formerly controlled by rebel armed groups from the north) followed by the plantation of cash crops (mainly cocoa).

2.5 Discussion

In this discussion section, we first highlight the importance of spatial interactions in understanding deforestation and the role of spatial econometrics in analyzing these interactions. The second part of the discussion documents how our study captures the causal effects of electrification on deforestation by controlling for spatial dependencies, conducting the analysis at a finer departmental level, and by considering extensive control variables to minimize biases. The discussion also explores the potential impact of targeted electrification policies on deforestation patterns. Finally, it suggests that understanding specific administrative rules governing electrification decisions could yield insights into mechanisms driving deforestation, inform policymakers, and address potential unintended consequences.

In the context of deforestation analysis, spatial interactions are essential to understand how deforestation in one locality can influence and be influenced by nearby areas ([Baggio & de Barros 2021](#)). For instance, if one locality experiences increased deforestation due to certain activities like agricultural expansion or logging, it can potentially create pressures for neighboring areas to follow a similar pattern. This could happen due to changes in migration patterns, land use dynamics, or resource demands. Spatial econometrics techniques help us explicitly model and account for these spatial interactions. By using such methods, we can identify the drivers of deforestation and gain insights into the spatial dynamics of deforestation processes ([Maddison 2006](#); [Choumert et al. 2013](#)). This understanding is crucial for policymakers as it allows them to devise targeted strategies to address deforestation in specific localities while considering potential spillover effects on neighboring areas. Additionally, spatial factors such as infrastructure development (e.g., roads or railways) can be related to the observed electrification and deforestation patterns ([Hargrave & Kis-Katos 2013](#); [Barber et al. 2014](#); [Ferreira & Coelho 2015](#); [Asher et al. 2020](#)). Infrastructure development can lead to easier access to remote areas, increasing their susceptibility to deforestation as economic activities expand. The integration of spatial factors in the analysis can help in understanding how electrification initiatives may influence deforestation patterns across various

localities. For instance, areas with better infrastructure and electricity access might experience increased economic activities, potentially leading to both positive and negative impacts on deforestation rates. To sum up, by incorporating spatial econometrics and considering spatial factors in deforestation analysis, policymakers can make informed decisions to strike a balance between promoting electricity access and combating deforestation. They can identify areas where electrification may lead to increased deforestation and implement appropriate measures to mitigate the negative impacts. Simultaneously, they can also support sustainable practices in areas where electrification might create opportunities for economic growth without significant forest loss. The use of spatial econometrics and the consideration of spatial factors in deforestation analysis provide valuable insights for policymakers to design effective strategies that harmonize the goals of expanding electricity access and conserving forests in Côte d'Ivoire. It highlights the importance of understanding the complex spatial relationships between electrification, deforestation, and other related factors to achieve sustainable development outcomes.

In addition, we have designed our study to leverage the exogenous variation introduced by the ongoing rural electrification program while accounting for potential endogeneity. First, we have collected a comprehensive dataset that includes spatial and temporal information on both electrification and deforestation across various localities (regions and departments) of Cote d'Ivoire. By utilizing a spatial panel data framework, we controlled for spatial dependencies and heterogeneity across regions while capturing the dynamic interactions between electrification and deforestation over time. Second, to account for spatial autocorrelation and potential spillover effects, we employ a random effects model with a spatial lag process. This model allowed us to examine how electrification in one department may impact deforestation in neighboring departments, thus capturing indirect causal effects that might arise due to geographical proximity. By adopting a spatial panel data methodology, we controlled for unobserved heterogeneity, time-varying confounders, and spatial dependencies, thereby providing a more rigorous assessment of the direct causal impacts of electrification on deforestation. Our study acknowledges and embraces the exogenous variation introduced by the rural electrification program and leverages it within a comprehensive analytical framework. Third, our analysis was conducted at a finer level of aggregation, specifically at the departmental level, which allowed us to capture localized variations in electrification and deforestation patterns. This granularity enabled us to identify nuanced relationships and account for

potential confounding factors that may have been overlooked in previous studies that used larger geographical units. Finally, we included an extensive set of control variables that encompassed various aspects, such as climate, economy, geography, demography, and infrastructure. The inclusion of these covariates allowed us to minimize the risk of spurious correlations and carefully controlled for omitted variable biases. By doing so, we mitigated potential endogeneity concerns and ensured that the observed effects were attributable to electrification. To sum up, our study contributes to the understanding of the impact of electrification on deforestation in Cote d'Ivoire by conducting an analysis at a finer level of aggregation while controlling for various confounding factors. We believe that our findings support a positive causal effect of electrification on deforestation rates, but we also acknowledge that causality cannot be definitively ascertained based solely on observational data. Thus, we encourage further research through experimental approaches to supplement our findings and advance the understanding of this critical issue.

Furthermore, considering administrative decisions in electricity provision, especially those targeting lower-income areas, might be a crucial aspect to explore in this kind of analysis. This led us here to provide a short discussion on how targeted electrification policies might have influenced deforestation patterns differently across various areas in the country. First, targeted electrification policies aimed at providing electricity to lower-income areas could lead to increased access to modern energy sources for communities that were previously underserved. Improved access to electricity in these areas can have positive socio-economic impacts, such as increased productivity, better living conditions, and enhanced economic opportunities. As a result, communities with improved access to electricity may engage in alternative income-generating activities, reducing their dependence on deforestation for livelihoods. Second, with targeted electrification, lower-income areas may witness shifts in land use patterns for instance. As access to electricity fosters economic diversification, communities may transition away from traditional agricultural practices that necessitate deforestation. Instead, they might embrace new income-generating activities that are less harmful to forests, such as small-scale industries, services, or value-added agricultural ventures. Third, targeted electrification initiatives often involve community engagement and awareness campaigns. As electricity becomes available in previously marginalized areas, there may be greater emphasis on forest conservation and sustainable resource management. Increased awareness of the environmental consequences of deforestation could lead to more responsible practices and a

reduction in illegal logging and forest degradation. In the same vein, to facilitate targeted electrification, there might be concurrent investments in infrastructure development, such as roads and transportation networks. While this could potentially increase accessibility to forest areas, it can also enable better monitoring and law enforcement to prevent illegal deforestation activities. This discussion on how targeted electrification policies might have impacted deforestation patterns differently in various areas in Cote d'Ivoire enhances the policy relevance and practical implications of our study. By investigating these nuanced aspects, we aim to provide a comprehensive understanding of the potential environmental and socio-economic impacts of electrification initiatives in the country, which could inform future policy decisions and contribute to sustainable development goals.

Finally, the discussion of the potential effects of the specific administrative rules that influenced electricity provision decisions for similar areas in Cote d'Ivoire could yield valuable insights into the mechanisms driving deforestation in electrified areas, thereby enhancing the robustness and policy relevance of our study. First, administrative rules and policies play a crucial role in shaping electrification strategies in any country. Cote d'Ivoire is likely no exception, and understanding the specific rules governing electricity provision is essential to contextualize our findings accurately. By identifying the rules that influenced electrification decisions, we can assess their potential impact on deforestation patterns more precisely. Second, investigating administrative rules can reveal the causal mechanisms underlying the relationship between electrification and deforestation. For example, certain rules may prioritize electrification in areas with high agricultural potential, leading to changes in land use and potential deforestation. By examining such mechanisms, we can provide a more nuanced understanding of the interactions between electrification policies and environmental outcomes. Third, knowledge of administrative rules can inform policymakers about the potential unintended consequences of electrification initiatives. If specific rules are found to have contributed to deforestation, policymakers can design targeted interventions to mitigate negative impacts while still promoting access to electricity. This could involve integrating sustainable land-use planning or conservation measures into electrification policies. Finally, the identification of administrative rules can also shed light on equity considerations in electricity provision. If specific rules result in uneven access to electricity among different socio-economic groups or geographic areas, understanding these disparities is essential for ensuring equitable and sustain-

able development. Overall, discussing an investigation of specific administrative rules governing electricity provision decisions in Cote d'Ivoire would help to provide policymakers with more nuanced and context-specific recommendations for sustainable development across the country.

2.6 Conclusion

The objective of our study was mainly to highlight the importance of spatial resolution and spatial interaction in studying the links between electrification and deforestation in Cote d'Ivoire. First, we tested the reliability of the night lights intensity data and documented that its is comparable at the regional level to the official data on electricity coverage provided by the Ivorian authorities. Second, we tested for the existence of spatial autocorrelation in deforestation both at the regional and departmental level. The results document that aggregating the data at regional level might hide the spatial autocorrelation observed at the departmental level. Third, we ran spatial statistical tests and documented that SAR model is the best specification both in cross-sectional and panel data model. Finally, we documented that taking into account both spatial auto-correlation and individual heterogeneity in the spatial panel framework allows to document that electrification have an overall positive impact on deforestation, with a positive direct impact and negative indirect impact of neighboring areas.

Our results suggest that electrification increases overall deforestation in Côte d'Ivoire. Nevertheless, as highlighted in some previous analyses, electrification could have partially favorable effects on specific deforestation factors (e.g. reduced wood collection, reduced need to expand arable farms for subsistence crops, etc.). In addition, electrification would be a powerful tool for reducing poverty. Electrification also might accelerate structural transformation and would be a source of job creation in most developing countries. While increasing access to electricity, Ivorian authorities should ensure that forest protection agents are in place, not only to enforce protected area designations, but also to create a barrier against pressure on forests all over the country.

2.7 Acknowledgment

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. It has been presented at the 20th International Workshop on Spatial

Econometrics and Statistic (SEW) in May 2022 (Lille, France). We thank the participants for their valuable comments.

Bibliography

- Alves, D. S. (2002), 'Space-time dynamics of deforestation in brazilian amazonia', *International Journal of Remote Sensing* **23**(14), 2903–2908.
- Amin, A., Choumert-Nkolo, J., Combes, J.-L., Motel, P. C., Kéré, E. N., Ongono-Olinga, J.-G. & Schwartz, S. (2019), 'Neighborhood effects in the brazilian amazônia: Protected areas and deforestation', *Journal of Environmental Economics and Management* **93**, 272–288.
- An, L., Lupi, F., Liu, J., Linderman, M. A. & Huang, J. (2002), 'Modeling the choice to switch from fuelwood to electricity: implications for giant panda habitat conservation', *Ecological Economics* **42**(3), 445–457.
- Anselin, L. (2013), *Spatial econometrics: methods and models*, Vol. 4, Springer Science & Business Media.
- Anselin, L., Bera, A. K., Florax, R. & Yoon, M. J. (1996), 'Simple diagnostic tests for spatial dependence', *Regional science and urban economics* **26**(1), 77–104.
- Asher, S., Garg, T. & Novosad, P. (2020), 'The ecological impact of transportation infrastructure', *The Economic Journal* **130**(629), 1173–1199.
- Baggio, I. S. & de Barros, P. H. B. (2021), 'The spatial relationship of transportation infrastructure and deforestation in brazil: a machine learning approach'.

- Bakehe, N. P. & Hassan, R. (2022), 'The effects of access to clean fuels and technologies for cooking on deforestation in developing countries', *Journal of the Knowledge Economy* pp. 1–17.
- Baltagi, B. H., Song, S. H. & Koh, W. (2003), 'Testing panel data regression models with spatial error correlation', *Journal of econometrics* **117**(1), 123–150.
- Barber, C. P., Cochrane, M. A., Souza Jr, C. M. & Laurance, W. F. (2014), 'Roads, deforestation, and the mitigating effect of protected areas in the amazon', *Biological conservation* **177**, 203–209.
- Beyer, R. C., Franco-Bedoya, S. & Galdo, V. (2021), 'Examining the economic impact of covid-19 in india through daily electricity consumption and nighttime light intensity', *World Development* **140**, 105287.
- Celentano, D., Sills, E., Sales, M. & Veríssimo, A. (2012), 'Welfare outcomes and the advance of the deforestation frontier in the brazilian amazon', *World Development* **40**(4), 850–864.
- Chakir, R. & Lungarska, A. (2017), 'Agricultural rent in land-use models: comparison of frequently used proxies', *Spatial Economic Analysis* **12**(2-3), 279–303.
- Choumert, J., Motel, P. C. & Dakpo, H. K. (2013), 'Is the environmental kuznets curve for deforestation a threatened theory? a meta-analysis of the literature', *Ecological Economics* **90**, 19–28.
- Christopher, D., Chi, F. et al. (2017), 'Viirs night-time lights', *International journal of remote sensing* .
- Cropper, M. & Griffiths, C. (1994), 'The interaction of population growth and environmental quality', *The American Economic Review* **84**(2), 250–254.
- Dai, Z., Hu, Y. & Zhao, G. (2017), 'The suitability of different nighttime light data for gdp estimation at different spatial scales and regional levels', *Sustainability* **9**(2), 305.
- Dube, P., Musara, C. & Chitamba, J. (2014), 'Extinction threat to tree species from firewood use in the wake of electric power cuts: a case study of bulawayo, zimbabwe', *Resources and Environment* **4**(6), 260–267.

- Elhorst, J. P. (2010), 'Applied spatial econometrics: raising the bar', *Spatial economic analysis* **5**(1), 9–28.
- Ferreira, M. D. P. & Coelho, A. B. (2015), 'Desmatamento recente nos estados da amazônia legal: uma análise da contribuição dos preços agrícolas e das políticas governamentais', *Revista de Economia e Sociologia Rural* **53**, 91–108.
- Florax, R. J., Folmer, H. & Rey, S. J. (2003), 'Specification searches in spatial econometrics: the relevance of hendry's methodology', *Regional Science and Urban Economics* **33**(5), 557–579.
- Geist, H. J. & Lambin, E. F. (2002), 'Proximate causes and underlying driving forces of tropical deforestation tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations', *BioScience* **52**(2), 143–150.
- Ghosh, T., L Powell, R., D Elvidge, C., E Baugh, K., C Sutton, P. & Anderson, S. (2010), 'Shedding light on the global distribution of economic activity', *The Open Geography Journal* **3**(1).
- Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S., Goetz, S. J., Loveland, T. R. et al. (2013), 'High-resolution global maps of 21st-century forest cover change', *science* **342**(6160), 850–853.
- Hargrave, J. & Kis-Katos, K. (2013), 'Economic causes of deforestation in the brazilian amazon: a panel data analysis for the 2000s', *Environmental and Resource Economics* **54**(4), 471–494.
- Insee (2018), 'Handbook of spatial analysis: theory and practical application with r', *Institut national de la statistique et des études économiques, Eurostat* .
- Kleinschroth, F., Laporte, N., Laurance, W. F., Goetz, S. J. & Ghazoul, J. (2019), 'Road expansion and persistence in forests of the congo basin', *Nature Sustainability* **2**(7), 628–634.
- Kumar, P., Sajjad, H., Joshi, P. K., Elvidge, C. D., Rehman, S., Chaudhary, B., Tripathy, B. R., Singh, J. & Pipal, G. (2019), 'Modeling the luminous intensity of beijing, china using dmsp-ols night-time lights series data for estimating population density', *Physics and Chemistry of the Earth, Parts A/B/C* **109**, 31–39.
- Lee, L.-F. (2004), 'Asymptotic distributions of quasi-maximum likelihood estimators for spatial autoregressive models', *Econometrica* **72**(6), 1899–1925.

- LeSage, J. & Pace, R. K. (2009), *Introduction to spatial econometrics*, Chapman and Hall/CRC.
- Maddison, D. (2006), 'Environmental kuznets curves: A spatial econometric approach', *Journal of Environmental Economics and management* **51**(2), 218–230.
- Manski, C. F. (1993), 'Identification of endogenous social effects: The reflection problem', *The review of economic studies* **60**(3), 531–542.
- Mensah, J. T. & Adu, G. (2015), 'An empirical analysis of household energy choice in Ghana', *Renewable and Sustainable Energy Reviews* **51**, 1402–1411.
- Millo, G. (2017), 'A simple randomization test for spatial correlation in the presence of common factors and serial correlation', *Regional Science and Urban Economics* **66**, 28–38.
- Nelson, A. (2008), 'Estimated travel time to the nearest city of 50,000 or more people in year 2000', *Ispra, Italy*.
- Newman, M. E., McLaren, K. P. & Wilson, B. S. (2014), 'Assessing deforestation and fragmentation in a tropical moist forest over 68 years; the impact of roads and legal protection in the cockpit country, Jamaica', *Forest Ecology and Management* **315**, 138–152.
- Openshaw, S. (1984), The modifiable areal unit problem, *catmog* 38, in 'Geo Abstracts, Norwich'.
- Pesaran, M. H. (2004), 'General diagnostic tests for cross section dependence in panels', *Available at SSRN 572504*.
- Piras, G. (2014), 'Impact estimates for static spatial panel data models in r', *Letters in Spatial and Resource Sciences* **7**(3), 213–223.
- Raleigh, C., Linke, A., Hegre, H. & Karlsen, J. (2010), 'Introducing acled: an armed conflict location and event dataset: special data feature', *Journal of peace research* **47**(5), 651–660.
- Robalino, J. A. & Pfaff, A. (2012), 'Contagious development: Neighbor interactions in deforestation', *Journal of Development Economics* **97**(2), 427–436.
- Sangne, C., Barima, Y., Bamba, I. & N'Doumé, C.-T. (2015), 'Dynamique forestière post-conflits armés de la forêt classée du haut-sassandra (côte d'ivoire)', *[VertigO] La revue électronique en sciences de l'environnement* **15**(3).
- Sutton, P. C., Elvidge, C. D., Ghosh, T. et al. (2007), 'Estimation of gross domestic product

- at sub-national scales using nighttime satellite imagery’, *International Journal of Ecological Economics & Statistics* **8**(S07), 5–21.
- Sutton, P., Roberts, D., Elvidge, C. & Baugh, K. (2001), ‘Census from heaven: An estimate of the global human population using night-time satellite imagery’, *International Journal of Remote Sensing* **22**(16), 3061–3076.
- Tacconi, L. (2011), ‘Developing environmental governance research: the example of forest cover change studies’, *Environmental Conservation* **38**(2), 234–246.
- Tanner, A. M. & Johnston, A. L. (2017), ‘The impact of rural electric access on deforestation rates’, *World Development* **94**, 174–185.
- Upton, G. J. & Fingleton, B. (1985), *Spatial data analysis by example: categorical and directional data*, Vol. 2, Wiley.
- Villoria, N. B., Byerlee, D. & Stevenson, J. (2014), ‘The effects of agricultural technological progress on deforestation: what do we really know?’, *Applied Economic Perspectives and Policy* **36**(2), 211–237.
- Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., Zhang, X., Tang, Q., Pan, M., Tang, Y., Tang, Q. et al. (2017), ‘Center for international earth science information network—ciesin—columbia university.(2016). gridded population of the world, version 4 (gpwv4): Population density. palisades. ny: Nasa socioeconomic data and applications center (sedac). doi: 10.7927/h4np22dq.’, *Atlas of Environmental Risks Facing China Under Climate Change* p. 228.

Appendices

E Concordance between night lights data and official data

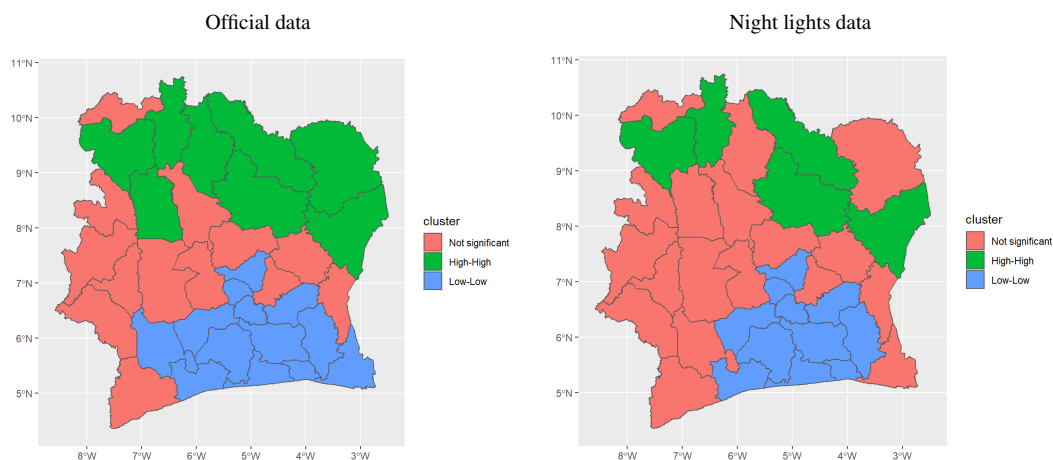


Figure E1: Local Indicators of Spatial Association (LISA)

Table E1: Forest loss AGR 2011-2018 as dependent variable, OLS Regression Results

	(1)	(2)
Night lights intensity AGR 2011-2018	0.088 (0.148)	
Electricity coverage AGR 2011-2018		0.332 (0.419)
Average temperature AGR 2011-2017	-4.962 (7.255)	-5.120 (7.190)
Average precipitation AGR 2011-2017	-3.080* (1.506)	-3.416** (1.330)
Percent forest cover in 2000	0.338 (0.222)	0.392 (0.244)
Population density AGR 2010-2020	1.463 (3.139)	1.569 (3.017)
Gross Domestic Product	-0.002 (0.001)	-0.002 (0.001)
ACLED Conflict Events	-0.045 (0.074)	-0.068 (0.079)
Travel time to major cities	-0.039 (0.030)	-0.035 (0.023)
Constant	14.033 (14.558)	11.906 (14.581)
Observations	33	33
R ²	0.356	0.363
Adjusted R ²	0.141	0.150
Residual Std. Error (df = 24)	11.259	11.198
F Statistic (df = 8; 24)	1.657	1.708

*p<0.1; **p<0.05; ***p<0.01

F Moran's I tests using alternatives neighbourhood matrix

F.1 Moran I for Regions

Table F1: Moran test for our main variables using Contiguity (gabriel) weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.289	-0.031	0.014	2.68	0.0036
Forest loss (randomisation)	0.289	-0.031	0.015	2.64	0.0041
Night lights (normality)	0.513	-0.031	0.014	4.57	2.5e-06
Night lights (randomisation)	0.513	-0.031	0.013	4.71	1.2e-06
Elec. coverage (normality)	0.698	-0.031	0.014	6.12	<1e-08
Elec. coverage (randomisation)	0.698	-0.031	0.014	6.12	<1e-08

Table F2: Moran test for our main variables using Distance (with k=1) weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.093	-0.031	0.016	0.977	0.16
Forest loss (randomisation)	0.093	-0.031	0.017	0.962	0.17
Night lights (normality)	0.550	-0.031	0.016	4.56	2.5e-06
Night lights (randomisation)	0.550	-0.031	0.015	4.7	1.3e-06
Elec. coverage (normality)	0.631	-0.031	0.016	5.19	1e-07
Elec. coverage (randomisation)	0.631	-0.031	0.016	5.19	1e-07

Table F3: Moran test for our main variables using Distance (with k=5) weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.0048	-0.0312	0.0028	0.676	0.25
Forest loss (randomisation)	0.0048	-0.0312	0.0029	0.666	0.25
Night lights (normality)	0.3659	-0.0312	0.0028	7.45	<1e-08
Night lights (randomisation)	0.3659	-0.0312	0.0027	7.67	<1e-08
Elec. coverage (normality)	0.4901	-0.0312	0.0028	9.78	<1e-08
Elec. coverage (randomisation)	0.4901	-0.0312	0.0028	9.78	<1e-08

Table F4: Moran test for our main variables using Triangulation weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.2180	-0.0312	0.0096	2.54	0.0055
Forest loss (randomisation)	0.2180	-0.0312	0.0099	2.5	0.0062
Night lights (normality)	0.4761	-0.0312	0.0096	5.17	1.2e-07
Night lights (randomisation)	0.4761	-0.0312	0.0091	5.33	4.9e-08
Elec. coverage (normality)	0.6622	-0.0312	0.0096	7.07	<1e-08
Elec. coverage (randomisation)	0.6622	-0.0312	0.0096	7.07	<1e-08

Table F5: Moran test for our main variables using 2-nearest neighbours weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.166	-0.031	0.023	1.3	0.097
Forest loss (randomisation)	0.166	-0.031	0.024	1.28	0.1
Night lights (normality)	0.573	-0.031	0.023	3.97	3.6e-05
Night lights (randomisation)	0.573	-0.031	0.022	4.09	2.1e-05
Elec. coverage (normality)	0.685	-0.031	0.023	4.71	1.3e-06
Elec. coverage (randomisation)	0.685	-0.031	0.023	4.71	1.3e-06

Table F6: Moran test for our main variables using 4-nearest neighbours weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.227	-0.031	0.011	2.41	0.008
Forest loss (randomisation)	0.227	-0.031	0.012	2.37	0.0089
Night lights (normality)	0.514	-0.031	0.011	5.1	1.7e-07
Night lights (randomisation)	0.514	-0.031	0.011	5.25	7.5e-08
Elec. coverage (normality)	0.679	-0.031	0.011	6.63	<1e-08
Elec. coverage (randomisation)	0.679	-0.031	0.011	6.63	<1e-08

Table F7: Moran test for our main variables using 6-nearest neighbours weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.2308	-0.0312	0.0071	3.12	0.00091
Forest loss (randomisation)	0.2308	-0.0312	0.0073	3.07	0.0011
Night lights (normality)	0.4250	-0.0312	0.0071	5.43	2.9e-08
Night lights (randomisation)	0.4250	-0.0312	0.0067	5.59	1.1e-08
Elec. coverage (normality)	0.5899	-0.0312	0.0071	7.39	<1e-08
Elec. coverage (randomisation)	0.5899	-0.0312	0.0071	7.39	<1e-08

F.2 Moran I for departments

Table F8: Moran test for our main variables using Contiguity (gabriel) weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.5054	-0.0093	0.0043	7.84	<1e-08
Forest loss (randomisation)	0.5054	-0.0093	0.0042	7.95	<1e-08
Night lights (normality)	0.5411	-0.0093	0.0043	8.38	<1e-08
Night lights (randomisation)	0.5411	-0.0093	0.0040	8.69	<1e-08

Table F9: Moran test for our main variables using Distance (with k=1) weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4313	-0.0093	0.0036	7.36	<1e-08
Forest loss (randomisation)	0.4313	-0.0093	0.0035	7.47	<1e-08
Night lights (normality)	0.6239	-0.0093	0.0036	10.6	<1e-08
Night lights (randomisation)	0.6239	-0.0093	0.0033	11	<1e-08

Table F10: Moran test for our main variables using Distance (with k=5) weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.25706	-0.00935	0.00087	9.04	<1e-08
Forest loss (randomisation)	0.25706	-0.00935	0.00084	9.17	<1e-08
Night lights (normality)	0.41993	-0.00935	0.00087	14.6	<1e-08
Night lights (randomisation)	0.41993	-0.00935	0.00081	15.1	<1e-08

Table F11: Moran test for our main variables using Triangulation weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4215	-0.0093	0.0031	7.78	<1e-08
Forest loss (randomisation)	0.4215	-0.0093	0.0030	7.89	<1e-08
Night lights (normality)	0.4448	-0.0093	0.0031	8.2	<1e-08
Night lights (randomisation)	0.4448	-0.0093	0.0028	8.51	<1e-08

Table F12: Moran test for our main variables using 2-nearest neighbours weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.6252	-0.0093	0.0078	7.2	<1e-08
Forest loss (randomisation)	0.6252	-0.0093	0.0076	7.3	<1e-08
Night lights (normality)	0.6418	-0.0093	0.0078	7.38	<1e-08
Night lights (randomisation)	0.6418	-0.0093	0.0072	7.66	<1e-08

Table F13: Moran test for our main variables using 4-nearest neighbours weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4931	-0.0093	0.0040	7.9	<1e-08
Forest loss (randomisation)	0.4931	-0.0093	0.0039	8.02	<1e-08
Night lights (normality)	0.5111	-0.0093	0.0040	8.19	<1e-08
Night lights (randomisation)	0.5111	-0.0093	0.0038	8.49	<1e-08

Table F14: Moran test for our main variables using 6-nearest neighbours weight matrix

	Moran I stat	E(I)	var(I)	st. deviation	p-value
Forest loss (normality)	0.4211	-0.0093	0.0026	8.39	<1e-08
Forest loss (randomisation)	0.4211	-0.0093	0.0026	8.51	<1e-08
Night lights (normality)	0.4457	-0.0093	0.0026	8.87	<1e-08
Night lights (randomisation)	0.4457	-0.0093	0.0024	9.2	<1e-08

G Bottom-up approach (Florax et al. 2003)

Table G1: Lagrange multiplier diagnostics for spatial dependence

Tests	Obs: 33 / X = Night light			Obs: 33 / X = Elec. Coverage			Obs: 108 / X = Night light		
	statistic	df	p.value	statistic	df	p.value	statistic	df	p.value
LMerr	2.040606	1	0.1531	2.39356	1	0.1218	24.95165	1	5.879e-07
LMlag	1.578866	1	0.2089	1.57515	1	0.2095	29.80226	1	4.784e-08
RLMerr	0.542341	1	0.4615	1.15133	1	0.2833	0.43516	1	0.5095
RLMlag	0.080601	1	0.7765	0.33292	1	0.5639	5.28577	1	0.0215

H Top-down approach (LeSage & Pace 2009)

Table H1: Likelihood ratio tests

Tests	First stage			Second stage		
	Statistics	df	p-value	Statistics	df	p-value
LR_{θ}	4.7053	8	0.7886			
LR_{ρ}	22.013	1	2.709e-06	27.833	1	1.323e-07
LR_{λ}	8.8829	8	0.3523			

I Two-way comparison approach

Table I1: Results of Likelihood ratio tests for spatial models

	statistic	df	p-value
OLS versus SEM ($H_0 : \lambda = 0$)	24	1	1.2e-06
OLS versus SAR ($H_0 : \rho = 0$)	28	1	1.3e-07
OLS versus SLX ($H_0 : \theta = 0$)	11	8	0.23
SAR versus SAC ($H_0 : \lambda = 0$)	8e-05	1	0.99
SAR versus SDM ($H_0 : \theta = 0$)	4.7	8	0.79
SEM versus SAC ($H_0 : \rho = 0$)	4.2	1	0.041
SEM versus SDM ($H_0 : \theta = -\rho\beta$)	8.9	8	0.35
SEM versus SDEM ($H_0 : \theta = 0$)	9.2	8	0.33
SLX versus SDM ($H_0 : \rho = 0$)	22	1	2.7e-06
SLX versus SDEM ($H_0 : \lambda = 0$)	22	1	2.3e-06
SDM versus GNS ($H_0 : \lambda = 0$)	0.35	1	0.55
SDEM versus GNS ($H_0 : \rho = 0$)	0.048	1	0.83
SAC versus GNS ($H_0 : \theta = 0$)	5.1	8	0.75

J Panel specification tests

Table J1: Specification tests under panel models

Tests name	Statistics	Alternative hypothesis
Hausman test for spatial models	chisq = 23.715, df = 8, p-value = 0.9829	one model is inconsistent
LM test for spatial lag dependence	LM = 912.28, df = 1, p-value < 2.2e-16	spatial lag dependence
LM test for spatial error dependence	LM = 889.81, df = 1, p-value < 2.2e-16	spatial error dependence
Robust LM test for spatial lag dependence	LM = 33.226, df = 1, p-value = 8.203e-09	spatial lag dependence
Robust LM test for spatial error dependence	LM = 10.754, df = 1, p-value = 0.001041	spatial error dependence
Pesaran CD test for cross-sectional dependence in panels	z = 67.209, p-value < 2.2e-16	cross-sectional dependence
Pesaran CD test for local cross-sectional dependence in panels	z = 39.267, p-value < 2.2e-16	cross-sectional dependence
Randomized W test for spatial correlation of order 1	p-value = 0.02	twosided
Baltagi, Song and Koh LM*-mu conditional LM test (assuming lambda may or may not be = 0)	LM*-mu = 52.588, p-value < 2.2e-16	Random regional effects
Baltagi, Song and Koh LM*-lambda conditional LM test (assuming $\sigma^2_{\mu} \geq 0$)	LM*-lambda = 32.25, p-value < 2.2e-16	Spatial autocorrelation

Power Sector Regulation and Private Investment in Power Generation: Evidence from Africa

3.1 Introduction

As of 2020, electricity access in Africa remains limited, with an estimated coverage of under 54%. This signifies that approximately 600 million Africans are still without electricity access.¹ This challenge can largely be attributed to insufficient investment in the power sector. African governments have faced difficulties in allocating essential public funds to stimulate sector growth due to fiscal constraints (ERI 2020). These constraints stem from persistent challenges in generating tax revenues (prevalence of the informal sector, complex taxation of agriculture) as well as the burden of public debt (debt services). Confronted with these financial constraints across the continent, the recommendations of the Bretton Woods institutions (IMF and World Bank) have been embraced. This shift has facilitated the involvement of private stakeholders in power generation, aiming to secure the necessary capital to address the challenges of achieving universal electricity access in Africa. Private participation is notably achieved through Independent Power Producers (IPPs) or Public-Private Partnerships (PPPs). Nevertheless, these private stakeholders encounter significant

¹Population without access to electricity in Africa, 2000-2020, IEA

obstacles: local capital markets exhibit fragility and limitations (with debts primarily denominated in foreign currencies), and the majority of inputs are imported. Financial resources are scarce in the region, and even when accessible, financing tends to be short-term, misaligned with the extended timelines of most energy projects (NEPAD-OECD Investment Initiative). Furthermore, local credit costs remain notably high (characterized by exorbitant interest rates). An additional challenge for these stakeholders is their reliance on foreign markets for sourcing both fixed inputs (capital) and variable inputs (fuels).

These financial risks therefore expose private stakeholders to currency and inflation shocks or crisis. Indeed, the weakness of domestic capital markets means that a large part of the debt of private stakeholders is denominated in foreign currency. Therefore, a devaluation of the national currency leads to an increase in the debt burden for private stakeholders. Moreover, this devaluation would increase the cost of imported inputs. Also, as the electricity price is generally rigid, even when an inflation crisis does not lead to a depreciation of the exchange rate, it can contribute to the increase of the domestic cost of the projects (salaries for example when they are indexed to inflation). Consequently, there is a compelling need for sectoral regulation, encompassing tariff regulation, to mitigate the risks confronting private stakeholders within the power sector across the majority of African countries. This entails the independent regulator setting tariffs that accurately reflect the actual costs of providing electricity, alongside an automated tariff adjustment mechanism that employs a predetermined formula to align tariffs with changing costs over regular intervals. Ensuring appropriate quality regulation is indispensable to guarantee the requisite transparency and predictability, creating an environment conducive to attracting and sustaining private investment in the pursuit of universal electricity access goals.

Nevertheless, the literature presents a somewhat mixed perspective on the impact of regulation on private investments. In general, a considerable body of analysis has underscored the favorable influence of sectoral regulation on encouraging private stakeholders to engage in investments (Paragal 2003; Wallsten 2002; Rubino & Cuomo 2015). These potentially positive effects of independent regulators on private investments are also mentioned in the context of developing countries (Andres et al. 2007; Cubbin & Stern 2005; Gassner et al. 2009), and more precisely in the context of the electricity sector (Bergara et al. 1998; Zhang et al. 2008; Cubbin & Stern 2006). However, some authors document an alternative viewpoint, contending that regulatory agencies may not

necessarily ensure an enhancement in private investment due to political interference or measures not adapted to the reality of the sector ([Bertoméu-Sánchez et al. 2018](#); [Parker & Kirkpatrick 2012](#); [Andrés et al. 2013](#); [Carvalho et al. 2012](#); [Estache et al. 2010](#)).

This paper is aiming at uncovering the potential impact of regulatory measures within the power sector on private investments in power generation across Africa. In pursuit of this aim, the paper undertakes a comprehensive examination of three key objectives. First, the study examines the potential effects of currency and inflation crises on the power generation in Africa. Second, the paper documents the mitigating influence stemming from the implementation an independent regulatory body, automatic tariff adjustment mechanism, and cost reflectivity. Finally, the paper engages in a comparative analysis to evaluate the effectiveness of distinct regulatory approaches in mitigating the adverse consequences of crises on private investments. In other words, how do currency and inflation crises potentially impact power generation in Africa, and what are their effects on the sector? To what extent does the presence of an independent regulatory body, an automatic tariff adjustment mechanism, and the incorporation of cost reflectivity help mitigate challenges within the power generation sector? How do various regulatory strategies compare in their efficacy to mitigate the negative effect of crises on private investments in the power generation industry?

Our contribution to the existing literature is threefold. First, we are conducting for the first time such kind of analysis including all African countries. In order to take into account all 54 countries of the continent, we have carried out preliminary work to collect data on the establishment of independent regulators (for 16 countries out of 54) from official sources. This allowed us to complete the documentary research initiated by [Eberhard et al. \(2016\)](#), [Foster et al. \(2017\)](#) and [Imam et al. \(2019\)](#). Second, in order to deepen the previous works, beyond the analysis of the relationship between regulation and participation of private stakeholders in a general way, we have mainly documented the role of tariff regulation in a specific way, more precisely the cost reflectivity and the automatic tariff adjustment mechanism, on private participation. Finally, to compensate for the unavailability of data on the evolution of power generation costs, we have approached it through two factors (inflation shocks and currency shocks). Indeed, as cost is the key determinant of profitability, we assume that a currency devaluation would have an impact both on the cost of a project via imported inputs and via the cost of financing the project (mainly foreign currency debt). As for the participation of private stakeholders in investments, it is approached by

the evolution of the available total installed capacity per country because investment in the sector has been undertaken mainly by private stakeholders over the last decades. Indeed, in the case of Africa, over the period 1990-2019 that we are considering, investments in the sector are essentially made by private stakeholders. Therefore, the evolution of available total installed capacity in Africa over this period is a fine proxy for private investments in the power generation.

The primary findings suggest that inflation and currency crises negatively affect private participation in power sector investment (proxied by changes in available total installed capacity) in the 54 African countries over the period 1990-2019. Moreover, currency crises appear to be much more severe than inflation crises over our period of analysis. Meanwhile, these negative effects of inflation and currency crises on private participation are mitigated for the group of countries that have established an independent power sector regulator compared to countries that have not yet done so.² This is especially true if regulators in these countries adopt automatic tariff adjustment mechanism and generation cost reflectivity for operators. Indeed, the empirical results document that cost reflectivity measures would be much more effective, followed by the automatic tariff adjustment mechanism, compared to a simple implementation of an independent power regulator (without these two types of policies).

The rest of the paper is subdivided as follows: literature review in section 3.2, private stakeholders and power sector in Africa in section 3.3, theoretical framework in section 3.4, main data in section 3.5, empirical methodology in section 3.6, results in section 3.7, robustness check in section 3.8, and section 3.9 concludes.

3.2 Literature review

The literature on this issue can be divided into three sub-sections, namely, private participation and performance, private participation and regulation, and the potential effects of the currency and inflation shocks on investment.

²But a regulatory agency cannot, on its own and without appropriate measures, correct all the negative effects of currency shocks (the most severe in our case) for instance.

3.2.1 Private participation and performance

Opinions are still very divided as to the benefits or not of private participation in various sectors. Authors such as [Koo et al. \(2013\)](#) suggest that private participation is in fact negatively associated with the efficiency of the electricity service. In the same vein, and in general, [Trujillo et al. \(2002\)](#) estimate that private participation in infrastructure negatively influences the efficiency of the service due to the aggravation of the agency problem. Nevertheless, the results of these two studies document that the negative effects of private participation on efficiency are reduced with the quality of regulation. Other authors like [Koo et al. \(2013\)](#), assume that there is no effect of private sector participation on the level of performance. Using a meta-analysis, they document that the performance of public enterprises is not significantly different from that of private enterprises and that privatisation has no beneficial effects on public services in transition economies. On the other hand, the prevailing or dominant thought is rather in favour of a positive effect of private participation in infrastructure. In this line, [Wallsten \(2001\)](#) found, for example, that the performance of telecommunications at national level is positively related to regulation and private participation. As regards other relevant studies, [Hawdon \(1996\)](#), documenting the performance of electricity sectors supported by World Bank loans, found that countries that had adopted privatisation had significantly higher efficiency than the group that had not privatised.

3.2.2 Private participation and Regulation

In general, a large number of studies have documented the favourable role of the regulation of a sector and the participation of private stakeholders. We are thinking in particular of the study by [Pargal \(2003\)](#) in which he documents that the absence of independent regulation can be a major obstacle to attract private sector investment in the infrastructures of developing countries. His results suggest that improving regulatory certainty and minimising the risk of expropriation through the establishment of independent regulatory bodies is a key determinant of the volume of private investment flows. In the same vein, [Wallsten \(2002\)](#) has documented that countries that have established independent regulatory agencies in the telecommunications sector have seen a faster increase in investment in the sector compared to countries that have not, and that investors are willing to pay more for these companies in countries that have undertaken reforms. Furthermore, [Rubino & Cuomo \(2015\)](#) document that the legal and regulatory framework adopted in the Euro-

pean Union (EU) favours the financing of the development of cross-border interconnections in the EU zone.

In the same vein, for [Bertoméu-Sánchez et al. \(2018\)](#), regulatory agencies are basically supposed to reduce the risk of companies taking control of the regulatory process by trying to influence the government, ministries or other public stakeholders and obtain favourable regulatory decisions. Such agencies would also reduce collusion between governments and private operators and political interference in prices, quantities, quality and profitability. They are therefore seen as sending a strong signal to the market that the government was taking regulation seriously, which should mitigate investment risks and thus make it easier to attract investors and private operators. These potentially positive effects of independent regulators on various types of private infrastructure investment in developing countries have also been described by [Andres et al. \(2007\)](#), [Cubbin & Stern \(2005\)](#) and [Gassner et al. \(2009\)](#). Evidence of the positive effect of regulatory agencies on investments has also been established in the electricity sector. This is notably the case in [Bergara et al. \(1998\)](#) who found that well-defined and credible political institutions were positively and significantly correlated with overall power generation capacity. Indeed, power generation is characterised by massive investments, hence the need to offer all the guarantees to investors to boost investments that would increase the available total installed capacity and power generation ([Zhang et al. 2008](#); [Laffont & Tirole 1993](#)).³ Finally, [Cubbin & Stern 2006](#) estimate, for 28 developing countries over the period 1980-2001, that the existence of regulatory law and better regulatory governance is positively and significantly associated with higher levels of per capita generation capacity and that this positive effect increases over time with the development of regulatory experience and reputation.

However, for some authors such as [Parker & Kirkpatrick \(2012\)](#), there is growing uncertainty about the effectiveness of regulatory agencies and reforms in attracting PPPs. Indeed, the emerging picture of the relationship between regulatory agencies and PPPs is complicated by the fact that there are countries with regulatory agencies and no PPPs and countries with PPPs and no regulatory agencies ([Bertoméu-Sánchez et al. 2018](#)). They also document that an independent regulator is not necessarily a sufficient condition for increasing private participation in water ser-

³Installed capacity is the maximum level of electrical power (electricity) that a power plant can deliver at a given time under certain conditions. In other words, it is the amount of electricity a generator can produce when operating at full capacity. This maximum amount of power is usually measured in megawatts (MW) or kilowatts and helps utilities predict how much electrical load a generator can handle.

vices for instance. Finally, for developing countries, [Andrés et al. \(2013\)](#), [Carvalho et al. \(2012\)](#) and [Estache et al. \(2010\)](#) suggest that, in general, regulatory agencies do not guarantee a major improvement in investment, access rates or efficiency in the water and sanitation sector. For this group of countries, this is largely due to the fact that institutional weaknesses make these agencies less independent and competent than they should be. In sum, the bias in favour of regulatory agencies may be positive in theory, but the practice seems to be quite different.

3.2.3 Currency and inflation crisis effects on investment

Commonly accepted beliefs suggest that when there is uncertainty about rising prices (inflation) or fluctuations in exchange rates (currency crisis), it tends to discourage businesses from investing ([Darby et al. 1999](#)). To put it simply, when companies are considering whether to invest in a project, they typically weigh the potential profits they can earn in the future. If they expect to make more money than they spend (a positive net present value or NPV), they will likely proceed with the investment. However, if they anticipate making less money than they put in, they will likely hold off on investing. This decision-making process becomes easier when investments can be easily reversed. In such cases, if the expected profits turn sour, the company can simply pull out. But when investments cannot be easily undone, like a one-time decision, companies are more cautious and may choose not to invest further if the outlook for profits worsens.

Inflation shocks and investment

Using panel data for OECD countries and arguing that inflation affects investment because it increases the cost of capital, [Madsen \(2003\)](#) documents that investment in non-residential buildings and structures and in machinery and equipment is strongly negatively related to inflation, suggesting that the low-inflation environment of the 1990s was an important contributor to the strong investment activity of the last decade in OECD countries. As for [Hochman & Palmon \(1983\)](#), they document that when the "Fisher effect" is assumed to exist, the cut-off rate of return on investment decreases with expected inflation, independently of the type of financing. However, if the real interest rate increases with inflation, inflation may increase the cut-off rate of return on investment. Finally, using data from about 100 countries between 1960 and 1990 to assess the effects of inflation on economic performance, [Barro \(2013\)](#) indicate that the effects of an average

inflation increase of 10 percentage points per year are a reduction in the growth rate of real GDP per capita by 0.2 to 0.3 percentage points per year and a decrease in the investment/GDP ratio by 0.4 to 0.6 percentage points.

Depreciation and investment

For [Harchaoui et al. \(2005\)](#), in theory and globally, exchange rate variations have two opposite effects on investment. When the national currency depreciates, the marginal benefit of investing an additional unit of capital is likely to increase, because the revenue from domestic and foreign sales is higher. In other words, a depreciation would therefore have a positive impact on investment due to higher demand in domestic and export markets.⁴ However, this positive effect is offset by the increase in variable costs and the price of imported capital. Since theoretical models do not give a clear indication of which effect dominates, the overall effect of exchange rates on investment remains an empirical question. Therefore, an exchange rate depreciation stimulates investment by increasing demand in the domestic and export markets, but reduces investment because of the increased cost of imported intermediate goods and the user cost of capital. In the very specific case of an electricity producer in Africa, with a high import of inputs and almost no export of electricity, we would most likely have an overall negative effect of depreciation on investment. Meanwhile, using industry-level data for 22 Canadian manufacturing industries over the period 1981-1997, [Harchaoui et al. \(2005\)](#) document that the overall effect of exchange rates on total investment is documented to be statistically insignificant.

Moreover, many studies have also documented the role of the change regime on the dynamics of investment. This is especially the case with the analysis of [Aizenman \(1992\)](#), which documents that overall investment is higher under a fixed change regime than under a flexible change regime, both for productivity shocks and for monetary shocks. However, welfare is not necessarily higher under either regime. Meanwhile, a flexible change regime is one of the means to stabilise employment during shocks. Also, the issue of exchange rate volatility and its link with investment is widely documented. Indeed, [Servén \(2003\)](#) examines the link between real exchange rate volatility and private investment in developing countries using a large cross-country time series data set. He develops a GARCH-based measure of real exchange rate volatility and finds that it

⁴Another illustration with Japan's FDI by industry, [Kiyota & Urata \(2004\)](#) find that the depreciation of the host country's currency attracts FDI. Their results suggest the need to avoid overvaluing the national currency.

has a negative and significant effect on investment. Moreover, this negative effect of real exchange rate volatility on investment is significantly larger in very open economies and in those with less developed financial systems.

Through this literature review, we can see that previous studies have been rather limited to a broad analysis of the role of regulation on the attraction of private investment, without detailing the type of regulation in question. Also the studies documenting the effect of currency or inflation shocks are rather general. This suggests that the impact of currency shocks, for example, could have both beneficial and detrimental effects on investment. Our contribution in this paper would therefore be, first, to focus on a specific regulation measure, the tariff regulation in the power sector through the cost reflectivity and the automatic tariff adjustment mechanism. Second, we document the effects of currency and inflation shocks in a specific sector (power generation) within African countries. This helps to clarify the adverse effect of, for example, currency shocks given the specific characteristics of the power sector in this part of the world (low electricity exports, dependence on imported inputs, foreign currency debts). Finally, we document how this tariff regulation plays a fundamental role in mitigating currency and inflation shocks and allows the attraction and the maintaining of private investments.

3.3 private stakeholders and power sector in Africa

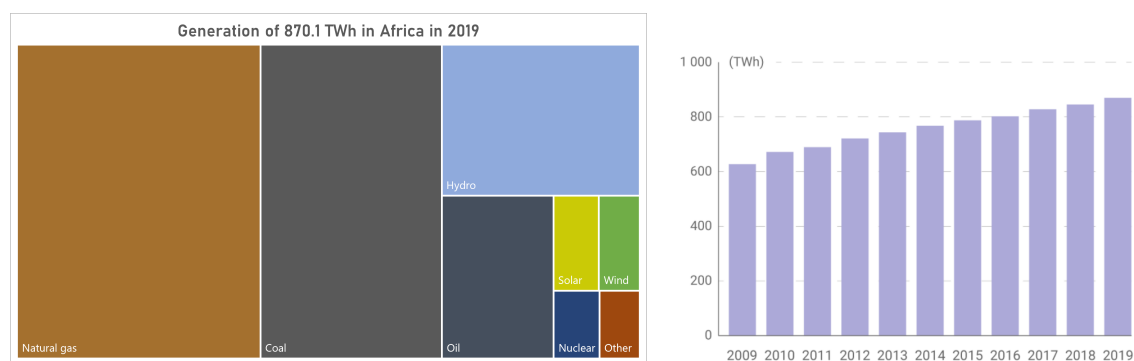


Figure 3.3.1: Energy mix and evolution of power generation in Africa

As documented in [Figure 3.3.1](#), global electricity generation across the African continent stood at 870.1 TWh in 2019. However, almost 80% of this electricity generation in Africa still comes from fossil fuels, while wind and solar account for just over 4% of the continent's electricity mix (over 15% for hydro). This dependence on fossil fuels increases vulnerability to depreciation

shocks, especially for countries that are net importers of gas, oil, and/or coal. Moreover, the last decade has been marked by the constant evolution of power generation as we can see on the right side of the figure, and this despite the budgetary difficulties of the Governments.

This increase in power generation across the continent has been achieved mainly through the involvement of private stakeholders, notably through PPPs and IPPs.⁵ IPPs have indeed become widespread across Africa and are now present in more than 30 countries. According to the African Development Bank, there are over 270 IPPs in operation or under construction in Africa (MIRA database, AfDB 2019). This represents approximately USD 51.7 billion in investments and 27.1 GW of installed generation capacity. Already in 2016, a report by Proparco (AFD) reported 77,800 MW due to IPPs in 20 selected countries on the continent, representing a 25.6% share of total generation (Table K1, appendix K). This share is close to 50% for the countries like Gambia (43%), Togo (49%) and Uganda (49%). In Côte d'Ivoire for instance, this share represents more than 50% (52% exactly).

If the conditions for profitable investment are met, the private sector would participate fully in power sector investments in Africa in the same way that private mobile phone operators have participated massively in financing.⁶ For example, Côte d'Ivoire has attracted more than 1 billion USD in investment in 18 months to increase the country's generation capacity by 30%. Uganda has halved the cost of electricity and tripled its electricity access rate, largely through privatisation of the service. Kenya is massively increasing its generation capacity, both thermal and renewable, through a series of new private producers, and South Africa has used the private sector to rapidly increase its solar and wind generation capacity. This documents that if countries put in place the required conditions to invest in private power generation, investors and financiers would respond. So, after establishing the theoretical link, from an empirical point of view we also test the hypothesis that the required tariff conditions would attract and retain these private investors.

⁵As a reminder, IPPs are producers that are usually not owned by the national state-owned electricity company. IPPs generate electricity for sale to the national, usually public, operator.

⁶Source: Les producteurs privés d'électricité : une solution pour l'Afrique ? Proparco (AFD), 2017

3.4 Theoretical framework

This theoretical framework aims at establishing a clear conceptual foundation for our study. It outlines the fundamental principles, concepts, and relationships that underlie our subject. This helps readers comprehend the context of our research and provides a solid starting point for discussing the specific dynamics of power sector regulation and private investment in African power generation. By tailoring this theoretical framework to the specific context of African power generation, we ensure that our analysis is directly relevant to the region's unique challenges, opportunities, and characteristics. This enhances the applicability and validity of our empirical findings.

First, the frequency of episodes of interaction between inflation and depreciation in many countries has raised concerns about the possibility of inflation-depreciation vicious circles. According to this vicious circle hypothesis, a higher domestic inflation rate than that prevailing abroad could trigger a cumulative and self-reinforcing process leading to a vicious circle between inflation and currency depreciation ([Ahmad 1984](#)). Indeed, a low inflation rate generally leads to an increase in the value of the currency, as its purchasing power increases relative to other currencies. Conversely, countries with higher inflation tend to see their currencies depreciate against those of their trading partners.⁷ More precisely, a depreciation of the domestic currency initially aggravates the rate of domestic price inflation through an immediate increase in the price of traded goods expressed in domestic currency, which quickly feeds through to the domestic price level. This inflation, in turn, requires a depreciation of the exchange rate, which causes further inflation.

Then, by assuming the precedent hypothesis of a potential vicious circle between inflation and currency depreciation, we develop a theoretical framework based on that of [Nucci & Pozzolo \(2001\)](#) in order to highlight theoretically the mitigating role of regulation with regard to the link between inflation shocks, followed by currency shocks on the dynamics of private investment in power generation in Africa. As the power sector investment is driven by expected returns in the light of a range of risks related to both costs and revenues ([Gross et al. 2010](#)), in this analysis we specifically formalise the effect of an exchange rate depreciation on private participation in the sector's investments by focusing mainly on the cost channel (rather negative effect due mainly to

⁷Source: OFX team, 6 factors influencing exchange rates and what you can do about it, 2019

the dependence on imported inputs).^{8,9} We refer to input costs and credit costs. The idea is that the impact of currency depreciation would increase, for example, with a dependence on imports of inputs and the share of private stakeholders' debt denominated in foreign currency.

Let $\pi(K_t, e_t)$ be the profit function of an IPP or under a PPP, where K_t is its capital stock (turbines, generators) at time t and e_t is the real exchange rate calculated in units of domestic currency per unit of foreign currency.¹⁰ The producer chooses his optimal level of investment I_t at date t . Given the adjustment costs associated with a change in the quantity of the capital factor, we assume that the accumulation process is subject to an adjustment cost, $C(I_t)$, which is increasing and convex in I_t .

We can therefore estimate the value of a representative power generation company as the maximum expected present value of its cash flows using the discounted cash flows (DCF) method which is the fundamental valuation method expressed as follows:¹¹

$$V_t(K_{t-1}) = \max_{I_t} \left([\pi(K_t, e_t) - I_t - C(I_t)] + \beta_{t+1}^t E_t [V_{t+1}(K_t)] \right) \quad (3.4.1)$$

where the cash flow in each period is expressed as $\pi(\cdot)$ net of aggregate capital expenditure, β_{t+1}^t denotes the producer's discount factor between periods t and $t + 1$, E_t is the expectation operator conditional on all information available at time t and the price of capital goods is normalised to 1. The capital stock K_t is governed by the standard accumulation equation $K_t = K_{t-1} + I_t$, where depreciation is ignored for reasons of simplicity. The first-order condition for maximising Equation 3.4.1 with respect to the capital stock provides the following expression:

$$\frac{\partial V_t(K_{t-1})}{\partial K_{t-1}} = \left[\frac{\partial \pi(K_t, e_t)}{\partial K_t} \right] + \beta_{t+1}^t E_t \frac{\partial V_{t+1}(K_t)}{\partial K_t} \quad (3.4.2)$$

⁸The revenue channel (positive effect) is not relevant enough in this case because there are very few interconnections between the power networks of African countries.

⁹Goldberg (1993) had observed, for example, that a real depreciation of the dollar had generated an expansion in commands for American capital goods.

¹⁰The turbine and the generator are the two main components of the power generation. With the exception of photovoltaic plants, power is generated by an alternator driven by a turbine or, for certain isolated systems, by an internal combustion engine (diesel generator with a power of a few MW to several tens of MW). Several turbine technologies are available depending on the fluid used to drive them: vapor turbine, combustion turbine or hydraulic turbine.

¹¹ K_{t-1} is due to the assumption that more than one time period is required for the construction of new productive capital or the notion of "Time to build". So, a delay for the installation of equipment is introduced (Kydland & Prescott 1982)

$$q_t = \left[\frac{\partial \pi(K_t, e_t)}{\partial K_t} \right] + \beta_{t+1}^t E_t(q_{t+1}) \quad (3.4.3)$$

where the variable q_t is the marginal valuation of capital: $\partial V_t / \partial K_{t-1}$.¹² Equation 3.4.3 gives us the following expression for q_t :

$$q_t = \frac{\partial \pi(K_t, e_t)}{\partial K_t} + \beta_{t+1}^t E_t \times \left[\frac{\partial \pi(K_{t+1}, e_{t+1})}{\partial K_{t+1}} \right] + \beta_{t+2}^t E_t(q_{t+2}) \quad (3.4.4)$$

$$q_t = \frac{\partial \pi(K_t, e_t)}{\partial K_t} + \beta_{t+1}^t E_t \times \left[\frac{\partial \pi(K_{t+1}, e_{t+1})}{\partial K_{t+1}} \right] + \beta_{t+2}^t E_t \times \left[\frac{\partial \pi(K_{t+2}, e_{t+2})}{\partial K_{t+2}} \right] + \dots + \beta_{t+j-1}^t E_t(q_{t+j-1}) \quad (3.4.5)$$

$$q_t = E_t \sum_{j=0}^{\infty} \beta_{t+j}^t \left[\frac{\partial \pi(K_{t+j}, e_{t+j})}{\partial K_{t+j}} \right] \quad (3.4.6)$$

which implies that q_t is equal to the present value of the future net returns of marginal capital income. The discount factor at period j is $\beta_{t+j}^t = \prod_{i=1}^j (1 + r_{t+i-1})^{-1}$ with r_t being the nominal rate of return required by the producer between periods t and $t + 1$. Moreover, the first-order condition for maximising Equation 3.4.1 with respect to investment gives the following expression:

$$1 + \left[\frac{\partial C(I_t)}{\partial I_t} \right] = q_t \quad (3.4.7)$$

Assuming that the adjustment cost is increasing and convex with the level of investment, the term appearing on the left side of Equation 3.4.7, which is the marginal cost of investment, is a positive and increasing function of I_t . Therefore, by reciprocal or inverse bijection, investment can be expressed as an increasing function of q_t . Substituting from Equation 3.4.3 we then have:

$$I_t = \phi \left\{ E_t \sum_{j=0}^{\infty} \beta_{t+j}^t \left[\frac{\partial \pi(K_{t+j}, e_{t+j})}{\partial K_{t+j}} \right] \right\} \quad (3.4.8)$$

where $\phi(\cdot)$ is an increasing function due to the properties of the adjustment cost function $C(I_t)$.

Now, to characterize the effect of a currency shock or depreciation on private sector participation in power generation investment, we determine an explicit expression for the marginal return on fixed capital. In each period, the producer maximizes its profit by choosing the level of fixed capital K^* (assumed to be entirely imported for producers based in Africa) and its variable capital

¹²So $q_{t+1} = \partial V_{t+1} / \partial K_t$

acquired at home L or imported L^* .¹³

$$\pi(K_t^*, e_t) = \max_{K^*, L, L^*} x(p_t) p(e_t) + e_t x^*(p_t^*) p^*(e_t) - w_t L_t - e_t w_t^* L_t^* \text{ s.t. } x_t + x_t^* = F(K_t^*, L_t, L_t^*) \quad (3.4.9)$$

where $x(p_t)$ and $x^*(p_t^*)$ denote the electricity demand functions faced by the producer on the domestic and foreign markets, with p_t and p_t^* being the price levels of the KWh on these markets; $w_t L_t$ and $e_t w_t^* L_t^*$ are the expenditures on locally produced and imported inputs, L_t and L_t^* , respectively. The power generation function, $F(\cdot)$, is homogeneous of degree 1, or monetary neutrality as defined by Leontief.

The first-order conditions in Equation 3.4.9 give the following expression for the marginal return on capital:

$$\frac{\partial \pi(\cdot)}{\partial K_t^*} = \frac{1}{K_t^*} \left[p_t x_t \frac{1}{\mu_t} + e_t p_t^* x_t^* \frac{1}{\mu_t^*} - w_t L_t - e_t w_t^* L_t^* \right] \quad (3.4.10)$$

where μ_t et μ_t^* are the producer's price-cost margins on the domestic and foreign markets; they can also be expressed in terms of the price elasticity of demand ($\vartheta_{t,x}$ and ϑ_{t,x^*}), such $\mu_t = (1 + 1/\vartheta_{t,x})^{-1}$ and $\mu_t^* = (1 + 1/\vartheta_{t,x^*})^{-1}$, respectively.

In this model, we assume that a potential imbalance arises from the start of the inflation-depreciation vicious circle. In other words, an inflation shock i_t at date t , through the decline in domestic competitiveness, leads to a depreciation of the exchange rate e_t . Let us also assume that private operators perceive this change in the value of money as permanent. Therefore, the level of the exchange rate in future periods is expected to be equal to today's exchange rate, i.e. $E_t(e_{t+1+j} - e_t) = 0, \forall j \geq 0$.

By differentiating Equation 3.4.8 with respect to the exchange rate e_t and, for simplicity, the firm's discount factor is assumed to be constant over time in Equation 3.4.3 such as $\beta_{t+1}^t = \beta, \forall t$, we have:

$$\frac{\partial I_t}{\partial e_t} = \frac{\partial \phi}{\partial e_t} \Leftrightarrow \frac{\partial I_t}{\partial e_t} = \frac{\partial \phi}{\partial q_t} \times \frac{\partial q_t}{\partial e_t} = \phi_q(\cdot) \times \frac{\partial q_t}{\partial e_t} \text{ with } q_t = \frac{1}{1-\beta} \left[\frac{\partial \pi(K_t^*, e_t)}{\partial K_t^*} \right] \quad (3.4.11)$$

¹³Here, the variable capital or inputs include mainly fuel and labour. The producer can therefore increase the number of KWh produced by only increasing the amount of variable inputs. However, only an increase in fixed capital could lead to an increase in available total installed capacity in MW.

And using [Equation 3.4.10](#), we can derive an expression for the effect of exchange rate changes on private sector investment or participation in power generation:

$$\frac{\partial I_t}{\partial e_t} = \phi_q(\cdot) \frac{1}{1-\beta} \times \left[\frac{\partial K_t^{-1} (p_t x_t \mu_t^{-1} + e_t p_t^* x_t^* \mu_t^{*-1})}{\partial e_t} \right] - \phi_q(\cdot) \frac{1}{1-\beta} \left[\frac{\partial K_t^{-1} (w_t L_t + e_t w_t^* L_t^*)}{\partial e_t} \right] \quad (3.4.12)$$

where $\phi_q(\cdot)$ is non-negative as previously indicated. Rearranging, we obtain :

$$\frac{\partial I_t}{\partial e_t} = \frac{\phi(\cdot)}{(1-\beta) \partial K_t^* \partial e_t} \times \left(\frac{p_t x_t}{\mu_t} + \frac{e_t p_t^* x_t^*}{\mu_t^*} - w_t L_t - e_t w_t^* L_t^* \right) \quad (3.4.13)$$

$$\frac{\partial I_t}{\partial e_t} = \frac{\phi(\cdot)}{(1-\beta) \partial K_t^* \partial e_t} \times \left[\left(\frac{p_t x_t}{\mu_t} - w_t L_t \right) - e_t \left(w_t^* L_t^* - \frac{p_t^* x_t^*}{\mu_t^*} \right) \right] \quad (3.4.14)$$

[Equation 3.4.14](#) documents the dependence of investment on a one-period change in the level of the exchange rate, isolating the effect on the revenue side from that on the cost side. The value $(w_t^* L_t^* - p_t^* x_t^* / \mu_t^*)$ tends towards its maximum value $w_t^* L_t^*$ when there is no power exports ($x_t^* = 0$). Indeed, with the lack of integration of inter-country power networks, the producers cannot benefit from the positive effects of depreciation linked to the sale of electricity abroad. To mitigate this negative effect of depreciation on private participation in investments, the role of an independent regulator would be to act here on the $p_t x_t$ value, more precisely on the p_t pricing of electricity sold in the country, notably through the automatic tariff adjustment mechanism or through the cost reflectivity following the variation of the cost of power generation relative to a currency fluctuation. This must be clear in the tariff methodology in order to mitigate the risk for private stakeholders, especially in countries facing recurrent currency crises.

A transformation of [Equation 3.4.12](#) allows us to go further and to highlight the role of some relevant factors in the evolution of the effect described above.¹⁴ Also, to simplify the notation, the temporal indices have been ignored for the rest of the framework:

$$\frac{\partial I}{\partial e} = \phi_q(\cdot) \frac{1}{1-\beta} \frac{TR}{K^* e} \left(\frac{1}{1+\mu^*} \chi \times [\eta_{p^*,e} (1 + \vartheta_{x^*}) + 1 - \varepsilon_{\mu^*,e}] + \frac{1}{1+\mu} (1 - \chi) \times [\eta_{p,e} (1 + \vartheta_x) - \varepsilon_{\mu,e}] - \frac{1}{\bar{\mu}} (1 + \eta_{w^*,e}) \alpha \right) \quad (3.4.15)$$

¹⁴See appendix [Nucci & Pozzolo \(2001\)](#) for more details on the transformation.

$$\text{Where } TR = p_t x_t + e_t p_t^* x_t^*; \quad \chi = \frac{e_t p_t^* x_t^*}{TR}; \quad \eta_{p,e} = \frac{\partial p_t}{\partial e_t} \times \frac{e_t}{p_t}; \quad \eta_{p^*,e} = \frac{\partial p_t^*}{\partial e_t} \times \frac{e_t}{p_t^*};$$

$$\varepsilon_{\mu,e} = \frac{\partial \mu_t}{\partial e_t} \times \frac{e_t}{\mu_t}; \quad \varepsilon_{\mu^*,e} = \frac{\partial \mu_t^*}{\partial e_t} \times \frac{e_t}{\mu_t^*}; \quad \alpha = \frac{e_t \omega_t^* L_t^*}{\omega_t L_t + e_t \omega_t^* L_t^*}; \quad \eta_{w^*,e} = \frac{\partial w_t^*}{\partial e_t} \times \frac{e_t}{w_t^*}$$

χ is the representative producer's share of foreign sales (share of exported electricity) with respect to total revenues (TR) or total sales; $\eta_{p,e}$ and $\eta_{p^*,e}$ are the exchange rate elasticities of prices in the domestic and foreign markets respectively; $\varepsilon_{\mu,e}$ and $\varepsilon_{\mu^*,e}$ are the elasticities of the mark-up with respect to the exchange rate, respectively, in the domestic and external markets; α is the share of imported input costs in total variable costs; $\eta_{w^*,e}$ is the price elasticity of imported inputs (in foreign currency units) with respect to the exchange rate and $\bar{\mu} = \mu_t + \mu_t^*$ represents the producer's cost-price margin obtained without distinction between the domestic and foreign markets.

Equation 3.4.15 provides a useful framework for isolating the main determinants of the change in profitability, and hence investment, induced by exchange rate depreciation. Through this equation, we see that the share of revenues from power exports χ mitigates the effect of depreciation on the producer's investment (a factor favourable to private participation) when $\frac{\eta_{p^*,e}}{1+\mu^*} (1 + \vartheta_{x^*}) > \frac{\eta_{p,e}}{1+\mu} (1 + \vartheta_x)$. However, a producer benefits little from this potential improvement in competitiveness due to currency depreciation when interconnection with other countries does not exist or is quite weak (low level of electricity exports).

As indicated just before, χ is then negligible in our application, so $(1 - \chi)$ tends almost to 1. So, in our case, Equation 3.4.15 can be rewritten as follows:

$$\frac{\partial I}{\partial e} = \phi_q(\cdot) \frac{1}{1-\beta} \frac{TR}{K^* e} \frac{1}{1+\mu} \times \left\{ [\eta_{p,e} (1 + \vartheta_x) - \varepsilon_{\mu,e}] - \frac{1}{\bar{\mu}} (1 + \eta_{w^*,e}) \alpha \right\} \quad (3.4.16)$$

Let us now turn to the elasticity of the domestic power price with respect to a variation in the exchange rate, $\eta_{p,e}$. In a regulated electricity sector, this variable could represent the automatic tariff adjustment mechanism. Indeed, the regulator can define in its tariff methodology an automatic tariff adjustment mechanism or a cost reflectivity measure in response to an exchange rate shock impacting producer's power generation costs (imported inputs and foreign credit costs). Thus, this positive elasticity helps to mitigate the negative effect of depreciation on investment. Also, since domestic demand for electricity is inelastic ($\vartheta_x = 0$), the increase in the price of electricity on the domestic market induced by a depreciation of the currency has no effect on the quantity of elec-

tricity sold.¹⁵ This leaves the regulator with the choice of either subsidising the tariff difference (in the case of an automatic tariff adjustment mechanism) or allowing the producers to increase the tariff (in the case of cost reflectivity measure) to compensate the depreciation shock. In this configuration, it is also assumed that the elasticity of the mark-up with respect to the exchange rate is zero (favorable to the investment). However, in the context of a regulated sector and in the absence of an automatic tariff adjustment mechanism or a cost reflectivity measure following an exchange rate shock, $\eta_{p,e}(1 + \vartheta_x) = 0$. That increases the negative effect of depreciation on power generation investment or private participation. Meanwhile, the elasticity of the mark-up with respect to the exchange rate $\varepsilon_{\mu,e}$ is negative and represents paradoxically a source of incentive for private stakeholders. This seemingly counter-intuitive result has an economic explanation. Indeed, the stakeholders who decide to remain on the market in this configuration would make investment decisions in order to restore part of their lost margin. These stakeholders could, for example, decide either to invest in renewable energy (to limit imports of fuels that are highly dependent on exchange rate fluctuations) or to invest in more efficient equipment in order to reduce their energy bill. Finally, the elasticity of input prices with respect to the exchange rate $\eta_{w^*,e}$ and the share of imported input costs in total variable costs α reinforce the harmful effect of a depreciation for a national electricity producer. Indeed, we assume that the elasticity of input prices with respect to the exchange rate $\eta_{w^*,e}$ is positive and that this share of imported input costs on total variable costs α is quite close to 1 when there is a high dependence of local producers on imported fuels. In general, in countries without an independent regulator with all appropriate measures in place, inflation or exchange rate shocks are likely to slow down the evolution of available total installed capacity. However, this negative effect should be mitigated depending on the country's integration into a regional electricity market, independence from imported inputs (e.g. fuel) and the ability to raise domestic funds.

The next section is devoted to the presentation of the data essential for the empirical testing of the main hypotheses developed in this theoretical framework. That is, we test the hypothesis that adequate tariff regulation can mitigate the effect of exchange rate and inflation shocks on private investment in power generation in Africa.

¹⁵In the same vein, using unique data on Swedish households, [Lanot & Vesterberg \(2021\)](#) find that the price elasticity is smaller than what many previous studies on electricity demand have found. More precisely, the response to prices is very small.

3.5 Main data and statistics

In this section we present all our main data sources for this analysis. These include mainly data on regulation and the quality of regulation and data on available total installed capacity (proxy of private investment in the power sector in Africa over the recent decades).

3.5.1 Establishment of Regulators in Africa

Table 3.5.1: Establishment of Electricity Sector Regulators in Africa

[Eberhard et al. \(2016\)](#) and updated with data from [Foster et al. \(2017\)](#) and [Imam et al. \(2019\)](#)

South Africa	1994
Egypt, Zambia	1997
Cameroon, Côte d'Ivoire, Senegal	1998
Madagascar, Niger, Uganda	1999
Ghana, Mali, Namibia, Togo	2000
Gambia, Mauritania, Rwanda, Tanzania	2001
Algeria	2002
Cabo Verde, Rep. Of Congo, Zimbabwe	2003
Lesotho, Mozambique	2004
Central African Republic, Nigeria, São Tomé and Príncipe	2005
Kenya	2006
Angola, Eswatini, Malawi	2007
Benin	2009
Burkina, Gabon	2010
Burundi, Sierra Leone, Sudan	2011
Seychelles	2012
Ethiopia	2014
Our update	
Liberia	2015
Dem. Rep. Of Congo, Mauritius, Morocco	2016
Botswana, Guinea	2017
Chad	2019
Comoros, Djibouti, Equatorial Guinea, Eritrea, Guinea-Bissau, Libya, Somalia, South Sudan, Tunisia	No IRA

Data on the years of establishment of an independent electricity regulator in Africa is crucial for our analysis. Indeed, we are able to track the establishment by country over our study period (1990-2019). As the existing source of data is limited to the year 2014, we completed this database with a large collection of official sources from different governments and institutions as documented in [Table 3.5.1](#). As [Zhang et al. \(2008\)](#), we use a dummy variable to indicate whether a country has established an Independent Regulatory Agency (IRA) in the power sector that is not directly under the control of a ministry.

3.5.2 Electricity Regulatory Index by AfDB

To approximate the quality of regulation, we exploit the Electricity Regulatory Index (ERI) data source which is a publication of the African Development Bank (AfDB) and aims to provide an overview of regulatory developments and issues in the electricity sector on the African continent. The first edition of the ERI was published in 2018 and has been updated and published annually since then, with the third edition being published in November 2020.¹⁶

The ERI 2020 report documents that the average score in Africa for economic regulation is 0.534, while the average score for technical regulation is 0.506.¹⁷ The ERI reports provide a number of recommendations on how these indicators can be improved. Beyond the concrete strategies for implementing the recommendations and other interventions in line with international best practice to improve the regulation of the electricity sector in Africa that the ERI report proposes to policymakers, our analysis aims to highlight the need to implement these strategies to make the sector more attractive to private investors.

3.5.3 Private Participation in the Electricity Sector

To capture the flow of private investment in the power sector, the World Bank's Private Participation in Infrastructure (PPI) database remains the most widely used in this literature. However, this database represents only a compilation of publicly available information on private sector investment in infrastructure in developing countries, and should not be considered as an exhaustive resource. Some projects - particularly those involving local and small-scale operators - tend to be omitted as they are generally not reported by the main information sources, databases, government websites and other sources used by the PPI Projects database authors.

Therefore, as in [Zhang et al. \(2008\)](#), we use available total installed capacity provided by U.S. Energy Information Administration (EIA) as a proxy for private investment. Indeed, according to [Izaguirre \(1998\)](#), the participation of private stakeholders in the electricity sector has been most evident in power generation, with three quarters of private investment concentrated in power plants.

¹⁶Guidelines for Advancing Economic and QoS Regulation in Africa's Electricity Sector, USAID, August 2021

¹⁷African Development Bank, "Electricity Regulatory Index for Africa, 2020"

3.5.4 Data summary and statistics

Table 3.5.2: Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Installed capacity (million kW)	1,594	2.45	7.16	0.002	58.22
Inflation, consumer prices (annual %)	1,407	15,719.55	586236.18	-11.69	2.20e+07
Official exchange rate (LCU per USD)	1,565	4.30e+06	1.70e+08	2.39e-09	6.72e+09
Currency depreciation (against USD)	1,509	-7.21	16.53	-100	39.34
Independent Regulation (Yes=1, No=0)	1,620	0.46	0.50	0	1
Auto. Tariff Adjustment (Yes=1, No=0)	1,620	0.09	0.28	0	1
Tariff Cost Reflectivity (Yes=1, No=0)	1,620	0.12	0.32	0	1
Inflation Crises (Yes=1, No=0)	1,408	0.23	0.42	0	1
Currency Crises (Yes=1, No=0)	1,531	0.11	0.31	0	1

Table 3.5.2 below gives an overview of most of the variables we use. Regarding available total installed capacity, the average value over the period 1990-2019 is 2.45 million kW per country. However, we could see, through the Std. Dev. or through the gap between the Min Value and the Max value, a strong heterogeneity between countries in terms of available total installed capacity. While the minimum value is 0.002 million kW for Liberia in the early 2000s, the maximum value is 58.22 million kW for South Africa (the continent's leading economic power) in 2019. Also, some of the averages, such as that for inflation (over 15,000%), which is mainly driven by Zimbabwe's hyperinflation of about 22 million percent in 2008, can be confusing. Over the same period, the depreciation rate of the LCU against the dollar averaged 7.21% per annual. This rate fluctuates between -100% (maximum depreciation) and 39.34% (maximum appreciation). Currency crises are declared based on Frankel & Rose (1996) who define an currency crisis as a significant variation in the nominal exchange rate, i.e. a nominal depreciation of a currency of at least 25%. Then, we declared an inflation crisis for an annual inflation rate of more than 10%.¹⁸ Inflation Crises are more frequent than Currency ones. And Cost reflectivity measure remains more frequent than the Automatic tariff adjustment.

¹⁸Data on inflation and exchange rate are provided by World Development Indicators (WDI) which is the primary World Bank collection of development indicators, compiled from officially recognized international sources.

3.6 Empirical methodology

3.6.1 Endogeneity concerns when estimating the effect of inflation or currency crisis on private investment

When estimating the effect of exchange rate or inflation crisis on private investment in the power generation sector in Africa, we should be concerned about potential endogeneity issues. Endogeneity arises when the explanatory variable (in this case, exchange rate or inflation crisis) is correlated with the error term in the regression equation, leading to biased and inconsistent estimates. In the context of our analysis, endogeneity could occur due to various reasons. First, exchange rates or inflation might respond to changes in private investment in the power generation sector. For example, increased private investment may lead to higher demand for foreign currency, causing exchange rates to depreciate. In the same vein, increased private investment may lead to higher demand for goods and services, causing inflation to rise. Second, there may be other factors potentially affecting both exchange rates (or inflation shocks) and private investment that are not included in our model. These omitted variables can introduce endogeneity. Finally, exchange rates (or inflation) and private investment may influence each other simultaneously, leading to endogeneity.

3.6.2 Identification strategy: Combining Local Projection and AIPW Estimator

As in [Jordà & Taylor \(2016\)](#) in estimating the time of austerity and in [Atsebi et al. \(2019\)](#) in assessing the trade costs of financial crises, to address the potential endogeneity issue described earlier and the absence of instantaneousness in the effects, we use a combined method of local projections (LP) à la [Jordà \(2005\)](#) and an impact assessment methodology (AIPW).¹⁹ This strategy consists of three steps. First, we estimate the propensity score, which is the conditional probability of receiving the treatment (currency or inflation crisis) given a set of observed covariates. In this case, inflation shocks are considered the treatment. After estimating the propensity scores, we calculate the inverse of the propensity scores for each observation. These inverse propensity scores act as weights. The idea behind weighting is to give more weight to observations that are less

¹⁹[Blagrove & Furceri \(2021\)](#) also applied Impulse Response Functions (IRFs) or LP to assess the macroeconomic effects of electricity sector privatization.

likely to receive the treatment (currency or inflation crisis) given their observed characteristics. This helps balance the observed covariates between the treatment and control groups. Second, we fit an outcome model in which changes in our outcome variables (private private participation or investment approximated here by the available total installed capacity) are explained by their determinants. Finally, we implement a semi-parametric estimator of the average treatment effect (ATE), namely the Augmented Inverse Propensity Weighted (AIPW), using the predicted propensity scores obtained in the first step, as well as the observed and potential values (predicted in the second step) of the change in available total installed capacity.²⁰

By combining propensity score weighting with augmentation to account for potential biases introduced by endogeneity, AIPW estimator is an approach that can help address endogeneity in estimating the effect of currency or inflation crisis on private investment in the power generation sector in Africa. In our analysis, we consider that crises (inflation crisis or currency crisis) represent the treatment variables, and changes in available total installed capacity at each h horizon represent the outcome variable. The average treatment effect (ATE) is defined as follows:

$$ATE = \Lambda^h = \mathbb{E}[y_{i,t+h} - y_{i,t} | D_{i,t} = 1] - \mathbb{E}[y_{i,t+h} - y_{i,t} | D_{i,t} = 0]; \forall h \quad (3.6.1)$$

But $\mathbb{E}[y_{i,t+h} - y_{i,t} | D_{i,t} = 0]$ is not observable. We must therefore use a counterfactual to approximate it. Under the assumption of independence $[y_{i,t+h} - y_{i,t}] \perp D_{i,t} | Z_{i,t}; \forall h$, i.e. for a crisis occurrence independent of potential outcomes conditional on a set of covariates $Z_{i,t}$, we estimate the ATE by comparing the outcome in countries with and without crisis conditional on the set of variables $Z_{i,t}$. The ATE becomes:

$$ATE = \Lambda^h = \mathbb{E}[y_{i,t+h} - y_{i,t} | D_{i,t} = 1; Z_{i,t}] - \mathbb{E}[y_{i,t+h} - y_{i,t} | D_{i,t} = 0; Z_{i,t}]; \forall h \quad (3.6.2)$$

To estimate the ATE in this paper, we use the AIPW estimator which requires the estimation of two models, the treatment model and the outcome model. For the treatment model, we estimate a probit for each crisis on the determinants, and obtain the propensity scores $\hat{p}_{i,t}$ and $1 - \hat{p}_{i,t}$ for country i in year t to be in the treatment and control group respectively. Introduced by Rosen-

²⁰For instance, [Imam et al. \(2019\)](#) used available total installed capacity as performance indicator in the power sector. Also, [Jamil et al. \(2022\)](#) have documented that the main benefit of private sector participation in Pakistan came from the timely expansion of available total installed capacity.

baum & Rubin (1983), the propensity score is of particular interest for our analysis in order to eliminate biases between the treatment and control groups, and we use the weighting by propensity scores to mimic a situation where crises occur at random. We predict the potential outcome $\widehat{\mathbb{E}}[y_{i,t+h} - y_{i,t} \mid D_{i,t} = d; Z_{i,t}]; \forall d \in \{0, 1\}$ for the whole sample, based on the characteristics of each group. This provides the potential outcome for countries in the treatment (control) group if they did (did not) experience crises, conditional on all control variables. Following the general expression for the AIPW provided by Lunceford & Davidian (2004), we calculate the estimated ATE of crises on our outcome variables for h years or horizons as:

$$\widehat{\Lambda}_{AIPW}^h = \frac{1}{n} \sum_i \sum_t \left(\left[\frac{D_{i,t} (y_{i,t+h} - y_{i,t})}{\widehat{p}_{i,t}} - \frac{(1 - D_{i,t}) (y_{i,t+h} - y_{i,t})}{1 - \widehat{p}_{i,t}} \right] - \frac{D_{i,t} - \widehat{p}_{i,t}}{\widehat{p}_{i,t} (1 - \widehat{p}_{i,t})} \times \right. \\ \left. \left[(1 - \widehat{p}_{i,t}) \widehat{\mathbb{E}}[y_{i,t+h} - y_{i,t} \mid D_{i,t} = 1; Z_{i,t}] + \widehat{p}_{i,t} \widehat{\mathbb{E}}[y_{i,t+h} - y_{i,t} \mid D_{i,t} = 0; Z_{i,t}] \right] \right) \quad (3.6.3)$$

This semi-parametric estimator has the particularity of being the most efficient of the doubly robust estimators, i.e. it is unbiased when at least the outcome or treatment model is correctly specified (Lunceford & Davidian 2004; Imbens 2004). Moreover, compared to the inverse propensity weighted (IPW) estimator, it includes an additional adjustment term consisting of the weighted average of the two predicted potential outcomes, which stabilises the estimator when the propensity scores are close to zero or one, and whose expectation is zero when the treatment or outcome model is correctly specified (Glynn & Quinn 2010). Finally, they conclude that the AIPW estimator has a mean square error comparable to or lower than competing estimators when both the treatment and outcome models are correctly specified, and outperforms them when one of these models is misspecified. The typical LP equation we estimate has the following form:

$$y_{i,t+h} - y_{i,t} = \alpha_i^h + \Lambda^h D_{i,t} + \beta_{L1}^h \Delta y_{i,t-1} + \beta_{L2}^h \Delta y_{i,t-2} + \beta_C^h y_{i,t}^C + v_{i,t+h} \quad (3.6.4)$$

for $h = 1, \dots, 5$, and where $y_{i,t+h} - y_{i,t}$ represents the cumulative change between time t and $t + h$ in private participation in the electricity sector (available total installed capacity), the α_i^h are country fixed effects, and $D_{i,t}$ represents the interest variable (a dummy variable indicating the presence

or absence of an inflation or currency shock).²¹ Furthermore, in order to control for the return to the potential trend in private participation, the term $y_{i,t}^C$ is the participation gap, denoting the cyclical component of the participation flows (available total installed capacity), and is represented here by the deviations of log Capacity from an estimated HP trend with a smoothing parameter of $\lambda = 100$.²² We use the indices $L1$ and $L2$ for the parameters β associated with $\Delta y_{i,t-l}$ for $l = 1, 2$.²³ Finally, $v_{i,t+h}$ is the error term.

To sum up, our empirical strategy employs a comprehensive approach to address potential endogeneity issues in analyzing the effect of currency/inflation crises on the available power sector total installed capacity in Africa. The various controls and techniques we have employed help mitigate the potential biases that could arise from endogeneity. We have included several control variables to account for potential confounding factors (such as elevated risk premium associated with private investment in some African countries, degree of regulatory independence as it might also influence on private investor confidence, corruption, rule of law, etc.). These include the cyclical component of the dependent variable ($y_{i,t}^C$), two lags of change in the dependent variable ($\Delta y_{i,t-1}$ and $\Delta y_{i,t-2}$), and country fixed effects (α_i^h). Controlling for these factors helps reduce omitted variable bias and increases the likelihood that the estimated relationship between currency/inflation crises and power sector available total installed capacity reflects a causal effect. Indeed, the use of the Hodrick-Prescott (HP) filter to extract the cyclical component of log y (dependent variable) helps capture underlying trends and fluctuations in the data. This filtering process helps isolate the non-cyclical, long-term relationship between currency/inflation crises and available total installed capacity. Additionally, by using the propensity score based on the probit model, we are addressing potential self-selection bias and endogeneity in the treatment variable (currency/inflation crises). Including various lagged values, cyclical components, and growth rates of inflation/exchange rate in the propensity score model helps control for unobserved factors that may influence both the treatment and outcome variables. Furthermore, incorporating country fixed effects in both the propensity score model and the Augmented Inverse Probability Weighting (AIPW) model helps

²¹We approach private participation through the evolution of available total installed capacity because over the last few decades, since the beginning of the liberalisation of the electricity sector in Africa in order to cope with the budgetary difficulties of the States in financing new power plants, most of the investments on the continent have been made by private stakeholders, notably through the PPPs or IPPs.

²²The Hodrick-Prescott filter (the so-called "HP filter"), developed by economists Edward C. Prescott and Robert J. Hodrick, is used to separate business cycles (short-term fluctuations or trends) from the long-term trend.

²³ $\Delta y_{i,t-1}$ and $\Delta y_{i,t-2}$ are respectively the change in the investment flows one and two years prior to the crisis.

account for time-invariant unobserved factors at the country level that may affect both the treatment assignment and the outcome. This further strengthens the identification strategy and reduces the potential bias from unobserved heterogeneity. Finally, by clustering standard errors at the country level, we account for potential heteroscedasticity and correlation within countries. This helps provide more accurate estimates and valid hypothesis tests, especially when there might be correlated errors within the same country over time. Overall, our study's combination of clustering, control variables, cyclical component extraction, propensity score matching, and fixed effects helps enhance the internal validity of our estimates and provides a comprehensive approach to address potential endogeneity concerns. This allows us to better isolate the causal relationship between currency/inflation crises and available total installed capacity (or private participation in power generation) in Africa.

3.7 Main Results

In line with standard procedures, the propensity score used in our first stage is based on a probit model. [Figure L1](#) and [Figure L2](#) (appendix L) provide smooth kernel density estimates of the propensity score distribution for the treated and control units to check for overlap. According to [Jordà & Taylor \(2016\)](#), one way to think about overlap is to consider what the overlap would be in an ideal RCT. In this case, the empirical distributions of the propensity score for the treated and control units would be uniform and identical to each other. At the other extreme, suppose that treatment is allocated mechanically on the basis of controls. In this case, the distribution of treated units would peak at one and be zero elsewhere, and the distribution of control units would peak at zero and be zero elsewhere. In our case, both figures document considerable overlap between the distributions, indicating that we have a satisfactory first-stage model for correctly identifying ATE using the AIPW method. However, both figures also indicate that some observations are likely to have very high weights. Specifically, there are (treated) control units with propensity scores close to zero (one). The AIPW estimator has the property that high weights are compensated at the same rate by the augmentation term, which makes truncation unnecessary in our case.

We then estimate the cumulative responses and their sum at the five-year horizon.²⁴ The crisis

²⁴[Barro \(2001\)](#) and [Park et al. \(2003\)](#) suggest that the persistence of the effects of the currency crises on growth is no more than five years for instance.

dummies (inflation and currency) are our treatment variables, so we estimate only the average treatment effects. As illustrated through [Table 3.7.1](#), our main results document that the effects of inflation and currency crises on private participation (available total installed capacity) are mitigated for the group of countries that have established an independent electricity regulator compared to the countries that have not yet done so. This is especially true if regulators in these countries adopt automatic tariff adjustment mechanism and power generation cost reflectivity for operators. For countries with a regulatory agency in place, the cumulative decline over five years due to a currency crisis, in terms of available total installed capacity, is 3.36% compared to 7.58% for countries without a regulatory agency in place. The decline is twice as great for the latter. When documenting the impact of an inflation crisis, the five-year decline in available total installed capacity is only 1.67% for countries with a regulatory agency in place, compared to 5.66% for countries without an independent regulatory agency.

For regulators who have put in place an automatic tariff adjustment mechanism, the cumulative decline over five years due to a currency crisis, in terms of available total installed capacity, is 2.31% compared to 5.47% for agencies that have not adopted this measure. The decline is twice as great for the latter because it is not only a question of setting up a regulator, but above all that this regulator, once established, should put in place incentives for private stakeholders. When we document the impact of an inflation crisis, we have no decline over five years in available total installed capacity for agencies that have opted for an automatic tariff adjustment mechanism, compared to 3.23% for agencies without this measure.

When documenting the impact of a currency crisis, the five-year decline in available total installed capacity is only 1.52% for regulators that have adopted cost reflectivity, compared to 6.19% for regulators that have not. Also, when documenting the impact of an inflation crisis, the five-year decline in available total installed capacity is only 2.36% for regulators that have adopted cost reflectivity, compared to 4.18% for regulators that have not.

[Figure 3.7.1](#) displays the coefficients documented in [Table 3.7.1](#). Broadly, our results underline that inflation or currency crises have negative effects on the evolution of available total installed capacity, both in terms of year-by-year impact and in terms of the cumulative five-year period. However, the establishment of an independent regulator, which in addition develops measures such as automatic tariff adjustment mechanism and power generation cost reflectivity, significantly

Table 3.7.1: AIPW Estimates

Panel A: Average Treatment Effect of Currency Crisis on available total Installed Capacity						
	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Independent Regulatory Agency = 1	-0.43 (0.78)	0.34 (0.75)	-0.26 (0.90)	-1.22 (0.93)	-2.62** (1.07)	-3.36** (1.28)
Independent Regulatory Agency = 0	0.19 (0.30)	-0.49 (0.44)	-2.66*** (0.73)	-4.54*** (1.26)	-7.75*** (1.82)	-7.58*** (2.17)
Auto. Tariff Adjust. Mechanism = 1	-3.15 (3.45)	0.26 (3.68)	-0.54 (3.21)	-1.78 (3.39)	-2.17 (3.47)	-2.31 (3.13)
Auto. Tariff Adjust. Mechanism = 0	0.18 (0.42)	-0.67 (0.53)	-2.42*** (0.84)	-3.38*** (1.01)	-5.41*** (1.26)	-5.47*** (1.44)
Tariff Cost-Reflectivity = 1	-4.77 (3.71)	-1.62 (3.59)	0.28 (2.75)	-1.30 (2.20)	-2.20 (2.26)	-1.52 (2.12)
Tariff Cost-Reflectivity = 0	0.11 (0.45)	0.38 (0.59)	-0.50 (0.70)	-2.21*** (0.68)	-4.89*** (1.05)	-6.19*** (1.39)
Observations	1105	1064	1023	981	939	897
Panel B: Average Treatment Effect of Inflation Crisis on available total Installed Capacity						
	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Independent Regulatory Agency = 1	-0.60 (0.74)	0.11 (0.82)	-0.18 (0.78)	-1.14 (0.80)	-0.74 (0.83)	-1.67 (1.08)
Independent Regulatory Agency = 0	-0.29 (0.68)	-2.04** (0.79)	-1.76*** (0.62)	-2.71*** (0.72)	-3.58*** (0.92)	-5.66*** (1.35)
Auto. Tariff Adjust. Mechanism = 1	-3.44 (3.69)	-0.46 (4.16)	1.22 (3.97)	0.60 (3.81)	0.52 (3.71)	0.07 (3.15)
Auto. Tariff Adjust. Mechanism = 0	-0.03 (0.41)	-0.29 (0.38)	-0.79 (0.51)	-1.32 (0.80)	-2.19** (0.85)	-3.23*** (0.98)
Tariff Cost-Reflectivity = 1	-2.34 (2.25)	-0.92 (2.00)	-0.31 (1.79)	-0.62 (1.63)	-0.39 (2.28)	2.36 (2.89)
Tariff Cost-Reflectivity = 0	-0.06 (0.43)	-0.38 (0.41)	-0.93* (0.50)	-1.51* (0.80)	-2.57*** (0.84)	-4.18*** (0.83)
Observations	1100	1057	1014	970	926	882

Notes: Empirical sandwich standard errors (clustered by country) in parentheses. ***/**/* Indicates $p < 0.01/0.05/0.10$. Controls: cyclical component y^C of y , two lags of change in y , country fixed effects. y^C is the cyclical component of $\log y$, from the HP filter with $k=100$. The propensity score is based on the probit model and includes $\text{treatment}(t-1)$, current and lagged values, cyclical component, and growth rate of inflation or exchange rate depending on the model. It includes also two lags of change in inflation/exchange rate. The specification includes country fixed effects in the propensity score model and in the AIPW model.

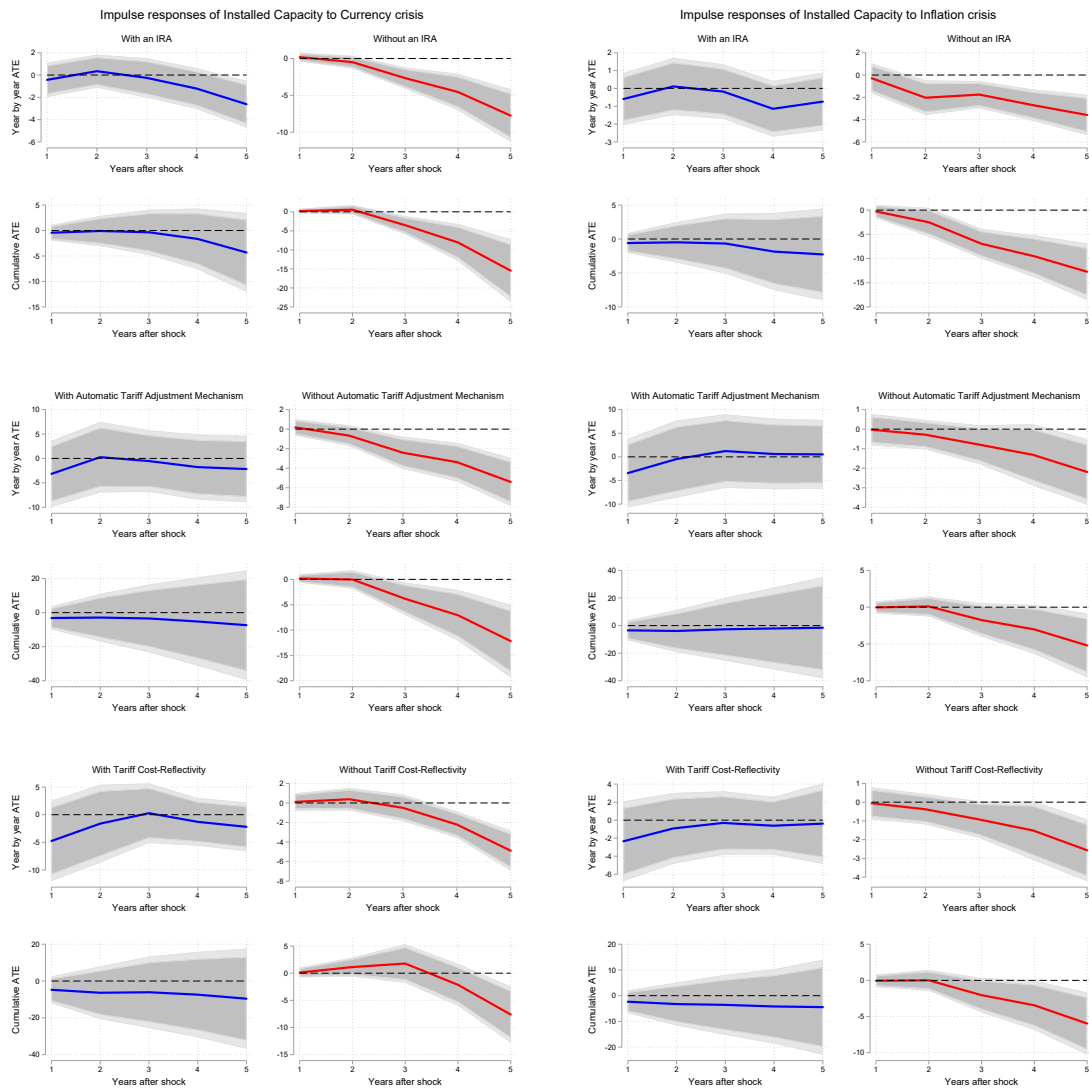


Figure 3.7.1: AIPW Estimates of the Response of the Output (Capacity), Deviations of Log Output (relative to Year 0, $\times 100$)

Notes: The accumulative ATE responses are based on $y_{t+h} - y_t$, while the accumulated ATE output decline is the running sum of the coefficients displayed in Table 3.7.1. 95% and 90% confidence bands displayed.

mitigates these negative effects.

It should also be noted that the establishment of an independent regulator is certainly necessary, but this is not sufficient to correct all the currency (-3.36% of cumulative decline over five years) and inflation (-1.67%) shocks. The implementation of an automatic tariff adjustment mechanism, for example, would reduce the impact of a currency shock to -2.31% and of inflation to +0.07%. Better still, the implementation of the cost reflectivity reduces the impact of currency shocks to only -1.52% and that of inflation to +2.36%. It should also be noted that the impact of a currency shock is on average more severe than that of an inflation shock. This could reflect the fact that

domestic wages would not be a priori indexed to inflation in most countries in Africa, so domestic inflation which does not lead to a depreciation of the exchange rate would not have necessary a considerable effect on the cost of power generation. It could also reflect the fact that the inflation-depreciation vicious cycle does not always have to be verified.

3.8 Robustness check

We test the robustness of our main findings to the new Difference-in-Differences Estimators of Intertemporal Treatment Effects proposed in [De Chaisemartin & d'Haultfoeuille \(2022\)](#). This estimation in Difference-in-Difference (DID) designs with multiple groups and periods as in our case and adds an extra layer of confidence to our study's findings. This approach helps ensure that the effects we observed regarding currency and inflation crises on private investment in the power sector are not driven by specific factors unique to our initial method. Indeed, it's always a good idea to make sure our results hold up under different methods. By applying this approach, which works well for situations with multiple groups and periods like ours, we can be more confident that what we found is truly reflecting the impact of currency and inflation crises on private investment. This robustness check helps us confirm that our original results are reliable and not just a coincidence or influenced by the specific method we initially used. It's a way of making sure our conclusions are solid and can withstand scrutiny.

Our DID results computed by using [De Chaisemartin & d'Haultfoeuille \(2022\)](#) estimator are documented in [Figure 3.8.1](#) and [Figure 3.8.2](#), which also allow us to indirectly test whether the parallel trends assumption holds. These figures document changes in available total installed capacity before and after a country experiences a crisis (currency crisis or inflation crisis). Prior to treatment, we find that available total installed capacity trends are generally similar in treated countries relative to control countries, which gives us confidence that the parallel trends assumption plausibly holds. When considering the results –without an IRA, Auto. Tariff Adjust. Mechanism, or Tariff Cost-Reflectivity– in the second columns, the post treatment effects are negative and statistically significant from time $t + 3$ onward (for most of them), confirming the earlier results that currency crisis or inflation crisis is associated with decline in available total installed capacity in Africa. Meanwhile, as in our main estimates, the post treatment effects remain non

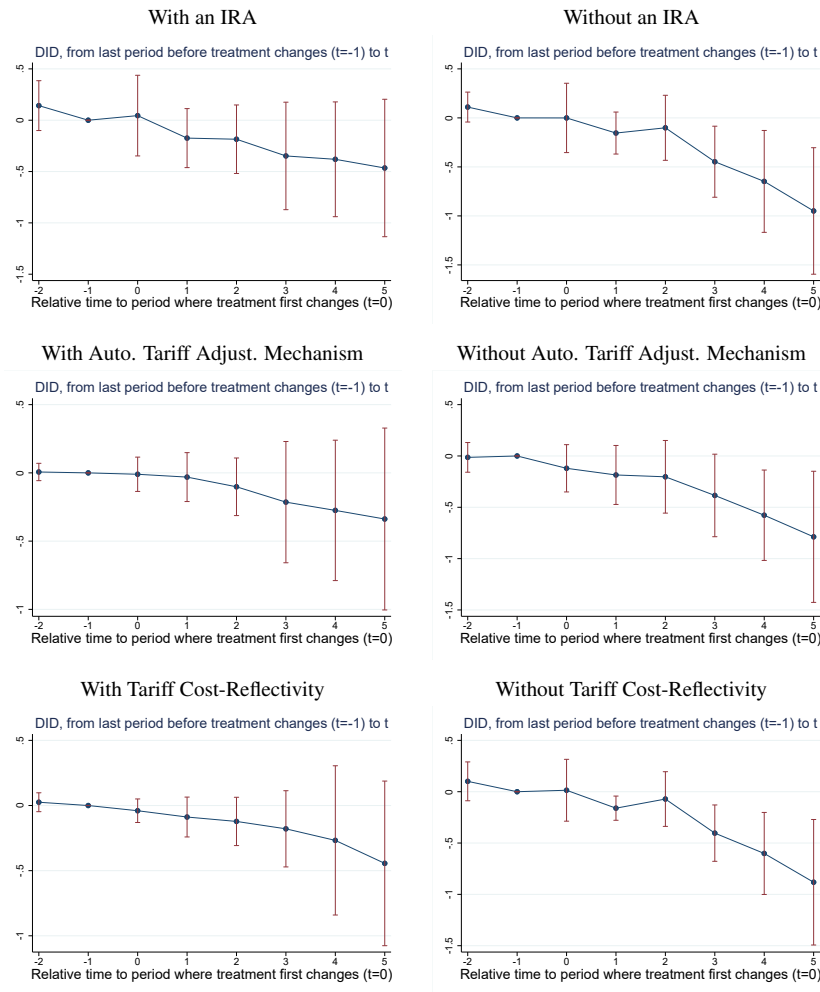


Figure 3.8.1: Robustness check using DID estimates (Currency crisis represents the treatment variable)

Notes: This graph documents point DID estimates and 95% confidence intervals of the relationship between currency crisis and available total installed capacity based on the [De Chaisemartin & d'Haultfoeuille \(2022\)](#) estimator. Standard errors are calculated using 100 bootstrap replications, clustered at the country level. We computed placebo estimators to test the non-anticipation, strong exogeneity, and parallel trends assumptions underlying the DID estimators. The estimator account for all the controls used in our baseline estimates.

significant with an IRA, Auto. Tariff Adjust. Mechanism, or Tariff Cost-Reflectivity.

3.9 Conclusion

To follow up on this literature on the relationship between regulation and investment in a global way, we focused on the African power sector and clarified what type of regulation (tariff regulation) and what type of shock it corrects (currency shock and inflation shock). First, our theoretical framework set out the ideas on how an inflation shock could give rise to a currency shock (vicious circle of inflation and depreciation), and then how these currency fluctuations impact the invest-

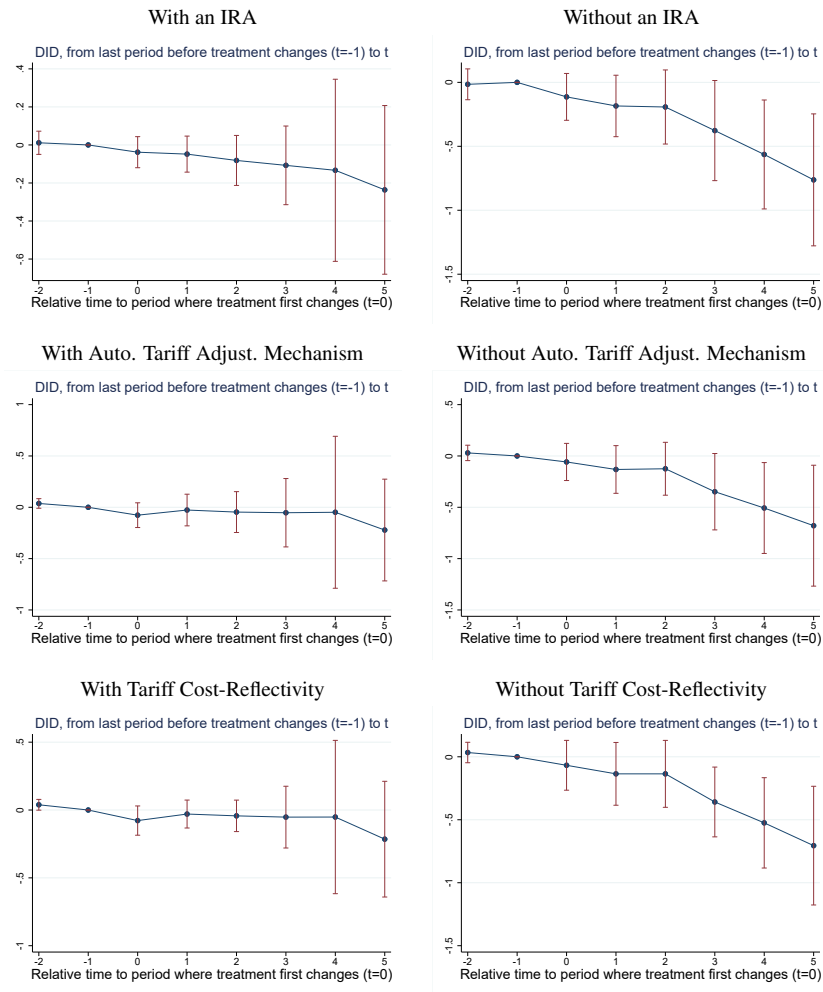


Figure 3.8.2: Robustness check using DID estimates (Inflation crisis represents the treatment variable)

Notes: This graph documents point DID estimates and 95% confidence intervals of the relationship between inflation crisis and available total installed capacity based on the [De Chaisemartin & d'Haultfoeuille \(2022\)](#) estimator. Standard errors are calculated using 100 bootstrap replications, clustered at the country level. We computed placebo estimators to test the non-anticipation, strong exogeneity, and parallel trends assumptions underlying the DID estimators. The estimator account for all the controls used in our baseline estimates.

ment decision, particularly of private stakeholders in power generation in Africa. Second, we have developed a methodology that combines impact assessment (AIPW) and local projections (LP) à la [Jordà \(2005\)](#) to capture the effect of inflation and currency crises on the evolution of available total installed capacity according to the characteristics of the electricity sectors on the African continent (existence of an independent regulatory agency, application of standard norms in terms of tariffs). We also tested the robustness of our findings to the new Difference-in-Differences Estimators of Intertemporal Treatment Effects proposed in [De Chaisemartin & d'Haultfoeuille \(2022\)](#).

To correct for potential endogeneity problems, we estimate the ATE of inflation and currency

crises by the AIPW Estimator. Broadly, our main results document that the effects of inflation and currency crises on private participation (available total installed capacity) are mitigated for the group of countries that have established an independent electricity regulator compared to the countries that have not yet done so. This mitigation effect is reinforced for countries whose regulator adopts an automatic tariff adjustment mechanism and the cost reflectivity for private operators in particular. Also, the establishment of a regulatory agency without some relevant measures cannot correct all the effects of currency and inflation shocks. Indeed, the empirical results document that cost reflectivity measures would be much more effective, followed by the automatic tariff adjustment mechanism, compared to a simple implementation of an independent regulatory agency. Finally, currency crises appear to be much more severe than inflation crises over the period of our analysis.

For the countries of the region, the authorities must imperatively ensure that domestic prices are controlled. As we have recalled in the vicious circle of inflation and depreciation, a rise in domestic prices could lead to a depreciation of the national currency against the currencies of trading partners. This, as we have documented through our theoretical framework, could penalise private stakeholders who import fixed capital (turbines, generators, etc.) and variable inputs such as fuel in their power generation process. If domestic prices cannot be controlled for structural reasons, the implementation of a fixed change regime could limit the link between domestic price increases and local currency depreciation. In the extreme case where the country is facing important exogenous shocks, which makes the fixed change regime inappropriate, then for the proper continuation of the electrification programs, as suggested by [Jamansb et al. \(2021\)](#), the authorities must imperatively put in place independent regulatory agencies which would in turn ensure that a proper tariff methodology is put in place in order to further incite the private sector to invest massively in the sector.

The authorities also should promote local production of equipment used in power generation in order to reduce foreign dependence in terms of fixed inputs. For net fossil fuel importing countries, it would be ideal to invest more in renewable energy sources in order to reduce energy bills, especially in times of currency depreciation. Finally, interconnection projects between the various power networks in the continent, for example through initiatives such as the West African Power Pool (WAPP), should be more frequent and supported by regional development institutions

such as the African Development Bank (AfDB) or the West African Development Bank (BOAD).

Finally, our findings open up promising avenues for further research and exploration in the realm of currency and inflation crises' impact on private investment in the African power sector, along with the role of regulatory bodies and other relevant structural factors, even if our empirical strategy allowed us to control for most of them. First, investigate strategies to mitigate the elevated risk premium associated with private investment in some African power sector. This could involve studying risk assessment frameworks, financial instruments, and innovative risk-sharing mechanisms that can help attract and retain investors even in the face of currency and inflation crises. Second, explore the feasibility and potential benefits of developing small-scale and decentralized power systems. Investigate how these systems can offer resilience against economic shocks, contribute to local development, and provide a pathway for increased private investment in regions with heightened risk profiles. Third, conduct in-depth analyses on the degree of regulatory independence and its influence on private investor confidence. Research avenues might include empirical studies evaluating how regulatory autonomy correlates with investment outcomes and exploring regulatory best practices that promote investor trust. Fourth, investigate the complex link between corruption, rule of law, and private investment in the sector. Examine how corruption hampers investment, the role of effective institutions in curbing corruption, and potential policy interventions to create a more conducive investment environment. Finally, undertake a comprehensive comparative analysis of the factors contributing to Latin America's relative attractiveness for private investment compared to Africa. Investigate policy frameworks, regulatory practices, geopolitical considerations, and market conditions that distinguish the two regions and inform strategies for enhancing Africa's investment appeal. To sum up, by pursuing these research avenues, we can build upon our existing findings and contribute to a more comprehensive understanding of the complex dynamics shaping private investment in the African power sector. These avenues offer opportunities to uncover practical insights, inform policy decisions, and contribute to the broader discourse on sustainable energy development and investment in the region.

3.10 Acknowledgment

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. It has been presented at the 43rd IAEE (International Association for Energy Economics) International conference: Mapping the Energy Future -Voyage in Uncharted Territory- in August 2022 (Tokyo, Japan). We thank the participants for their valuable comments.

Bibliography

- Ahmad, J. (1984), The vicious circle of inflation and depreciation, *in* 'Floating Exchange Rates and World Inflation', Springer, pp. 143–162.
- Aizenman, J. (1992), 'Exchange rate flexibility, volatility, and domestic and foreign direct investment', *Staff Papers* **39**(4), 890–922.
- Andres, L. A., Guasch, J. L. & Straub, S. (2007), 'Do regulation and institutional design matter for infrastructure sector performance?', *World Bank Policy Research Working Paper* (4378).
- Andrés, L. A., Schwartz, J. & Guasch, J. L. (2013), *Uncovering the drivers of utility performance: Lessons from Latin America and the Caribbean on the role of the private sector, regulation, and governance in the power, water, and telecommunication sectors*, World Bank Publications.
- Atsebi, J.-M. B., Combes, J.-L. & Minea, A. (2019), 'The trade costs of financial crises'.
- Barro, R. J. (2001), 'Economic growth in east asia before and after the financial crisis'.
- Barro, R. J. (2013), 'Inflation and economic growth.', *Annals of Economics & Finance* **14**(1).
- Bergara, M. E., Henisz, W. J. & Spiller, P. T. (1998), 'Political institutions and electric utility investment: A cross-nation analysis', *California management review* **40**(2), 18–35.
- Bertoméu-Sánchez, S., Camos, D. & Estache, A. (2018), 'Do economic regulatory agencies mat-

- ter to private-sector involvement in water utilities in developing countries?', *Utilities policy* **50**, 153–163.
- Blagrave, P. & Furceri, D. (2021), 'The macroeconomic effects of electricity-sector privatization', *Energy Economics* **100**, 105245.
- Carvalho, P., Marques, R. C. & Berg, S. (2012), 'A meta-regression analysis of benchmarking studies on water utilities market structure', *Utilities Policy* **21**, 40–49.
- Cubbin, J. & Stern, J. (2005), *Regulatory effectiveness and the empirical impact of variations in regulatory governance: Electricity industry capacity and efficiency in developing countries*, Vol. 3535, World Bank Publications.
- Cubbin, J. & Stern, J. (2006), 'The impact of regulatory governance and privatization on electricity industry generation capacity in developing economies', *The World Bank Economic Review* **20**(1), 115–141.
- Darby, J., Hallett, A. H., Ireland, J. & Piscitelli, L. (1999), 'The impact of exchange rate uncertainty on the level of investment', *The Economic Journal* **109**(454), 55–67.
- De Chaisemartin, C. & d'Haultfoeuille, X. (2022), Difference-in-differences estimators of intertemporal treatment effects, Technical report, National Bureau of Economic Research.
- Eberhard, A., Gratwick, K., Morella, E. & Antmann, P. (2016), *Independent power projects in Sub-Saharan Africa: Lessons from five key countries*, World Bank Publications.
- Estache, A., Baldwin, R., Cave, M., Lodge, M. et al. (2010), Regulation in developing economics: A survey of theory and evidence, Technical report, ULB–Université Libre de Bruxelles.
- Foster, V., Witte, S. H., Banerjee, S. G. & Vega Moreno, A. (2017), 'Charting the diffusion of power sector reforms across the developing world', *World Bank Policy Research Working Paper* (8235).
- Frankel, J. A. & Rose, A. K. (1996), 'Currency crashes in emerging markets: An empirical treatment', *Journal of international Economics* **41**(3-4), 351–366.
- Gassner, K., Popov, A. A. & Pushak, N. (2009), *Does private sector participation improve performance in electricity and water distribution?*, Vol. 6, World Bank Publications.

- Glynn, A. N. & Quinn, K. M. (2010), 'An introduction to the augmented inverse propensity weighted estimator', *Political analysis* **18**(1), 36–56.
- Goldberg, L. S. (1993), 'Exchange rates and investment in united states industry', *The review of economics and statistics* pp. 575–588.
- Gross, R., Blyth, W. & Heptonstall, P. (2010), 'Risks, revenues and investment in electricity generation: Why policy needs to look beyond costs', *Energy Economics* **32**(4), 796–804.
- Harchaoui, T., Tarkhani, F. & Yuen, T. (2005), The effects of the exchange rate on investment: Evidence from canadian manufacturing industries, Technical report, Bank of Canada.
- Hawdon, D. (1996), 'Performance of power sectors in developing countries-a study of efficiency and world bank policy using data development analysis'.
- Hochman, S. & Palmon, O. (1983), 'The irrelevance of capital structure for the impact of inflation on investment', *The Journal of Finance* **38**(3), 785–794.
- Imam, M., Jamasb, T. & Llorca, M. (2019), 'Political economy of reform and regulation in the electricity sector of sub-saharan africa'.
- Imbens, G. W. (2004), 'Nonparametric estimation of average treatment effects under exogeneity: A review', *Review of Economics and statistics* **86**(1), 4–29.
- Izaguirre, A. K. (1998), 'Private participation in the electricity sector: recent trends'.
- Jamasb, T., Llorca, M., Khetrapal, P. & Thakur, T. (2021), 'Institutions and performance of regulated firms: Evidence from electricity distribution in india', *Economic Analysis and Policy* **70**, 68–82.
- Jamil, M. H., Ullah, K., Saleem, N., Abbas, F. & Khalid, H. A. (2022), 'Did the restructuring of the electricity generation sector increase social welfare in pakistan?', *Renewable and Sustainable Energy Reviews* **157**, 112017.
- Jordà, Ò. (2005), 'Estimation and inference of impulse responses by local projections', *American economic review* **95**(1), 161–182.
- Jordà, Ò. & Taylor, A. M. (2016), 'The time for austerity: estimating the average treatment effect of fiscal policy', *The Economic Journal* **126**(590), 219–255.

- Kiyota, K. & Urata, S. (2004), 'Exchange rate, exchange rate volatility and foreign direct investment', *World Economy* **27**(10), 1501–1536.
- Koo, J., Yoon, G.-S., Hwang, I. & Barnerjee, S. G. (2013), 'A pitfall of private participation in infrastructure: a case of power service in developing countries', *The American review of public administration* **43**(6), 674–689.
- Kydland, F. E. & Prescott, E. C. (1982), 'Time to build and aggregate fluctuations', *Econometrica: Journal of the Econometric Society* pp. 1345–1370.
- Laffont, J.-J. & Tirole, J. (1993), 'A theory of incentives in regulation and procurement'.
- Lanot, G. & Vesterberg, M. (2021), 'The price elasticity of electricity demand when marginal incentives are very large', *Energy Economics* **104**, 105604.
- Lunceford, J. K. & Davidian, M. (2004), 'Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study', *Statistics in medicine* **23**(19), 2937–2960.
- Madsen, J. B. (2003), 'Inflation and investment', *Scottish Journal of Political Economy* **50**(4), 375–397.
- Nucci, F. & Pozzolo, A. F. (2001), 'Investment and the exchange rate: An analysis with firm-level panel data', *European Economic Review* **45**(2), 259–283.
- Pargal, S. (2003), 'Regulation and private sector participation in infrastructure', *The limits of stabilization: infrastructure, public deficits, and growth in Latin America* pp. 171–97.
- Park, Y. C., Lee, J.-W. et al. (2003), 'Recovery and sustainability in east asia', *NBER Chapters* pp. 275–320.
- Parker, D. & Kirkpatrick, C. (2012), 'Measuring regulatory performance', *The economic impact of*.
- Rosenbaum, P. R. & Rubin, D. B. (1983), 'The central role of the propensity score in observational studies for causal effects', *Biometrika* **70**(1), 41–55.
- Rubino, A. & Cuomo, M. (2015), 'A regulatory assessment of the electricity merchant transmission investment in eu', *Energy Policy* **85**, 464–474.

- Servén, L. (2003), 'Real-exchange-rate uncertainty and private investment in Idcs', *Review of Economics and Statistics* **85**(1), 212–218.
- Trujillo, L., Martin, N., Estache, A. & Campos, J. (2002), *Macroeconomic effects of private sector participation in Latin America's infrastructure*, Vol. 2906, World Bank Publications.
- Wallsten, S. (2002), 'Does sequencing matter? regulation and privatization in telecommunications reforms', *Regulation and Privatization in Telecommunications Reforms (February 2002)* .
- Wallsten, S. J. (2001), 'An econometric analysis of telecom competition, privatization, and regulation in africa and latin america', *The Journal of industrial economics* **49**(1), 1–19.
- Zhang, Y.-F., Parker, D. & Kirkpatrick, C. (2008), 'Electricity sector reform in developing countries: an econometric assessment of the effects of privatization, competition and regulation', *Journal of regulatory Economics* **33**(2), 159–178.

Appendices

K Private participation in power sector in selected African countries

Table K1: Private sector share of installed capacity available in 2016 in 20 African countries

<i>Country</i>	<i>Capacity (MW)</i>	<i>IPP's share (%)</i>
Cabo verde	100	20
Cameroon	1,300	24
Côte d'Ivoire	1,900	52
Gambia	100	43
Ghana	3,800	18
Kenya	2,200	25
Madagascar	500	10
Mauritius	800	39
Mozambique	2,700	10
Namibia	600	2
Nigeria	4,900	31
Rwanda	200	34
Senegal	900	32
South Africa	50,200	11
Swaziland	200	23
Tanzania	1,600	19
Togo	200	49
Uganda	900	49
Zambia	2,600	15
Zimbabwe	2,100	6
Total	77,800	25.6

Proparco, IEA, WEO 2016

L Kernel density

L.1 Inflation Crisis

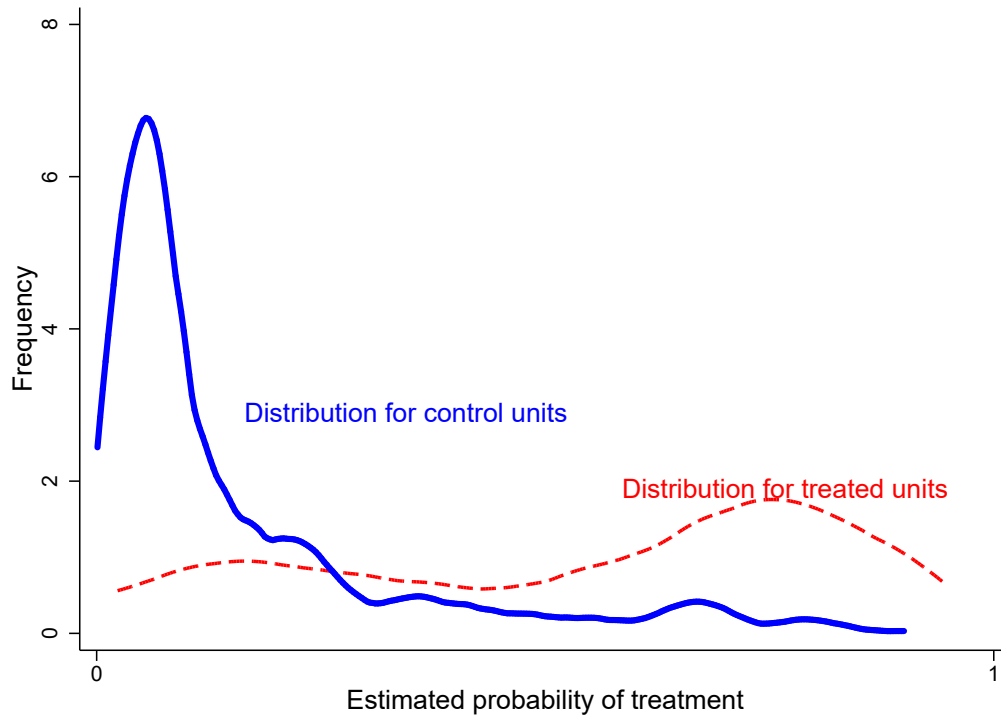


Figure L1: Kernel density of the distribution of the propensity scores for the treated and control groups (Inflation Crisis)

Notes: The propensity score is based on the probit model and includes treatment($t - 1$), current and lagged values, cyclical component, and growth rate of exchange rate. It includes also two lags of change in exchange rate and the country fixed effects. The figure documents the predicted treatment probabilities with a dashed line for the treatment observations and a solid line for the control observations.

L.2 Currency Crisis

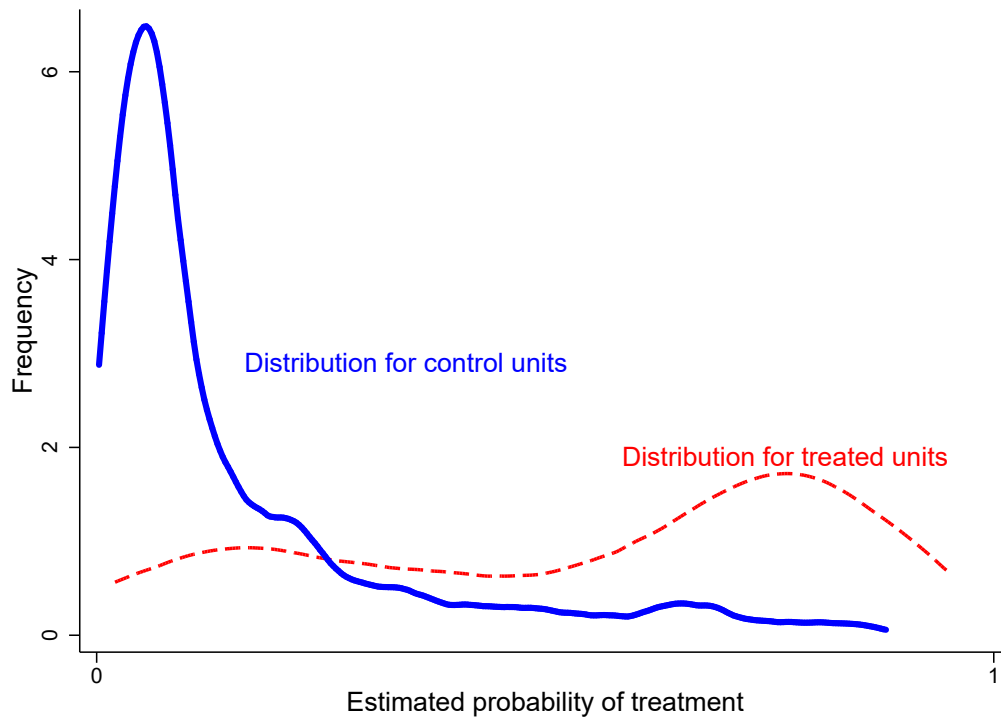


Figure L2: Kernel density of the distribution of the propensity scores for the treated and control groups (Currency Crisis)

Notes: The propensity score is based on the probit model and includes treatment($t - 1$), current and lagged values, cyclical component, and growth rate of inflation. It includes also two lags of change in inflation and the country fixed effects. The figure documents the predicted treatment probabilities with a dashed line for the treatment observations and a solid line for the control observations.

Power Constraints and Firm-Level Total Factor Productivity in Developing Countries

This chapter is a joint work with Ablam Estel Apeti. A version of this paper is published under the reference: Apeti, Ablam Estel & Ly, Alpha, 2023. "Power Constraints and Firm-Level Total Factor Productivity in Developing Countries," *Policy Research Working Paper Series 10510*, The World Bank.

4.1 Introduction

Low levels of infrastructure development and poor quality services within a country can increase production costs for domestic firms and divert their technological choices to sub-optimal solutions. This reduces their level of competitiveness compared to foreign competitors in general. Furthermore, the economic literature suggests that better power infrastructure significantly stimulates economic growth and improves a range of development outcomes. However, in developing countries, firms generally have difficulty connecting to the power grid or, when they are connected, they face frequent scheduled or unscheduled power outages ([Alam 2013](#)). Voltage fluctuations and the frequency of power outages therefore lead to material losses and have a negative effect on

manufacturing costs and production.

As drivers of economic growth, a major part of the firms in these developing countries cite power as the major obstacle or one of the main constraints to their activities (Asiedu et al. 2021). Indeed, power is the second most important constraint after access to finance. Two regions are particularly affected, namely South Asia and Sub-Saharan Africa. In fact, about 45.9% of firms in Sub-Saharan Africa and 41.2% of firms in South Asia report that power is a major or severe constraint to their operations. The issue of power thus appears to be of greater concern to these firms than many other issues such as corruption and transport in most of these regions.

Given the major role of manufacturing firms in developing countries and the gradual improvement of firm-level data availability and quality, a recent literature is emerging on the empirical assessment of the effect of power constraints on firms' performance.¹ However, this literature on power constraints and firms' productivity is still scarce and the results remain rather inconsistent when compared to each other. For example, some studies find a statistically significant negative effect of these constraints on the performance of firms (Hardy & McCasland 2021; Abeberese et al. 2021), other studies find a statistically significant but weak effect (Grainger & Zhang 2017) and still others do not find a statistically significant relationship between these power obstacles and the productivity of firms (Scott et al. 2014). This lack of consistency in the previous results from the literature could reflect the potential limitations of the different empirical approaches adopted in this literature so far. For example, Xiao et al. (2022) consider power outages or constraints as a completely exogenous explanatory variable. Meanwhile, authors like Fisher-Vanden et al. (2015); Allcott et al. (2016); Cole et al. (2018) or Elliott et al. (2021) consider this variable as potentially endogenous and propose an instrumental variables technique based on variations in the power supply from hydroelectric generation as an instrument.

The aim of this study is to empirically investigate the impact of power constraints on the productivity and competitiveness of manufacturing firms in developing countries. By analyzing the relationship between power constraints and firms' performance, this research seeks to contribute to a better understanding of the role that power constraints play in hindering or shaping the economic growth and development outcomes of these firms. In pursuit of this aim, this analysis establishes

¹In the rest of this paper, the terms "power constraints" and "energy constraints" are used interchangeably. These terms refer to limitations on the total amount of energy (measured in watt-hours or kilowatt-hours) that can be generated, stored, or consumed over a specific period.

four key objectives. First, assess the extent to which power constraints affect the productivity and competitiveness of manufacturing firms in developing countries. Second, examine the variations in the impact of power constraints based on the severity of the constraints they experience. Third, investigate potential mechanisms through which power constraints influence firms' performance. Finally, explore potential heterogeneity in the effects of power constraints based on the level of economic development and geographical regions of the countries under study. In other words, how do power constraints influence the productivity and competitiveness of manufacturing firms in developing countries? How does the impact of power constraints on manufacturing firms' productivity and competitiveness vary based on the severity of the constraints they experience? What are the potential pathways through which power constraints affect firms' productivity? How do the effects of power constraints on manufacturing firms' performance vary across different levels of economic development and geographical regions within the countries under study? By addressing these research questions, this study aims to contribute to the existing literature by providing a more nuanced understanding of the complex relationship between power constraints and the performance of manufacturing firms in developing countries. The findings will offer valuable insights for policymakers, stakeholders, and researchers striving to promote sustainable economic growth and development in regions facing severe power constraints.

This paper contributes to the empirical literature on the potential effects of power outages or constraints on firm-level TFP by proposing a new matching-based approach (Entropy Balancing) and by extending the previous results from the literature to the degree of severity of the power constraints. First, contrary to [Xiao et al. \(2022\)](#) who present the power outages variable as an exogenous energy shock, we document statistically that the outages treatment variable is not random for manufacturing firms in developing countries. Second, in order to compensate for the limits linked to the instrumentation technique by the hydroelectric variable in some analysis of this literature (as in [Fisher-Vanden et al. 2015](#); [Allcott et al. 2016](#); [Cole et al. 2018](#); [Elliott et al. 2021](#)) and to properly account for potential endogeneity with respect to exposure to power constraints, but also to address the lack of a balanced panel structure (survey data), we use a matching-based approach (Entropy Balancing). Our analysis is based on the idea that exposure to constraints represents a treatment. The firms exposed to the constraints constitute the treatment group, the unexposed firms constitute a potential control group. Third, we establish a strong link between

the severity of self-reported power constraints or obstacles by firms (minor, moderate, major, severe, and biggest) and the magnitude of productivity loss for firms. In other words, the greater the level of power constraints self-reported by a firm, the greater the effect of these constraints on its productivity, and vice versa.

Broadly, our approach documents that the overall effect of power outages on revenue-based total factor productivity (TFPR) is negative and statistically significant. Additionally, we document that other mechanisms such as the acquisition of back-up generators, or investment in R&D allow firms to fight against the severe constraints encountered in the power sector. We also document that constraints in the power sector affect firm's revenue-based total factor productivity mainly through the channel of non-optimal reorganization of firm's operations (reduced capacity utilization) and through the channel of production losses due to power outages.

The rest of the paper is as follows: the literature review in section 4.2, the theoretical framework in section 4.3, empirical strategy and data in section 4.4, empirical results in section 4.5, robustness, heterogeneity and mechanisms in section 4.6, and section 4.7 concludes.

4.2 Related literature

Some analyses have focused on the effect of inputs market constraints on productivity (Prescott 2002; Hsieh & Klenow 2009; Jones 2011). These analyses suggest that input market constraints prevent the achievement of an efficient allocation of resources, thus reducing total factor productivity. In the same vein, Brandt et al. (2013) find that TFP losses due to input market constraints are still high in many countries. More specifically in our field of research, energy market constraints are also assessed. Indeed, Shi & Sun (2017) find that energy price instability negatively affects output growth in the short and long run. As for Bernanke (1983), he documents that uncertainty about energy prices can induce firms to postpone their investment decisions, thus leading to a decline in overall output. Similarly, Elder & Serletis (2009) suggest that oil price uncertainty may tend to reinforce the negative response of production to oil shocks. Finally, Cheng et al. (2019) document that an increase in oil price volatility reduces real GDP and investment, while a decrease stimulates the economy.

With respect to power sector constraints, Cole et al. (2018) find that power outages have a

negative and significant effect on firm's sales in 14 African countries. The effect found is larger when endogeneity is taken into account.² They also find that power outages affect firm's profits and total factor productivity. Furthermore, also using a hydro-instrumental variable strategy, [Elliott et al. \(2021\)](#) document that Vietnamese firms with less reliable power have lower productivity in 2005 and 2015. They conclude that reducing the length of power outages by 1% would have increased overall revenues by 4.66 billion USD. In the same line of instrumental variables, [Allcott et al. \(2016\)](#) also use changes in power supply from hydroelectric generation as an instrument to estimate the effect of power outages on the Indian manufacturing sector. Finally, a similar approach is taken by [Fisher-Vanden et al. \(2015\)](#) who examine the effects of power outages on firm's performance in China.

Meanwhile, the economic literature remains relatively well-supplied on the other common determinants of firm-level performance. Among these determinants, we can mention international development aid, financial inclusion, bank concentration, financial innovation, inflation, or taxation. International aid is a key factor in improving the performance of firms by alleviating infrastructure and financing constraints in developing countries. In this sense, [Chauvet & Ehrhart \(2018\)](#) find a positive effect of foreign aid on the growth of firms' sales. Furthermore, [Chauvet & Jacolin \(2017\)](#) find that financial inclusion, i.e. the distribution of financial services in firms, has a positive effect on firm's growth. This positive effect is amplified when there is greater competition between banks. In the same vein, [Lee et al. \(2020\)](#) document that financial inclusion helps firms to increase their sales growth. On the other hand, they paradoxically find that financial innovation has a negative effect on the growth rate of firms' sales. In their paper, [Bambe et al. \(2022\)](#) document that inflation targeting increases the growth and productivity of firms in targeted countries compared to non-targeted countries. Indeed, inflation targeting improves the performance of developing countries by reducing the level and volatility of inflation ([Lin & Ye 2009](#)). Finally, [Chauvet & Ferry \(2021\)](#) document that tax revenues boost the performance of firms through the financing of essential infrastructure for business development.

In this paper, we mainly contribute to this literature on the effects of power outages or constraints by proposing a new matching-based approach (Entropy Balancing) and by extending the previous results from the literature to the degree of severity of the power constraints.

²Use of a hydro-instrumental strategy.

4.3 Theoretical framework

The main purpose of this theoretical framework is twofold. First, we highlight the difficulty of directly drawing conclusions about how energy shocks would affect firm-level total factor productivity from a theoretical framework. The second main objective is to establish theoretically that productivity loss increases with the severity of energy constraints facing manufacturing firms.

Although some of the studies in this literature point out that economic growth, for instance, decreases in the event of an energy shock (Cheng et al. 2019; Sadorsky 1999), we document in this theoretical framework that this could have rather contrasting effects on the total factor productivity of manufacturing firms depending on the market structure. Since power constraints are an important manifestation of input market distortion, our theoretical framework is closely related to the literature on the relationship between input market distortion and firm-level total factor productivity.

This theoretical framework of intermediate goods and output price adjustment caused by an energy shock is based on that of Hsieh & Klenow (2009) and Xiao et al. (2022). We derive the expression for total factor productivity at the firm-level and document the effect of energy shocks on firm-level TFP.

We assume monopolistic competition with heterogeneous firms that face different degrees of energy constraints. Indeed, there are several reasons why we consider power constraints to be firm-specific rather than sector-specific in this framework. First, the power infrastructure of a country or region can vary considerably in terms of reliability and quality. Some firms may be located in areas with better power infrastructure, while others may suffer frequent constraints like outages due to inadequate infrastructure or maintenance. Second, some firms may have invested in backup generators or alternative power sources to mitigate the impact of power constraints. These firms would be less affected by general disruptions to the power supply than those without such back-up systems. Third, firms in the same sector may have different operational requirements and production processes. Some firms may be highly dependent on a continuous power supply, such as those involved in refrigeration or other electricity-intensive operations. On the other hand, some firms may have more flexible production processes that can adapt to temporary power supply interruptions. Finally, firms may adopt different mechanisms to cope with power constraints. For

instance, some firms may adjust their production schedules, switch to off-peak hours or implement energy-saving measures during outages, helping them to minimize the negative impact of power disruptions.

In a fully competitive final output market, there is a single final product Y , and it is aggregated from the output Y_s of S manufacturing industries (or branches) by the following production function:

$$Y = \prod_{s=1}^S Y_s^{\theta_s}, \text{ where } \sum_{s=1}^S \theta_s = 1 \quad (4.3.1)$$

where θ_s is an output elasticity parameter for industry s . Minimizing production costs implies:

$$P_s Y_s = \theta_s P Y \quad (4.3.2)$$

P_s is the price of the output Y_s of the industry s , and the price of the final product is $P \equiv \prod_{s=1}^S \left(\frac{P_s}{\theta_s} \right)^{\theta_s}$.

The output Y_s of the industry s is the CES aggregate of M_s types of differentiated products:

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad (4.3.3)$$

where σ is the elasticity of substitution between the differentiated products within the industry s .

The production function of each differentiated product is given by a Cobb-Douglas function of the firm's TFP and three production inputs, including capital, labor and energy:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} E_{si}^{1-\alpha_s-\beta_s} \quad (4.3.4)$$

where α_s denotes the capital share of industry s , β_s denotes the labor share of industry s , $(1 - \alpha_s - \beta_s)$ denotes the share of intermediate products or the share of energy of industry s , and A_{si} denotes the level of TFP of firm i . Note also that this framework allows input shares to differ between different industries but not between firms in the same industry.

The profit maximization program for monopolistically competitive firms with respect to K_{si} , L_{si} ,

and E_{si} is as follows:

$$\begin{aligned} \max \pi_{si} &= P_{si}Y_{si} - rK_{si} - wL_{si} - (1 + \tau_{E_{si}})P_E E_{si} \\ \text{s.t. } Y_{si} &= A_{si}K_{si}^{\alpha_s}L_{si}^{\beta_s}E_{si}^{1-\alpha_s-\beta_s} \end{aligned} \quad (4.3.5)$$

where r represents the price of capital, w represents the labour cost, P_E represents the cost of intermediate inputs, i.e. energy. $\tau_{E_{si}}$ represents the energy constraints (increase in the cost of energy, power outages leading to additional costs for back-up generators, increase in losses for firms, etc.) facing a representative firm i .

The maximization of the profit (Equation 4.3.5) using the Lagrangian method of optimization combined with the first order conditions yields:

$$\left\{ \begin{aligned} \lambda A_{si} \alpha_s K_{si}^{\alpha_s-1} L_{si}^{\beta_s} E_{si}^{1-\alpha_s-\beta_s} - r &= 0 \quad \text{where } \lambda = \frac{\sigma-1}{\sigma} P_{si} \end{aligned} \right. \quad (4.3.6)$$

$$\left\{ \begin{aligned} K_{si} &= \frac{w}{r} \frac{\alpha_s}{\beta_s} \times L_{si} \end{aligned} \right. \quad (4.3.7)$$

$$\left\{ \begin{aligned} E_{si} &= \frac{w}{P_E} \frac{1-\alpha_s-\beta_s}{\beta_s} \frac{1}{(1+\tau_{E_{si}})} \times L_{si} \end{aligned} \right. \quad (4.3.8)$$

By substituting Equation 4.3.7 and Equation 4.3.8 into Equation 4.3.6, we obtain the standard condition that the firm's output price is a fixed markup over its marginal cost (r , w , P_E):

$$P_{si} = \frac{\sigma}{\sigma-1} \left(\frac{r}{\alpha_s} \right)^{\alpha_s} \left(\frac{w}{\beta_s} \right)^{\beta_s} \times \left(\frac{P_E}{1-\alpha_s-\beta_s} \right)^{1-\alpha_s-\beta_s} \times \frac{(1+\tau_{E_{si}})^{1-\alpha_s-\beta_s}}{A_{si}} \quad (4.3.9)$$

The output price is increasing with the energy constraints $\tau_{E_{si}}$ facing the representative firm. Under the assumption that the output price increases with the level of energy constraint facing the representative firm, this could lead to a generalized price increase in the output market if a significant number of firms face energy constraints in the economy. Indeed, many analyses point out that energy shocks generate output prices adjustment by producers in the economy (Barth III & Ramey 2001; Bodenstein et al. 2011; Choi et al. 2017).³ This is called cost-push inflation or output market distortion. Depending on the strength of the interactions between the different sectors of the economy, a distortion of the output market as a result of energy constraints may lead to distortions

³For example, for Choi et al. (2017), a 10% increase in international oil prices raises inflation by 0.4 percentage points on average.

of the labor, capital and even energy markets again, thus leading to a dangerous vicious circle.

Now, let us recall our definition of the TFP. We opted for the revenue-based TFP (TFPR). Here, the TFP is measured by revenue productivity or revenue-based productivity such that $\text{TFPR}_{si} = A_{si}P_{si}$ (as in [Hsieh & Klenow 2009](#)). From [Equation 4.3.9](#), we can therefore express the TFPR_{si} of firm i in the sector s as follows:

$$\text{TFPR}_{si} = \frac{\sigma}{\sigma - 1} \left(\frac{r}{\alpha_s} \right)^{\alpha_s} \left(\frac{w}{\beta_s} \right)^{\beta_s} \times \left(\frac{P_E}{1 - \alpha_s - \beta_s} \right)^{1 - \alpha_s - \beta_s} \times (1 + \tau_{E_{si}})^{1 - \alpha_s - \beta_s} \quad (4.3.10)$$

The analysis of the effect of energy constraints $\tau_{E_{si}}$ on [Equation 4.3.10](#) revenue-based TFP leads to:

$$\frac{\partial \text{TFPR}_{si}}{\partial \tau_{E_{si}}} = \frac{\sigma}{\sigma - 1} \left(\frac{r}{\alpha_s} \right)^{\alpha_s} \left(\frac{w}{\beta_s} \right)^{\beta_s} \times \left(\frac{P_E}{1 - \alpha_s - \beta_s} \right)^{1 - \alpha_s - \beta_s} \times \frac{1 - \alpha_s - \beta_s}{(1 + \tau_{E_{si}})^{\alpha_s + \beta_s}} \quad (4.3.11)$$

Based on the value taken by the elasticity of substitution σ in monopolistic competition, the final expression obtained in [Equation 4.3.11](#) is either negative (when $\sigma < 1$), positive (when $\sigma > 1$), or indefinite (when $\sigma \rightarrow 1$). Therefore, it is not possible to draw here any conclusion about how energy shocks would affect total factor productivity at the firm-level from a theoretical perspective (H_1). That means for instance, the analysis of the effect of power constraints on the productivity of firms thus remains an empirical question that we document in the next section [4.4](#).

Furthermore, as the $\lim_{\tau_{E_{si}} \rightarrow +\infty} \frac{\partial \text{TFPR}_{si}}{\partial \tau_{E_{si}}}$ converges toward zero, we can also hypothesize that the greater the energy constraints facing firms ($\tau_{E_{is}}$ is large), the more the reverse effects of power constraints on TFP are significant (H_2). For instance, this would mean that the greater the level of power constraints faced by a firm, the greater the effect of these constraints on its productivity, and vice versa.

The main purpose of our following empirical approach is to test these two main hypotheses (H_1 and H_2) put forward through this theoretical framework.

4.4 Empirical strategy and data

4.4.1 Empirical strategy

One of the main challenges in quantifying the effect of power sector constraints on firm's performance is that facing or not power constraints might be non-random (Alam 2013; Cole et al. 2018; Elliott et al. 2021). Indeed, the power constraints faced by firms in a country can be explained by the macroeconomic/institutional phenomena of the country in question (low quality of regulation, lack of financing, political instability, etc.) and/or firm's characteristics such as size, maturity, quality of management or even ownership (public or private, domestic or foreign). These realities can also explain the low level of performance of firms operating in that country. Even within the same country, we can mention targeted public investment in energy infrastructure near the best performing firms to support their operations, and public investment in infrastructure (roads and railways) that can both improve the reliability of power supply (ease of maintenance of power transmission lines) and the transportation of products for firms.

To deal with this identification issue, some authors in this literature have opted for the instrumental variables technique based on variations in the power supply from hydroelectric generation as an instrument (Fisher-Vanden et al. 2015 in China; Allcott et al. 2016 in India; Cole et al. 2018 in 14 selected Sub-Saharan African countries; Elliott et al. 2021 in Vietnam). Meanwhile, we believe that this identification strategy might potentially have three major limitations:

First, it is not applicable to a larger sample, as not all countries have an energy mix based mainly on hydropower. As a result, studies using this identification strategy frequently focus on a single country, or on a small number of countries similar in terms of energy mix mainly based on hydro-generation of the electricity, thus reducing the external validity of their conclusions.

The second and more fundamental limitation might be that very often, these countries that are largely dependent on hydro-generation set up substitute generators or fossil power plants ready to take over following the fluctuations in dam water (climate shocks). This reality could cut the link between hydro-generation (the instrument) and power constraints (treatment). The validity of this type of instrument would therefore be partly questioned.

Finally, even when a valid instrument is available, the fact that the exposure to the treatment is non-random could result in poor estimates when using an instrumental variable strategy approach,

as pointed out by [Ertefaie et al. \(2016\)](#) and [Canan et al. \(2017\)](#), who stress the relevance of the matching approach in the presence of this specific source of endogeneity.

So, to overcome these potential limitations described above and to properly account for potential endogeneity issue with respect to exposure to power constraints, but also to address the lack of a balanced panel structure (survey data), we propose a matching-based approach (Entropy Balancing). Our analysis is based on the idea that exposure to constraints represents a treatment. Firms exposed to the constraints constitute the treatment group, while firms not exposed constitute a potential control group. The average treatment effect on treated firms (ATT) is defined as follows:

$$\tau_{\text{ATT}} = E[y(1) | T = 1] - E[y(0) | T = 1] \quad (4.4.1)$$

$y(\cdot)$ is the outcome variable (the TFPR). T indicates whether a unit or firm is exposed to treatment/constraints ($T = 1$) or not ($T = 0$). Therefore, $E[y(1) | T = 1]$ is the expected outcome after treatment and $E[y(0) | T = 1]$ is the counterfactual outcome, i.e. the outcome that a unit exposed to treatment would have obtained if it had not experienced to treatment. As the counterfactual outcome is not observable, we need an appropriate proxy to identify the ATT. If the treatment is randomly assigned, then the average outcome of the units not exposed to the treatment, $E[y(0) | T = 0]$, is an appropriate proxy. However, as we saw earlier, exposure to the constraints and hence selection into the treatment could be endogenous due to the potential confounding factors we mentioned earlier.

The idea of matching-based estimators is to mimic randomization with respect to treatment assignment. The unobserved counterfactual outcome is imputed by matching treated units with untreated units that are as similar as possible with respect to all observable characteristics that: (i) are associated with selection into treatment (i.e. the probability of being exposed to constraints), and (ii) influence the outcome of interest. The realizations of the productivity gap measure for these matches are then used as an empirical proxy for the unobserved counterfactual. Formally, the matching-based ATT estimate is defined as follows:

$$\tau_{\text{ATT}}(x) = E[y(1) | T = 1, X = x] - E[y(0) | T = 0, X = x] \quad (4.4.2)$$

where x is a vector of relevant observable characteristics (see the description of the firm-level and country-level control variables in subsection 4.4.2), $E[y(1) | T = 1, X = x]$ is the expected outcome for the units that received the treatment, and $E[y(0) | T = 0, X = x]$ is the expected outcome for the best matches of the treated units. Entropy balancing estimates the causal effect under the unconfoundedness assumption or conditional independence assumption (CIA). The CIA implies that the selection into the treatment group is only conditional to a set of observed covariates. Specifically, it assumes that conditional on the observed covariates (after controlling-for the covariates), the treatment assignment is independent of the potential outcomes.⁴

In this study, as [Neuenkirch & Neumeier \(2016\)](#) in the analysis of the effect of US sanctions on the poverty gap in the target countries and [Apeti \(2023a\)](#) in the analysis of the effects of mobile money on household consumption volatility, we use Entropy Balancing to select matches for units exposed to the treatment and to estimate the ATT.⁵ Entropy Balancing is a method proposed by [Hainmueller \(2012\)](#). This method is implemented in two steps. First, weights are calculated and assigned to the units not subject to treatment. These weights are chosen to satisfy prespecified equilibrium constraints involving sample moments of the observable features while at the same time remaining as close as possible to the uniform base weights. In our analysis, the equilibrium constraints require equal covariate means between the treatment and control groups, which ensures that the control group contains, on average, non-treatment units that are as similar as possible to the treatment units. Second, the weights obtained in the first step are used in a regression analysis with the treatment indicator as an explanatory variable. This yields an estimate of the ATT, i.e. the conditional difference in the means of the outcome variable between the treatment group and the control group.⁶ Broadly, the idea of Entropy Balancing here is to compare the productivity gap of firms exposed to power constraints with that of unexposed firms that are as similar as possible to the exposed firms. The average difference in productivity between the exposed firms and the "closest" unexposed firms must then be due to the treatment, i.e. the exposure to the power constraints. In this sense, the empirical approach mimics a randomized experiment by balancing the treatment and control groups on the basis of observable characteristics.

⁴In other words, CIA implies that after conditioning on the observed covariates, there are no unobserved confounding factors that influence both the treatment assignment and the potential outcomes. We empirically test the CIA in our subsection 4.5.2.

⁵See also [Apeti & Edoh \(2023\)](#); [Apeti \(2023b\)](#); [Apeti et al. \(2023\)](#).

⁶In the regression step, we additionally control for the covariates used in the first step. This is equivalent to including control variables in a randomized experiment to increase the efficiency of the estimation.

By combining matching and regression analysis, Entropy Balancing has some advantages over other treatment effect estimators. A particularly important advantage over regression-based approaches (including DiD estimation) as well as propensity score-based matching methods is that Entropy Balancing is non-parametric in the sense that no empirical model for the outcome variable or selection into treatment needs to be specified. Moreover, unlike regression-based analyses, there is no multicollinearity, as the reweighting scheme orthogonalizes the covariates to the treatment variable. Furthermore, unlike other matching methods, Entropy Balancing ensures a high balance of covariates between treatment and control groups, even in small samples.

Then, by combining a reweighting scheme with regression analysis, Entropy Balancing allows us to control for both country fixed effects and year fixed effects in the second step of the matching approach, i.e. the regression analysis.⁷ The inclusion of country fixed effects is particularly useful to account for the potential unobserved heterogeneity between firms from different countries and to control for time-invariant country-specific conditions that could lead to differences in the productivity gap between firms. Also, knowing that productivity varies with firm and economic characteristics (Syverson 2011), we include a large set of control variables at the firm and country level.

Finally, as recalled by Chauvet & Ehrhart (2018), the statistical bias resulting from the attempt to measure the effect of macro variables on micro-units was underlined by Moulton (1990).⁸ Therefore, as in Chauvet & Ehrhart (2018) and Bambe et al. (2022), the standard errors are clustered at the country level (as we have country level control variables such as economic growth, bank concentration, inflation, etc.).⁹

4.4.2 Data and variables

In this analysis, we consider 31,406 manufacturing firms in 84 developing countries from 2006 to 2019, 30 of which are in Sub-Saharan Africa (AFR), 8 in East Asia and Pacific (EAP), 14 in Europe and Central Asia (ECA), 20 in Latin America and the Caribbean (LAC), 6 in the Middle East and North Africa (MNA), and 6 in South Asia (SAR).

⁷We also include region and income group fixed effects in our econometric specification.

⁸Random disturbances in the correlated regression within the groupings that are used to merge the aggregate data with the micro data can lead to a downward bias in the ordinary least squares standard errors (Moulton 1990).

⁹Clustering the standard errors at the industry level also yields similar results as the country level clustering (see robustness check in subsection 4.6.1).

Firm-level data

We mainly use the World Bank Enterprise Survey (WBES) data in this analysis. The strata of the enterprise surveys are firm's size, industry and geographical region within a country. The firm's size levels are 5-19 (small), 20-99 (medium), and 100+ employees (large). It is important to note, however, that these surveys are limited to formal firms with five or more employees and with over 1% private ownership or participation. In this analysis, we start with the year 2006 because most surveys from this year onwards use stratified sampling and contain weights based on this information. Earlier surveys may not contain any information on weights. All monetary variables are adjusted to 2009 levels using a World Bank GDP deflator and then transformed to US dollars using the International Monetary Fund's purchasing power parity (PPP) index.

Our treatment variables (dummy variables taking 0 or 1) characterize the different levels of power constraints that firms report being exposed to. One advantage of this measure is that it reflects firms' perceptions of the extent to which power constrains their operations. This is important because the firm's perception is one of the most important factors influencing their operational and investment decisions (Asiedu & Freeman 2009).

To approximate the level of performance of each firm, we opt for total factor productivity (TFP), the part of output that is not explained by the quantity of inputs used.¹⁰ The productivity of firms, i.e. the ability to generate greater output with fewer inputs, is one of the key elements of economic growth. As a reminder, productivity is estimated from a Cobb-Douglas VA (value added) function of the following form:

$$VA_i = A_i K_i^{\alpha_k} L_i^{\alpha_l} \quad (4.4.3)$$

where value added at the firm-level VA_i is a function of the inputs of capital (K_i) and labour (L_i).¹¹ The efficiency of firms' production is measured by the term A_i which is the part of output that cannot be directly attributed to inputs used. Equation 4.4.3 could be rewritten as:

¹⁰World Bank Group, Enterprise Analysis Unit. 2017. "firm-level Productivity Estimates".

¹¹VA is represented by the difference between the establishment's total annual sales and the total annual cost of inputs, K is represented by the replacement value of machinery, vehicles and equipment; L is represented by the total annual labor cost.

$$\log(VA_i) = \alpha_0 + \alpha_k \log(K_i) + \alpha_l \log(L_i) + \varepsilon_i \quad (4.4.4)$$

$\log(\text{TFP}_i)$ is estimated as a sum of the constant and the residual, i.e., $\log(\text{TFP}_i) = \hat{\alpha}_0 + \hat{\varepsilon}_i$.¹² Therefore, the TFP is the part of output that is not explained by the quantity of inputs used.

In [Equation 4.4.3](#), TFP A_i is estimated separately for each industry. This avoids the assumption of a common production technology (i.e. α_k and α_l are the same within the sample). In addition, wherever possible, the elasticities of output with respect to capital and labor (i.e. α_k and α_l) can vary according to the income level group of the corresponding economy. Finally, as in [Halvorsen et al. \(1980\)](#), the country and year effects are controlled via dummy variables for each country and year. [Table 4.4.1](#) documents an average $\log(\text{TFP})$ of 2.46 for our sample of firms. However, we have a large heterogeneity between our firms as it varies from -3.23 for the least productive firms to 8.83 for the best performing firms.

At the firm-level, we control for the age of the firm, the size of the firm, whether or not the firm has a website, and most importantly, the ownership of the firm.¹³ Indeed, over time, firms tend to find ways to solve or mitigate the problem of power constraints. In addition, older firms are found to be more productive ([Majumdar 1997](#)). Moreover, a positive relationship between firm's size and TFP is found in the manufacturing sector in general ([Leung et al. 2008](#); [Tovar et al. 2011](#)). Also, we use the possession of a website by a firm as a good signal of the quality of the firm's marketing, it can influence its productivity. Finally, [Asiedu et al. \(2021\)](#) find that the probability of facing power constraints is lower for state-owned firms with majority ownership. However, a high level of private participation in a firm could reveal significant levels of firm's attractiveness or performance.

Further details on the firm-level variables can be found in the appendix [M](#) (see [Table M1](#)).

Country-level data

At the country level, we control the quality of regulation, financial development, bank concentration, foreign aid, inflation, economic growth, and the level of wealth. Indeed, [Agostino et al.](#)

¹²Where $\log(A_i) = \log(\text{TFP}_i)$

¹³We include both age and size because, contrary to popular belief, [St-Pierre et al. \(2010\)](#) have documented that firm's size and age are not substitutes in an exploratory study of 288 Quebec manufacturing firms.

Table 4.4.1: Summary statistics on our main variables

	Mean	SD	Min	Max	N
<i>Panel A: Firm-level controls</i>					
Firm's longevity (Years)	29.72	16.77	3.00	351.00	31406
Firm size (Small=1, Medium=2 or Large=3)	1.81	0.77	1.00	3.00	31406
Own website (No=0, Yes=1)	0.42	0.49	0.00	1.00	31406
Foreign private participation (%)	7.75	24.93	0.00	100.00	31406
<i>Panel B: Country-level controls</i>					
Regulatory Quality, Percentile Rank (0-100)	42.67	18.55	5.21	91.75	31406
Financial development index	0.28	0.14	0.03	0.70	31406
Bank concentration (%)	61.49	20.04	22.60	100.00	31406
Net ODA received (% of GNI)	2.42	4.16	0.01	37.37	31406
Inflation, consumer prices (annual %)	7.58	8.58	-1.05	84.86	31406
GDP growth (annual %)	4.34	4.44	-25.91	14.01	31406
GDP per capita (constant 2015 USD)	3976.76	3208.01	302.07	14086.02	31406
<i>Panel C: Outages related variables</i>					
Outages frequency (occurrences per month)	7.31	8.69	0.00	31.00	16821
Outages intensity (hours per occurrence)	4.45	6.98	0.00	96.00	16416
<i>Panel D: Performance related variables</i>					
Log revenue-based TFP (TFPR)	2.46	1.50	-3.23	8.83	31406
Cost of inputs per unit of sales (2009 USD)	0.40	0.22	0.00	0.99	31406
Sales per labor cost (2009 USD)	11.71	21.32	0.11	646.50	31406
Capacity Utilization (%)	73.48	21.12	0.00	100.00	30714
Losses due to Outages (% of annual Sales)	8.12	11.85	0.00	100.00	12813

(2020) establish strong evidence that better local institutions (the rule of law and government efficiency) help small and medium-sized firms become more productive in Europe over the period 2010-2014. We also have evidence of a positive effect of foreign aid on firm's sales growth (Chauvet & Ehrhart 2018). Furthermore, financial development and greater competition between banks (strong bank concentration) favor the performance of firms (Chauvet & Jacolin 2017; Lee et al. 2020). Finally, Bambe et al. (2022) document that inflation targeting increases the growth and productivity of firms in targeted countries compared to non-targeted countries. Indeed, inflation targeting improves the performance of developing countries by reducing the level and volatility of inflation (Lin & Ye 2009).

Further details on the country-level variables in the appendix M (see Table M1).

4.5 Empirical results: Main results

4.5.1 Descriptive statistics

Table 4.5.1 presents a summary of our treatment variables (power constraints) in this study. With respect to power outages, 16,816 firms out of 30,403 firms faced power outages, or about 53.6% of the firms in our sample. In addition, for 19,551 firms, power is an obstacle, representing 62.3% of firms. Of these firms, 17.6% faced minor obstacles in the power sector, 15.1% faced moderate obstacles, 16.2% faced major obstacles, 13.2% faced severe obstacles, and 11.7% considered power to be the major challenge in their operations. Finally, while outages are one of the main manifestations of constraints in the power sector in these countries, there are a number of other constraints (high cost of power, voltage fluctuations, connection problems, etc.) that are not readily observable through the survey data. Indeed, we can see here that 32.7% of the firms that faced obstacles did not experience any outages. Similarly, 39.1% of firms that experienced minor obstacles, 28.3% of firms that experienced moderate obstacles, 28.9% of firms that experienced major obstacles, 33.8% of firms that experienced severe obstacles, and 27.2% of firms that reported power as their greatest challenge.

Table 4.5.2 documents that 52.9% of our firms are small firms employing fewer than 20 people, and 35.3% are intermediate firms employing between 20 and 99 people. Finally, large firms (more than 100 employees) represent 11.8% of firms. For each category of these firms, the frequency of

Table 4.5.1: Summary statistics on the treatment variables

	<i>No Outages</i>			<i>Outages</i>			<i>Total</i>		
	Count	Row percentages	Column percentages	Count	Row percentages	Column percentages	Count	Row percentages	Column percentages
Power is an obstacle									
No	8,198	3,654	11,852	69.2%	30.8%	100.0%	56.2%	21.7%	37.7%
Yes	6,388	13,163	19,551	32.7%	67.3%	100.0%	43.8%	78.3%	62.3%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
Power as minor obstacle									
No	12,420	13,446	25,865	48.0%	52.0%	100.0%	85.1%	80.0%	82.4%
Yes	2,167	3,371	5,538	39.1%	60.9%	100.0%	14.9%	20.0%	17.6%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
Power as moderate obstacle									
No	13,242	13,406	26,648	49.7%	50.3%	100.0%	90.8%	79.7%	84.9%
Yes	1,345	3,410	4,755	28.3%	71.7%	100.0%	9.2%	20.3%	15.1%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
Power as major obstacle									
No	13,114	13,191	26,305	49.9%	50.1%	100.0%	89.9%	78.4%	83.8%
Yes	1,472	3,625	5,098	28.9%	71.1%	100.0%	10.1%	21.6%	16.2%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
Power as severe obstacle									
No	13,182	14,060	27,242	48.4%	51.6%	100.0%	90.4%	83.6%	86.8%
Yes	1,404	2,756	4,161	33.8%	66.2%	100.0%	9.6%	16.4%	13.2%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
Power as biggest obstacle									
No	13,097	13,835	26,932	48.6%	51.4%	100.0%	93.1%	84.2%	88.3%
Yes	968	2,588	3,556	27.2%	72.8%	100.0%	6.9%	15.8%	11.7%
Total	14,065	16,423	30,488	46.1%	53.9%	100.0%	100.0%	100.0%	100.0%
N	11,808	18,680	30,488						

experiencing outages exceeds 50 percent. On the other hand, only 19.1% of firms invest in R&D, and of these, a significant 62.3% are roughly firms that suffer from power constraints. Similarly, of the 21.5% of firms that own back-up generators, 77.2% are actually firms that face power constraints.

The next figures present some stylized facts. In [Figure 4.5.1](#), the white lines in the middle of the boxes indicate the respective medians. After a quasi-constant evolution within minor and moderate obstacles, we observe a drop in median total factor productivity as soon as the constraints become major for the firms (box plots 1). It can be seen that this deterioration in the power sector lowers the median total factor productivity of firms. Similarly, the box plots 2 documents a decrease in median firms' capacity utilization with the level of power constraints. We can see that this deterioration in the power sector reduces the median capacity utilization. The box plots 3 documents that the median losses incurred by firms increases with the level of constraints encountered in the power sector. The deterioration in the power sector increases median losses.

[Figure 4.5.2](#) documents the effects of constraints on losses with a breakdown by geographical

Table 4.5.2: Summary statistics on our main categorical variables

	<i>No Outages</i>	<i>Outages</i>	<i>Total</i>	<i>No Outages</i>	<i>Outages</i>	<i>Total</i>	<i>No Outages</i>	<i>Outages</i>	<i>Total</i>
	Count			Row percentages			Column percentages		
Firm size									
Small(<20)	7,974	8,639	16,613	48.0%	52.0%	100.0%	54.7%	51.4%	52.9%
Medium(20-99)	4,984	6,087	11,071	45.0%	55.0%	100.0%	34.2%	36.2%	35.3%
Large(100 And Over)	1,629	2,091	3,719	43.8%	56.2%	100.0%	11.2%	12.4%	11.8%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
R&D									
No	8,726	9,492	18,219	47.9%	52.1%	100.0%	84.4%	78.0%	80.9%
Yes	1,617	2,672	4,289	37.7%	62.3%	100.0%	15.6%	22.0%	19.1%
Total	10,344	12,164	22,508	46.0%	54.0%	100.0%	100.0%	100.0%	100.0%
Generator									
No	13,016	11,596	24,612	52.9%	47.1%	100.0%	89.5%	69.0%	78.5%
Yes	1,533	5,202	6,735	22.8%	77.2%	100.0%	10.5%	31.0%	21.5%
Total	14,549	16,798	31,347	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
Own website									
No	9,327	10,983	20,309	45.9%	54.1%	100.0%	63.9%	65.3%	64.7%
Yes	5,260	5,834	11,094	47.4%	52.6%	100.0%	36.1%	34.7%	35.3%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
WB income group									
Low Income	281	1,386	1,666	16.8%	83.2%	100.0%	1.9%	8.2%	5.3%
Lower Middle Income	7,634	10,411	18,045	42.3%	57.7%	100.0%	52.3%	61.9%	57.5%
Upper Middle Income	6,672	5,020	11,692	57.1%	42.9%	100.0%	45.7%	29.9%	37.2%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
Region									
AFR	2,542	3,075	5,616	45.3%	54.7%	100.0%	17.4%	18.3%	17.9%
EAP	3,790	4,315	8,105	46.8%	53.2%	100.0%	26.0%	25.7%	25.8%
ECA	1,605	967	2,573	62.4%	37.6%	100.0%	11.0%	5.8%	8.2%
LAC	2,993	2,747	5,740	52.1%	47.9%	100.0%	20.5%	16.3%	18.3%
MNA	2,076	2,487	4,563	45.5%	54.5%	100.0%	14.2%	14.8%	14.5%
SAR	1,581	3,225	4,806	32.9%	67.1%	100.0%	10.8%	19.2%	15.3%
Total	14,587	16,816	31,403	46.4%	53.6%	100.0%	100.0%	100.0%	100.0%
N	12,317	19,086	31,403						

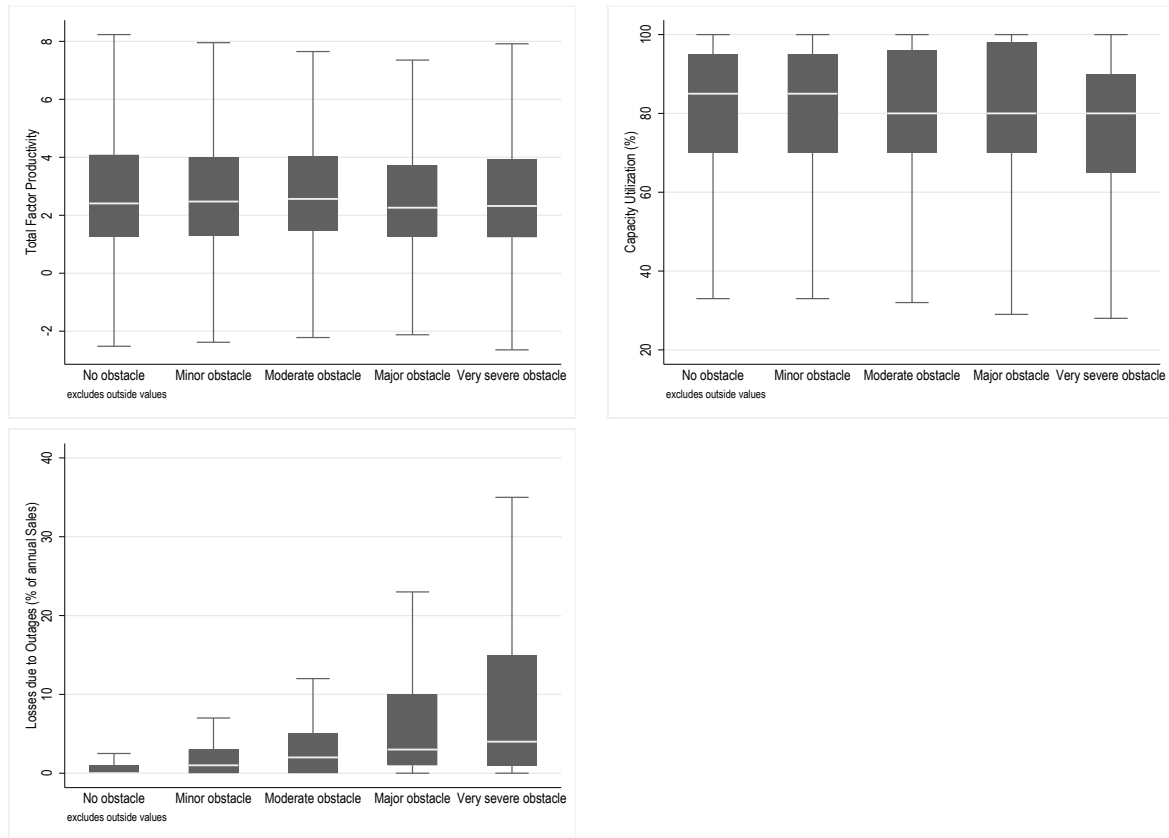


Figure 4.5.1: Degree of power constraints, declining total factor productivity and capacity utilization in %, and increasing losses in % of total sales

region. We can see that the negative effects of power constraints on losses by region are reinforced when the constraints become major or severe, especially for the Sub-Saharan Africa, MENA and South Asia regions.

Figure 4.5.3 highlights the combined effect of outages and other constraints. When the outages are not associated with the highest level of constraints, we can see the decrease in productivity only for two regions (EAP and LAC). However, when the outages are associated with the highest level of constraints, then we find the decrease in productivity in four regions (AFR, EAP, ECA, SAR). Moreover, intra-regional volatility in total factor productivity becomes more important between firms within the same region.

Table 4.5.3 documents the sample means of all matching covariates, divided into two groups: observations of firms facing power constraints (outages) or the treatment group (column 1) and observations of firms not facing power constraints or the potential control group (column 2).¹⁴

¹⁴As Asiedu et al. (2021), we log some of our macroeconomic variables to mitigate the effect of outliers.

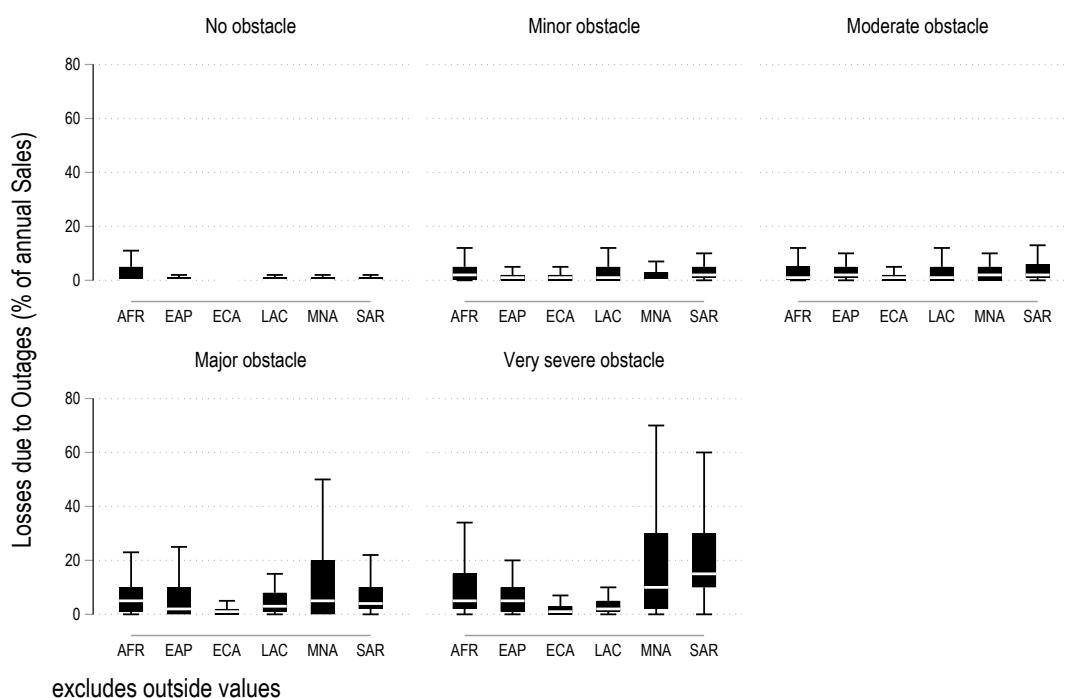


Figure 4.5.2: Breakdown losses by degree of power constraints and by region

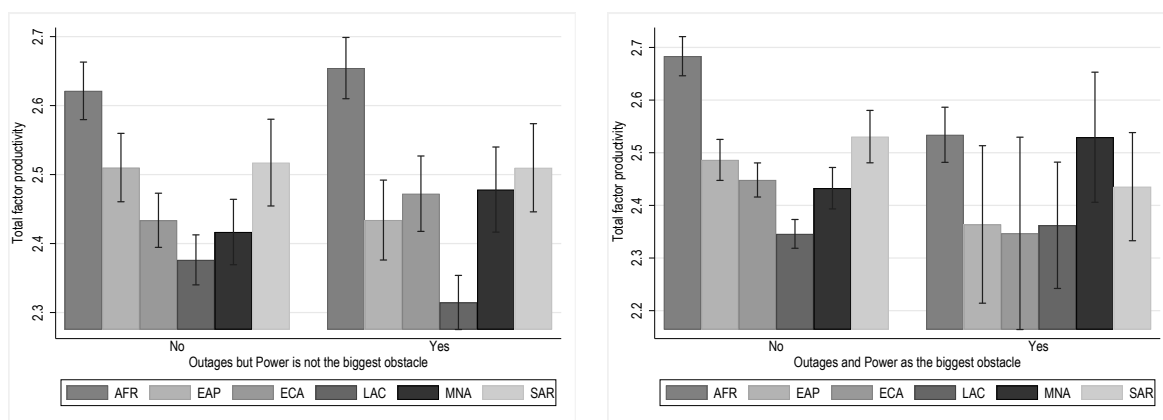


Figure 4.5.3: The combined effects of outages and other power constraints

The last column documents the standardized differences in means between these two groups with the corresponding level of significance in each case.

The analysis of the results for all relevant observable characteristics reveals that firms facing power constraints differ drastically and operate in very different environments compared to firms not facing power constraints. Indeed, we find that firms facing power constraints are on average smaller than those not facing power constraints. In the same vein, these firms facing the constraints

Table 4.5.3: Descriptive Statistics (T=Power Outages)

	[1]	[2]	[1] – [2]
	Outages	No Outages	Diff.
Firm size	1.802	1.831	-0.038***
Firm's longevity	29.690	29.737	-0.003**
Own website	0.386	0.471	-0.173***
Foreign private participation	8.082	7.222	0.034**
GDP growth (annual %)	3.321	4.995	-0.511***
Inflation (annual %)	7.726	7.480	0.043***
log(Bank concentration in %)	4.047	4.084	-0.108***
log(FD index)	-1.496	-1.243	-0.436***
log(GDP per capita)	7.771	8.231	-0.542***
log(Net ODA in % of GNI)	-0.185	-0.883	0.392***
log(Regulatory Quality)	3.601	3.784	-0.370***
Observations	19086	12317	

Notes: This Table documents the sample means of all matching covariates, divided into two groups: observations of firms facing outages or the treatment group (column 1) and observations of firms not facing outages or the potential control group (column 2). The last column documents the standardized differences in means between these two groups with the corresponding level of significance in each case. The analysis of the results for all the relevant observable characteristics reveals that firms facing outages differ drastically compared to firms not facing outages.

are on average younger than those not facing the constraints. We also note that firms not facing constraints have on average a better marketing management (approximated by the possession of a website). Finally, we also notice that the firms that face constraints more often in terms of power services are the firms that are mostly owned by foreign private stakeholders.

Furthermore, the economic and policy environment in which these power-constrained firms operate is generally worse. Economic growth is lower, inflationary pressures are higher, financial development and banks concentration are lower, and the quality of regulation is weaker. These firms are also found to be located in poorer and less resilient countries and therefore receive more international development assistance and aid. These descriptive results illustrate the importance of selecting an appropriate control group using a matching-based approach before calculating treatment effects, as otherwise the effect of power constraints on firms' total factor productivity could be miss-estimated.

[Table 4.5.4](#) compares the sample means of all matching covariates in the treatment group (column 1) and the synthetic control group obtained via Entropy Balancing (column 2). The last column documents the standardized differences in means with the corresponding significance level in each case. The comparison of the average realizations of the observable characteristics of the treatment group with those of the synthetic control group reveals the effectiveness of Entropy Balancing. All covariates are perfectly balanced and no statistically significant differences remain. Furthermore, [Figure 4.5.4](#) and [Figure 4.5.5](#) display the kernel densities of our covariates for the treatment and control group and document how balancing constraints have affected the reweighted covariate distributions. Therefore, we can say that the control groups in the subsequent empirical analysis are composed of relevant counterfactuals for the sample of firms facing power constraints.

Table 4.5.4: Covariate balancing (T=Power Outages)

	[1]	[2]	[1] – [2]
	Outages	Control	Diff.
Firm size	1.802	1.802	0.000
Firm’s longevity	29.737	29.736	0.000
Own website	0.386	0.386	-0.000
Foreign private participation	8.082	8.082	0.000
GDP growth (annual %)	4.995	4.994	0.000
Inflation (annual %)	7.480	7.482	-0.000
log(Bank concentration in %)	4.047	4.047	-0.000
log(FD index)	-1.496	-1.496	-0.000
log(GDP per capita)	7.771	7.771	-0.000
log(Net ODA in % of GNI)	-0.185	-0.185	-0.000
log(Regulatory Quality)	3.601	3.601	-0.000
Weighted observations	19086	19086	

Notes: This Table compares the sample means of all matching covariates in the treatment group (column 1) and the synthetic control group obtained via Entropy Balancing (column 2). The last column documents the standardized differences in means with the corresponding significance level in each case. The comparison of the average realizations of the observable characteristics of the treatment group with those of the synthetic control group reveals the effectiveness of Entropy Balancing. All covariates are perfectly balanced and no statistically significant differences remain.

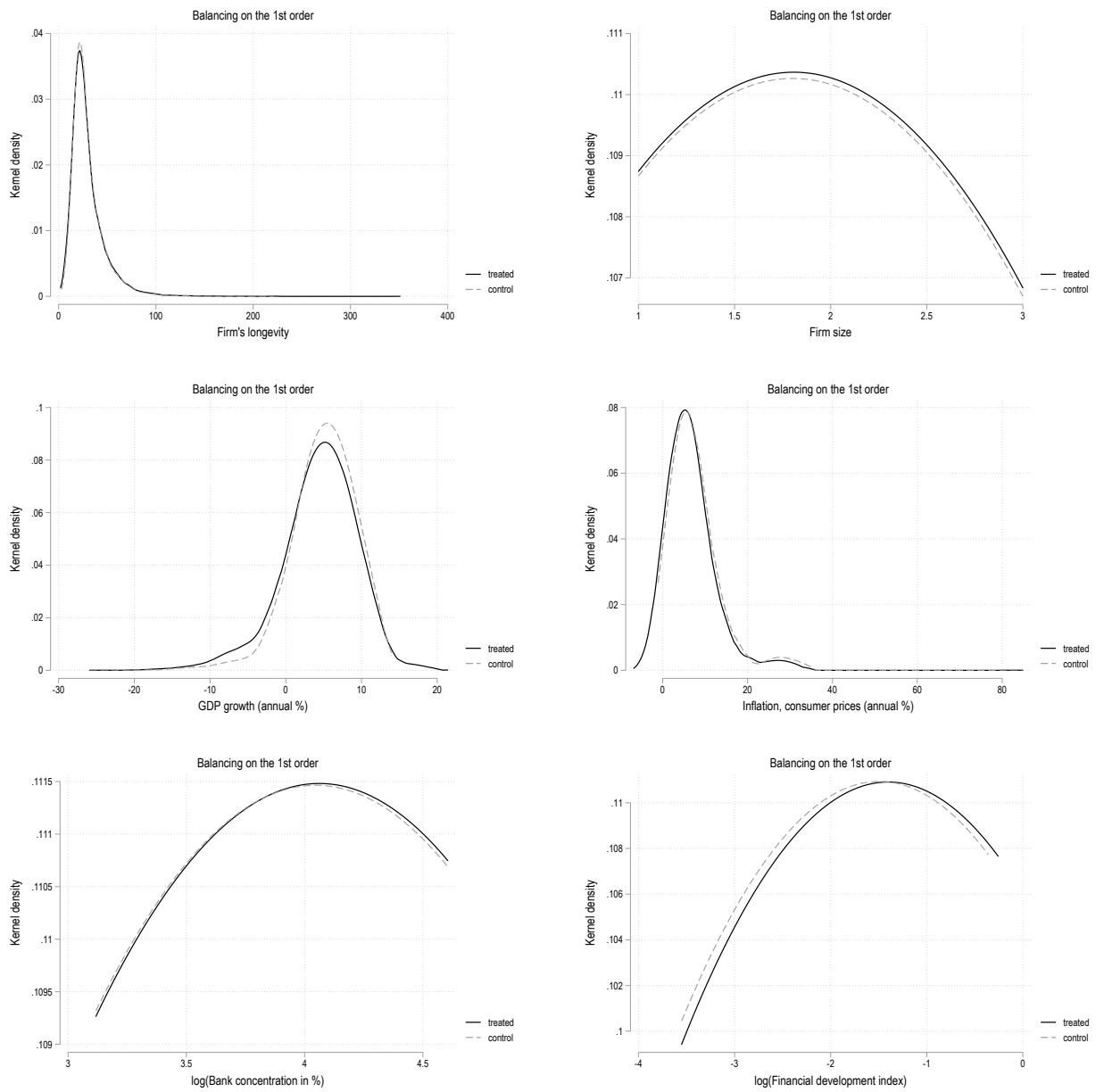


Figure 4.5.4: Kernel densities of the covariates for the treatment and control group (Set 1)

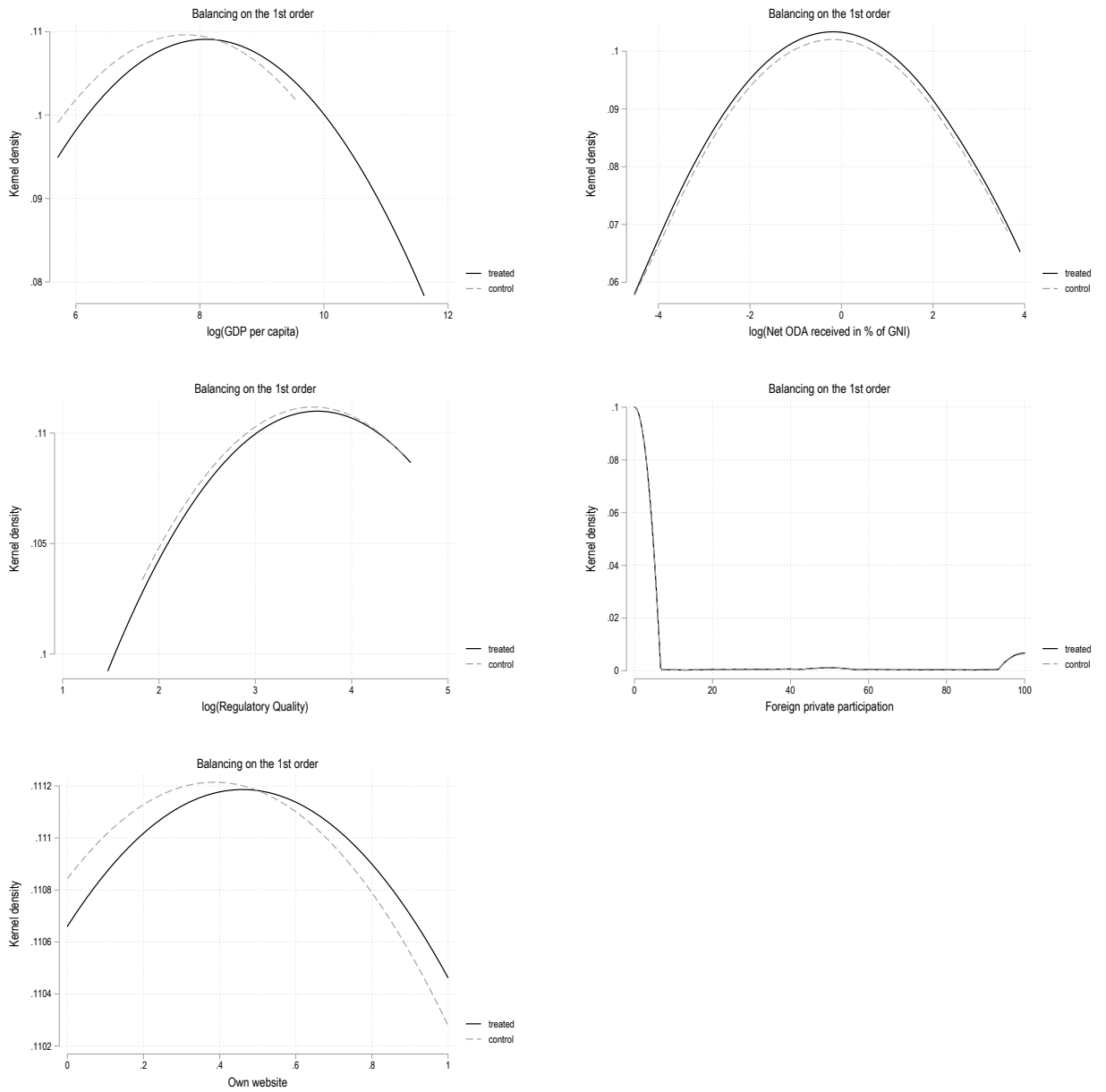


Figure 4.5.5: Kernel densities of the covariates for the treatment and control group (Set 2)

4.5.2 Treatment effects

Based on the treatment effects for endogenous treatments described in [Wooldridge \(2010\)](#), we performed an endogeneity test to ensure that the conditional independence assumption (CIA) is respected before running the regressions based on entropy balancing. The results documents that conditional on our covariates, the treatment and outcome unobservables are uncorrelated (H0).¹⁵ We can be sure that our estimates below from entropy balancing represent the consistent treatment effects on the treated (ATT).

The results of [Table 4.5.5](#) indicate that power constraints characterized by outages negatively affect exposed firms, since we observe a negative and significant coefficient associated with power outages dummy variable of 0.102, i.e., 1.1 percentage points or 9% of the unconditional average productivity (column 1). This first result supports those found by a large part of this literature ([Cole et al. 2018](#); [Abdisa 2018](#); [Elliott et al. 2021](#); [Xiao et al. 2022](#)). However, we note that the effects of the constraints are not statistically significant when the levels of constraints are not severe (columns 2 to 5), even if they are gradually increasing. As soon as the constraints become very important (severe), the effect becomes negative and statistically significant (column 6). In column (7), the adverse effect is greatest when power proves to be the firm's biggest obstacle (ahead of factors such as access to finance, problems with the tax administration, transport problems or problems related to corruption). The visualization of these coefficients are documented in [Figure 4.5.6](#).

In [Table 4.5.6](#), we consider the interaction of the outages treatment variable with each specific level of obstacles encountered by firms in the power sector (the other treatment variables in our analysis). In column (1), when we consider the outages treatment variable and no constraints or obstacles, we have no effect of outages on firms' productivity. This implies that most firms manage to deal with outages when other sources of constraints in the power sector are absent (voltage problems, high cost of service, connection difficulties, etc.). In column (2), the effect becomes negative when we consider the presence of minor constraints. The negative effect becomes progressively stronger when we consider the presence of moderate and major obstacles, until it becomes significant when we consider the presence of severe obstacles for firms. This negative

¹⁵Test of endogeneity. H0: Treatment and outcome unobservables are uncorrelated. $\chi^2(2) = 0.40$; Prob > $\chi^2 = 0.8191$). We cannot reject H0.

Table 4.5.5: The effect of power outages and constraints on the firm's revenue-based TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Power Outages	-0.102*** (0.032)						
Power is not an obstacle		0.041 (0.027)					
Power as minor obstacle			0.040 (0.026)				
Power as moderate obstacle				0.004 (0.031)			
Power as major obstacle					-0.032 (0.028)		
Power as severe obstacle						-0.044* (0.025)	
Power as biggest obstacle							-0.148*** (0.025)
Observations	31403	31406	31406	31406	31406	31406	30491

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-7). In each regression, the treatment variable represents a specific degree of power constraints for firms. Firm-level controls variables are: Firm's size, Firm's longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. The variation in the number of observations is related to the fact that the treatment variables are derived from three separate survey questions. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

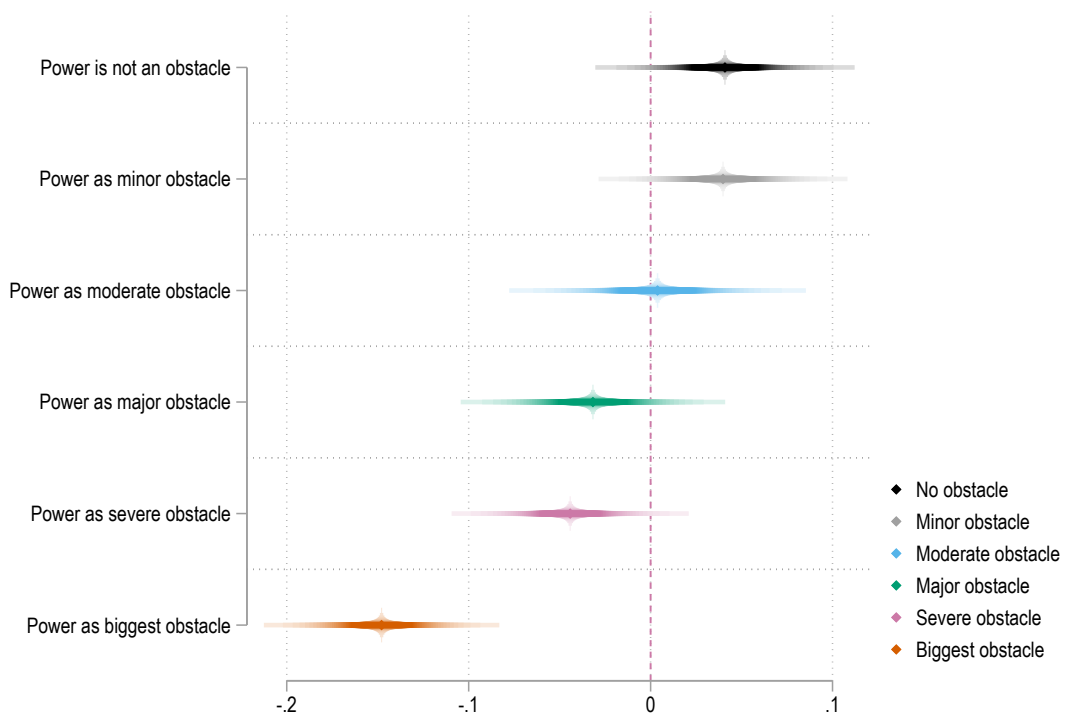


Figure 4.5.6: The effect of power constraints on the firm's revenue-based TFP

Notes: Figure documents the coefplots with the smoothed confidence intervals (1, 3, 5, ..., 99) of the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing) from Table 4.5.5. The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions. In each regression, the treatment variable represents a specific degree of power constraints for firms. Firm-level controls variables are: Firm's size, Firm's longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors are clustered at country level.

effect is reinforced and becomes very significant when power becomes the greatest obstacle for firms.

Table 4.5.6: The combined effect of power outages with each level of power constraints on the firm's revenue-based TFP

	(1)	(2)	(3)	(4)	(5)	(6)
Outages × No obstacle	0.016 (0.027)					
Outages × Minor obstacle		-0.014 (0.037)				
Outages × Moderate obstacle			-0.035 (0.040)			
Outages × Major obstacle				-0.044 (0.028)		
Outages × Severe obstacle					-0.079** (0.031)	
Outages × Biggest obstacle						-0.173*** (0.026)
Observations	31406	31406	31406	31406	31406	31406

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-6). In each regression, the treatment variable represents a specific degree of power constraints for firms and outages dummy variable. Firm-level controls variables are: Firm's size, Firm's longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6 Empirical results: Robustness, heterogeneity and mechanisms

4.6.1 Robustness tests

The World Bank study suggests clustering by industry when each industry has at least 500 observations.¹⁶ Otherwise, the appropriate clustering is by economies or countries as we have done so far. However, in order to test the sensitivity of our results to this, we have repeated our regressions by clustering by industry (see Table 4.6.1) even though we have fewer than 500 observations for some industries in our sample. Although we have some small variations in our standard errors, the

¹⁶World Bank Group, Enterprise Analysis Unit. 2017. "firm-level Productivity Estimates".

results remain almost the same (in quality and magnitude) as our initial results with the clustering by country.

Table 4.6.1: Robustness tests – The effect of power outages and constraints on the firm’s revenue-based TFP by clustering standards errors at industry level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Power Outages	-0.102*** (0.018)						
Power is not an obstacle		0.041 (0.025)					
Power as minor obstacle			0.040 (0.029)				
Power as moderate obstacle				0.004 (0.025)			
Power as major obstacle					-0.032 (0.022)		
Power as severe obstacle						-0.044* (0.022)	
Power as biggest obstacle							-0.148*** (0.042)
Observations	31403	31406	31406	31406	31406	31406	30491

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-7). In each regression, the treatment variable represents a specific degree of power constraints for firms. Firm-level controls variables are: Firm’s size, Firm’s longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors in parentheses are clustered at industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We also wanted to test the robustness of our results using the ordinary least squares (OLS) estimator in [Table 4.6.2](#) to reassure that our results are not highly influenced or biased by our choice of Entropy Balancing estimator. Obviously, we have some small differences in magnitudes for some of the coefficients due to the downward bias of the OLS estimates in presence of endogeneity ([Neuenkirch & Neumeier 2016](#)), but they remain qualitatively unchanged. As Entropy Balancing, the OLS estimator also allows us to see the adverse and progressive effect of power sector constraints on firm’s productivity in developing countries.

In [Table 4.6.3](#), we opt for alternative measures of firm’s productivity. Although our main variable (TFPR) is suitable to approximate the level of performance of manufacturing firms in developing countries, it also faces some criticism in the literature. Indeed, the estimation of the TFPR

Table 4.6.2: Robustness tests – The effect of power outages and constraints on the firm’s revenue-based TFP by using least squares regressions (without entropy balancing re-weighting scheme)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Power Outages	-0.083*** (0.028)						
Power is not an obstacle		0.041 (0.026)					
Power as minor obstacle			0.031 (0.022)				
Power as moderate obstacle				-0.000 (0.029)			
Power as major obstacle					-0.028 (0.028)		
Power as severe obstacle						-0.047** (0.024)	
Power as biggest obstacle							-0.131*** (0.027)
Observations	31403	31406	31406	31406	31406	31406	30491

Notes: Table documents the coefficients obtained by least squares regressions. The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-7). In each regression, the treatment variable represents a specific degree of power constraints for firms. Firm-level controls variables are: Firm’s size, Firm’s longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

can potentially be problematic for certain reasons such as selection, simultaneity or problems related to the use of monetary measures (as opposed to physical measures) of production and inputs (Levinsohn & Petrin 2003, Foster et al. 2008, Hsieh & Klenow 2009). To ensure that our results are not biased or influenced by the choice of this measure, we also test the robustness of our results using alternative measures to approximate the productivity of firms (in the form of factor ratios). These are simple ratios of the corresponding variables. These measures of firm's performance based on factor shares also have the advantage of being simple and very informative. In column (1), we repeat the estimation with our main variable (TFPR). In column (2), we estimate the effect of the power constraints on labor costs per USD of sales. The result suggests that the constraints induces an increase in production costs for the treated firms. Finally, in column (3), the constraints lead to a decrease in the amount of total sales per worker (in 2009 USD).

Table 4.6.3: Robustness tests – The effect of power outages on the firm's revenue-based TFP and factor share based estimates of productivity

	(1)	(2)	(3)
	revenue-based TFP	Cost of inputs per unit of sales	Sales per labor cost
Power Outages	-0.102*** (0.032)	0.010** (0.005)	-1.193*** (0.439)
Observations	31403	31403	31403

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity in regression (1), Cost of inputs per unit of sales in regression (2) and Sales per labor cost in regression (3). In each regression, the treatment variable represents power outages dummy variable. Firm-level controls variables are: Firm's size, Firm's longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table M2 in appendix M, we added additional potentially relevant control variables to minimize potential bias due to unobserved confounding factors. These variables are exports, size of the locality of firms, public ownership versus other stakeholders' ownership, gender of the top manager, quality certification, informal payment, investment in fixed assets, bank account and access to credit. These variables are potentially relevant variables in our model according to this literature. For each case, our results remain statistically significant. This further demonstrates the stability of our main results.

4.6.2 Heterogeneity check

We also tested the evolution of our results following the income group of the countries in which the firms operate and following the geographical regions. In [Table 4.6.4](#), we have the effect of power constraints on TFPR following the income level of countries. We see that the negative effect found in Lower Income countries far exceeds those found in Middle Income countries. Indeed, the magnitude found in these Lower Income countries is 2.5 times that found in Upper Middle Income countries and 4.5 times that found in Lower Middle Income countries. For the Lower Income countries, this negative effect could be explained by the low level of resilience for firms in these fragile environments. For the Upper Middle Income countries, part of the explanation could lie in the fact that firms in these countries are relatively more energy-intensive, and therefore more exposed to energy constraints. The absence of a significant effect in the Middle Income countries would reflect the fact that firms in these countries are relatively more resilient than those in the Lower Income countries, and energy intensity is lower than in the Upper Middle Income countries.

Table 4.6.4: Heterogeneity check – The effect of power outages on the firm’s revenue-based TFP by countries income group

	(1) Low Income	(2) Lower Middle Income	(3) Upper Middle Income
Power Outages	-0.214** (0.082)	-0.047 (0.031)	-0.085* (0.044)
Observations	6848	14215	10340

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-3). In each regression, the treatment variable represents power outages dummy variable. Firm-level controls variables are: Firm’s size, Firm’s longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE and a Constant. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In [Table 4.6.5](#), we then provide further evidence that the overall negative effect is particularly driven by Sub-Saharan African (column 1) and MENA countries (column 5). This highlights to some extent the low resilience of firms in these regions (lack of alternative solutions such as back-up generators, low level of investment in R&D). Although the effect is negative in all regions, it

remains statistically non-significant in the other regions. Firms in South Asia (SAR) remain the most resilient, followed by those in Europe and Central Asia (ECA).

Table 4.6.5: Heterogeneity check – The effect of power outages on the firm’s revenue-based TFP by geographical regions

	(1)	(2)	(3)	(4)	(5)	(6)
	AFR	EAP	ECA	LAC	MNA	SAR
Power Outages	-0.223*** (0.052)	-0.052 (0.092)	-0.028 (0.059)	-0.082 (0.050)	-0.115*** (0.026)	-0.026 (0.066)
Observations	7714	3586	3132	9120	3168	4683

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-6). In each regression, the treatment variable represents power outages dummy variable. Firm-level controls variables are: Firm’s size, Firm’s longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Income group FE and a Constant. Sub-Saharan Africa (AFR), East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and Caribbean (LAC), Middle East and North Africa (MNA), South Asia (SAR). Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6.3 Transmission channels

Our intuition is that power constraints directly affect the operations of firms by influencing their operating regime (capacity utilization) and inducing losses related to power outages (losses in % of sales). Column (1) in [Table 4.6.6](#) indicates that power constraints significantly reduce the capacity utilization of the firms affected. This is linked to the fact that, in the event of a outage or a rise in the cost of kwh, firms can no longer operate at full capacity, so they first seek to readjust and reorganize their operating regime. Indeed, one of the consequences of the increase in power costs is a decrease in the size of the firm and productivity ([Allcott et al. 2016](#)), and therefore a lower profitability for the affected firm. Similarly, power outages, for example, cause sizeable damage to firms. This leads to considerable losses (increased losses) especially for firms that are not very resilient and do not have alternative measures such as back-up generators (column 2).

Table 4.6.6: Main channels – The effect of power outages on the firm’s Capacity Utilization (%) and Losses due to Outages (% of annual Sales)

	(1)	(2)
	Capacity Utilization (%)	Losses (% Sales)
Power Outages	-1.390** (0.692)	6.680*** (0.700)
Observations	30711	14397

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-2). In each regression, the treatment variable represents power outages dummy variable. Firm-level controls variables are: Firm’s size, Firm’s longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6.4 Mitigating factors

Many developing countries are not able to provide their industrial sectors with reliable power, so many firms have to deal with an insufficient and unreliable power supply (Alby et al. 2013). The response of firms to unreliable power supply can vary. In its simplest form, it means additional costs if, for example, the firm has to buy and run a back-up generator, which also results in a higher unit cost of power (Elliott et al. 2021). It has to be said that affected firms often opt for self-generation of power, even though this is widely considered to be a second-best solution (Abdisa 2018). Indeed, in Africa, for example, self-generated power is on average 313% more expensive than power from the grid (Alby et al. 2013). Are back-up generators really a solution to the constraints in the power sector in developing countries? In column (3) and (4) of Table 4.6.7, we can see that having a back-up generator reduces the negative effect of power constraints by half, even if it does not fully correct the shock (Abdisa 2020).

Given the prominent role of research and development (R&D) in the operation of firms in general, we also tested a potential mitigating role for the R&D investments of the firms in our analysis. Through R&D, firms can mitigate the effect of unreliable energy supply by switching to less energy-intensive technologies (Alam 2013), or can replace power with other types of fuels

(Allcott et al. 2016) or materials (Fisher-Vanden et al. 2015). R&D can also instruct firms on the production of energy-intensive intermediates to be externalized instead of producing them internally. R&D also allows firms to effectively modify their production strategy. This ability to re-optimize decisions can therefore limit the negative effects of poor quality of power service for the affected firms (Alam 2013). This is why we were also keen to test the mitigating role of R&D in column (1) and (2). The results suggest that investments in R&D allow firms to mitigate the negative effects of the constraints encountered in the power sector.

Table 4.6.7: Mitigating factors – The effect of power outages on the firm’s revenue-based TFP

	(1)	(2)	(3)	(4)
	No R&D	R&D	No Generator	Generator
Power Outages	-0.151*** (0.034)	-0.093 (0.093)	-0.179*** (0.035)	-0.098** (0.042)
Observations	16152	5683	20229	10210

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-4). In each regression, the treatment variable represents power outages dummy variable. Firm-level controls variables are: Firm’s size, Firm’s longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6.5 Placebo tests

Finally, we perform some placebo tests to ensure that the effect captured is essentially that of the constraints observed in the power sector. To do this, in Table 4.6.8, we have dummy variables (1/2 1/2), (1/3 2/3), (2/3 1/3), (1/4 3/4) and (3/4 1/4). When replacing each of these random dummies in our baseline model, we find no statistically significant effect on firm-level revenue-based total factor productivity.

Table 4.6.8: Placebo tests – The non-significant effects of random treatment variables on the firm’s revenue-based TFP

	(1)	(2)	(3)	(4)	(5)
Random treatment (1/2 1/2)	0.012 (0.021)				
Random treatment (1/3 2/3)		-0.002 (0.021)			
Random treatment (2/3 1/3)			-0.025 (0.022)		
Random treatment (1/4 3/4)				-0.006 (0.017)	
Random treatment (3/4 1/4)					0.030 (0.019)
Observations	31406	31404	31404	31405	31404

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variables is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-5). In each regression, the treatment variable represents a random treatment variable. Firm-level controls variables are: Firm’s size, Firm’s longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.7 Conclusion

The objective of this paper was to document the role of power sector constraints on the performance level of firms in developing countries. Theoretically, we have documented that it is relatively complex to conclude the expected overall effect. Indeed, the constraints on the power sector lead to two types of effects in opposite directions on the productivity of firms, namely a direct negative effect and an indirect mitigating effect (output prices adjustment producers). Empirically, our approach based on Entropy Balancing to control endogeneity documents that the overall effect of power outages on revenue-based total factor productivity (TFPR) is negative and statistically significant. Indeed, we observed a 9% lower unconditional average productivity for exposed firms compared to non-exposed firms. Moreover, we establish a robust link between the severity of self-reported power constraints or obstacles by firms (minor, moderate, major, severe, and biggest) and the magnitude of productivity loss for firms. In other words, the greater the level of power constraints self-reported by a firm, the greater the effect of these constraints on its productivity, and vice versa. Our results are robust to changes in the level of clustering, the estimation model, and the measure of our productivity variable.

We also document that the most affected firms operate mainly in Sub-Saharan Africa and in the MENA region. Our results suggest that power constraints affect the TFPR by reducing firms' capacity utilization (they no longer operate at full capacity) and by increasing direct losses due to numerous power outages. Finally, we have identified the acquisition of back-up generators and R&D investments as important factors in mitigating power constraints for firms in developing countries.

In terms of recommendations, we would like first to recall that manufacturing firms are the main drivers of economic growth in developing countries. To fully play their part in the path to emergence, these firms need to benefit from a modern, reliable and affordable power service. However, this requires the establishment of a financially viable power sector. To achieve this, on the supply side, the authorities must set up independent regulatory agencies in order to put in place appropriate measures, notably tariff (automatic tariff adjustment mechanisms, cost reflectivity, etc.) and non-tariff measures (development of a master plan for instance) to reassure investors. Combined with the opening-up of the power generation to private stakeholders (through IPPs, PPPs, etc.), this would make it possible to move capital into the sector and thus reduce the investment gap. In

parallel with this effort to improve the power infrastructure, strengthen the quality of the country's institutions as a whole in order to attract foreign investors in various sectors and boost economic growth (Acemoglu et al. 2002; Rodrik 2006) in order to drive the demand for power for the viability of the entire power sector. A viable power sector attracts more capital and provides quality power service to firms, which would in turn be more productive and competitive. This would create a virtuous circle for the whole economy.

4.8 Acknowledgment

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. It has been presented at LEDa PhD Presentation Workshop in march 2023 (Paris, France). We thank the participants for their valuable comments.

Bibliography

- Abdisa, L. T. (2018), 'Power outages, economic cost, and firm performance: Evidence from ethiopia', *Utilities Policy* **53**, 111–120.
- Abdisa, L. T. (2020), 'Role of investment in self-generation in mitigating outage loss: Evidence from sub-saharan african firms', *Energy, Ecology and Environment* **5**(6), 407–420.
- Abeberese, A. B., Ackah, C. G. & Asuming, P. O. (2021), 'Productivity losses and firm responses to electricity shortages: Evidence from ghana', *The World Bank Economic Review* **35**(1), 1–18.
- Acemoglu, D., Johnson, S. & Robinson, J. A. (2002), 'Reversal of fortune: Geography and institutions in the making of the modern world income distribution', *The Quarterly journal of economics* **117**(4), 1231–1294.
- Agostino, M., Di Tommaso, M. R., Nifo, A., Rubini, L. & Trivieri, F. (2020), 'Institutional quality and firms' productivity in european regions', *Regional Studies* **54**(9), 1275–1288.
- Alam, M. (2013), 'Coping with blackouts: Power outages and firm choices', *Department of Economics, Yale University* .
- Alby, P., Dethier, J.-J. & Straub, S. (2013), 'Firms operating under electricity constraints in developing countries', *The World Bank Economic Review* **27**(1), 109–132.

- Allcott, H., Collard-Wexler, A. & O’Connell, S. D. (2016), ‘How do electricity shortages affect industry? evidence from india’, *American Economic Review* **106**(3), 587–624.
- Apeti, A. E. (2023a), ‘Household welfare in the digital age: Assessing the effect of mobile money on household consumption volatility in developing countries’, *World Development* **161**, 106110.
- Apeti, A. E. (2023b), ‘Sovereign debt default and inequality’, *Industrial and Corporate Change* .
- Apeti, A. E., Bambe, B.-W.-W. & Combes, J.-L. (2023), *On the Macroeconomic Effects of Fiscal Reforms: Fiscal Rules and Public Expenditure Efficiency*, hal-03961062f.
- Apeti, A. E. & Edoh, E. D. (2023), ‘Tax revenue and mobile money in developing countries’, *Journal of Development Economics* **161**, 103014.
- Asiedu, E., Azomahou, T. T., Gaekwad, N. B. & Ouedraogo, M. (2021), ‘The determinants of electricity constraints by firms in developing countries’, *Energy Economics* **104**, 105605.
- Asiedu, E. & Freeman, J. (2009), ‘The effect of corruption on investment growth: Evidence from firms in latin america, sub-saharan africa, and transition countries’, *Review of Development Economics* **13**(2), 200–214.
- Bambe, B.-W.-W., Combes, J. L., Kaba, K. & Minea, A. (2022), Inflation targeting and developing countries’ performance: Evidence from firm-level data, Technical report, Orleans Economics Laboratory/Laboratoire d’Economie d’Orleans (LEO
- Barth III, M. J. & Ramey, V. A. (2001), ‘The cost channel of monetary transmission’, *NBER macroeconomics annual* **16**, 199–240.
- Bernanke, B. S. (1983), ‘Irreversibility, uncertainty, and cyclical investment’, *The quarterly journal of economics* **98**(1), 85–106.
- Bodenstein, M., Erceg, C. J. & Guerrieri, L. (2011), ‘Oil shocks and external adjustment’, *Journal of International Economics* **83**(2), 168–184.
- Brandt, L., Tombe, T. & Zhu, X. (2013), ‘Factor market distortions across time, space and sectors in china’, *Review of Economic Dynamics* **16**(1), 39–58.
- Canan, C., Lesko, C. & Lau, B. (2017), ‘Instrumental variable analyses and selection bias’, *Epidemiology (Cambridge, Mass.)* **28**(3), 396.

- Chauvet, L. & Ehrhart, H. (2018), 'Aid and growth: evidence from firm-level data', *Journal of Development Economics* **135**, 461–477.
- Chauvet, L. & Ferry, M. (2021), 'Taxation, infrastructure, and firm performance in developing countries', *Public Choice* **187**, 455–480.
- Chauvet, L. & Jacolin, L. (2017), 'Financial inclusion, bank concentration, and firm performance', *World Development* **97**, 1–13.
- Cheng, D., Shi, X., Yu, J. & Zhang, D. (2019), 'How does the chinese economy react to uncertainty in international crude oil prices?', *International Review of Economics & Finance* **64**, 147–164.
- Choi, S., Furceri, D., Loungani, M. P., Mishra, M. S. & Poplawski-Ribeiro, M. (2017), *Oil prices and inflation dynamics: evidence from advanced and developing economies*, International Monetary Fund.
- Cole, M. A., Elliott, R. J., Occhiali, G. & Strobl, E. (2018), 'Power outages and firm performance in sub-saharan africa', *Journal of Development Economics* **134**, 150–159.
- Elder, J. & Serletis, A. (2009), 'Oil price uncertainty in canada', *Energy Economics* **31**(6), 852–856.
- Elliott, R. J., Nguyen-Tien, V. & Strobl, E. A. (2021), 'Power outages and firm performance: A hydro-iv approach for a single electricity grid', *Energy economics* **103**, 105571.
- Ertefaie, A., Small, D., Flory, J. & Hennessy, S. (2016), 'Selection bias when using instrumental variable methods to compare two treatments but more than two treatments are available', *The international journal of biostatistics* **12**(1), 219–232.
- Fisher-Vanden, K., Mansur, E. T. & Wang, Q. J. (2015), 'Electricity shortages and firm productivity: evidence from china's industrial firms', *Journal of Development Economics* **114**, 172–188.
- Foster, L., Haltiwanger, J. & Syverson, C. (2008), 'Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?', *American Economic Review* **98**(1), 394–425.
- Grainger, C. A. & Zhang, F. (2017), 'The impact of electricity shortages on firm productivity: Evidence from pakistan', *World Bank Policy Research Working Paper* (8130).

- Hainmueller, J. (2012), 'Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies', *Political analysis* **20**(1), 25–46.
- Halvorsen, R., Palmquist, R. et al. (1980), 'The interpretation of dummy variables in semilogarithmic equations', *American economic review* **70**(3), 474–475.
- Hardy, M. & McCasland, J. (2021), 'Lights off, lights on: The effects of electricity shortages on small firms', *The World Bank Economic Review* **35**(1), 19–33.
- Hsieh, C.-T. & Klenow, P. J. (2009), 'Misallocation and manufacturing tfp in china and india', *The Quarterly journal of economics* **124**(4), 1403–1448.
- Jones, C. I. (2011), Misallocation, economic growth, and input-output economics, Technical report, National bureau of economic research.
- Lee, C.-C., Wang, C.-W. & Ho, S.-J. (2020), 'Financial inclusion, financial innovation, and firms' sales growth', *International Review of Economics & Finance* **66**, 189–205.
- Leung, D., Meh, C. & Terajima, Y. (2008), Firm size and productivity, Technical report, Bank of Canada.
- Levinsohn, J. & Petrin, A. (2003), 'Estimating production functions using inputs to control for unobservables', *The review of economic studies* **70**(2), 317–341.
- Lin, S. & Ye, H. (2009), 'Does inflation targeting make a difference in developing countries?', *Journal of Development economics* **89**(1), 118–123.
- Majumdar, S. K. (1997), 'The impact of size and age on firm-level performance: some evidence from india', *Review of industrial organization* **12**(2), 231–241.
- Moulton, B. R. (1990), 'An illustration of a pitfall in estimating the effects of aggregate variables on micro units', *The review of Economics and Statistics* pp. 334–338.
- Neuenkirch, M. & Neumeier, F. (2016), 'The impact of us sanctions on poverty', *Journal of Development Economics* **121**, 110–119.
- Prescott, E. C. (2002), 'Prosperity and depression', *American Economic Review* **92**(2), 1–15.
- Rodrik, D. (2006), 'Goodbye washington consensus, hello washington confusion? a review of

- the world bank's economic growth in the 1990s: learning from a decade of reform', *Journal of Economic literature* **44**(4), 973–987.
- Sadorsky, P. (1999), 'Oil price shocks and stock market activity', *Energy economics* **21**(5), 449–469.
- Scott, A., Darko, E., Lemma, A. & Rud, J.-P. (2014), 'How does electricity insecurity affect businesses in low and middle income countries', *Shaping policy for development* pp. 1–80.
- Shi, X. & Sun, S. (2017), 'Energy price, regulatory price distortion and economic growth: a case study of china', *Energy Economics* **63**, 261–271.
- St-Pierre, J., Julien, P.-A. & Morin, M. (2010), 'L'effet de l'âge et de la taille sur la performance financière et économique des pme', *Journal of Small Business & Entrepreneurship* **23**(2), 287–306.
- Syverson, C. (2011), 'What determines productivity?', *Journal of Economic literature* **49**(2), 326–65.
- Tovar, B., Ramos-Real, F. J. & De Almeida, E. F. (2011), 'Firm size and productivity. evidence from the electricity distribution industry in brazil', *Energy Policy* **39**(2), 826–833.
- Wooldridge, J. M. (2010), *Econometric analysis of cross section and panel data*, MIT press.
- Xiao, Z., Gao, J., Wang, Z., Yin, Z. & Xiang, L. (2022), 'Power shortage and firm productivity: Evidence from the world bank enterprise survey', *Energy* **247**, 123479.

Appendices

M Complementary tables

Table M1: Main variables description

Variables	Description	Source
TFPR	TFPR (VAKL model)	World Bank Group, Enterprise Analysis Unit, 2017. "firm-level Productivity Estimates".
Cost	Cost of inputs per unit of sales	–
Sales	Sales per labor cost	–
Capacity	Capacity Utilization (%)	The World Bank Enterprise Surveys (WBES)
R&D	Investmet in R&D	–
Generator	Generator acquisition by the firm	–
Losses	Losses due to Outages (% of annual Sales)	–
Outages	Firm facing Power Outages	–
Obstacles	How Much Of An Obstacle: Electricity To Operations Of This Establishment?	–
Biggest	Power as biggest obstacle	–
Size	Firm's size	–
Age	Firm's longevity	–
Private	Foreign private participation	–
Website	Own website	–
Regulation	Regulatory Quality	Worldwide Governance Indicators - World Bank DataBank
Bank	Bank concentration in %: Assets of three largest commercial banks as a share of total commercial banking assets. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax assets, discontinued operations and other assets.	Bankscope and Orbis Bank Focus, Bureau van Dijk (BvD)
ODA	Net official development assistance (ODA) received in % of GNI:	World Development Indicators DataBank
Inflation	Inflation, consumer prices (annual %)	–
Growth	GDP growth (annual %)	–
Capita	GDP per capita in USD	–
FINDEX	Financial development index	Global Financial Development Database - World Bank
Exports	Direct Exports (% of Sales)	The World Bank Enterprise Surveys (WBES)
Locality	Size Of Locality	–
Government	% Owned By Government/State	–
Other	% Owned By Other	–
Female	Is The Top Manager Female?	–
Certification	Does Establishment Have An Internationally-Recognized Quality Certification?	–
Informal	Percent Of Total Annual Sales Paid In Informal Payments	–
Investment	Did This Establishment Purchase Any Fixed Assets In Last Fiscal Yr?	–
Account	Does This Establishment Have A Checking And-Saving Account?	–
Credit	Establishment Has A Line Of Credit Or Loan From A Financial Institution?	–

Table M2: Robustness tests – The effect of power outages on the firm’s revenue-based TFP by including additional control variables to the baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Power Outages	-0.102*** (0.032)	-0.090*** (0.029)	-0.086** (0.035)	-0.091*** (0.029)	-0.091*** (0.029)	-0.078** (0.035)	-0.091*** (0.029)	-0.087*** (0.031)	-0.095*** (0.029)	-0.087*** (0.028)	-0.090*** (0.029)
Direct Exports (% of Sales)		0.001* (0.001)									
Size Of Locality			-0.068*** (0.023)								
% Owned By Government/State				-0.000 (0.003)							
% Owned By Other					0.002** (0.001)						
Female Top Manager						-0.017 (0.024)					
Recognized Quality Certification							0.007 (0.008)				
Informal Payments (% Of Sales)								0.003 (0.002)			
Purchase of Fixed Assets									-0.048*** (0.012)		
Checking/Saving Account										-0.011 (0.013)	
Line Of Credit Or Loan											0.014 (0.008)
Observations	31403	31402	25217	31403	31403	22999	31397	25342	31402	30448	31401

Notes: Table documents the average treatment effects on the treated obtained by weighted least squares regressions (Entropy Balancing). The dependent variable is the logarithm of the firm-level revenue-based total factor productivity for all regressions (1-11). In each regression, the treatment variable represents power outages dummy variable. Firm-level controls variables are: Firm’s size, Firm’s longevity, Own website, Foreign private participation. Country-level controls variables are: GDP growth (annual %), Inflation (annual %), log(Bank concentration in %), log(FD index), log(GDP per capita), log(Net ODA in % of GNI), log(Regulatory Quality). Each row represents an additional control variable. Each estimate includes Year FE, Country FE, Region FE, Income group FE and a Constant. Standard errors in parentheses are clustered at country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table M3: Summary statistics on revenue-based TFP by outages and over regions

	Mean	Std. dev.	Min	Max	N
No Outages					
AFR	2.76	1.49	-1.47	8.58	1504.00
EAP	2.47	1.46	-1.89	8.11	1535.00
ECA	2.12	1.58	-2.13	8.51	2015.00
LAC	2.41	1.41	-2.44	7.41	4271.00
MNA	2.59	1.51	-2.13	8.45	1553.00
SAR	2.54	1.58	-1.79	7.53	1439.00
Outages					
AFR	2.63	1.44	-1.85	8.04	6210.00
EAP	2.32	1.46	-1.76	8.83	2051.00
ECA	2.22	1.64	-2.52	8.16	1117.00
LAC	2.34	1.46	-3.23	7.54	4849.00
MNA	2.53	1.53	-1.92	7.24	1615.00
SAR	2.50	1.56	-1.86	8.29	3244.00

Table M4: Summary statistics on capacity utilization by outages and over regions

	Mean	Std. dev.	Min	Max	Obs.
No outages					
AFR	73.74	22.80	0.00	100.00	1469.00
EAP	82.31	21.05	0.00	100.00	1498.00
ECA	71.57	24.31	0.00	100.00	1958.00
LAC	72.20	20.70	0.00	100.00	4192.00
MNA	67.99	23.11	1.00	100.00	1487.00
SAR	82.59	16.79	10.00	100.00	1435.00
Outages					
AFR	71.08	20.56	1.00	100.00	6075.00
EAP	79.34	21.17	1.00	100.00	2017.00
ECA	68.95	24.12	1.00	100.00	1088.00
LAC	71.39	20.47	0.00	100.00	4709.00
MNA	71.91	21.38	1.00	100.00	1556.00
SAR	76.79	16.21	2.00	100.00	3227.00

Table M5: Summary statistics on the number of observations by region and over years of survey

Year of survey	Region						Total
	AFR	EAP	ECA	LAC	MNA	SAR	
2006	1,416			3,254			4,670
2007	3,434		204				3,638
2008			303				303
2009	257	1,523	601	686		109	3,176
2010	117			3,945			4,062
2011	27					230	257
2012		28					28
2013	936	57	536		1,910	1,423	4,862
2014	364	179				2,863	3,406
2015	232	630				58	920
2016	227	999		282	761		2,269
2017	72			953			1,025
2018	519	66	237				822
2019	113	104	1,251		497		1,965
Total	7,714	3,586	3,132	9,120	3,168	4,683	31,403

Table M6: Summary statistics on the number of observations by region and by income group

WB income group	Region						Total
	AFR	EAP	ECA	LAC	MNA	SAR	
Low Income	5,381		111			1,356	6,848
Lower Middle Income	1,433	3,098	1,184	2,774	2,399	3,327	14,215
Upper Middle Income	900	488	1,837	6,346	769		10,340
Total	7,714	3,586	3,132	9,120	3,168	4,683	31,403

Table M7: Summary statistics on the number of observations by industry and by region

	Region						Total
	AFR	EAP	ECA	LAC	MNA	SAR	
Industry stratification							
Basic Metals & Metal Products					83	300	383
Basic Metals/Fabricated Metals/Machinery & Equip.	83			398			481
Chemicals & Chemical Products	8	132		588	184	326	1,238
Chemicals, Non-Metallic Mineral, Plastics & Rubber				38			38
Chemicals, Plastics & Rubber	97			367			464
Electronics		63		99			162
Electronics & Communications Equip.		62				209	271
Fabricated Metal Products	68	154	181	183	65	240	891
Food	1,768	413	442	1,726	662	515	5,526
Furniture	116			227	92	81	516
Garments	906	438	227	696	340	266	2,873
Leather Products				75	119	100	294
Machinery & Equipment			165	302		279	746
Machinery & Equipment, Electronics & Vehicles					49		49
Manufacturing	1,524	1,067	1,539	1,111	68	328	5,637
Manufacturing Panel	62						62
Metals, Machinery, Computer & Electronics	57						57
Minerals, Metals, Machinery & Equipment				55			55
Mining Related Manufacturing	15						15
Motor Vehicles				61		188	249
Motor Vehicles & Transport Equip.						29	29
Non-Metallic Mineral Products	68	302	163	229	260	220	1,242
Other Manufacturing	2,367	541	415	995	673	1,094	6,085
Petroleum products, Plastics & Rubber					89		89
Printing & Publishing	50				33		83
Rest of Universe	358			901			1,259
Rubber & Plastics Products		261		128	86	255	730
Textiles	24	153		222	152	253	804
Textiles & Garments	143			719	83		945
Wood Products					57		57
Wood products, Furniture, Paper & Publishing					73		73
Total	7,714	3,586	3,132	9,120	3,168	4,683	31,403

Table M8: Summary statistics on the number of observations by industry and over years of survey

Industry stratification	Year of survey															Total
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019		
Industry stratification																
Basic Metals & Metal Products									300		83					383
Basic Metals/Fabricated Metals/Machinery & Equip.					398			83								481
Chemicals & Chemical Products	396	8		173	118			219	213	33	78					1,238
Chemicals, Non-Metallic Mineral, Plastics & Rubber	38															38
Chemicals, Plastics & Rubber					367			47					50			464
Electronics	99			36							27					162
Electronics & Communications Equip.									209		62					271
Fabricated Metal Products	42	103		65	141			65	264	89					122	891
Food	1,173	910	33	338	607	83		765	320	161	309	200	234	393		5,526
Furniture		70		84	110			194	25		33					516
Garments	656	724	39	322	106	72		474	17	120	120		52	171		2,873
Leather Products				75				162			57					294
Machinery & Equipment	131		47	83	88			22	279						96	746
Machinery & Equipment, Electronics & Vehicles											49					49
Manufacturing		690	163	914	886	27	28	838	241		810	342	119	579		5,637
Manufacturing Panel									62							62
Metals, Machinery, Computer & Electronics														57		57
Minerals, Metals, Machinery & Equipment					55											55
Mining Related Manufacturing								15								15
Motor Vehicles				61					188							249
Motor Vehicles & Transport Equip.								29								29
Non-Metallic Mineral Products	229			223				193	246	113	105				133	1,242
Other Manufacturing	856	736	21	464	615	75		1,309	546	309	138	273	272	471		6,085
Petroleum products, Plastics & Rubber											89					89
Printing & Publishing		39						33	11							83
Rest of Universe	901	358														1,259
Rubber & Plastics Products				112	128			86	255	35	114					730
Textiles	149			226				199	230							804
Textiles & Garments					443			72		33	149	210	38			945
Wood Products								57								57
Wood products, Furniture, Paper & Publishing											73					73
Total	4,670	3,638	303	3,176	4,062	257	28	4,862	3,406	920	2,269	1,025	822	1,965	31,403	

Table M9: Sub-Saharan Africa (AFR) 1

Official Country Name	WB income group			Total
	Low Income	Lower Middle Income	Upper Middle Income	
Angola		206		206
Benin	53			53
Botswana			158	158
Burkina Faso	26			26
Burundi	134			134
Cameroon			120	120
Congo, Dem. Rep.	298			298
Eswatini		64		64
Ethiopia	259			259
Gambia, The	83			83
Ghana	278	186		464
Guinea	5			5
Kenya	600	261		861
Lesotho		39		39
Liberia	66			66
Madagascar	230			230
Mali	350			350
Mauritania	77	13		90
Mauritius			57	57
Mozambique	532			532
Namibia		94	13	107
Niger	6			6
Nigeria	930	216		1,146
Rwanda	171			171
Senegal	250	86		336
South Africa			672	672
Tanzania	362			362
Togo	19			19
Uganda	353			353
Zambia	299	148		447
Total	5,381	1,433	900	7,714

Table M10: Sub-Saharan Africa (AFR) 2

Official Country Name	Year of survey											Total	
	2006	2007	2009	2010	2011	2013	2014	2015	2016	2017	2018		2019
Angola	199			7									206
Benin									53				53
Botswana	110			48									158
Burkina Faso			26										26
Burundi	98						36						134
Cameroon			55						65				120
Congo, Dem. Rep.	143			49		106							298
Eswatini	64												64
Ethiopia					27			232					259
Gambia, The	30									53			83
Ghana		278				186							464
Guinea									5				5
Kenya		387				213					261		861
Lesotho									39				39
Liberia										66			66
Madagascar			119			111							230
Mali		291		13					46				350
Mauritania	77						13						90
Mauritius			57										57
Mozambique		327									205		532
Namibia	94						13						107
Niger										6			6
Nigeria		930						216					1,146
Rwanda	58											113	171
Senegal		250					86						336
South Africa		672											672
Tanzania	254					108							362
Togo									19				19
Uganda	289					64							353
Zambia		299				148							447
Total	1,416	3,434	257	117	27	936	364	232	227	72	519	113	7,714

Table M11: East Asia and Pacific (EAP) 1

Official Country Name	WB income group		Total
	Lower Middle Income	Upper Middle Income	
Cambodia	109		109
Indonesia	529		529
Lao PDR	198		198
Mongolia	283		283
Myanmar	477		477
Philippines	579		579
Thailand		488	488
Vietnam	923		923
Total	3,098	488	3,586

Table M12: East Asia and Pacific (EAP) 2

Official Country Name	Year of survey									Total
	2009	2012	2013	2014	2015	2016	2018	2019		
Cambodia						109				109
Indonesia	529									529
Lao PDR		28				104	66			198
Mongolia	122		57					104		283
Myanmar				179		298				477
Philippines	324				255					579
Thailand						488				488
Vietnam	548				375					923
Total	1,523	28	57	179	630	999	66	104		3,586

Table M13: Europe and Central Asia (ECA) 1

Official Country Name	WB income group			Total
	Low Income	Lower Middle Income	Upper Middle Income	
Albania		25	78	103
Armenia		81		81
Azerbaijan			92	92
Belarus			324	324
Bosnia and Herzegovina			168	168
Croatia			179	179
Georgia		101	94	195
Kazakhstan			555	555
Kyrgyz Republic	54	107		161
Moldova		159		159
North Macedonia			133	133
Serbia			214	214
Tajikistan	57			57
Ukraine		711		711
Total	111	1,184	1,837	3,132

Table M14: Europe and Central Asia (ECA) 2

Official Country Name	Year of survey						Total
	2007	2008	2009	2013	2018	2019	
Albania	25			14		64	103
Armenia			58	23			81
Azerbaijan			70	8		14	92
Belarus		40		47	237		324
Bosnia and Herzegovina			64	60		44	168
Croatia	179						179
Georgia		66		35		94	195
Kazakhstan			102	35		418	555
Kyrgyz Republic			54	25		82	161
Moldova			90	13		56	159
North Macedonia			60	73			133
Serbia			103	55		56	214
Tajikistan		57					57
Ukraine		140		148		423	711
Total	204	303	601	536	237	1,251	3,132

Table M15: Latin America and Caribbean (LAC) 1

Official Country Name	WB income group		Total
	Lower Middle Income	Upper Middle Income	
Bolivia	303		303
Brazil		686	686
Chile		1,024	1,024
Colombia		946	946
Costa Rica		195	195
Dominican Republic		96	96
Ecuador	250	187	437
El Salvador	597		597
Guatemala	484	79	563
Guyana	57		57
Honduras	321		321
Jamaica		80	80
Mexico		1,760	1,760
Nicaragua	321		321
Panama		21	21
Paraguay	201	39	240
Peru	240	792	1,032
St. Lucia		47	47
Suriname		73	73
Uruguay		321	321
Total	2,774	6,346	9,120

Table M16: Latin America and Caribbean (LAC) 2

Official Country Name	Year of survey					Total
	2006	2009	2010	2016	2017	
Bolivia	215		35		53	303
Brazil		686				686
Chile	435		589			1,024
Colombia			540		406	946
Costa Rica			195			195
Dominican Republic			76	20		96
Ecuador	250		88		99	437
El Salvador	310		77	210		597
Guatemala	273		211		79	563
Guyana			57			57
Honduras	196		73	52		321
Jamaica			80			80
Mexico	798		962			1,760
Nicaragua	249		72			321
Panama			21			21
Paraguay	131		70		39	240
Peru	240		515		277	1,032
St. Lucia			47			47
Suriname			73			73
Uruguay	157		164			321
Total	3,254	686	3,945	282	953	9,120

Table M17: Middle East and North Africa (MNA) 1

Official Country Name	WB income group		Total
	Lower Middle Income	Upper Middle Income	
Djibouti		2	2
Egypt, Arab Rep.	2,057		2,057
Jordan			210
Lebanon			330
Morocco	340		340
Tunisia			229
Total	2,399		769

Table M18: Middle East and North Africa (MNA) 2

Official Country Name	Year of survey			
	2013	2016	2019	Total
Djibouti	2			2
Egypt, Arab Rep.	1,296	761		2,057
Jordan	183		27	210
Lebanon	106		224	330
Morocco	94		246	340
Tunisia	229			229
Total	1,910	761	497	3,168

Table M19: South Asia (SAR) 1

Official Country Name	WB income group			Total
	Low Income	Lower Middle Income		
Bangladesh	1,028			1,028
Bhutan			58	58
India			2,863	2,863
Nepal	328			328
Pakistan			176	176
Sri Lanka			230	230
Total	1,356		3,327	4,683

Table M20: South Asia (SAR) 2

Official Country Name	Year of survey					Total
	2009	2011	2013	2014	2015	
Bangladesh			1,028			1,028
Bhutan					58	58
India				2,863		2,863
Nepal	109		219			328
Pakistan			176			176
Sri Lanka		230				230
Total	109	230	1,423	2,863	58	4,683

General conclusion

This thesis has documented the complex interplay between electrification, environment, and economic development in the context of Côte d'Ivoire, other African countries and other developing countries. Its four chapters explored the impacts of electrification on arable farm expansion, firewood collection, and overall deforestation rates. It also explored the potential effect of external shocks such as currency and inflation crises on private investment in the power generation sector and identified the mitigation effects of some specific regulatory measures such as automatic tariff adjustment and cost reflectivity. Finally, it documented the detrimental effects that power sector constraints might have on firm-level productivity or performance. These findings provide valuable insights into the challenges and opportunities that electrification presents, both for economic growth and environmental sustainability. In this concluding chapter, we synthesize the key findings, identify policy implications, and open up some promising research avenues that should further enrich our understanding of critical development issues and guide future investigations.

Chapter 1 demonstrated that electrification has a significant effect on reducing average arable farms size and biomass fuel consumption in Côte d'Ivoire. We examined this question at the household level by looking at the percentage of households involved in firewood collection and the size of their arable farms. To address any possible endogeneity issues, we used a pseudo-panel fixed effects regression model and various alternative specifications (inclusion of time FE; inclusion of time trends; inclusion of cocoa price trends; probit model; entropy balancing; IPW regression adjustment; nearest-neighbor matching; propensity-score matching). The estimates are based on a sample of 138 cohorts of households for the years 1998, 2002, 2008 and 2015. Our

results suggest that electricity access can contribute to forest loss mitigation by reducing arable farm size and firewood collection. However, the identified electrification threshold effect of 80% on arable farm size emphasizes the need for careful planning and targeted policies to ensure that electrification does not inadvertently lead to further forest loss in the country.

This chapter underlines the importance of expanding electricity access in rural areas to alleviate the dependence on biomass fuel consumption. By providing electricity to households, particularly in remote areas, governments can reduce the need for firewood and charcoal, curbing deforestation. Therefore, investing in rural electrification programs should be a priority for sustainable forest conservation in tropical countries like Cote d'Ivoire. Additionally, this research also highlights the need for targeted policies that consider the potential impact of electrification on arable farm size. While electrification can reduce the need for expansion of farmland, an electrification threshold of 80% beyond which farm size could increase indicates the necessity of complementary measures. Policymakers should carefully monitor and manage such thresholds, possibly through zoning regulations or incentives for sustainable farming practices, to prevent unintended negative consequences on forest areas in Cote d'Ivoire.

Chapter 2 documented a positive link between electrification and overall or global deforestation rates in Côte d'Ivoire. To document this finding, we first tested the reliability of the night lights intensity data and showed that it is comparable at the regional level to the official data on electricity coverage provided by the Ivorian authorities, and we showed that aggregating the data at regional level might potentially hide the spatial autocorrelation observed at the departmental level (finer aggregation level). Our findings suggest that electrification increases deforestation, as the country pursues ambitious electrification programs, deforestation continues to expand. This finding calls for a more comprehensive approach to electrification that considers environmental conservation alongside economic development.

Our findings emphasize the importance of a balanced approach to expanding electricity access while ensuring environmental conservation. Governments should integrate forest conservation considerations into their electrification programs. This could involve measures such as promoting energy-efficient technologies, encouraging sustainable land use practices, and incorporating reforestation and afforestation efforts into electrification projects.

Chapter 3 provided insights into the challenges faced by private stakeholders in the power sector in African countries. We first combined an impact assessment (AIPW) proposed by [Lunceford & Davidian \(2004\)](#) and local projections (LP) à la [Jordà \(2005\)](#) to capture the effect of inflation and currency crises on change in available total installed capacity according to the characteristics of the electricity sectors on the African continent (existence of an independent regulatory agency, application of standard norms in terms of tariffs). Our findings highlight the negative effects of currency and inflation crises on private investment. Indeed, currency and inflation risks pose significant obstacles to private investment in power generation in Africa. Meanwhile, the identified measures, such as automatic tariff adjustment and cost reflectivity, have the potential to mitigate these risks and encourage private sector involvement, ultimately enhancing universal access to electricity. Our findings are also robust to the new Difference-in-Differences Estimators of Intertemporal Treatment Effects proposed in [De Chaisemartin & d'Haultfoeuille \(2022\)](#).

The policy implications of this chapter revolve around fostering a conducive environment for private investments in the power sector, especially in the face of financial constraints and inflation or currency crises. Establishing and empowering independent regulatory bodies is crucial to providing stability and predictability for private investors. Additionally, implementing automatic tariff adjustment mechanisms and promoting cost reflectivity can help mitigate the negative effects of currency and inflation shocks on private investments in power generation in Africa. Furthermore, policymakers should also consider targeted financial incentives or support mechanisms to help private stakeholders manage the risks associated with currency fluctuations or inflationary shocks. Strengthening local capital markets, enhancing access to long-term financing, and promoting collaboration with international financial institutions (such as the International Finance Corporation) could help alleviate the financial constraints faced by private investors in the power generation segment.

Chapter 4 demonstrated the detrimental impact of power constraints on firm-level total factor productivity in developing countries. Our approach, based on Entropy Balancing to address potential endogeneity concerns, shows that the overall effect of power outages on revenue-based total factor productivity (TFPR) is negative and statistically significant as we observed a 9% lower unconditional average productivity for exposed firms compared to non-exposed firms. Moreover, we establish a robust link between the severity of firms' self-reported power constraints or obsta-

cles and the magnitude of those firms' productivity losses. In other words, the higher the level of power constraints self-reported by a firm, the greater the effect of these constraints on its productivity, and vice versa. Ensuring a stable power supply is crucial for fostering economic growth and competitiveness, especially for manufacturing firms in developing countries.

The implications of this chapter are that a multi-faceted approach is required to address power constraints and enhance firms' productivity. Policymakers should prioritize investments in reliable and stable power infrastructure to minimize power outages and voltage fluctuations. This could involve upgrading transmission and distribution systems, investing in alternative energy sources, and improving maintenance and grid management. Alternatively, the findings suggest that supporting firms' adoption of backup power solutions, such as generators, can act as a buffer against power constraints. Policymakers could facilitate access to finance or provide incentives for firms to invest in backup power systems. Additionally, promoting research and development (R&D) initiatives within firms can enhance their resilience to power challenges and drive technological innovation.

To sum up, our research carries valuable policy implications that can guide decision-makers and stakeholders in shaping effective strategies for sustainable development in developing countries. The findings and insights from each chapter offer recommendations to address key challenges related to electricity access, environmental conservation, and economic development.

Finally, the insights and findings presented in this thesis open up several promising research avenues that could further enrich our understanding of critical development issues and guide future investigations. These research avenues emerge from the gaps, questions, and complexities highlighted in the dissertation, offering opportunities for deeper exploration and broader impact.

First, our thesis lays the foundation for further research into the intersection of electrification and environmental conservation. One avenue of exploration could be to conduct similar studies in other developing countries with high deforestation rates. By comparing the effects of electrification on forest loss in different contexts, researchers could identify common patterns and factors that influence the relationship. Additionally, a comprehensive assessment of the social and economic impacts of rural electrification programs could shed light on the broader benefits beyond environmental conservation. Understanding how improved electricity access affects education,

healthcare, and overall livelihoods in rural communities would provide a more holistic perspective on the outcomes of such initiatives.

Second, building upon the insights of this thesis, future research could document the potential synergies between electrification and sustainable land use. Investigating how electrification programs can be designed to support agro-forestry initiatives or encourage environmentally-friendly agricultural practices could provide practical strategies for minimizing forest loss while enhancing electricity access. Additionally, exploring the role of renewable energy sources, such as solar and wind power, in electrification efforts could offer insights into environmentally-friendly energy solutions. Research could assess the feasibility and impact of integrating these renewable sources into electrification projects to achieve dual objectives of energy access and environmental conservation.

Furthermore, our findings pave the way for more nuanced investigations into the role of regulatory mechanisms in promoting private investments in various sectors. Researchers could examine the effectiveness of specific regulatory measures, such as automatic tariff adjustments and cost reflectivity, in mitigating the adverse effects of economic crises on different industries. Additionally, comparative studies across regions and countries could reveal variations in the impact of regulation on private sector engagement. Exploring how different regulatory approaches interact with local economic and institutional contexts would offer insights into tailoring regulatory strategies to optimize private investment in specific contexts.

Additionally, this study initiates a valuable research avenue in understanding the mechanisms through which power constraints influence firms' performance. Further investigation could focus on the adoption and utilization of backup power solutions, examining factors that drive firms to invest in these alternatives and their subsequent impact on productivity and competitiveness. Furthermore, exploring the dynamic relationship between power constraints and innovation within firms could yield insights into the role of technological adaptation in mitigating the challenges posed by unreliable power supplies. Researchers could investigate how firms' R&D efforts are influenced by power constraints and how innovation contributes to overall resilience.

In conclusion, the research avenues emerging from this thesis offer exciting opportunities for scholars and policymakers to deepen overall understanding of critical development challenges

and to design evidence-based strategies that drive positive change. By addressing these research avenues, future studies can contribute to more effective and targeted interventions that promote sustainable development in developing countries.

Bibliography

De Chaisemartin, C. & d'Haultfoeuille, X. (2022), Difference-in-differences estimators of intertemporal treatment effects, Technical report, National Bureau of Economic Research.

Jordà, Ò. (2005), 'Estimation and inference of impulse responses by local projections', *American economic review* **95**(1), 161–182.

Lunceford, J. K. & Davidian, M. (2004), 'Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study', *Statistics in medicine* **23**(19), 2937–2960.

RÉSUMÉ

Cette thèse examine la relation entre l'électrification, la déforestation et le développement économique dans les pays en développement, en particulier en Côte d'Ivoire et dans d'autres pays africains. Elle explore les impacts de l'électrification sur la soutenabilité environnementale et la croissance économique, fournissant des indications politiques pour la promotion du développement durable. La recherche met en évidence l'impact positif potentiel de l'électrification sur l'atténuation de la déforestation, tout en soulignant la nécessité d'une planification minutieuse pour éviter les conséquences imprévues. Elle aborde également les défis du secteur de l'électricité et souligne l'importance d'une offre d'électricité stable pour la productivité économique. La thèse se termine par des implications politiques qui guident les décideurs dans la promotion d'un équilibre harmonieux entre le progrès et la préservation de l'environnement dans les efforts d'électrification.

MOTS CLÉS

Electrification, Environnement, Développement économique, Pays en développement, Afrique, Côte d'Ivoire

ABSTRACT

This thesis examines the relationship between electrification, deforestation, and economic development in developing countries, with a focus on Côte d'Ivoire and other African nations. It explores the impacts of electrification on environmental sustainability and economic growth, providing policy insights for promoting sustainable development. The research highlights the potential positive impact of electrification on deforestation mitigation while emphasizing the need for careful planning to avoid unintended consequences. It also addresses challenges in the power sector and emphasizes the importance of a stable power supply for economic productivity. The thesis concludes with policy implications that guide decision-makers in fostering a harmonious balance between progress and environmental conservation in electrification efforts.

KEYWORDS

Electrification, Environment, Economic development, Developing countries, Africa, Côte d'Ivoire

